BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Thesis Master of Science
Final master thesis – Counts 80% of total grade

The effects of the implementation of MiFID on stock liquidity

Navn:	Mina Randjelovic, Ingrid Kristine Ueland Revheim

Start:	02.03.2018 09.00
Finish:	03.09.2018 12.00

Mina Randjelovic
Ingrid Kristine Ueland Revheim

Master Thesis

GRA 19502

THE EFFECTS OF THE IMPLEMENTATION OF MIFID ON STOCK LIQUIDITY

Submission date:
14.08.2018

Supervisor:

Siv Jønland Staubo

BI Norwegian Business School, Oslo
Master of Science in Business with Major in Finance

Acknowledgements

We would like to express our gratitude to our supervisor Siv Jønland Staubo, who challenged and inspired us during the writing of this thesis. Her guidance and knowledge has been a valuable resource throughout the process.

We would also like to thank the Oslo Stock Exchange for providing us with the data necessary for us to conduct our research.

Last but not least, we would like to thank Magnus Nybø for revising and proofreading our analysis.

Abstract

The purpose of this thesis is to investigate the effect of the Markets in Financial Instruments Directive (MiFID) on stock liquidity for the Norwegian equity market. Our objective is to find out whether the implementation of MiFID has had an effect on stock liquidity, and if it has, we seek to research whether this effect has been positive (increased liquidity) or negative (decreased liquidity). MiFID abolished the "concentration rule" and allowed for trading on alternative trading venues, introducing market fragmentation in the Norwegian equity market. Our research focuses on the OBX index, which includes the 25 most liquid stocks on the Oslo Stock Exchange, in the period of 2006 - 2017. We employ the methodology presented by Gresse (2011) where we utilize the panel regression method to study the effects of competition and market fragmentation on stock liquidity as measured by the bid – ask spread. In the regression we include trading volume, stock price and return volatility as control variables, and use binary time variables to study the effects of different levels of market fragmentation on liquidity. We find that there is a significant effect of MiFID on stock liquidity. Our results show a positive effect on stock liquidity following the introduction of MiFID, as demonstrated by a decrease in bid-ask spreads.

Keywords:
MiFID, liquidity, OBX index, bid-ask spread, Oslo Stock Exchange, market fragmentation, alternative trading venues, market competition.

Table of contents

1. Introduction ………………………………………………………….. **6**
1.1. Markets in Financial Instruments Directive (MiFID) …………... ..…6
1.2. MTF …………………………………………………………….…7
1.3. Dark Pools ………………………………………………………...8
1.4. High Frequency Trading ……………………………….........8
1.5. Market fragmentation ……………………………………….…..9
1.6. Market fragmentation and liquidity ………………………….....9
1.7. Contribution to current research ………………………….….…11

2. Literature review …………………………………………………**12**

3. Theory ………………………………………………….……..**14**

4. **Methodology** ……………………………………………........**17**
4.1. Measure of liquidity ……………………………………...…17
4.2. Approach ……………………………………………........17
4.3. Interpretation ………………………………………………..18
4.4. Justification of explanatory variables ………………….......18
4.4.1. *Volume* …………………………………………….…19
4.4.2. *Return volatility* ……………………………………..19
4.4.3. *Stock Price* ………………………………………......19
4.5. Data ………………………………………………….…...20

5. Data ………………………………………………………….…..**20**
5.1. Data collection …………………………………………….....21
5.2. Data trimming ……………………………...…………......22
5.2.1. *Bid-ask spread outliers* …………………...………........22
5.2.2. *Large changes in closing prices* …………...…….……..23
5.3. Descriptive statistics of daily data ……………….…….……. 24
5.4. Defining variables ……………………………….………... 28
5.4.1. *Defining and calculating return volatility*………….………. 29
5.4.2. *Converting to monthly data* ……………………....…… 30
5.5. The financial crisis of 2008 ………………………..….... 33

5.6. Stationarity ………………………………………………………… 34
5.7. Multicollinearity …………………………………………………… 34

6. Results and analysis……………………………………………….… **36**
6.1. Defining the panel regression ……………………………………… 36
6.2. Regression results …………………………………………….….... 37
6.3. Robustness………. ………………………………………………… 40
6.4. Alternative arguments……………………………………………… 42
6.4.1. *Arguments highlighting market maker behaviour*………....... 42
6.4.2. Emergence of a dominant market…………………………… 43

7. Conclusion ……………………………………………………………… **44**

8. Bibliography ………………………………………………………… **47**

9. Appendices ……………………………………………………….... **53**
9.1. Appendix 1: Overview of companies included in the OBX index …. 53
9.2. Appendix 2: Overview of name changes / Mergers & Acquisitions ...56
9.3. Appendix 3: Bid-ask spread outliers …………………………………57
9.4. Appendix 4: Company events ………………………………………. 58
9.5. Appendix 5: Ten largest brokers present on Oslo Stock Exchange based on percentage turnover ………………………………………. 59
9.6. Appendix 6: Market fragmentation on the Oslo Stock Exchange ….. 60

1. Introduction

This master thesis seeks to investigate the effects of the Markets in Financial Instruments Directive (MiFID) on the stock liquidity in the Norwegian equity market. The directive, which was implemented in November 2007, allowed for trading on alternative cross-border trading venues, such as multilateral trading facilities (MTF), in addition to the regulated stock exchanges. This directive therefore facilitated market fragmentation, by allowing alternative trading platforms to compete with the primary exchange. This paper seeks to investigate if and how market fragmentation in the Norwegian equity market has affected the stock liquidity of the stocks included in the OBX index on the Oslo Stock Exchange. By utilizing the methodology presented by Gresse (2011), we find that market fragmentation has had a significant effect on stock liquidity and that the liquidity, measured by the bid-ask spread, on the Oslo Stock Exchange improved following the introduction of MiFID.

1.1 Markets in Financial Instruments Directive (MiFID)

The Markets of Financial Instruments Directive (MiFID) replaced the Investment Services Directive (ISD) which was adopted in 1993, and set out a regulatory regime with the goal of improving the organisation of investment firms, facilitating cross border trading, increasing transparency, and ensuring strong investor protection. MiFID eliminated the "concentration rule" implemented with the ISD, which implied that countries affected could no longer require investment firms to direct orders only to regulated stock exchanges (European Commission, 2007). According to the European Commission, MiFID was needed to replace the ISD as the concentration rule signified an impediment for competitive trading, as well as to attract foreign investors to the European capital markets through stronger investor protection. Stronger investor protection also implies that when executing client orders, investment firms are required to ensure the "best execution" on behalf of their customers (European Commission, 2007).

The Norwegian Ministry of Finance was obliged by the EEA law and regulations to implement the MiFID regulation into the Norwegian “Verdipapirloven” (Norges Offentlige utredninger 2006:3, 2006).

A timeline of the implementation of MiFID in Norway is presented in the table below.

Table 1: The MiFID timeline

Year	2004	2005	29/06/2007	01/11/2007
	MiFID is adopted by the European Council and the European Parliament	MiFID regulation is implemented in the EEA Agreement	The revised MiFID compliant “Verdipapirloven” is announced by the Norwegian Ministry of Finance	MiFID regulation comes to effect in Norway.

Table 1 shows the timeline of the implementation of MiFID in the Norwegian market from it was adopted by the European Parliament in 2004 until it was in effect in Norway November 1st 2007.
Source: Norges Offentlige utredninger 2006:3 (2006)

1.2 MTF

Before the introduction of MiFID, all orders for Norwegian stocks, including block trades, were routed directly to the Oslo Stock Exchange. This implied a simpler overview of the order book and trades involving Norwegian stocks. The introduction of trading in Norwegian stocks on alternative trading venues implied that each multilateral trading facility created its own order book, which complicated the overview of all executed trades. A MTF must be both pre-trade and post-trade transparent, meaning that all orders must be visible through an order book and that the MTF must provide a real-time overview of trade executions. A MTF offers trading in stocks, but cannot list new stocks itself, implying that for the Norwegian equity market, the Oslo Stock Exchange will determine which companies fulfil the necessary requirements to have their stock listed on the exchange (Pareto Securities, 2017). Making trading on alternative trading venues available is an important incentive in order to increase competition, decrease trading related costs, and increase market efficiency (Haas, 2007). The multilateral trading facilities where Norwegian stocks can be traded are among others Cboe CXE, Cboe BXE, Turquoise, Nasdaq OMX and Aquis.

1.3 Dark Pools

In addition to multilateral trading facilities, dark pools are another type of alternative trading venues. Dark pools are trading venues without pre-trade transparency, where traders are allowed to trade large volumes anonymously. Dark pool trading increased after the implementation of MiFID, as order information in dark pools is not revealed until after the trade execution (Petrescu and Wedow, 2017). In dark pools, orders are usually executed at the mid-spread and the mid-spread is normally calculated using the bid-ask spread from the Oslo Stock Exchange. Trading in dark pools is mostly done by institutional investors seeking to execute large, anonymous trades as a way of avoiding impacting the market (Pareto Securities, 2017). Another possible reason for an increase in dark pool trading was the need for protection of high frequency trading (HTF). According to Harris (2013) the best way to protect HFT-traders is to reduce trade information.

1.4 High Frequency Trading

High frequency trading (HFT) is a subset of algorithmic trading and is a result of technology improvement over the last decade. Using HFT, investors receive high-speed price information from trading venues making them able to execute a high number of trades to the best possible price (Gomber, Arndt, Lutat, and Uhle, 2015). One possible effect of high frequency trading is improved liquidity, as one common HTF strategy is to act as a liquidity provider (Gomber, Arndt, Lutat, and Uhle, 2015). MiFID opened up for trading in different trading venues, and at the same time there was an increase in technological development in the order-execution process. This increased competition between trading venues led to a decrease in fees, while technology development led to a decrease in trade sizes on the major stock exchanges. All this cultivated the rise of HTF (Chlistalla, Speyer, Kaiser and Mayer, 2011). Although HFT may have had a positive impact on stock liquidity, its impact on liquidity falls beyond the scope of this master thesis.

1.5 Market fragmentation

The market fragmentation that took place in light of the increased competition created by the MTF's and dark pools has been evident in the years after the introduction of MiFID. According to the Fidessa Fragmentation Index, which seeks to create an unbiased measure of stock fragmentation across primary markets and alternative venues, approximately 50% of the turnover in the stocks included in the OBX index are traded on alternative venues rather than on the lit Oslo Stock Exchange. The OBX index includes the 25 most liquid stocks on the Oslo Stock Exchange. Table 2 illustrates the market fragmentation categorizing the percentage turnover on the lit (Oslo Stock Exchange and MTF's) and dark (dark pools) markets for the years 2008, 2012, 2016 and 2017.

Table 2: Market fragmentation by percentage turnover

	2008	**2012**	**2016**	**2017**
Oslo Stock Exchange	98,85	67,30	48,49	49,44
Cboe CXE	0,72	16,83	15,67	17,50
Cboe BXE	0,00	6,54	6,90	7,17
Turquoise	0,04	4,41	13,67	6,93
Nasdaq OMX	0,00	1,69	1,61	0,36
Aquis	0,00	0,00	1,67	4,06
Other*	0,00	0,26	0,00	0,01
% Oslo Stock Exchange and MTF	99,61	97,03	88,01	85,47
% Dark Pools	0,39	2,97	11,99	14,53
Total	100	100	100	100

* Including DNSE, North Sea, ONSE, MNSE, Burgundy, NYSE Arca.

Table 2 illustrates the market fragmentation by the percentage turnover in the lit and dark markets offering trading in Norwegian equity, including the Oslo Stock Exchange and different MTFs. Table 2 illustrates how market fragmentation in the Norwegian equity market has increased since the introduction of MiFID in November 2007, as demonstrated by a decrease in the percentage turnover on the Oslo Stock Exchange.

Source: Fidessa Fragmentation Index (2018).

1.6 Market fragmentation and liquidity

The shift from consolidated markets (pre-MiFID) to fragmented markets (post-MiFID) poses a question regarding the effect of order flow fragmentation on stock liquidity on the Oslo Stock Exchange. This research question is of great importance as high liquidity increases the probability of executing an order at the desired price. High liquidity implies that numerous investors are attempting to buy or sell a certain stock on the exchange, making it easier to locate a counterparty willing to accept one's bid. In essence, an exchange should therefore be concerned with attracting bidders, i.e. increase the liquidity, as this would increase the total turnover on the exchange. We therefore seek to investigate the effect of market fragmentation on the stock liquidity on the Oslo Stock Exchange. In addition, our analysis may serve useful to regulators in other countries where off-exchange trading is prohibited. As market fragmentation on the Norwegian equity market was not present before the introduction of MiFID in 2007, this event creates an exceptional basis for research of the effects of market fragmentation.

To address this research question, this paper will examine the liquidity of the Norwegian stocks included in the OBX index on the Oslo Stock Exchange before and after the introduction of MiFID in November 2007. The objective is to determine whether the introduction of MiFID has had a significant effect on stock liquidity, and to determine whether this effect has been positive or negative. Said liquidity will be measured by the bid-ask spread on the selected stocks. The bid-ask spread measures the difference between the buy and sell price of a given stock, and therefore presents as a natural measure of liquidity: if numerous investors are attempting to buy or sell a given stock, they will try to outbid each other in order to increase their chances of locating a counterparty, and we would therefore expect the bid-ask spread to be low for a highly liquid stock. We use the following terminology when addressing a stock's liquidity and bid-ask spread:

Increased liquidity = a reduction in the bid-ask spread
Reduced liquidity = an increase in the bid-ask spread

Our hypothesis which will be formally tested in this thesis, can be stated as:

H_0 = MiFID has no effect on stock liquidity
H_1= MiFID has an effect on stock liquidity

If our results show that MiFID has an effect on stock liquidity (reject H_0), we will also seek to determine if this effect has been positive (increased liquidity) or negative (reduced liquidity).

An immediate challenge represents itself when considering the financial crisis of 2008. As this event coincides with the observed effects of market fragmentation, it will need to be analysed to determine if it should be isolated, as to separate it from the effects of MiFID on stock liquidity in the Norwegian equity market.

1.7 Contribution to current research

This paper will supplement the current available research on this subject by isolating the effect on the Norwegian equity market. In addition, contrary to earlier research such as Gresse (2011), our analysis is based on a much broader time period, allowing us to research the long-term effects of market fragmentation. Given the size of our data set, we are also able to better determine the effects of our control variables on stock liquidity. Furthermore, we illustrate that although market fragmentation increased dramatically in the first years subsequent to the MiFID implementation, it has since stagnated. By conducting this research ten years after the implementation of the EU-directive, we are able to provide an analysis of the effects of market fragmentation on stock liquidity for very different levels of market fragmentation. In addition, we focus our research on the OBX index, which includes the 25 most liquid stocks on the Oslo Stock Exchange. By doing this, we isolate the effect of market fragmentation on very liquid stocks, avoiding fusing the effect of market fragmentation on illiquid as well as very liquid stocks.

The rest of the thesis will be organized as follows. Chapter 2 consists of a literature review, where we will analyse and assess the research and findings of other articles endeavouring to examine the effects of market fragmentation on stock liquidity. We will discuss the methodological differences of the existing research, and identify possible gaps in the literature. Chapter 3 will present theories related to market fragmentation and stock liquidity, which are the basis for our hypothesis. Chapter 4 will describe the applied methodology and what tests are needed in order to confirm or reject the hypothesis. Chapter 5 consists of a description of our data, while Chapter 6 presents our results and analysis. Chapter 7 concludes.

2. Literature review

In this chapter we seek to determine how market fragmentation has affected the stock liquidity on the Oslo Stock Exchange by using the findings of other articles. The most relevant article for this study is Gresse (2011), which compares global and local liquidity before and after the introduction of MiFID, for a sample of stocks listed on the London Stock Exchange and Euronext. The article seeks to explain how liquidity correlates to market fragmentation and internalization. Gresse (2011) finds that market fragmentation has an effect on stock liquidity and that it improves global and local liquidity, where global liquidity refers to the liquidity in the market as a whole and local liquidity refers to the liquidity of the primary exchange. The study finds that spreads decrease with market competition, which is interpreted as increased liquidity with competition. This article also acknowledges the challenge of the financial crisis of 2008 occurring soon after the introduction of MiFID. Gresse (2011) chooses to study three monthly periods in 2009, avoiding the year 2008 completely. The three monthly periods also denote three different levels of fragmentation. The methodology used consists of two analyses: a panel regression with binary time variables representing different periods subsequent to the MiFID introduction, and a two-stage regression analysis. Gresse (2011) seeks to avoid the effects of the financial crisis by avoiding using periods in the year 2008. However, this method does not guarantee that the effects of the financial crisis on stock liquidity have been isolated: the effects of the financial crisis may extend beyond the year 2008.

O'Hara and Ye (2011) examine through regression analysis how market fragmentation affects market quality in the US equity market, where market quality is measured by effective spreads, realized spreads, and execution speeds. Their findings show that market quality is not harmed by market fragmentation. This study is based on data collected in the period January 2 - June 30 in 2008. As the analysis considers the US equity market, it is important to discuss whether the data has been distorted by abnormal market conditions due to the financial crisis.

If we consider the event of September 29, 2008 where the Dow Jones Industrial Average fell by 778 points in intra-day trading (Bradford, 2011), the data period in this study takes place before this event, and we therefore agree with the authors that abnormal market conditions were not present during the data sample. However, this study chooses to focus on the US equity market which may operate under different levels of market conditions and market fragmentation than the European equity market. In addition, the limitations of O'Hara and Ye (2011) also include the fact that the data used in the article is not categorized by specific trading venues, making it difficult to determine how variation in trading systems can cause variation in execution quality.

Foucault and Menkveld (2008) investigate the effects on Dutch stocks from market competition between the London Stock Exchange and Euronext. Foucault and Menkveld (2008) measure liquidity by depth. Depth is defined as the volume of pending orders on the ask and bid side. The results of this article show that liquidity, as measured by market depth, is affected by market fragmentation, and that it increased when market fragmentation increased. Similarly, Degryse, De Jong, and Van Kervel (2015) investigate the effect of market fragmentation on market depth for large- and mid-cap Dutch stocks. Opposed to the other studies related to this topic, they examine the effects on market fragmentation differentiating between the lit and dark markets. In contrast to the related studies on this topic, Degryse, De Jong, and Van Kervel (2015) find that visible fragmentation (fragmentation in the lit market) improves the liquidity of the combined market, but *lowers* liquidity at the primary exchange. In line with these findings, a 2001 study conducted by the Securities and Exchange Commission, examines the difference between stocks in the US equity market traded on the consolidated NYSE and on the more fragmented Nasdaq market. When stocks switch from Nasdaq to NYSE the order flow becomes more consolidated. Findings show lower effective spreads on NYSE than on Nasdaq (Securities and Exchange Commission, 2001). Bennett and Wei (2006) also study the effects of a switch from Nasdaq to NYSE on market quality. Their results reveal improved market quality after the switch to the more consolidated NYSE.

In conclusion, the literature review shows mixed results when considering the effects of market fragmentation on liquidity. While the reviewed research shows that the introduction of competition has a significant effect on stock liquidity, the research shows that this effect can be both positive and negative. The reviewed studies differ on several levels. First of all, the studies do not solely focus on the European equity market. The US equity market may face different market conditions and therefore have dissimilar effects of market fragmentation on liquidity. Furthermore, the reviewed articles have chosen different measures of liquidity; variables such as effective spreads, but also market depth, are used. In addition, several articles differ between measuring liquidity on the global and local level. The effects of market fragmentation due to MiFID cannot be determined from articles where data collected from the US equity market is considered, as the EU-directive is not implemented in the US. This, along with the fact that the EU and US may face different market conditions, leads us to the conclusion that these studies alone cannot explain the effects of market fragmentation on liquidity on the Oslo Stock Exchange. The studies conducted based on solely EU-data also present several challenges. First of all, the primary exchanges of different countries may face different levels of competition. The market fragmentation and competition may have emerged at different speeds, and the competition faced by the Oslo Stock Exchange and for example Euronext can be very different. More noticeably, the reviewed studies have been conducted several years ago. We wish to include more recent data, spanning over several years, in order to capture the effect of market fragmentation on liquidity for the Oslo Stock Exchange for different levels of fragmentation. In addition, several of the reviewed studies have been conducted in a more immediate post-MiFID period, which happened to coincide with the occurrence of the 2008 financial crisis. By investigating our research question a decade after the introduction of MiFID, we are able to include several different periods which better equips us to research the effects of market fragmentation on liquidity for the Oslo Stock Exchange.

3. Theory

As discussed in the literature review, empirical evidence show mixed results regarding the effects of market fragmentation on stock liquidity. However, the concept of market fragmentation and its implications have also been widely discussed in theoretical literature. In this chapter we seek to present the various theories developed on this subject. These theories will be the basis for the main hypothesis of this master thesis, which will be formally tested in the upcoming chapters.

In his work "Treatise on money", John M. Keynes argued that an asset is liquid "if it is more certainly realizable at short notice without loss" (Keynes, 1930). This argument has been quoted in numerous other works, such as Pagano (1989). His interpretation of Keynes' (1930) argument suggests that the liquidity of an asset is correlated with its volume and price volatility. In the presence of market fragmentation, total trading volume will be divided among different trading venues instead of being concentrated in a single location, arguably reducing the total volume at the exchange. Considering the volume aspect of Keynes (1930) argument, one can argue that fragmentation will reduce the liquidity.

Mendelson (1987) theoretically studied the relationship between market fragmentation, consolidation and market performance. According to the theory presented by Mendelson, market fragmentation can have negative effects on liquidity, as it reduces the benefits of economies of scale. This implies that instead of all orders being directed to one single market place, they will be sent to different venues, and this therefore reduces the probability of executing a trade at each single location. A single location, like a primary exchange, will therefore experience a smaller total number of buyers and sellers of a stock, which makes it more difficult for a single investor to locate a counterparty which is willing to accept his or hers trade. Mendelson's theory includes an argument that fragmented markets will experience a higher volatility in transaction prices, a reduction in the quantity traded, and reductions in general gains from a trade. These findings are related to the argument presented by Keynes (1930), where low liquidity is accompanied by higher volatility and lower volume. To summarize the theoretical argument presented by Mendelson (1987), a market has *network externalities*: it becomes more attractive as the number of traders increase.

The idea behind network externalities is also evident from the theoretical work of Stoll (2003). Along with Mendelson (1987), Stoll argues that the attractiveness of an exchange depends on the number of traders present. This increases the probability of being able to execute a trade at the optimal price. According to Stoll (2003) centralization will also lead to a reduction of the average cost of a trade on the exchange due to economies of scale. Lower costs of trading have a possibility of attracting more traders, and hence, one can argue that the bid-ask spread will be reduced. Stoll (2003) also finds that the introduction of transparency regulations and competition has reduced some of the advantages of market centralization. Increased transparency, stronger investor protection, as well as increased competition, were some of the main reasons for the introduction of MiFID (European Commission, 2007). Stoll (2003) argues that transparency implies traders can find at which price the stock is trading at all venues, making sure they are able to execute their trade at the best possible price. Stoll (2003) therefore claims that the forces of centralization are strong, but are being weakened by technology, transparency and fragmentation. The theoretical work of Stoll (2003) was introduced before the implementation of MiFID, and based on the US regulation SEC. However, it still provides theoretical arguments on how regulations, by introducing transparency and fragmentation, can have an effect on market liquidity. To conclude, Stoll (2003) presents two forces of centralization which we have argued can lead to higher liquidity: on the *supply* side the market reaps economies of scale, and on the *demand* side it generates network externalities.

Based on the theoretical models and implications of market fragmentation on liquidity presented by Keynes (1930), Mendelson (1987) and Stoll (2003), we find that theory supports the notion that competition does have an effect on stock liquidity, and that this effect should be negative (increased bid-ask spread). We therefore predict that MiFID has had an effect on stock liquidity in the Norwegian equity market, and that this effect is negative (reduced liquidity). In the following chapter we describe the chosen methodology which will be used to test our hypothesis of whether the introduction of MiFID has had an effect on stock liquidity, and if this effect has been positive or negative.

4. Methodology

In this chapter, we describe the methodology to be used in order to formally test the hypothesis stated under Chapter 1. This master thesis seeks to follow an approach similar to that of Gresse (2011). Our approach to test the effects of market fragmentation on stock liquidity is similar to the first approach suggested by Gresse (2011): a panel regression with explanatory variables measuring liquidity as well as binary time variables representing different levels of market fragmentation.

4.1 Measure of liquidity

In this master thesis, the liquidity measure to be used will be the quoted bid-ask spread of the stocks traded on the Oslo Stock Exchange. According to Stoll (2003), the bid-ask spread can be used to measure liquidity as well as the cost of trading. An alternate way to quantify liquidity could be to measure how long it would take to trade a specified amount of a stock to a desired price (Lippman and McCall, 1986). However, according to Stoll (2003), these two methods will converge as the bid-ask spread can be interpreted as “the amount paid to someone else to take on the unwanted position and dispose of it optimally.” (Stoll, 2003). We therefore conclude that the bid-ask spread of an asset is an appropriate measure of asset liquidity.

4.2 Approach

The panel regression approach suggested by Gresse (2011) involves measuring both global and local liquidity by using three different liquidity measures: quoted spreads, effective spreads and market depth. Due to considerations of availability of data, this master thesis will focus on local quoted spreads as a measure of liquidity. The approach suggests three explanatory variables to be used in the panel regression: standard deviation of daily closing returns of each stock (return volatility), the trading volume of each stock, and the inverse of the average primary market’s closing price of each stock. In addition, Gresse (2011) includes three dummy variables representing three different monthly time periods, which depict different levels of fragmentation. We follow this panel regression approach by using the same explanatory variables, as well as including binary time variables for different levels of market fragmentation. How many binary variables will be included, and which periods they will represent, will be decided after further examination of the data. The approach therefore seeks to investigate the effects of market fragmentation on liquidity, as measured by the bid-ask spread, for several different periods where the market fragmentation was at different levels.

4.3 Interpretation

In order to interpret if (and how) market fragmentation has had an effect on the local liquidity, we turn to the coefficients of the dummy variables. Each dummy variable represents a different time period. In Gresse (2011) for example, they represented different monthly periods. A dummy variable representing January 2009, would take on the value 1 if the period is January 2009, and 0 otherwise. By running the regression, we can observe the coefficients of the dummy variables. A negative, significant coefficient of for example -0.001 for one of the dummy variables would indicate that in that given month (which represents a certain level of fragmentation), the bid-ask spread is lower and therefore, the liquidity is improved. Similarly, a positive, significant coefficient would therefore imply that the bid-ask spread is higher, and that the liquidity deteriorated. In our analysis, we seek to investigate if the coefficients of the time dummies (which represent different levels of market fragmentation) are significantly different from zero and whether their signs are positive (an increase in the bid-ask spread) or negative (a decrease in the bid-ask spread). This tells us whether the liquidity improved or deteriorated with different levels of market fragmentation. We can reject H_0 if our results show that there is a significant effect of market fragmentation on stock liquidity.

4.4 Justification of explanatory variables

The explanatory variables we will use in our panel regression are those proposed by Gresse (2011), as these variables have been proposed and used by numerous empirical studies seeking to investigate the determinants of bid-ask spreads. This subsection seeks to explain in what way we believe the three explanatory variables affect the bid-ask spread.

4.4.1 Volume

The trading volume represents the number of stocks traded on a daily basis. As discussed under Chapter 3, one of the determinants of liquidity would be volume, as a high volume implies that the market is able to absorb a sale without adverse price changes. Therefore, volume relates to availability of a stock in the market. It has been argued that the higher the trading volume of a stock, the easier it is to execute an immediate exchange (Benston and Hagerman, 1974). On the basis of empirical and theoretical research, we believe that trade volume is an important determinant of the bid-ask spread, as a stock with a higher trade volume should have a smaller bid-ask spread than a stock which is traded less frequently (Bollen, Smith and Whaley, 2004). Using the bid-ask spread as the dependent variable, we expect the coefficient of the explanatory variable representing trading volume to be negative.

4.4.2 Return volatility

The return volatility is another variable which we believe has an effect on the bid-ask spread. Return volatility is the measure of the return dispersion for a stock. When a stock has a high volume and is being frequently traded, the risk of the stock is lower than for stocks which are less frequently traded. Volatility of a stock usually increases when there is a decline in the market or there is high uncertainty in the change in the stock's price. When a stock has a low volatility, it implies that the price of the stock will not fluctuate dramatically, but will change steadily over time. A stock with a higher volatility will have a wider bid-ask spread since investors will be less willing to pay a high price for the stock. Spreads will increase because dealers are risk averse (Harris, 1994). We therefore expect that in our regression, the coefficient of the explanatory variable representing return volatility will be positive.

4.4.3 Stock price

The third explanatory variable to be included in our analysis is the stock price. Why the stock price is included as a determinant of the bid-ask spread is related to *inventory-holding costs* (Bollen, Smith and Whaley, 2004). These are costs which a market maker has. A market maker supplies a market with liquidity by quoting bid and ask prices. Therefore, he acquires a position in a stock when an investor chooses to accept his bid or ask price. The inventory-holding costs of a market maker consist of the opportunity cost of funds tied up in holding an asset, and the risk that this asset will experience unfavourable price changes (Bollen, Smith and Whaley, 2004). According to Demsetz (1968), stock price is a proxy for the opportunity cost of funds. The bid-ask spread of a stock will increase when the stock price increases, in order to equalize the cost of transacting (Bollen, Smith and Whaley, 2004). As we will be utilizing the same methodology as presented in Gresse (2011), the explanatory variable representing the stock price will be the inverse of the stock's closing price. Because we are using the inverse closing price, we expect the coefficient of this variable to be negative in our regression.

4.5 Data

The required data for this analysis encompasses daily closing prices, traded volume, and the difference between the bid and ask prices from the Oslo Stock Exchange. In our analysis, we choose to focus on the stocks included in the OBX index. The OBX index includes, as stated in the introduction, the 25 most liquid stocks traded on the Oslo Stock Exchange (Oslo Stock Exchange, 2018a). The reason behind this selection is to be able to avoid fusing the effect of market fragmentation on very liquid, and less liquid, stocks. We therefore wish to include only the most liquid stocks traded on the Oslo Stock Exchange.

5. Data

The data has been obtained for the time period January 2nd 2006 to December 29th 2017. Appendix 1 illustrates the composition of stocks in the OBX index for the years 2006 – 2017, provided by the Oslo Stock Exchange. As evident, the composition of stocks is not identical year to year as the composition of the OBX index is reviewed every six months and based on the most liquid stocks in the reviewed period. As our research is not firm specific, but index specific, we only obtain the needed information for each firm on the OBX index only for the time the firm has been a part of the index. Appendix 1 also includes firms that have been a part of the OBX index for multiple time periods, but that have experienced a change in company name and/or mergers and acquisitions. An overview of these companies and their history of name changes has been provided in Appendix 2. The collected data includes company name, daily closing prices, daily traded volume, and daily bid and ask prices on the Oslo Stock Exchange for each firm's stock. This data is the basis for the dependent and independent variables which we will use in our panel regression. The daily closing price equals the last traded price of each firm's stock. We therefore use the term "last price" or "closing price" when referencing to the end-of-day closing price of a firm. Chapter 5 of this thesis begins with a description of the data collection and the data trimming process, before moving on to a description of the daily bid prices, ask prices, spread, traded volume and last price data. We continue by defining the dependent and independent variables, as described in Chapter 4 and utilized by Gresse (2011), which will be the basis of our panel regression. Chapter 5 concludes with descriptive statistics of the variables for our regression.

5.1 Data collection

The above-mentioned data was originally provided by the Oslo Stock Exchange. However, upon closer examination of the provided data, missing values were discovered. The missing data was replaced with data retrieved from Bloomberg, as the data available on Bloomberg was originally retrieved from the Oslo Stock Exchange. In order to verify that these two data sources provided the same information, we compared the data provided by the Oslo Stock Exchange with the data retrieved from Bloomberg for time periods where data was available from both sources. This confirmed that the two data sources provided the same values.

In addition, we discovered values in our data set provided by the Oslo Stock Exchange that appeared to have been recorded, collected or downloaded incorrectly. For instance, the bid and ask prices for the DNB stock showed identical values for all time periods before the year 2015. This resulted in our liquidity measure, the difference between the bid and ask price, being equal to zero for the entire period. It was therefore necessary to investigate whether this was due to an error in data collection, as the bid-ask spread was consistent and equal to zero across multiple time periods. We isolated the part of the data set that appeared to be biased and retrieved data from Bloomberg for the same time periods. This investigation showed that the Bloomberg and Oslo Stock Exchange values were identical for the period where we did not suspect any collection errors, but were not equal during the periods where we did suspect collection errors. Therefore, the Oslo Stock Exchange data for these periods were replaced with data collected by Bloomberg.

5.2 Data trimming

In this section, we describe the data trimming process. The exclusion of extreme observations is essential in this study, as we eventually convert our data from daily to monthly observations by creating monthly averages. It is therefore very important to exclude extreme observations as to not distort the monthly averages, which serve as the basis for the dependent and independent variables in our panel regression. In order to obtain a correct inference of our study, we implemented the following changes to the final data set.

5.2.1 Bid-ask spread outliers

Appendix 3 illustrates the values for the 5^{th}, 25^{th}, 50^{th}, 75^{th} and 95^{th} percentiles of our data set, which also illustrates the minimum and maximum values of the variables included in the data set. It is evident from Appendix 3 that our data set includes outliers, which should be eliminated from the data set. For example, the minimum value for the bid-ask spread is -138.9 NOK and the maximum value is 124.3 NOK. A negative spread should not technically be observed as this represents an arbitrage opportunity that would have been traded away by the end of the trading day, ultimately resulting in a positive spread. We trimmed our dataset with respect to the bid-ask spread, as to only include values between the 5^{th} and 95^{th} percentile. By doing this, we eliminate extreme values from our data set, in addition to negative spreads and spreads equal to zero. Table 3 illustrates our data set subsequent to the data trimming.

Table 3: Observation values subsequent to the data trimming

Variable	**Min**	**p5**	**p25**	**p50**	**p75**	**p95**	**Max**
Spread	0.01	0.01842	0.070	0.10323	0.252	0.800	2
Closing Price	0.650	14.690	46.250	85.550	150	309.100	3417.223
Bid	0.650	14.678	46.210	85.485	149.8819	309.000	3417.223
Ask	0.660	14.730	46.300	85.65	150.1313	309.500	3418.590
Volume	1575	121993	482565	1470050	3430068	1.39e+07	2.82e+09

Table 3 illustrates the data set subsequent to the data trimming. After the trimming process, the data set is reduced from 71 620 observations to 64 593 observations across 50 firms. The data set is trimmed with respect to the bid-ask spread as to only include values between the 5^{th} and 95^{th} percentile in Appendix 3. This table illustrates values for the 5^{th}, 25^{th}, 50^{th}, 75^{th} and 95^{th} percentiles of our data set, as well as the minimum and maximum values, after the trimming process.

We see that after the trimming, the minimum bid-ask spread is 0.01 NOK and the maximum bid-ask spread is 2.00 NOK.

5.2.2 Large changes in closing prices

We further investigated whether the companies included in our data set have experienced abnormal and sudden changes in their end-of-day closing prices and the cause of these changes. The rationale behind this investigation is to determine if any of the companies have been subject to a corporate action event such as a stock split, a reversed stock split, or been subject to a merger within the observed time periods, or if the large price changes are a result of poor financial performance and subpar future prospects. A company that decides to undergo a stock split or reversed stock split increases (decreases) its current number of outstanding shares by a certain factor, and by doing so, reduces (increases) the stock price. Therefore, if a certain company did undergo a corporate action event that suddenly reduced or increased its stock price, the stock price could be multiplied with an adjustment factor in order to bring the stock price back to its original level. In addition to the fact that the stock price is an explanatory variable. it is important to investigate the cause behind large price changes, as they provide the basis for the return volatility, which is also an explanatory variable in our panel regression. We wish to avoid artificially inflated return volatilities that are a result of corporate actions.

Our investigation shows that seven firms experienced abnormal and sudden changes in their end-of-day closing prices, but that none of these were a result of a corporate action event. Therefore, the stock prices could not be adjusted and brought back to their original levels. Appendix 4 provides an overview of which companies experienced large price drops and the events that lead to these large price reductions.

In addition, we choose to not make any adjustments for stock dividends paid by the companies in the OBX index over the given period. Usually, when a company pays dividends, its stock price decreases on the ex dividend date (Bali and Hite, 1998). However, this does not represent a permanent decrease in the stock price as the market adjusts itself over time. We therefore believe that it is unnecessary to make any changes with regards to stock price changes due to dividends for our research.

5.3 Descriptive statistics of daily data

After the data trimming, we are left with 64,593 daily observations with regards to bid and ask prices, traded volume, and end-of-day closing prices for the 50 firms that made up the OBX index in the period of January 2006 to December 2017. Table 4 provides the summary statistics including the mean, standard deviation, and the minimum and maximum values for the daily observations of the bid, ask, volume, last price and spread variables.

Table 4: Summary statistics

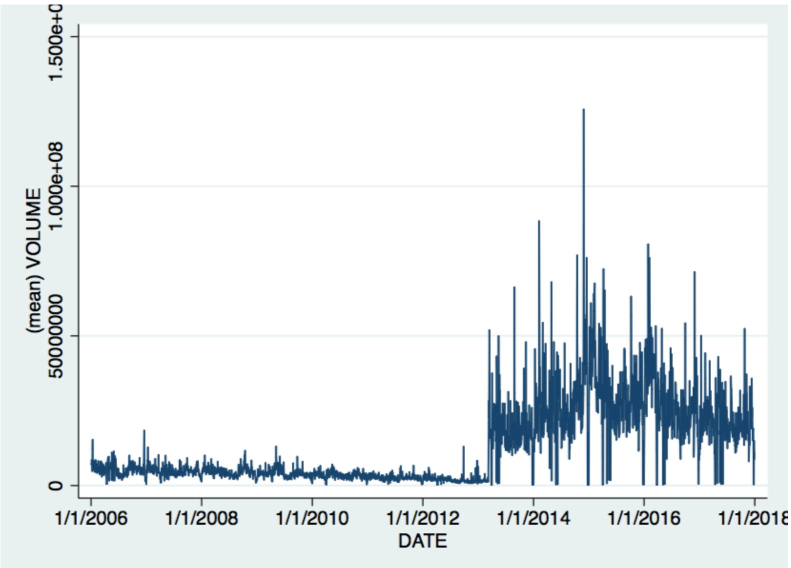
Variable	Mean	Std.Dev	Min	Max	Observations
Closing price	125.1005	180.1501	0.65	3417.223	N = 64593 n = 50
Volume	1.35e+07	8.40e+07	1575	2.82e+09	N = 64593 n = 50
Spread	0.2337	0.2806	0.01	2.00	N = 64593 n = 50
Bid	124.8733	179.5063	0.65	3417.223	N = 64593 n = 50
Ask	125.107	179.6408	0.66	3418.590	N = 64593 n = 50

Table 4 includes summary statistics for the daily observations included in our data set. The sample period is January 2nd 2006 to December 31st 2017, and includes 64,593 daily observations across 50 firms. The summary statistics include the mean, standard deviation, minimum and maximum values of the closing price, volume, spread, bid price and ask price data.

Table 4 illustrates the large deviation in the end-of-day closing prices. While the minimum price is 0,65 NOK, the maximum price is 3,417.22 NOK. This deviation is also evident in the bid- and ask-prices.

We also provide a visual representation of the daily traded volume, spread and closing prices in the period of January 2006 to December 2017. For each date in our dataset, we compute a mean of each measure across all included firms. Graph 1 describes the average traded volume for each day, while Graph 2 and 3 represent the average bid-ask spread and last traded price, respectively.

Graph 1: Average daily traded volume



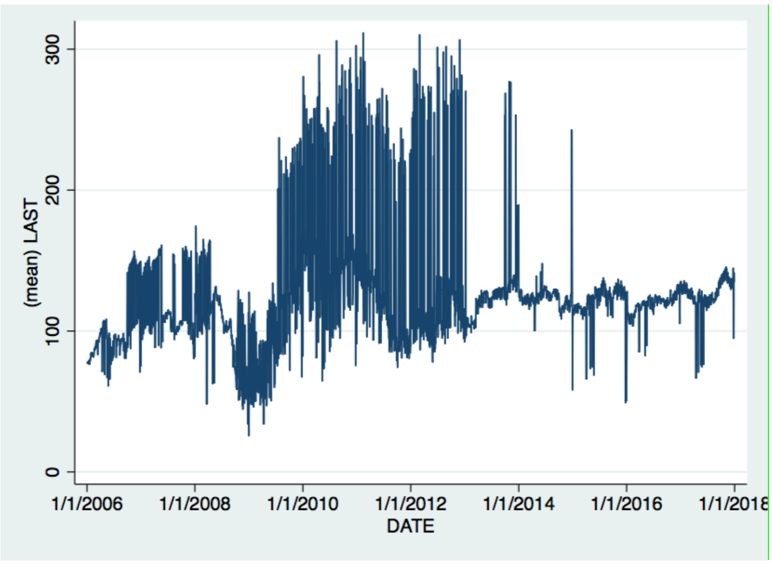
Graph 1 illustrates the average daily traded volume on the OBX index from January 2nd 2006 to December 31st 2017. The average daily traded volume is estimated by computing the mean traded volume for each date across all firms included in the data set. The average daily traded volume spiked in 2013 and maintained a high level throughout 2017.

As evident from Graph 1, the average trading volume of the OBX index on the Oslo Stock Exchange spiked in 2013 and maintained a high level throughout the rest of our sample. There are several possible explanations for this pattern. From the autumn of 2013 Oslo Stock Exchange experienced a sharp increase in the volume of share trading (Oslo Stock Exchange, 2013). One of the possible reasons for this increase could be the introduction of the new trading platform "Millenium Exchange" at the Oslo Stock Exchange by the end of 2012. The new trading platform was introduced with the intention of attracting international brokers and global investors (Oslo Stock Exchange, 2012a). The globalization of the Norwegian market was in part driven by technological development allowing more effective electronic trading (Grünfeld, Jakobsen, Eide, and Mellbye, 2011). Increased amount of international investors could have caused the large increase in daily traded volume. Appendix 5 illustrates the ten largest brokers trading on the Oslo Stock Exchange. From 2008 to 2017, the composition of the top ten largest brokers went through major changes. In 2008 six out of the ten largest brokers on the Oslo Stock Exchange were Norwegian brokers, while in 2017 seven out of the ten largest brokers were international brokers (Oslo Stock Exchange, 2018b).

Another possible cause for the increased trading volume in 2013 were the 12 new listings on the Oslo Stock Exchange, which made the exchange the most active capital market among the Nordic Stock Exchanges (Oslo Stock Exchange, 2013). In the following years, large price movements led to a bigger record in trading volume, where there were more equity instruments traded in 2014 than ever before (Oslo Stock Exchange, 2014). The volume on the Oslo Stock Exchange also increased in 2015, breaking the record of number of equity instruments traded from 2014 (Oslo Stock Exchange, 2015). In 2016, Oslo Stock Exchange reported that they had experienced their best year since 2013 with a 12,1% price increase in the OBX benchmark index (Oslo Stock Exchange, 2016).

Other possible causes for the large increase in trading volume mentioned by the Oslo Stock Exchange include more listings than the other Nordic stock exchanges in 2013 (Oslo Stock Exchange, 2013), increased savings in shares for regular investors as well as a broader diversity of sectors due to new listings in 2016 (Oslo Stock Exchange, 2016), and the oil price increase and a record number of new listings in 2017 (Oslo Stock Exchange, 2017).

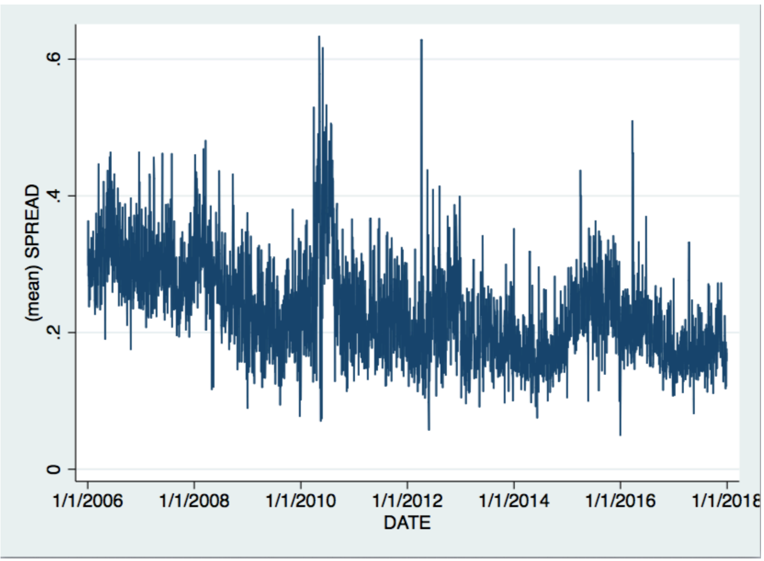
Graph 2: Average daily closing price



Graph 2 illustrates the average daily closing price on the OBX index from January 2nd 2006 to December 31st 2017. The average daily closing price is estimated by computing the mean closing price for each date across all firms included in the data set.

From Graph 2 we see that closing prices were much more volatile in the period of 2009 – 2013, as the daily changes in closing prices were much larger than in the post 2013 period. The year of 2010 was affected by the debt situation in some European countries, which caused uncertainty and may have contributed to large fluctuations in the stock prices (Oslo Stock Exchange, 2010). The volatility in stock prices continued in 2011, which also proved to be influenced by insecure macroeconomic issues in several European countries. This insecurity created a certain pessimism among the investors (Oslo Stock Exchange, 2011). 2012 proved to also be a highly insecure year for the investors, where pessimism and uncertainty in the market were present (Oslo Stock Exchange, 2012b).

Graph 3: Average daily bid-ask spread



Graph 3 illustrates the average daily bid-ask spread on the OBX index from January 2nd 2006 to December 31st 2017. The average daily bid-ask spread is estimated by computing the mean bid-ask spread for each date across all firms included in the data set.

Graph 3 illustrates a spike in the average bid-ask spread in 2010. We also witness two spikes in 2012 and 2016, but the spike in 2010 seems to be larger and persist for a longer period of time. Possible explanations for these spikes in the average bid-ask spread could be the due to the uncertainty in the European economy (Oslo Stock Exchange, 2010)(Oslo Stock Exchange, 2012), and the political uncertainty due to the Brexit vote and the presidential election in the US in 2016 (Oslo Stock Exchange, 2016).

5.4 Defining variables

In this section, we seek to define the dependent and independent variables of our panel regression as described in Chapter 4 and utilized by Gresse (2011). The collected data consists of daily observations which will be transformed into monthly observations. This is due to the fact that our regression analysis contains return volatility as an independent variable, which measures the stocks return volatility over a monthly period. These are therefore monthly observations, and so the rest of our sample needs to be converted into monthly periods as well. We start this subsection by defining the variables which will be used in our panel regression.

LQS_{im} = Local quoted spread for stock i over month m, where the spread is defined as the ask price for stock i over month m less the bid price for stock i over month m. This is our dependent variable.

σ_{im} = The standard deviation of logarithmic daily closing returns for stock i over month m. This is the return volatility.

V_{im} = Logarithm of the total trading volume for stock i over month m.

$1/P_{im}$ = The inverse of the end-of-day closing price of stock i over month m.

5.4.1 Defining and calculating return volatility (σ_{im})

To calculate the return volatility, we started by first calculating the logarithm of the daily continuously compounded return of each stock. The continuously compounded return was calculated using the following formula as stated in Brooks (2014):

$$Continuously\ compunded\ return = 100\%\ x\ \left(\frac{P_{t-1}}{P_t}\right)$$

By calculating the continuously compounded returns, the return across different stocks can be aggregated more easily across time periods. After calculating the logarithm of the return stated above, we calculated the monthly standard deviation of the logarithmic daily closing returns by using the following formula:

$$Monthly\ standard\ deviation = \sigma = \sqrt{\frac{\sum(y_i - \bar{y})^2}{N-1}}$$

The monthly standard deviation of the logarithm of the continuously compounded return is defined as the *return volatility* of each stock. The observations of this explanatory variable are stated on a monthly basis, and therefore, the rest of our variables need to be converted into monthly observations.

5.4.2 Converting to monthly data

To convert the bid-ask spread, traded volume, and last price daily data into monthly observations, we calculated monthly averages across these variables. Having already trimmed our daily data, we avoid disturbing the monthly mean with extreme observations. Converting our original daily observations to monthly observations, we are left with 3,288 monthly observations across 50 firms. Table 5 illustrates the summary statistics for the variables described in this subsection.

Table 5: Summary statistics for calculated monthly observations

Variable	**Mean**	**Std.Dev**	**Min**	**Max**	**Observations**
Spread (LQS_{im})	0.2480	0.2559	0.010	1.767	N = 3288
					n = 50
Volume (V_{im})	14.1247	1.6672	7.3620	20.6628	N = 3288
					n = 50
Return Volatility (σ_{im})	3.0045	1.6769	0.2120	45.8474	N = 3288
					n = 50
Closing Price ($1/P_{im}$)	0.0279	0.0743	0.003	1.4174	N = 3288
					n = 50

Table 5 includes summary statistics for the computed monthly observations in our data set. The sample period is January 2nd 2006 to December 31st 2017, and includes 3,288 monthly observations across 50 firms The summary statistics include the mean, standard deviation, minimum and maximum values of the spread, volume, return volatility and closing price variables.

As in the previous subsection, we also report summary statistics based on different percentiles, where 50% represents the median for each variable. This is illustrated in Table 6.

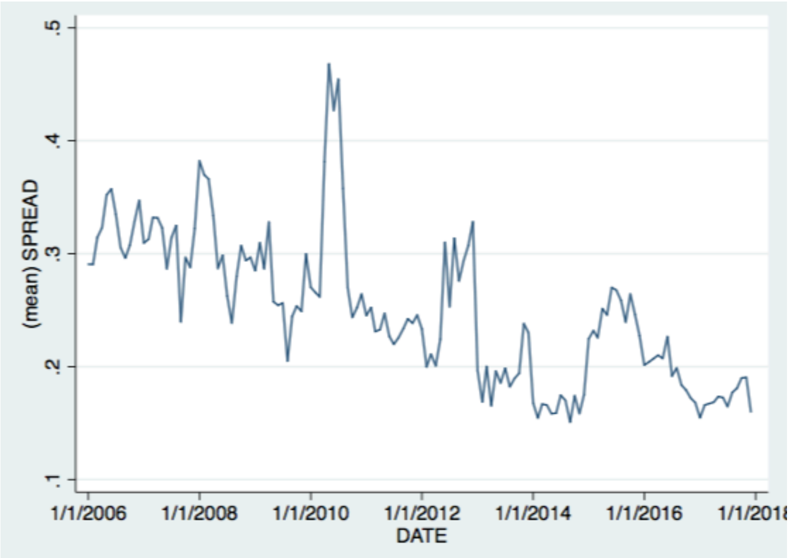
Table 6: Summary statistics for calculated monthly observations based on percentiles

Variable	**Min**	**p5**	**p25**	**p50**	**p75**	**p95**	**Max**
Spread (LQS_{im})	0.010	0.0242	0.0937	0.1636	0.3091	0.8478	1.7670
Return Volatility (σ_{im})	0.2120	1.5848	2.1534	2.7039	3.4034	5.6362	45.8474
Volume (V_{im})	7.3620	11.6813	13.0555	14.2608	15.0199	16.4986	20.6628
Closing Price ($1/P_{im}$)	0.0003	0.0029	0.0065	0.0117	0.0222	0.0970	1.4174

Table 6 depicts values for the 5th, 25th, 50th, 75th and 95th percentiles of the spread, return volatility, volume and closing price variables, as well as their minimum and maximum values. The sample period is January 2nd 2006 to December 31st 2017, and includes 3,288 monthly observations across 50 firms.

Furthermore, we present graphs to illustrate the defined variables across the time period January 2006 to December 2017. As in the previous subsection, we calculate an average for each month across all firms for each variable.

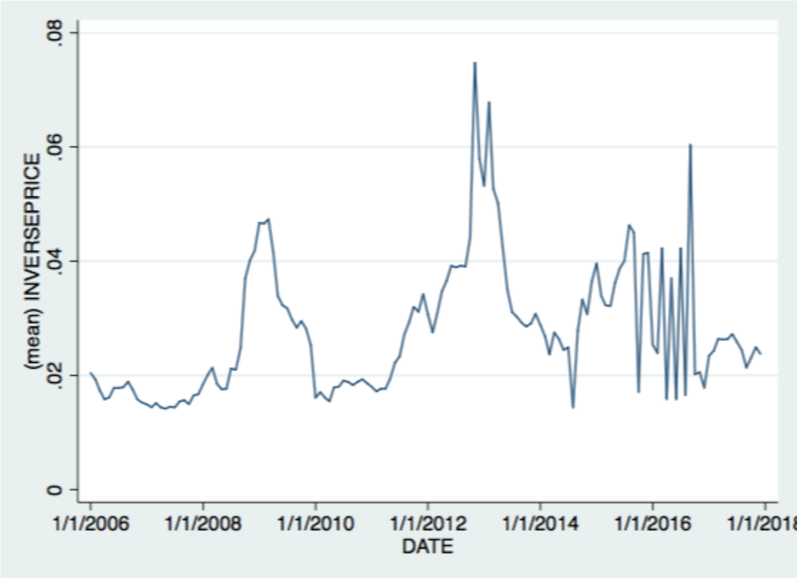
Graph 4: Average monthly bid-ask spread



Graph 4 illustrates the calculated average monthly bid-ask spread on the OBX index from January 2006 to December 2017. The average monthly bid-ask spread is estimated by computing the mean monthly bid-ask spread for each month across all firms included in the data set.

Graph 4 illustrates the average monthly bid-ask spread. From the graph it is evident that although the average spread has varied over time, it is at lower level in 2017 versus 2006. The average bid-ask spread was approximately 0,3 NOK in the period between 2006 and 2010, and approximately 0,15 - 0,18 NOK in 2017. This reduction in the average monthly bid-ask spread can be inferred as an improvement in liquidity following the introduction of MiFID.

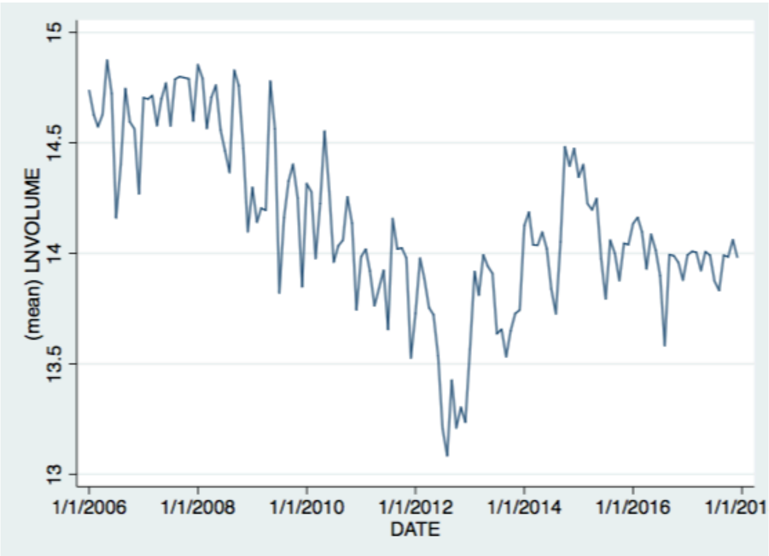
Graph 5: Average monthly inverse closing prices



Graph 5 illustrates the calculated average monthly inverse closing prices on the OBX index from January 2006 to December 2017. The average monthly inverse closing prices are estimated by computing the mean monthly inverse closing price for each month across all firms included in the data set.

Graph 5 illustrates the average monthly inverse closing prices. From the graph we see two large spikes, one in 2009 and one in 2013. A spike in this graph indicates a lower than normal average closing price, as the graph illustrates inverse closing prices. Furthermore, the period of 2014-2016 suggest volatile average end-of-day closing prices, before levelling out in 2017 at roughly the same or slightly higher level as in 2006.

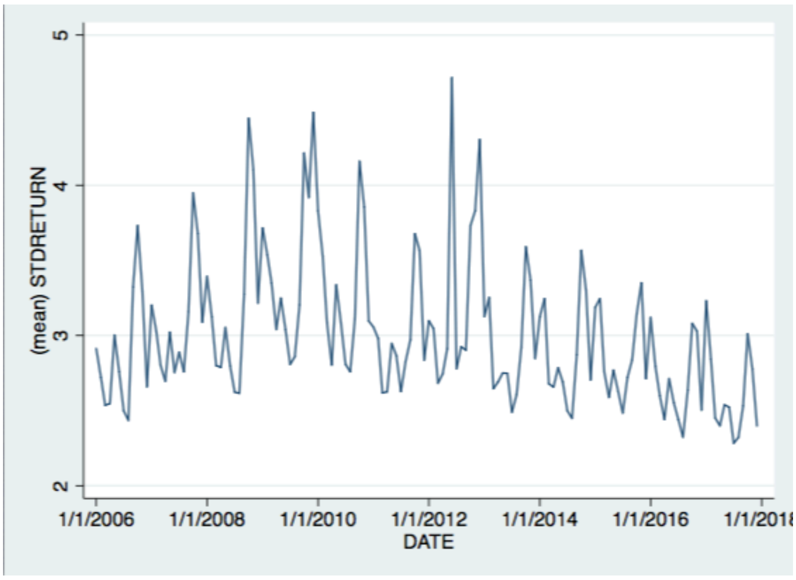
Graph 6: Average monthly logarithmic trading volume



Graph 6 illustrates the calculated average monthly logarithmic trading volume on the OBX index from January 2006 to December 2017. The average monthly logarithmic trading volume is estimated by computing the mean monthly logarithmic trading volume for each month across all firms included in the data set.

Graph 6 illustrates average monthly logarithmic trading volume. We see a decline which persists until 2012, before the average monthly logarithmic volume increases and levels out in 2017.

Graph 7: Average monthly return volatility



Graph 7 illustrates the calculated average monthly return volatility on the OBX index from January 2006 to December 2017. The average monthly logarithmic trading volume is estimated by computing the mean monthly logarithmic trading volume for each month across all firms included in the data set.

Graph 7 illustrates the average monthly return volatility. From this graph we observe yearly spikes throughout the sample, which seem to be much smaller in the period of 2013 – 2017 compared to the previous years. In addition, we observe a slow decline in the average monthly return volatility in the period of 2013 – 2017.

5.5 The financial crisis of 2008

Gresse (2011) chose to exclude data for the year 2008 in order to avoid fusing the effects of the 2008 subprime financial crisis with the effects of market fragmentation and increased competition. However, comparing graphs 4, 5, 6 and 7, we find no abnormal pattern within our dependent and independent variables for the year 2008 which would warrant such an exclusion. It is therefore not obvious from these graphs that we should exclude a certain year from our analysis, and we therefore choose to not edit our data further considering the 2008 financial crisis.

5.6 Stationarity

Having defined the appropriate variables for our regression, we turn to the issue of stationarity in our data set. An examination of whether our data is stationary or not is important because it can strongly influence the behaviour and properties of the data. In addition, the use of non-stationary data can result in a spurious regression. We wish to test for stationarity by utilizing the unit root test, where the null hypothesis states that a unit root is present and the alternative hypothesis states that the series is stationary (Brooks, 2014). However, the properties of our data do not make it suitable for a unit root test.

Our panel data set includes monthly observations across 50 firms in the period 2006-2017. However, company data was only included for the time period the firm was a part of the OBX index, implying that our data set includes very few monthly observations for the companies included in the OBX index for a short period of time. In addition, the data trimming process described in section 5.2 further reduced the number of observations for these firms. As a result, our panel data set includes companies for which we do not have enough monthly observations to conduct a Dickey-Fuller test using Stata.

5.7 Multicollinearity

When utilizing a panel regression, a problem can occur when the explanatory variables are highly correlated with each other, known as multicollinearity (Brooks, 2014). We discuss this issue as we find it plausible that the trading volume, closing price and return volatility of firm correlate. For instance, due to the opportunity costs of funds, one can argue that more expensive stocks are less frequently traded. We can therefore expect to see a negative correlation between the trading volume and the closing price of a firm. The main problem with multicollinearity is that it becomes very difficult to observe the individual contribution of each variable in the regression. The coefficients of the regression will also be very sensitive to any changes, so that adding or removing a variable will cause large changes in the coefficients and the significance of the variables. In addition, significance tests may give inaccurate conclusions, as multicollinearity will cause very wide confidence intervals (Brooks, 2014). We utilize two methods for measuring multicollinearity.

The first method is presented in Brooks (2014), and involves examining the matrix of correlations between the explanatory variables. Table 7 presents said correlation matrix.

Table 7: Matrix of correlations between the explanatory variables

Variable	Volume (V_{im})	Closing Price ($1/P_m$)	Return Volatility (σ_{im})
Volume (V_{im})	1.0000	-	-
Closing Price ($1/P_m$)	0.2963	1.0000	-
Return Volatility (σ_{im})	0.0104	0.3340	1.0000

Table 7 presents a matrix of correlations between the volume, closing price, and return volatility variables. This matrix of correlations represents the first method of measuring potential multicollinearity in our set of variables. We seek to determine whether the correlation between two explanatory variables is negligible or non-negligible.

In line with our prediction, we find that the closing prices and trading volume are negatively correlated. Because the closing price variable is defined as the inverse of the closing price, we find a positive correlation. In addition, we find a positive correlation between the inverse closing price and the return volatility. At this point, we are presented with the challenge of determining whether the correlation depicted in Table 7 is negligible or non-negligible. Brooks (2014) presents an example of a correlation matrix with three fictional variables. In this example, a correlation of 0.8 is viewed as very high and non-negligible. In contrast, 0.3 is viewed as negligible, as Brooks (2014) states that in a practical context “the correlation between explanatory variables will be non-zero”. Following Brooks (2014) example, the depicted correlations in Table 7 can be classified as negligible. To support this view, we present a second approach of measuring multicollinearity.

The second approach for measuring multicollinearity involves using the variance inflation factor (VIF). As a rule of thumb, a VIF value of 10 or greater means that the variable could be deemed to be a linear combination of other explanatory variables (Chen, Ender, Mitchell and Wells, 2003). The VIF values of our explanatory variables are summarized in Table 8 below.

None of our explanatory variables present with a VIF value greater than 10, and we therefore conclude that multicollinearity is not present.

Table 8: Variance Inflation Factor (VIF)

Variable	VIF	1/VIF
Closing Price ($1/P_{im}$)	1.25	0.802694
Return Volatility (σ_{im})	1.14	0.879841
Volume (V_{im})	1.11	0.903388
Mean VIF	1.16	

Table 8 illustrates the variance inflation factor (VIF) of the closing price, return volatility and volume variables. A VIF value of 10 or greater means that the variable could be deemed to be a linear combination of other explanatory variables, implying multicollinearity. Table 8 depicts no value greater than 10, and we therefore conclude that multicollinearity is not present.

6. Results and analysis

Using regression analysis to investigate the effect of increased competition and fragmentation has been used by several other researchers within this subject, such as O'Hara and Ye (2011), Foucault and Menkveld (2008) and Gresse (2011). We define our panel regression in the same manner as Gresse (2011), but in contrast to Gresse (2011), we choose different time periods for our binary time variables. This decision is discussed in the following subsection.

6.1 Defining the panel regression

To define the panel regression that will be used to answer our research question, we need to determine which binary time variables will be included in the regression. Gresse (2011) utilizes three binary time variables corresponding to the periods of January 2009, June 2009 and September 2009, which represented different levels of fragmentation. In order to determine which periods will be included in our regression, we analyse the levels of market fragmentation in Norway. Appendix 6 is an extension of Table 2 and illustrates the market fragmentation when regarding the OBX index in the time period of 2008 - 2017. The market fragmentation, which was a result of the introduction of MiFID in 2007, has been steadily increasing since 2008. This is illustrated by the fact that

98,85 percent of the turnover belonged to the Oslo Stock Exchange in 2008, compared to only 49,44 percent in 2017. In order to capture the effect of the competition, we choose three periods corresponding to different levels of fragmentation. Based on Appendix 6, we choose to include year 2008, 2012 and 2016 corresponding to a percentage turnover on the Oslo Stock Exchange of 98,85, 67,30 and 48,49 percent. The panel regression can then be defined as:

$$LQS_{im} = \beta_0 + \beta_1 V_{im} + \beta_2 1/P_{im} + \beta_3 \sigma_{im} + \beta_4 Time_{2008} + \beta_5 Time_{2012} + \beta_6 Time_{2016} + u_{im}$$

In order to be able to reject H_0, which states that the implementation of MiFID and the corresponding increase in market fragmentation has had no effect on stock liquidity, the coefficients of the binary time variables need to be significantly different from zero. If we can reject H_0, we seek to determine if this effect has been positive (increased liquidity as measured by a decrease in the bid-ask spread) or negative (decreased liquidity as measured by an increase in the bid-ask spread). The effect of the implementation of MiFID and the corresponding increase in market fragmentation has been positive if the coefficient sign is significant and negative (a decrease in the bid-ask spread) or negative if the coefficient sign is significant and positive (an increase in the bid-ask spread).

6.2 Regression results

The regression results are presented in Table 9 below. Standard errors are presented in the parentheses below the coefficients.

Table 9: Regression results

Variable	Coefficient	Z
Volume (V_{im})	-0.0287856***	-8.47
	(0.0034)	
Closing Price ($1/P_{im}$)	-0.1894339***	-4.51
	(0.0419)	
Return Volatility (σ_{im})	0.0034292*	1.71
	(0.0020)	
$Time_{2008}$	0.065026***	7.36
	(0.0088)	
$Time_{2012}$	-0.0455217***	-5.30
	(0.0086)	
$Time_{2016}$	-0.0461616***	-5.43
	(0.0085)	
Constant	0.7254319***	13.88
	(0.0523)	
R^2		0.3598
Number of observations		3288
Number of groups		50

Table 9 illustrates the regression results sorted by the independent variables. The dependent variable is the bid-ask spread which is our measure of liquidity. The sample period is January 2nd 2006 to December 31st 2017, including 3288 observations across 50 firms. Variables used in the regression consist of monthly observations. The control variables consist of trading volume, closing price and return volatility. The table presents the intercept and coefficient estimates for the binary time variables and the control variables, with the standard error for each variable presented in the parentheses.
*** implies $p < 0.01$ and represents a statistical significance at a 1% level, ** implies $p < 0.05$ and represents a statistical significance at a 5% level, and * implies $p < 0.1$ and represents statistical significance at a10% level.

In this subsection, we discuss the results of the panel regression. We start by first examining the regression results with respect to our control variables, and discuss whether the signs of their coefficients are in line with our predictions as stated in Chapter 4. As evident, the volume and closing price variables are both significant at a 1% significance level. The return volatility variable is significant at a 10% significance level.

The variable representing trading volume has a negative coefficient of -0.028785 implying that an increased trading volume reduces the quoted spread. This is in line with our prediction, as high volume implies that the market is able to absorb a sale without adverse price changes. The higher the trading volume of a stock, the easier it is to execute an immediate exchange (Benston and Hagerman, 1974). The closing price variable has a negative coefficient of -0.1894339. However, it is important to recall that this variable is defined as the *inverse* of the closing price. Therefore, a higher closing price does not imply a lower, but a higher bid-ask spread. This is also in line with our prediction in Chapter 4, where we state that the spread will increase with an increase in price, in order to equalize the cost of transacting (Bollen, Smith and Whaley, 2004). The return volatility variable has a positive coefficient of 0.0034292 implying that an increase in return volatility increases the bid-ask spread. This result is also consistent with our prediction, as we argue that spreads will increase because dealers are risk averse (Harris, 1994). A stock with a higher volatility will have a wider bid-ask spread since investors will be less willing to pay a high price for the stock.

We now turn to the coefficients of the binary time variables which represent different levels of market fragmentation. We use these results to either reject or not reject H_0 as stated in Chapter 1. As evident from Table 9, all of the three binary time variables have coefficients which are significantly different from zero, at the 1% significance level. This implies that we can reject the null hypothesis stating that the implementation of MiFID and the corresponding increase in market fragmentation has had no effect on stock liquidity as measured by the bid-ask spread. As we are able to reject H_0, we seek to determine whether this effect has been positive or negative. In order to determine this, we turn to the signs of the coefficients.

The coefficient for the variable representing 2008 is positive and has a value of 0.065026, while the variables representing 2012 and 2016 are negative and have values of -0.0455217 and -0.0461616, respectively. The positive coefficient of the binary variable representing the time period of 2008, indicates that after controlling for the effects of the trading volume, closing prices and the return volatility, the bid-ask spread is higher in this time period. What is of special interest is that even though the three binary time variables represent different levels of market fragmentation subsequent to the introduction of MiFID, their coefficients do not have identical signs. The coefficient of the binary time variable representing the year of 2008 is positive, while the coefficients of the binary variables representing 2012 and 2016 are negative. However, in 2008, the percentage turnover for the Oslo Stock Exchange was 98,85 percent, implying virtually no market fragmentation at all, while the percentage turnover for the Oslo Stock Exchange was considerably lower in 2012 and 2016, implying much higher levels of market fragmentation. Our results therefore imply that the spreads decreased over time as market fragmentation and competition increased. In addition, we note that the coefficient for the 2016 binary variable is more negative than the coefficient for the 2012 binary variable, which is of interest as the level of market fragmentation is higher in 2016 than 2012. These results indicate that the bid-ask spreads have *decreased* following the introduction of MiFID. This implies that the implementation of MiFID has had a positive effect on stock liquidity, as smaller bid-ask spreads indicate improved liquidity (as discussed in Chapter 1).

6.3 Robustness

In this section, we include interaction terms in our original regression to check the robustness of our original results. We replace the binary time variables with interaction terms multiplying the time variables with the volume variable. This helps us to see how the spread reacts in these time periods with an increase in volume. The results of this regression are summarized in Table 10.

Table 10: Regression results with interaction terms

Variable	**Coefficient**	**Z**
Volume (V_{im})	-0.0281929***	-8.28
	(0.0034)	
Closing Price ($1/P_{im}$)	-0.1839352***	-4.37
	(0.0421)	
Return Volatility (σ_{im})	0.0033985*	1.69
	(0.0020)	
Volume x $Time_{2008}$	0.004125***	6.86
	(0.0006)	
Volume x $Time_{2012}$	-0.0033527***	-5.38
	(0.0006)	
Volume x $Time_{2016}$	-0.0032089***	-5.37
	(0.0005)	
Constant	0.7171491***	13.68
	(0.0524)	
R^2		0.3587
Number of observations		3288
Number of groups		50

Table 10 illustrates the regression results sorted by the independent variables. The dependent variable is the bid-ask spread which is our measure of liquidity. The sample period is January 2nd 2006 to December 31st 2017, including 3288 observations across 50 firms. Variables used in the regression consist of monthly observations. The control variables consist of trading volume, closing price and return volatility. The table presents the intercept and coefficient estimates for the binary time variables and the control variables, with the standard error for each variable presented in the parentheses.

*** implies $p < 0.01$ and represents a statistical significance at a 1% level, ** implies $p < 0.05$ and represents a statistical significance at a 5% level, and * implies $p < 0.1$ and represents statistical significance at a10% level.

The regression results show that an increase in volume in 2008 contributes to a more positive spread, while an increase in volume in 2012 and 2016 contributes to a more negative spread. Comparing the regression that includes interaction terms with our original regression, we see that the coefficients representing the bid-ask spread in 2008, 2012 and 2016 are still significant using 1% significance level, and they have the exact same signs: we still see an increase in spread in 2008 and a decrease in spread in 2012 and 2016.

Our findings are consistent with our theoretical prediction in Chapter 3, where we argue that there should be a significant effect of market fragmentation on stock liquidity. However, our findings are *not* consistent with our theoretical prediction regarding *how* market fragmentation effects stock liquidity; we argue that the bid-ask spread should increase with market fragmentation based on the theoretical work of Keynes (1930), Mendelson (1987) and Stoll (2003). In the next subsection, we provide alternative theories as to why we find an increase in stock liquidity (as measured by a decrease in the bid-ask spread) instead of a decrease in stock liquidity.

Our findings are consistent with the empirical findings of Gresse (2011), where market fragmentation is found to improve both global and local liquidity for stocks listed on the London Stock Exchange and Euronext. They are also consistent with the findings of O'Hara and Ye (2011) who find that market quality of the US market, as measured by effective spreads, realized spreads and execution speeds, is not harmed by market fragmentation. Our results differ from those of Degryse, De Jong and Van Kervel (2015) who find that fragmentation in lit markets improves the liquidity of the consolidated market, but lowers the liquidity at the primary exchange.

6.4 Alternative arguments

Alternative arguments that may explain why we find an improvement in liquidity following an increase in market fragmentation can be grouped in to two categories: those highlighting market maker behaviour, and those focusing on the emergence of a dominant market.

6.4.1 Arguments highlighting market maker behaviour

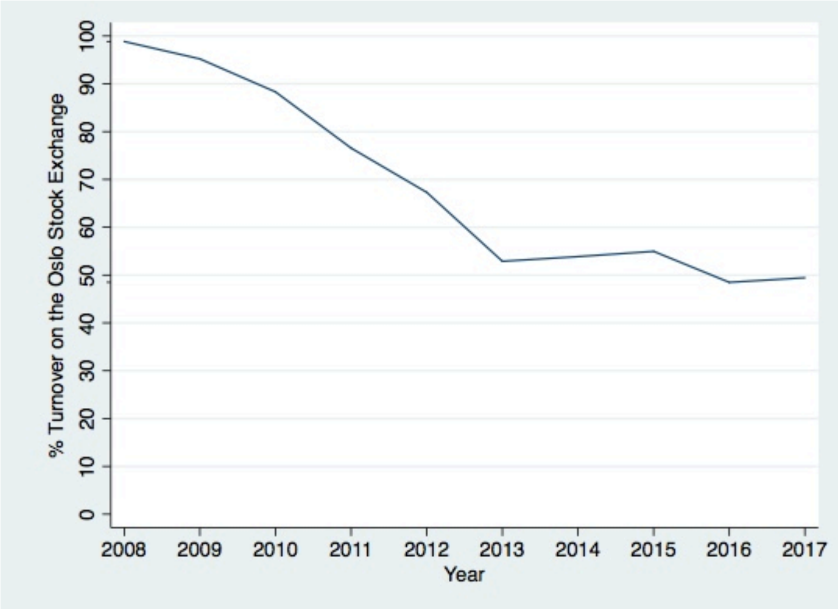
In his study of marketplace fragmentation, Hamilton (1979) argues that there are possibly two opposite effects: the competitive effect and the fragmentation effect. The competitive effect states, among other things, that competition created from multiple marketplaces might cause market makers to narrow their spreads. The basis for this argument, according to Porter and Thatcher (1998), relates to the total trading volume. With marketplace competition, the total trading volume is divided among different trading venues, reducing the trading volume on the exchange. According to the competition effect argument, market makers operating on the primary exchange would therefore need to narrow their quoted spreads in an attempt to keep some of the volume on the primary exchange.

Foucault and Menkveld (2008) study the ramification of the introduction of a new limit order market. A limit order differs from a market order where a broker on behalf of an investor executes the order at the best current available price. A limit order is set by a participant to buy or sell a stock at a specified price or better. Foucalt and Menkveld (2008) argue that a new limit order market will increase the competition among limit order traders and therefore reduce the rents of the liquidity providers (market makers). This will then lead to a reduction in trading costs for other investors, represented by a deeper market.

6.4.2 Emergence of a dominant market

Chowdhry and Nanda (1991) argue that in a competitive trading environment, one trading venue will emerge as the dominant market, creating a “winner takes most” equilibrium. This market will capture most of the order flow and have the lowest trading costs. They argue that small liquidity traders will decide to participate in the market with the lowest expected trading costs, and they show that these traders will concentrate in the market that has the largest number of liquidity traders who cannot choose to trade in another market. This market will in turn attract even more traders. In other words, the liquidity will naturally cluster in a particular market. One can certainly make the argument that this theory explains our results. Graph 8 creates a visual interpretation of Appendix 6, where we have reported the annual percentage turnover for the Oslo Stock Exchange in the period 2008 – 2017. As evident from Graph 8, the percentage turnover for the primary exchange has been in decline since 2008, as competition from alternative trading venues has emerged. However, while the decline in the percentage turnover has been steep in the period of 2008 – 2012, it has since stagnated.

Graph 8: Percentage turnover on the Oslo Stock Exchange



Graph 8 illustrates the percentage turnover on the Oslo Stock Exchange from January 2008 to December 2016.

Even though competition and market fragmentation have been in place since 2008, the percentage turnover on the Oslo Stock Exchange has been at approximately 50 percent for several years. The rest of the turnover does not belong to a single marketplace, and is divided among several smaller trading venues. One can therefore argue that the Oslo Stock Exchange has emerged as the dominant market, capturing most of the order flow. According to the argument presented by Chowdhry and Nanda (1991) the Oslo Stock Exchange, being the dominant market, would be the marketplace where the liquidity naturally clusters.

7. Conclusion

The implementation of MiFID in the Norwegian equity market in November 2007 and its abolishment of the concentration rule opened up for trading in Norwegian equity on several trading venues such as MTFs and dark pools. This gave rise to competition and market fragmentation, which is the basis for our research on its effect on stock liquidity.

Our empirical research is based on the methodology presented by Gresse (2011), where we used the panel regression method to study the effects of market fragmentation on stock liquidity. We use monthly observations from January 2006 to December 2017 of stocks included in the OBX index, which consists of the 25 most liquid stocks listed on the Oslo Stock Exchange. This helps us isolate the effect of market fragmentation on very liquid stocks. Our measure of liquidity is the quoted bid – ask spread for each stock, during the time the stock was a part of the OBX index. In our panel regression we use trading volume, closing prices and return volatility as control variables.

Aside from our control variables, we employ three binary time variables that represent three different levels of market fragmentation in the Norwegian equity market. We turn to the significance and signs of the coefficients of the binary time variables to see the effect on the bid-ask spread in the years 2008, 2012 and 2016, having controlled for trading volume, closing prices and return volatility of each stock. Our panel regression results show that there has been a significant effect of the implementation of MiFID on stock liquidity, leading to the rejection of our null hypothesis. Our panel regression results also show that spreads decreased over time while market fragmentation increased, which is in contrast to our theoretical prediction. We originally argued that spreads should increase with market fragmentation based on the theoretical work presented by Keynes (1930), Mendelson (1987), and Stoll (2003), which present liquidity-improving effects of centralization. Our empirical findings are in line with the findings of Foucault and Menkveld (2008), Gresse (2011), and O'Hara and Ye (2011).

This paper supplements the current available research on this subject by isolating the effect on the Norwegian equity market. Our analysis is based on a much broader time period, allowing us to research the long-term effects of market fragmentation. Given the size of our data set, we are also able to better determine the effects of our control variables on stock liquidity. By conducting this research a decade after the implementation of the EU-directive, we are able to provide an analysis of the effects of market fragmentation on stock liquidity for very different levels of market fragmentation.

The limitations of this study relate to the effect of high frequency trading on stock liquidity. As MiFID opened up for trading on alternative trading venues, HFT may have had an impact on stock liquidity. We were not able to take account for the effect of HFT on stock liquidity due to data availability, and we therefore suggest the inclusion of HFT effects in further research. In addition we suggest including the effect of trading fees for market makers on stock liquidity. If there were an effect of increased competition and market fragmentation on trading fees, it would be of interest to analyse its effects on stock liquidity. We therefore suggest these two factors for further research on MiFID's effect on stock liquidity in the Norwegian market.

Bibliography

Algeta. (2013). *Algeta results for the fourth quarter and full year 2013.* Retrieved from: http://hugin.info/134655/R/1759211/594922.pdf

Bali, R., & Hite, G. L. (1998). Ex dividend day stock price behavior: discreteness or tax-induced clienteles?. *Journal of Financial Economics, 47(2),* 127-159.

Bennett, P., & Wei, L. (2006). Market structure, fragmentation, and market quality. *Journal of Financial Markets*, *9*(1), 49-78.

Benston, G. J., & Hagerman, R. L. (1974). Determinants of bid-asked spreads in the over-the-counter market. *Journal of Financial Economics*, *1*(4), 353-364.

Bollen, N. P., Smith, T., & Whaley, R. E. (2004). Modeling the bid/ask spread: measuring the inventory-holding premium. *Journal of Financial Economics*, *72*(1), 97-141.

Brooks, C. (2014). *Introductory Econometrics for Finance* (3rd Edition). United Kingdom: Cambridge University Press.

Bradford, H. (2011, October 5th). 10 Worst Single-Day Drops In Dow Jones History. *Huffington Post*. Retrieved from: https://www.huffingtonpost.com/entry/dow-jones-biggest-drops-falls_n_919216?guccounter=2

Chen, X., Ender, P., Mitchell, M., Wells, C. (2003). *Regression with Stata*. Retrieved from: https://stats.idre.ucla.edu/stata/webbooks/reg/

Chlistalla, M., Speyer, B., Kaiser, S., & Mayer, T. (2011). High-frequency trading. *Deutsche Bank Research, 7.*

Chowdhry, B. & Nanda, V. (1991). Multimarket trading and market liquidity. *Review of Financial Studies 4,* 623–656.

Degryse, H., De Jong, F., & Kervel, V. V. (2015). The impact of dark trading and visible fragmentation on market quality. *Review of Finance*, *19*(4), 1587-1622.

Demsetz, H. (1968). The cost of transacting. *The quarterly journal of economics*, *82*(1), 33-53.

European Commission. (2007). Markets in Financial Instruments Directive (MiFID): Frequently Asked Questions. Retrieved from: http://europa.eu/rapid/press-release_MEMO-07-439_en.htm?locale=en

Fidessa Fragmentation Index. (2018). Fragulator. Retrieved from: http://fragmentation.fidessa.com/fragulator/

Foucault, T., & Menkveld, A. J. (2008). Competition for order flow and smart order routing systems. *The Journal of Finance*, *63*(1), 119-158.

Gomber, P., Arndt, B.,, Lutat, M., and Uhle, T. (2015). High-Frequency Trading. *SSRN eLibrary*.

Gresse, C. (2011). Effects of the competition between multiple trading platforms on market liquidity: evidence from the MiFID experience. *SSRN eLibrary*.

Grünfeld, L. A., Jakobsen, E. W., Eide, L. E., & Mellbye, C. S. (2011). En kunnskapsbasert finansnæring. (Forskningsrapport 11/2011). Oslo: *Handelshøyskolen BI.*

Haas, F. (2007). *The Markets in Financial Instruments Directive: banking on market and supervisory efficiency* (No. 7-250). International Monetary Fund.

Hamilton, J. L. (1979). Marketplace fragmentation, competition, and the efficiency of the stock exchange. *The Journal of Finance, 34(1),* 171-187.

Harris, L. E. (1994). Minimum price variations, discrete bid–ask spreads, and quotation sizes. *The Review of Financial Studies, 7(1),* 149-178.

Harris, L. (2013). What to do about high-frequency trading. *Financial Analysts Journal.*

Henriksen, Ø., Andersen, T. Ø., & Sundberg, J. D. (2008, February 6th). Kostnadssprekk for Rec. *E24.* Retreived from: https://e24.no/makro-og-politikk/renewable-energy-corporation/kostnadssprekk-for-rec/2240177

Keynes, J. M. (1930). *Treatise on money, volume 2: applied theory of money*. London: Macmillan

Koren, M., A., Landre, E. & Nilsen, S., R. (2011, November 11th). Frontline kollapser fullstendig på børsen. *E24*. Retrieved from: https://e24.no/boers-og-finans/frontline/frontline-kollapser-fullstendig-paa-boersen/20123861

Lippman, S. A., & McCall, J. J. (1986). An operational measure of liquidity. *The American Economic Review*, *76*(1), 43-55.

Mendelson, H. (1987). Consolidation, fragmentation, and market performance. *Journal of Financial and Quantitative Analysis*, *22*(2), 189-207.

Norges Offentlige Utredninger 2006:3. (2006). *Om markeder for finansielle Instrumenter. Gjennomføring av MiFID og transparencydirektivet.*
Retrieved from:
https://www.regjeringen.no/contentassets/1ca7b4c5c4124599964e55bee13b3f2c/no/pdfs/nou200620060003000dddpdfs.pdf

O'Hara, M., & Ye, M. (2011). Is market fragmentation harming market quality?. *Journal of Financial Economics*, *100*(3), 459-474.

Oslo Stock Exchange. (2010). *2010: A year with big fluctuations – but a strong finish.* Retrieved from: https://www.oslobors.no/ob_eng/Oslo-Boers/About-Oslo-

Boers/News-from-Oslo-Boers/2010-A-year-with-big-fluctuations-but-a-strong-finish

Oslo Stock Exchange. (2011). *2011 – A year marked by uncertainty.* Retrieved from: https://www.oslobors.no/ob_eng/Oslo-Boers/About-Oslo-Boers/News-from-Oslo-Boers/2011-A-year-marked-by-uncertainty

Oslo Stock Exchange. (2012a). *New Oslo Børs trading platform for equities and fixed income instruments.* Retrieved from: https://www.oslobors.no/ob_eng/Oslo-Boers/About-Oslo-Boers/News-from-Oslo-Boers/New-Oslo-Boers-trading-platform-for-equities-and-fixed-income-instruments

Oslo Stock Exchange. (2012b). *2012 – Yet another turbulent year.* Retrieved from: https://www.oslobors.no/ob_eng/Oslo-Boers/About-Oslo-Boers/News-from-Oslo-Boers/2012-Yet-another-turbulent-year

Oslo Stock Exchange. (2013). *Strongest growth in share prices since 2009.* Retrieved from: https://www.oslobors.no/ob_eng/Oslo-Boers/About-Oslo-Boers/News-from-Oslo-Boers/Strongest-growth-in-share-prices-since-2009

Oslo Stock Exchange. (2014). *Oslo Børs marketplaces defy the biggest drop in the price of oil in recent times.* Retrieved from: https://www.oslobors.no/ob_eng/Oslo-Boers/About-Oslo-Boers/News-from-Oslo-Boers/Oslo-Boers-marketplaces-defy-the-biggest-drop-in-the-price-of-oil-in-recent-times

Oslo Stock Exchange. (2015). *The Oslo Børs Benchmark Index defies the oil price article.* Retrieved from: https://www.oslobors.no/ob_eng/Oslo-Boers/About-Oslo-Boers/News-from-Oslo-Boers/The-Oslo-Boers-Benchmark-Index-defies-the-oil-price-article

Oslo Stock Exchange. (2016). *The best year for Oslo Børs since 2013.* Retrieved from: https://www.oslobors.no/ob_eng/Oslo-Boers/About-Oslo-Boers/News-from-Oslo-Boers/The-best-year-for-Oslo-Boers-since-2013

Oslo Stock Exchange. (2017). *An exceptionally good year for the Oslo stock exchange.* Retrieved from: https://www.oslobors.no/ob_eng/Oslo-Boers/About-Oslo-Boers/News-from-Oslo-Boers/An-exceptionally-good-year-for-the-Oslo-stock-exchange

Oslo Stock Exchange. (2018a). *Minileksikon.* Retrieved from: https://www.oslobors.no/Oslo-Boers/Om-Oslo-Boers/Minileksikon#o

Oslo Stock Exchange. (2018b). Meglerstatistikk. Retrieved from: https://www.oslobors.no/Oslo-Boers/Statistikk/Meglerstatistikk/(year)/2008/(month)/12

Pagano, M. (1989). Trading volume and asset liquidity. *The Quarterly Journal of Economics*, *104*(2), 255-274.

Pareto Securities. (2017). *Det nye Børslandskapet.* Retrieved from: http://www.paretosec.com/download/produktark/Det%20nye%20b%C3%B8rslandskapet.pdf

Petrescu, M., & Wedow, M. (2017). *Dark pools in European equity markets: emergence, competition and implications.* (ECB Occasional Paper 193). Frankfurt.

Porter, D. C., & Thatcher, J. G. (1998). Fragmentation, competition, and limit orders: new evidence from interday spreads. *The Quarterly Review of Economics and Finance*, *38*(1), 111-128.

Rørheim, J., & Ripegutu, H. (2015, August 10th). Derfor raser Opera Software. *Dagens Næringsliv.* Retrieved from: https://www.dn.no/nyheter/finans/2015/08/10/1149/Opera-Software/derfor-raser-opera-software

Securities and Exchange Commission. (2001). *Report on the Comparison of Order Execution Across Equity Market Structures.* US Government Printing Office, Washington, DC.

Stoll, H. R. (2003). Market microstructure. *Handbook of the Economics of Finance*, *1*, 553-604.

TDN Finans. (2008, October 2nd). Kutter etter kurskollaps. *Dagens Næringsliv.* Retrieved from: https://www.dn.no/nyheter/2008/10/02/kutter-etter-kurskollaps

Appendix 1: Overview of companies included in the OBX index for the years 2006 – 2017.

2006	
Acergy	ACY
Aker	AKER
Aker Kværner	AKA
Awilco Offshore	AWO
DnB NOR	DNB
DNO	DNO
Fred. Olsen Energy	FOE
Frontline	FRO
Norsk Hydro	NHY
Norske Skogindustrier	NSG
Ocean Rig	OCR
Orkla	ORK
Pan Fish	MHG
Petroleum Geo-Services	PGS
Prosafe	PRS
Seadrill	SDRL
Storebrand	STB
Statoil	STL
Subsea 7	SUBC
Tandberg Television	TAT
Telenor	TEL
TGS-NOPEC Geophysical Company	TGS
Tomra Systems	TOM
Tandberg	TAD
Yara International	YAR

2007	
Acergy	ACY
Aker Kværner	AKA
Aker Yards	STXEUR
Awilco Offshore	AWO
DnB NOR	DNB
DNO	DNO
Fred. Olsen Energy	FOE
Frontline	FRO
Golden Ocean Group	GOGL
Marine Harvest	MHG
Norsk Hydro	NHY
Norske Skogindustrier	NSG
Orkla	ORK
Petroleum Geo-Services	PGS
Prosafe	PRS
Renewable Energy Corporation	REC
Seadrill	SDRL
StatoilHydro	STL
Storebrand	STB
Subsea 7	SUBC
Tandberg	TAD
Telenor	TEL
TGS-NOPEC Geophysical Company	TGS
Tomra Systems	TOM
Yara International	YAR

2008	
Acergy	ACY
Aker	AKER
Akastor	AKA
DnB NOR	DNB
DNO International	DNO
Fred. Olsen Energy	FOE
Frontline	FRO
Golden Ocean Group	GOGL
Marine Harvest	MHG
Norsk Hydro	NHY
Norske Skogindustrier	NSG
Orkla	ORK
Petroleum Geo-Services	PGS
Prosafe	PRS
Renewable Energy Corporation	REC
Schibsted	SCHA
Seadrill	SDRL
Sevan Marine	SEVAN
Storebrand	STB
StatoilHydro	STL
Subsea 7	SUBC
Telenor	TEL
TGS-NOPEC Geophysical Company	TGS
Tandberg	TAD
Yara International	YAR

2009	
Acergy	ACY
Akastor	AKA
DnB NOR	DNB
DNO International	DNO
Fred. Olsen Energy	FOE
Songa Offshore	SONG
Frontline	FRO
Golden Ocean Group	GOGL
Marine Harvest	MHG
Norsk Hydro	NHY
Orkla	ORK
Petroleum Geo-Services	PGS
Prosafe	PRS
Renewable Energy Corporation	REC
Schibsted	SCHA
Seadrill	SDRL
Sevan Marine	SEVAN
Storebrand	STB
StatoilHydro	STL
Subsea 7	SUBC
Telenor	TEL
TGS-NOPEC Geophysical Company	TGS
Royal Caribbean Cruises	RCL
Norwegian Property	NPRO
Yara International	YAR

2010	
Acergy	ACY
Akastor	AKA
DnB NOR	DNB
Fred. Olsen Energy	FOE
Frontline	FRO
Gjensidige Forsikring	GJF
Golden Ocean Group	GOGL
Marine Harvest	MHG
Norsk Hydro	NHY
Orkla	ORK
Petroleum Geo-Services	PGS
Prosafe	PRS
Questerre Energy Corporation	QEC
Renewable Energy Corporation	REC
Royal Caribbean Cruises	RCL
Schibsted	SCHA
Seadrill	SDRL
Sevan Marine	SEVAN
Statoil	STL
Statoil Fuel & Retail	SFR
Storebrand	STB
Subsea 7	SUBC
Telenor	TEL
TGS-NOPEC Geophysical Company	TGS
Yara International	YAR

2011	
Akastor	AKA
Algeta	ALGETA
Cermaq	CEQ
DNB	DNB
DNO	DNO
Fred. Olsen Energy	FOE
Frontline	FRO
Gjensidige Forsikring	GJF
Golar LNG	GLNG
Marine Harvest	MHG
Norsk Hydro	NHY
Orkla	ORK
Petroleum Geo-Services	PGS
Prosafe	PRS
Renewable Energy Corporation	REC
Royal Caribbean Cruises	RCL
Schibsted	SCHA
Seadrill	SDRL
Statoil	STL
Statoil Fuel & Retail	SFR
Storebrand	STB
Subsea 7	SUBC
Telenor	TEL
TGS-NOPEC Geophysical Company	TGS
Yara International	YAR

2012	
Akastor	AKA
Algeta	ALGETA
Det norske oljeselskap	AKERBP
DNB	DNB
DNO International	DNO
Electromagnetic Geoservices	EMGS
Fred. Olsen Energy	FOE
Gjensidige Forsikring	GJF
Golar LNG	GLNG
Marine Harvest	MHG
Norwegian Air Shuttle	NAS
Norsk Hydro	NHY
Orkla	ORK
Petroleum Geo-Services	PGS
Prosafe	PRS
Renewable Energy Corporation	REC
Royal Caribbean Cruises	RCL
Schibsted	SCHA
Seadrill	SDRL
Songa Offshore	SONGA
Statoil	STL
Storebrand	STB
Subsea 7	SUBC
Telenor	TEL
TGS-NOPEC Geophysical Company	TGS

2013	
Akastor	AKA
Algeta	ALGETA
Det norske oljeselskap	AKERBP
DNB	DNB
DNO International	DNO
Fred. Olsen Energy	FOE
Gjensidige Forsikring	GJF
Golden Ocean Group	GOGL
Marine Harvest	MHG
Norwegian Air Shuttle	NAS
Norsk Hydro	NHY
Opera Software	OTELLO
Orkla	ORK
Petroleum Geo-Services	PGS
Prosafe	PRS
Renewable Energy Corporation	REC
Royal Caribbean Cruises	RCL
Schibsted	SCHA
Seadrill	SDRL
Statoil	STL
Storebrand	STB
Subsea 7	SUBC
Telenor	TEL
TGS-NOPEC Geophysical Company	TGS
Yara International	YAR

2014	
Akastor	AKA
Aker Solutions	AKSO
BW LPG	BWLPG
Det norske oljeselskap	AKERBP
DNB	DNB
DNO	DNO
Fred. Olsen Energy	FOE
Gjensidige Forsikring	GJF
Golden Ocean Group	GOGL
Marine Harvest	MHG
Norwegian Air Shuttle	NAS
Norsk Hydro	NHY
Opera Software	OTELLO
Orkla	ORK
Petroleum Geo-Services	PGS
Renewable Energy Corporation	REC
Royal Caribbean Cruises	RCL
Schibsted	SCHA
Seadrill	SDRL
Statoil	STL
Storebrand	STB
Subsea 7	SUBC
Telenor	TEL
TGS-NOPEC Geophysical Company	TGS
Yara International	YAR

2015	
Avance Gas Holding	AVANCE
Bakkafrost	BAKKA
BW LPG	BWLPG
Det norske oljeselskap	AKERBP
DNB	DNB
DNO	DNO
Frontline	FRO
Gjensidige Forsikring	GJF
Marine Harvest	MHG
Norwegian Air Shuttle	NAS
Norsk Hydro	NHY
Nordic Semiconductor	NOD
Opera Software	OTELLO
Orkla	ORK
Petroleum Geo-Services	PGS
Renewable Energy Corporation	REC
Schibsted ser. A	SCHA
Schibsted ser. B	SCHB
Seadrill	SDRL
Statoil	STL
Storebrand	STB
Subsea 7	SUBC
Telenor	TEL
TGS-NOPEC Geophysical Company	TGS
Yara International	YAR

2016	
Aker BP	AKERBP
Aker Solutions	AKSO
Bakkafrost	BAKKA
BW LPG	BWLPG
DNB	DNB
DNO	DNO
Frontline	FRO
Gjensidige Forsikring	GJF
Grieg Seafood	GSF
Lerøy Seafood Group	LSG
Marine Harvest	MHG
Norwegian Air Shuttle	NAS
Norsk Hydro	NHY
Orkla	ORK
Petroleum Geo-Services	PGS
Renewable Energy Corporation	REC
SalMar	SALM
Schibsted ser. A	SCHA
Schibsted ser. B	SCHB
Statoil	STL
Storebrand	STB
Subsea 7	SUBC
Telenor	TEL
TGS-NOPEC Geophysical Company	TGS
Yara International	YAR

2017	
Aker BP	AKERBP
Aker Solutions	AKSO
Bakkafrost	BAKKA
BW LPG	BWLPG
DNB	DNB
DNO	DNO
Gjensidige Forsikring	GJF
Golden Ocean Group	GOGL
Grieg Seafood	GSF
Lerøy Seafood Group	LSG
Marine Harvest	MHG
Norwegian Air Shuttle	NAS
Norsk Hydro	NHY
Norwegian Finance Holding	NOFI
Orkla	ORK
Petroleum Geo-Services	PGS
Questerre Energy Corporation	QEC
SalMar	SALM
Schibsted ser. A	SCHA
Statoil	STL
Storebrand	STB
Subsea 7	SUBC
Telenor	TEL
TGS-NOPEC Geophysical Company	TGS
Yara International	YAR

Appendix 2: Overview of name changes / Mergers & Acquisitions

Company	Year	Type of change	New name
Acergy (ACY)	2011	Name change	Subsea 7 (SUBC)
Aker Kværner (AKVER)	2008	Name change	Aker Solutions (AKSO)
Aker Solutions (AKSO)	2014	Name change	Akastor (AKA)
Aker Solutions (AKSO)	2014	Demerger	
Algeta (ALGETA)	2014	Delisted	
Avance Gas Holding (AVANCE)	2014	Listed	
Awilco Offshore (AWO)	2008	Delisted	
Bakkafrost (BAKKA)	2010	Listed	
BW LPG (BWLPG)	2013	Listed	
Cermaq (CERMAQ)	2014	Delisted	
Det norske oljeselskap (DETNOR)	2016	Name change	Aker BP (AKERBP)
DnB NOR (DNBNOR)	2011	Name change	DNB (DNB)
DNO (DNO)	2008	Name change	DNO International (DNO)
Electromagnetic Geoservices (EMGS)	2007	Listed	
Gjensidige Forsikring (GJF)	2010	Listed	
Golar LNG (GOL)	2012	Delisted	
Golden Ocean Group (GOGL)	2015	Listed	
Grieg Seafood (GSF)	2007	Listed	
Pan Fish (PAN)	2007	Name change	Marine Harvest (MHG)
Norwegian Finance Holding (NOFI)	2016	Listed	
Norwegian Property (NPRO)	2006	Listed	
Ocean Rig (OCR)	2008	Delisted	
Pertra (PERTRA)	2007	Name change	Det norske oljeselskap (DETNOR)
Renewable Energy Corporation (REC)	2013	Name change	REC Silicon (REC)
Royal Caribbean Cruises (RCL)	2016	Delisted	
SalMar (SALM)	2007	Listed	
Schibsted (SCH)	2015	Name change	Schibsted ser. A (SCHA)
Schibsted ser. B (SCHB)	2015	Listed	
Songa Offshore (SONG)	2006	Listed	
Statoil (STL)	2007	Name change	StatoilHydro (STL)
StatoilHydro (STL)	2009	Name change	Statoil (STL)
Statoil Fuel & Retail (SFR)	2012	Delisted	
Stolt Offshore S.A. (STO)	2006	Name change	Acergy (ACY)
Subsea 7 (SUB)	2011	Merger	Acergy (ACY)
Tandberg (TAA)	2010	Delisted	
Tandberg Television (TAD)	2007	Delisted	

The table provides an overview of company events of firms included in the OBX index from 2006 to 2017 including mergers, name changes, listings and delistings from Oslo Stock Exchange.

Appendix 3: Bid-ask spread outliers

Variable	Min	p5	p25	p50	p75	p95	Max
Spread	-138.9	0.01	0.05	0.11	0.30	2	124.326
Closing Price	0.6280	9.845	45.11	88.0455	163	750	4309.967
Bid	0.6275	9.69	45.25	88.14177	162.975	749.5	4299.607
Ask	0.6280	9.68	45.08	88.03739	163	751	4309.967
Volume	1063	65730	413372.5	1422408	3513457	1.69e+07	2.82e+09

Appendix 3 illustrates the values for the 5th, 25th, 50th, 75th and 95th percentiles of the variables included in our data set, which also illustrates the minimum and maximum values of the included variables. The data set contains 71 620 daily observations from January 2nd 2006 to December 31st 2017 for firms included in the OBX index for the same period. The table serves to show extreme values which need to be excluded from the data set as to not distort the monthly averages of the daily observations.

Appendix 4: Company events

Firm	Year	Event
Algeta	2013	The announcement of a voluntary offer caused a considerable increase in the stock price.
Frontline	2011	Poor quarterly figures caused a large stock price reduction in 2011.
Yara International	2008	Poor quarterly figures caused a large reduction in the firm's stock price in 2008.
Opera Software	2015	Poor quarterly figures caused a stock price reduction of almost 44% in 2015.
Renewable Energy Corporation	2008	A large unexpected expense caused the firms stock price to fall by more than 20% in 2008.
Aker Yards	2007	No public information available.
Tandberg Television	2006	No public information available.

Appendix 4 provides an overview over company events which caused large and unexpected stock price changes for the mentioned stocks in the period between January 2006 and December 2017. The objective is to determine whether these companies conducted a stock split, which would justify adjusting the stock prices back to their original levels. As evident from the table, none of the companies conducted a stock split, and the stock prices were therefore not adjusted.

Sources: Algeta (2013), Koren, Landre, and Nilsen, (2011). TDN Finans. (2008), Rørheim, and Ripegutu, (2015), Henriksen, Andersen, and Sundberg, (2008).

Appendix 5: Ten largest brokers present on Oslo Stock Exchange based on percentage turnover

2008

Broker	% turnover
SEB	8.14
DNB	7.29
ABG Sundal Collier	6.94
Carnegie	5.51
Nordnet	5.06
Morgan Stanley	4.84
Svenska Handelsbanken	4.56
Pareto Securities	4.11
Arctic Securities	4.00
First Securities	3.66

2010

Broker	% turnover
DNB	8.04
SEB	7.71
Svenska Handelsbanken	6.47
Nordnet	6.16
Credit Suisse Securities	5.66
ABG Sundal Collier	5.25
Pareto Securities	4.85
Carnegie	4.69
First Securities	4.12
Arctic Securities	3.71

2013

Broker	% turnover
DNB	9.43
Merrill Lynch International	9.27
Morgan Stanley	7.07
SEB	5.49
Credit Suisse Securities	5.37
Pareto Securities	4.76
Svenska Handelsbanken	4.17
Nordnet	4.01
Deutsche Bank	3.58
ABG Sundal Collier	3.56

2017

Broker	% turnover
Morgan Stanley	13.01
Merrill Lynch	11.55
DNB	9.24
Credit Suisse	4.92
Instinet	4.35
Nordnet	4.24
JP Morgan	3.81
Pareto	3.78
Nordea	3.51
UBS	3.10

Source: Oslo Stock Exchange (2018b)

Appendix 6: Market fragmentation on the Oslo Stock Exchange

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Oslo Stock Exchange	98,85	95,21	88,31	76,56	67,30	52,89	53,87	54,97	48,49	49,44
Cboe CXE	0,72	2,41	4,36	8,51	16,83	17,32	17,90	18,29	15,67	17,50
Cboe BXE	0,00	0,00	1,35	4,40	6,54	5,44	5,19	4,66	6,90	7,17
Turquoise	0,04	0,37	1,06	2,95	4,41	6,69	8,62	8,34	13,67	6,93
Nasdaq OMX	0,00	1,46	3,90	5,41	1,69	11,21	6,06	3,94	1,61	0,36
Aquis	0,00	0,00	0,00	0,00	0,00	0,00	0,09	0,74	1,67	4,06
Other*	0,00	0,22	0,22	0,31	0,26	0,18	0,00	0,00	0,00	0,01

* Including DNSE, North Sea, ONSE, MNSE, Burgundy, NYSE Arca.

The appendix illustrates the market fragmentation by the percentage turnover in the lit and dark markets offering trading in Norwegian equity, including the Oslo Stock Exchange and different MTFs. Table 2 illustrates how market fragmentation in the Norwegian equity market has increased since the introduction of MiFID in November 2007, as demonstrated by a decrease in the percentage turnover on the Oslo Stock Exchange.

Source: Fidessa Fragmentation Index (2018).