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Does Transparency Impact Market Liquidity?

Evidence from the European Union and United States Equity Markets

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Abstract

We find evidence for increased market transparency to have a positive effect on equity market liquidity. Using data from EU and US equity markets, we estimate the effect of the implementation of the Markets in Financial Instruments Directive to increase liquidity in EU stock markets. To measure different dimensions of market liquidity we use bid-ask spreads, the percentage daily range, the Hui-Heubel liquidity ratio, the Market Efficiency Coefficient, trading volume and Amihud's Illiquidity ratio. These metrics are used to measure the tightness, immediacy, breadth, resiliency, depth, and general liquidity of the market, respectively. We use a staggered Difference-in-Difference analysis to estimate an increase in all liquidity dimensions except immediacy, which decreases. This provides evidence for a positive relationship between market transparency and liquidity, but also suggests that the increase in some liquidity dimensions may come at the expense of others. However, for some of the liquidity metrics it is doubtful whether the parallel trends assumption holds, which limits the causal interpretation of these findings. The results should therefore be interpreted with caution. Although we do not provide a conclusive answer regarding the mechanisms through which transparency affects liquidity, we argue that the positive liquidity effects likely come as transparency lowers risk for price-setting market makers while also causing traders to change their strategies in ways that are conducive to liquidity.

Keywords – MiFID, Market Transparency, Stock Market Liquidity

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1. Introduction

The purpose of this thesis is to analyze whether market transparency impacts stock market liquidity. The relationship between these two attributes is ambiguous, as previous research has suggested that transparency can both increase (Boehmer, Saar, & Yu, 2005; Pagano & Röell, 1996) and decrease (Bloomfield & O'Hara, 1999; Madhavan, Porter, & Weaver, 2005) liquidity. Furthermore, other researchers have found no significant effect (Gemmill, 1996). This thesis will analyze the introduction of the Markets in Financial Instruments Directive (MiFID) as a “shock” to transparency and measure its effect on stock market liquidity. We will perform a comparative analysis by using the largest stocks in the EU and the US, respectively. This analysis will be performed on two portfolios before and after the official implementation date, which is November 1st, 2007 (European Commission, 2006).

Many of the theorems in finance rely on the assumption that markets are frictionless, and that no single order can impact the market price. Furthermore, many equilibrium asset pricing models do not account for the trading process through which equilibrium is reached, as well as the frictions that may impact price formation (Chordia, Roll, & Subrahmanyam, 2001). However, in real life liquidity is essential for a well-functioning market, as a liquid market allows buyers and sellers to find each other and agree upon a fair price quickly. As such, a liquid market increases market efficiency through improved allocation of economic resources (Sarr & Lybek, 2002). Furthermore, shocks to liquidity supply in financial markets have shown that market liquidity may directly impact real economic activity (Goldberg, 2015). As of late, concerns about liquidity “drying up” in financial markets have sparked debate about their stability and the possible increased vulnerability of markets to crises (PwC, 2015). As regulators are focused on improving liquidity conditions in financial markets, it is interesting to examine whether the regulations introduced have the intended effect.

A key goal of MiFID is the creation of deep and liquid capital markets (HM Treasury, 2007). Within the directive, there is a considerable focus on increasing transparency in European financial markets. However, the theoretical and empirical literature examining the effect of market transparency on liquidity is divided, where the theoretical literature largely suggests that transparency should matter for liquidity while the empirical literature is mixed (Bloomfield & O'Hara, 1999). This implies that there is considerable uncertainty about what effects increased transparency will have on the market, with researchers suggesting that it may both increase (Boehmer, Saar, & Yu, 2005; Pagano & Röell, 1996) and decrease (Bloomfield

& O'Hara, 1999; Madhavan, Porter, & Weaver, 2005) liquidity. Furthermore, new regulatory regimes tend to build on existing regimes, as the introduction of MiFID II demonstrates. It is therefore important to analyze and understand the effects of increased transparency to provide guidance for future regulations. This is highly relevant today, as the advent of Brexit has sparked debate about a potential "MiFID III" (Ricketts & Agini , 2019). These considerations are the motivation behind the chosen research topic for this thesis: *How does market transparency affect stock market liquidity?*

2. Literature Review

This section of the thesis will discuss central topics for the research question, namely what liquidity is, what determines the liquidity of a market and how transparency relates to liquidity. In addition, this section will provide an overview of the Markets in Financial Instruments Directive (MiFID). MiFID is a broad and complex directive, and we will thus present a general overview in addition to the relevant parts of the directive. The literature review forms the basis for our research topic, which is presented in the last subsection.

2.1 Market Liquidity

Despite being the focus of both regulators and researchers, liquidity is not easily defined. According to Amihud et al. (2012, p. ix) liquid markets are characterized by the ability to transact large quantities of securities quickly and at a low cost. Cooper et al. (1985) define liquidity as "the relationship between volume of trading and changes in market price". Foucault et al. (2013, p. 8) define liquidity as "the ability to trade a security quickly at a price close to its consensus value". These definitions are somewhat overlapping and highlight different aspects of liquidity. The first definition implies that liquid markets have high trading volume and trading activity allowing for large orders to be disseminated quickly, and that fees and other trading costs are low. The second suggests that in a liquid market, orders should have minimal price impact. The last definition implies that in a liquid market, transactions take place at a price close to the agreed fair value of the security.

Sarr and Lybek (2002) present five distinct characteristics of a liquid market; *tightness*, *immediacy*, *depth*, *breadth* and *resiliency*. *Tightness* refers to transaction costs such as the bid-ask spread, which are low in a liquid market. *Immediacy* is order execution speed, reflecting the efficiency of trading, clearing and settlement systems. *Depth* describes the abundancy of orders present above and below the current trading price. *Breadth* is the market's ability to absorb large and numerous orders with minimal price impact. *Resiliency* describes the market's ability to quickly correct mispricing that occurs when order imbalances temporarily push prices away from the fundamental value.

According to Sarr and Lybek (2002), a liquid market offers improved allocation and informational efficiency compared to a less liquid market, making liquidity a desirable trait for financial markets. However, the relationship between liquidity and informational efficiency is ambiguous. Bernstein (1987) argues that there is a trade-off between liquidity and efficiency, as a less liquid market may move more rapidly to reflect new information as it arrives. Regulators' focus on increasing market liquidity suggests that greater liquidity is a net positive for the functioning of financial markets. To fully understand why and how liquidity matters, it is beneficial to examine what implications it has for different market participants. This will be discussed in the following paragraph.

From the definitions of liquidity presented above, one can easily deduct that market liquidity is important. But the diversity of definitions also suggests that it is important for different market participants for different reasons. For institutional investors, as well as large individual investors, liquidity is important as it allows them to buy and sell large blocks of stock without inducing an unacceptably large price movement (Cooper, Groth, & Avera, 1985). Furthermore, liquid markets have lower transaction costs (Hasbrouck & Schwartz, 1988), allowing traders to buy and sell at lower costs. For firms, Amihud and Mendelson (1986) and Jacoby et al. (2000) find that the liquidity of their stock affects their cost of capital, as investors require higher yields on less liquid stocks. Thus, firms have an incentive to increase the liquidity of their stock to reduce their cost of capital (Amihud & Mendelson, 1986). Their findings also suggest a positive relationship between stock liquidity and firm value. According to Brau and Fawcett (2006), the liquidity offered in secondary markets is an important reason for firms to go public. They also find that the main purpose of equity offerings is to finance future acquisitions. It follows that market liquidity has important implications for firms' financing decisions. Furthermore, the liquidity of secondary markets impacts firms' choice of underwriters, where CEOs who value liquidity are more likely to hire prestigious underwriters (Mantecon & Poon, 2009). Thus, liquidity is important not only for the firm issuing stock and those who subsequently trade it, but also for the intermediaries who facilitate the issuance.

2.2 Determinants of Market Liquidity

As liquidity is multifaceted, there are many factors that determine the liquidity of a market. Arbel et al. (1983) and Merton (1987) suggest that firms with larger market capitalization garner more attention from analysts and investors. This implies a "size effect" where the stocks of large companies will display greater liquidity than those of smaller companies. The findings of Amihud and Mendelson (1986) support the existence of a negative relationship between firm size and the bid-ask spread. This implies that larger-capitalization stocks will be more liquid as measured by market tightness. Furthermore, Apergis et al. (2015) find that during times of economic uncertainty, investors tend to reallocate capital from less liquid small-capitalization stocks to more liquid large-capitalization stocks. This "flight-to-quality" effect indicates that stock liquidity may be self-reinforcing during times of uncertainty, thus magnifying the size effect.

In addition to firm size, the "age" of a firm as measured by time since IPO seems to be an important determinant of trading activity. Booth and Chua (1996) argue that issuers have an incentive to underprice IPOs to attract broad initial ownership, thereby increasing secondary market liquidity. This suggests that newly listed firms may display greater liquidity than more established firms. However, the empirical literature is conflicted about the relationship between "age" and liquidity. Chordia et al. (2007) find that young firms experience greater trading activity, supporting the theory presented by Booth and Chua (1996). However, Camilleri and Galea (2019) find that in most cases, younger firms are less actively traded than more established firms. Despite the divergence in the literature as to what effect firm "age" may have, both find this characteristic to be a significant determinant of liquidity. It is therefore pertinent to include this characteristic when analyzing stock liquidity.

In addition to the market capitalization and "age" characteristics, there are many firm-specific determinants that on surface level may seem important for liquidity. Camilleri and Galea (2019) provide a comprehensive study of determinants of stock trading activity. They estimate a model of liquidity based on five possible trading activity determinants, namely market capitalization, dividend yield, earnings yield, company growth rate and established versus recently listed firms. They find market capitalization and established versus recently listed firms to be significant determinants, where market capitalization was found to be the most important determinant. Earnings yield, dividend yield and company growth rate were found to not be important determinants of trading activity (Camilleri & Galea, 2019).

As previously mentioned, liquid markets display the ability to disseminate large orders cheaply. This implies that measurements based on trading costs, volume and price impact of trades can all provide proxy measurements for liquidity. According to Hasbrouck and Schwartz (1988), liquidity measures based on trading costs capture execution cost, meaning the implicit costs of trading an asset quickly. Measures based on trading volume may include either the outright number of securities traded, or more sophisticated measures such as turnover rates that capture the average number of times each security has changed hands (Sarr & Lybek, 2002).

2.3 Transparency and Liquidity

This section supplements the previous section by exploring market transparency as another possible determinant of liquidity. Before pursuing this question, it is pertinent to define market transparency. Madhavan et al. (2005) define market transparency as “the ability of market participants to observe information about the trading process”. Pagano and Röell (1996) suggest a similar definition of transparency as “the degree to which the size and direction of the current order flow are visible to the competing market makers involved in setting prices”. They further distinguish between two forms of market transparency, namely pre- and post-trade transparency. They define pre-trade transparency as “visibility of the best price at which any incoming order can be executed”, and post-trade transparency as “public visibility of recent trading history”. Foucault et al. (2013, p. 280) elaborate on the definition of pre-trade transparency by specifying three forms of pre-trade transparency, namely visibility of quotes, visibility of incoming orders and visibility of traders’ identities. Based on this, this thesis will use a general definition of transparency as the degree to which market participants can observe information about quotes as well as the size, direction, and origin of current and past order flow. This definition is meant to cover both pre- and post-trade transparency as defined by Pagano and Röell (1996), and thus their definitions as well as the definition by Foucault et al. (2013, p. 280) will be relied upon when it is necessary to be more specific about the type of transparency discussed.

Theoretical and empirical research into the relationship between transparency and liquidity has yielded different results. Some studies have found that transparency positively impacts liquidity because it reduces the risk for market makers, thereby allowing them to offer narrower spreads to compete for orders (Pagano & Röell, 1996). Others have found transparency to increase liquidity because traders adapt their strategies to place smaller orders and cancel orders faster, thus reducing the orders’ price impact (Boehmer, Saar, & Yu, 2005). However, others have found that transparency reduces liquidity by making it easier for market makers to access order flow data to gain information about market fundamentals, and thus they have less incentive to compete for order flow themselves (Bloomfield & O'Hara, 1999). Some studies have also found that transparency reduces liquidity, as the cancellation of orders by limit order traders reduces market depth and thus increases the price impact of orders (Madhavan, Porter, & Weaver, 2005).

Pagano and Röell (1996) find that greater market transparency improves liquidity, as a more transparent market offers lower average trading costs for liquidity traders. According to the authors, a transparent market allows the market makers to make more precise inferences about whether orders are information- or liquidity-driven. This allows market makers to better protect themselves against losses to informed traders, allowing them to offer narrower spreads and thereby lower trading costs to uninformed traders (Pagano & Röell, 1996). The authors argue that due to competition with other market makers, each market maker has incentives to lower trading costs as they compete for order flow. Although the authors emphasize that the reduction in trading costs may not apply to all order sizes, they find that in all cases analyzed, the average trading costs for uninformed traders decrease in a more transparent market. Based on their findings, Pagano and Röell (1996) suggest that policy makers wishing to reduce trading costs for uninformed traders should ensure that order flow is publicly disseminated as quickly as possible, and that information from inter-dealer networks is made more widely accessible to market participants. According to the authors, this favors centralized electronic execution systems with automatic and real-time reporting and publication. Furthermore, they argue, exchanges should either be consolidated to one centralized exchange or integrated into a network subject to tight publication requirements.

The idea that transparency increases liquidity is empirically supported by the findings of Boehmer et al. (2005). They find that making the limit order book public on the New York Stock Exchange, thereby increasing pre-trade transparency, lead to traders changing their strategies to manage their limit-order exposure. More specifically, they find that traders submit smaller orders and cancel orders faster. According to the authors, this reduction in order size lessened the price impact of orders, thus reducing the compensation for liquidity provision offered to market makers such as specialists, as well as limit-order suppliers. Furthermore, they find that without privileged information about the order book, floor brokers and specialists reduced their activity as they were crowded out by increased activity from traders using electronically submitted limit orders.

However, other researchers have found that increased transparency may have the opposite effect. In a report published by London Economics (2010), they argue that "greater transparency may lead to losses among limit-order providers to momentum traders, which would cause a reduction in market depth". This is similar to the findings of Boehmer et al. (2005), who also find that limit-order suppliers may experience a loss of profit due to increased transparency. Boehmer et al. (2005) argue that the loss of profit for liquidity providers happens as increased transparency deepens the order book, which ultimately lowers spreads and thereby the compensation for liquidity provision. These differing conclusions about the net effect on market depth suggest that the effect of increased transparency on different aspects of liquidity may be ambiguous.

The argument that transparency may have an adverse effect on liquidity is supported by studies performed by Bloomfield and O'Hara (2000). They find that greater transparency in the form of trade disclosure cause transaction prices to converge more rapidly, thereby increasing their informational efficiency. This supports the view purported by Sarr and Lybek (2002). However, in contrast to the theory presented by Pagano and Röell (1996), Bloomfield and O'Hara (1999) find that increased informational efficiency reduces market makers' incentive to compete for order flow, causing spreads to widen as transparency increases. The authors argue that in a less transparent market, the market maker will gain valuable information about market fundamentals from the order flow attracted by narrow spreads. In a transparent market, however, this information is publicly disseminated and thus the market maker has less incentive to attract order flow (Bloomfield & O'Hara, 1999).

Madhavan et al. (2005) find that making the limit order book public, thus increasing pre-trade transparency, lead to higher execution costs and greater price volatility on the Toronto Stock Exchange. This indicates that market transparency may reduce liquidity. Like Boehmer et al. (2005), the findings of Madhavan et al. (2005) are consistent with the theory that traders adjust their trading strategies as a response to the level of transparency. However, Madhavan et al. (2005) conclude that the withdrawal of orders by limit-order providers will reduce market depth. They argue that the thinner limit order book will cause the order flow to have greater price impact, thus increasing volatility and execution costs.

As this section has revealed, research into the relationship between transparency and liquidity has yielded diverging results. This is also suggested by Gemmill (1996), who find that changing the level of post-trade transparency on the London Stock Exchange did not significantly affect liquidity, further indicating that the relationship between market transparency and liquidity is not clear-cut. The considerable attention given to market transparency in MiFID exemplifies the focus dedicated by regulators to this issue. However, without a clear answer to what effect greater transparency may have on the market, regulations may not have the intended effect. In the worst-case scenario, such regulations may have considerable adverse effects on financial markets. The following section provides an overview of MiFID before discussing these potential issues.

2.4 Markets in Financial Instruments Directive (MiFID)

The Markets in Financial Instruments Directive (MiFID) came into force on November 1st, 2007 with the goal of providing a harmonized set of rules governing markets and investment services in the European Union (European Commission, 2006). The new regulation replaced the Investment Services Directive (ISD), aiming to address multiple issues with its predecessor. ISD had proven ineffective in promoting business between countries in the European single market, while also failing to cover several activities such as investment advice and derivatives trading (HM Treasury, 2007). Furthermore, the ISD allowed countries to limit which trading venues orders could be routed to (London Economics, 2010), possibly limiting competition between venues.

The ISD's "concentration rule" allowed EU member countries to require all retail orders be executed on a regulated market (London Economics, 2010). Naturally, such rules may impede competition between trading venues, as alternative trading venues may not be allowed to compete with regulated markets. As discussed previously, Pagano and Röell (1996) and Bloomfield and O'Hara (1999) suggest that competition between market makers lowers spreads, as they are incentivized to offer competitive spreads to attract order flow. By extension, if market makers on regulated exchanges face less competition from alternative venues, they may have less incentive to provide the best possible spread. Higher trading costs would imply lower liquidity as measured by market tightness.

To facilitate greater competition, MiFID removed the concentration rule, thus enabling other platforms to compete with regulated markets (London Economics, 2010). More specifically, MiFID defines three distinct infrastructures through which trading may take place. A regulated market (RM) is a multilateral system bringing together third-party buyers and sellers of a financial instrument. The RM is operated by a market operator who facilitates trade between buyers and sellers in a non-discretionary manner. The market operator thus acts as a neutral intermediary. A Multilateral Trading Facility (MTF) operates in much the same way as an RM, facilitating multilateral trade between third-party buyers and sellers. They provide an alternative to the RM and may be operated by an investment firm. In addition to the RM and MTF, trading may take place with a systematic internalizer (SI). The SI is an investment firm that deals on its own account by executing client orders outside a RM or an MTF. Unlike the RM and MTF, the SI is not an intermediary, but executes the orders by trading directly with the clients as the counterparty in the transaction. By removing the concentration rule, MTF´s and SI´s are allowed to compete with RM´s across the EU, including countries where such competition may previously have been restricted.

In addition to changing the competitive environment, MiFID sought to bolster transparency requirements "with the two-fold aim of protecting investors and ensuring the smooth operation of securities markets" (European Commission, 2004, p. 5). The changes to market transparency are meant to be symbiotic with the changes in the competitive environment, which is apparent from Article I (34) of the directive:

"

Fair competition requires that market participants and investors be able to compare the prices that trading venues (i.e. regulated markets, MTFs and intermediaries) are required to publish. To this end, it is recommended that Member States remove any obstacles which may prevent the consolidation at European level of the relevant information and its publication. (European Commission, 2004, p. 4)

"

This highlights the connection between transparency and competition: By ensuring visibility of quotes, which is an aspect of pre-trade transparency, and making such information easily available and comparable, the directive aims to foster competition between trading venues. The European Commission (2004) further specifies pre-trade transparency requirements for each of the trading venues that comprise the market infrastructure. SI's are required to publish quotes for those stocks that trade on an RM, while for those stocks not trading on a liquid market, they are required to disclose quotes to clients on request (2004, p. 22). For MTF's and RM's, MiFID requires that current bid and offer prices as well as the depth of trading interest at those prices is "made available to the public on reasonable commercial terms and on a continuous basis during normal trading hours" (European Commission, 2004). MiFID also outlines post-trade transparency requirements for each of the trading venues. SI's are required to publicize the volume, price, and timestamps of their transactions "as close to real-time as possible, on a reasonable commercial basis, and in a manner which is easily accessible to other market participants" (European Commission, 2004, p. 23). MTF's and RM's are also required to make public the volume, price and timestamps of transactions in stocks admitted to their platform, on "a reasonable commercial basis" and "as close to real-time as possible" (European Commission, 2004).

2.5 Thesis Question and Hypotheses

A key goal of MiFID is the creation of deep and liquid capital markets (HM Treasury, 2007). It is therefore reasonable to assume that the transparency requirements outlined in the directive seek to aid the creation of such markets. The introduction of requirements to publicize information from the order book such as bids and offers, volume and depth of interest resembles the case studied by Boehmer et al. (2005). Consequently, one may expect an increase in market liquidity following the implementation. However, an equally similar case is that studied by Madhavan et al. (2005). Their findings, when applied to the case of MiFID, suggest that the comprehensive transparency regime introduced by the directive may in fact have the opposite effect. If so, the directive may reduce liquidity in the form of increased transaction costs and reduced market depth. Furthermore, when applying the findings of Bloomfield and O'Hara (1999), the increase in post-trade transparency may improve informational efficiency but at the expense of transactional efficiency. If so, the post-trade disclosure requirements may increase transaction costs. This considerable uncertainty about the effects of transparency on liquidity, and by extension the effects of MiFID on liquidity, has motivated the research question that this thesis seeks to answer:

How does market transparency affect stock market liquidity?

It is evident from the literature review that there are several mechanisms through which transparency may affect liquidity. When examining these mechanisms, the research tends to focus on different market participants, namely individual and institutional traders or market makers and trading venues. To supplement the thesis question, we will therefore present several hypotheses about *why* we may observe an effect on liquidity through the lens of different market participants.

2.5.1 Market Makers and Trading Venues

Firstly, transparency may affect liquidity through influencing the behavior of market makers and trading venues. As the literature review reveals, this effect may be either negative or positive. In line with Pagano and Röell (1996), liquidity may increase as market makers face reduced risk of losses to informed traders. As market makers compete for order flow, the reduced cost may be captured by uninformed traders as market makers narrow their spreads to remain competitive. If so, we are likely to observe increased tightness from lower trading costs. The lower spread implies less price impact for orders as the incremental change in market price caused by market orders executed at the bid or ask is reduced. Lower trading costs are likely to attract more traders, and market depth and resiliency is therefore likely to increase. The effect on immediacy is unclear, but it will either remain unchanged or increase due to increased depth. Breadth may increase due to more numerous orders from uninformed traders, while the size of orders may either increase due to smaller price impact or decrease due to lower profits for informed traders from trading with market makers. As such, breadth is likely to remain unchanged or increase. The net effect of these factors is an increase in liquidity. This hypothesis will be referred to as the "*Market Maker Competition Hypothesis*".

$$H_1\text{: } \textbf{\textit{Lower risk for competitive market makers leads to increased market liquidity}}$$

However, as Bloomfield and O'Hara (1999) suggest, transparency may also induce market maker behavior that reduces liquidity. More specifically, public dissemination of order flow information reduces the informational advantage for market makers from trading with market participants. As such, they may be more inclined to freeload on order flow information from other market makers or trading venues rather than attract their own order flow through narrowing spreads. If so, we are likely to observe a reduction in tightness from increased transaction costs. However, as per the findings of Bloomfield and O'Hara (1999), prices are likely to converge faster in this setting, implying an increase in resiliency. Due to higher transaction costs, the price impact of orders is likely to increase while market depth is likely to decrease. Furthermore, higher transaction costs may discourage small traders, while the informational edge of informed traders is likely to decrease or remain unchanged. As such, market breadth is likely to decrease. The effect on immediacy is unclear, but the net effect of these factors is a decrease in liquidity. This hypothesis will be referred to as the "*Market Maker Freeloading Hypothesis*".

$$\boldsymbol{H_2\text{: Market makers' informational freeloading leads to reduced market liquidity}}$$

2.5.2 Individual and Institutional Traders

Secondly, transparency may affect the behavior and strategies of individual and institutional traders, thereby affecting liquidity. The mechanisms behind our two trader-focused hypotheses are similar, but with two different implications. Both hypotheses state that increased transparency will reduce profits for limit order traders, making traders adapt their strategies to reduce limit-order exposure by submitting smaller orders and withdrawing orders quicker. In line with Madhavan et al. (2005), the first hypothesis is that this will lead to reduced depth, and by extension larger price impact. This implies a loss of resiliency and increased trading costs. The effect on breadth will either be negative or unchanged, as orders are smaller but may not be less numerous. In total, this will lead to reduced market liquidity. This hypothesis will be referred to as the "*Limit Order Aversion Hypothesis*".

$$\boldsymbol{H_3\text{: The withdrawal of orders from limit order traders leads to reduced market liquidity}}$$

The second trader-focused hypothesis is based on the same mechanism outlined in the previous paragraph. However, in line with Boehmer et al. (2005), the last hypothesis states that the reduction in order size will lessen their price impact, and by extension reduce the compensation for liquidity suppliers. This implies increased resiliency and tightness. The reduction in price impact of orders is also likely to increase depth, as found by Boehmer et al. (2005). The impact on breadth is unclear but is likely to either remain unchanged or increase in line with the increased depth. In total, this implies an increase in market liquidity. This hypothesis will be referred to as the "*Trader Adaption Hypothesis*".

H_4: ***Reduced order sizes from limit order traders leads to increased market liquidity***

Although there are four distinct hypotheses, they are not necessarily mutually exclusive. The hypotheses focus on two groups of market participants, namely market makers and traders. It is possible that both traders and market makers are affected by a change in market transparency. If so, it is likely that each group will have its own response to the change, and thus any liquidity effects observed may be a result of a combination of market maker and trader mechanisms. It is also possible that participants within the two groups have different responses. However, it is likely that one response will be more optimal for the group on aggregate, and thus any effects found in our analysis is likely to stem from the dominant mechanism. In summary, we expect any effects on liquidity to be explained by of one of the hypotheses, or a combination of one market maker hypothesis and one trader hypothesis.

Table 1 summarizes the hypotheses with the corresponding liquidity effects. These effects will be used to identify two main findings for this thesis, namely how increased transparency affects stock market liquidity and through which mechanism this effect occurs.

Liquidity Dimension	MM Competition	MM Freeloading	Trader Adaption	LO Aversion
Tightness	+	-	+	+
Immediacy	?/+	?	?	?
Breadth	=/+	-	=/+	=/-
Depth	+	-	+	-
Resiliency	+	+	+	-
Net Liquidity Effect	**Increase**	**Decrease**	**Increase**	**Decrease**

Table 1: Sub-hypotheses

This table summarizes the dimension-specific liquidity effects for the four presented hypotheses. We will thus be using this table as the reference for interpreting the empirical results.

3. Methodology

In this section of the thesis, we will present the different empirical methods for measuring the effect of MiFID on stock market liquidity. When performing the initial analysis, we will be using standard Ordinary Least Squares (OLS) regression. In order to test for causality, we will be using the difference-in-difference (DiD) analysis.

3.1 Standard Ordinary Least Squares

For our initial analysis, we will be performing multiple regressions on different liquidity metrics by using the OLS method. The multiple regression model extends the simple regression model by including several control variables. As the literature review shows, there are several determinants of market liquidity. Thus, several explanatory variables will be included to reduce the omitted variables bias. The OLS is performed upon a timeframe of 6 months pre and post implementation.

The OLS estimator seeks to minimize the error between the fitted values and the observed values (3.1). More specifically, this is done by minimizing the Sum of Squared Errors (SSE) (Buse, Ganea, & Circiumaru, 2021). The results from this model (3.1) alone, does not return a causal interpretation (Akramov, 2015).

$$\min (SSE) = \min \left(\textstyle\sum_{i=1}^{n} (y_i - \bar{y})^2\right) \tag{3.1}$$

$$L_i = \beta_0 + \beta_i X_i + \varepsilon_{it}$$

L_i: *Liquidity measurement metrics*

β_0: *Constant term, the fixed liquidity effects*

β_i: *The coefficient for the explanatory variables*

X_i: *Variables used to estimate liquidity*

ε_{it}: *Error term*

3.1.1 Interpretation of OLS Regressions

As presented in section 2, we will be using a combination of five liquidity dimensions to capture the mechanism and liquidity effect through the four hypotheses. The estimated coefficients from the OLS regressions indicate whether the specific liquidity dimensions experience a change. Hence, by evaluating the sign of the coefficient together with the significance level, we will be able to evaluate whether the presented hypotheses can be considered as rejected.

3.2 Difference-in-Difference Method

The empirical study of this thesis seeks to determine the effect of transparency on liquidity by examining the introduction of MiFID. Hence, we are evaluating the possible changes before and after the directive´s implementation. The DiD is the most frequently used method in impact evaluation studies (Fredriksson & Magalhaes, 2019). This method compares two time periods, *pre* and *post*, and two groups, *treatment* and *control.* This is done by comparing two groups of dependent variables that have similar trends before the treatment. While the former group receives the treatment and the latter does not, the difference in the trends after the treatment is used to draw conclusions about the effect of the treatment (Peterson, 1989). In this thesis, we will be using the DiD model to evaluate whether the stock market liquidity in the EU has changed after the implementation of MiFID, compared to the US where MiFID was not introduced.

In order to determine causalities, we will have to eliminate the confounding effects from other variables (Fredriksson & Magalhaes, 2019). This includes eliminating the effects from non-included explanatory variables to isolate transparency´s impact on stock market liquidity. This effect is visible when the difference between the pre and post population is caused by the treatment. However, a simple OLS regression using MiFID as a dummy variable to measure the pre and post liquidity is unlikely to account for the unbundling effects from omitted variables (Leigtner, 2012). In addition, it is reasonable to believe that there are differences in the level of liquidity between the EU and US markets. The DiD model measures the changes after the treatment rather than the absolute levels and is thus an appropriate model for measuring changes in liquidity after the implementation of MiFID.

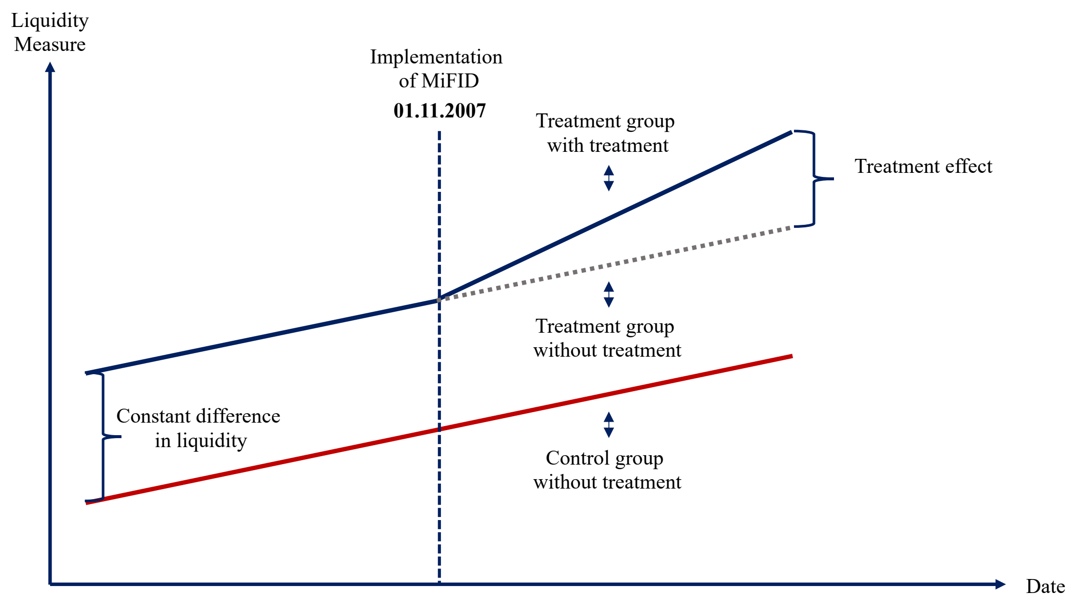

Figure 1: Difference-in-Difference Model

This figure visualizes the Difference-in-Difference Model. The treatment and control group are defined by the difference in color while the pre and post groups can be defined by the dashed line.

In order to evaluate whether stock market liquidity has increased, we will be performing the DiD analysis on different liquidity measures. The purpose of this is to evaluate whether and how MiFID has affected different dimensions of liquidity. As equation 3.2 shows, the DiD is essentially an estimation of the changes in the response variable for the control and treatment group before and after the treatment. The first term in the equation computes the liquidity change pre and post treatment. The second term estimates the same change, but for the control group which does not receive the treatment (MiFID). The difference in the change (difference) is thus the DiD estimator: The greater the DiD, the greater the change in liquidity from the treatment. In order to evaluate the statistical significance level of the DiD estimator, we will be using the DiD estimator as an explanatory variable within the OLS framework (3.1) (Pischke, 2019).

$$DiD = (\bar{L}_{S\,=\,Treatment,t=After} - \bar{L}_{S\,=\,Treatment,t=Before}) - (\bar{L}_{S\,=\,T=Control,\ t=After} - \bar{L}_{S\,=\,Control,\ t=Before}) \tag{3.2}$$

$$Y_{it} = \alpha_t + c_i + \beta DiD_{it} + \theta X_i + \varepsilon_{it} \quad (3.3)$$

In equation 3.3, Y_{it} is the outcome variable (liquidity metric), α_t as the time-fixed effects and c_i is the security-specific effects. DiD_{it} represents the treatment indicator (dummy variable), which takes the value of 1 if the security *i* is treated at time *t.* The significance level is derived from the estimation of β, which represents the effect the MiFID has on stock liquidity. Furthermore, the vector of observable security-specific characteristics are the explanatory variables, X_i. Lastly, the undefined variables will be expressed through the error term, ε_{it}.

When using a DiD estimator as an explanatory variable, one solution is to estimate a dummy which identifies all four dimensions (pre, post, treatment, and control). As equation 3.4 shows, whether MiFID has been implemented is defined as a dummy based on the implementation date (1st of November 2007).

$$MiFID: 1 = After\ 01.11.2007, 0 = Before\ 01.11.2007 \quad (3.4)$$

Furthermore, whether the security is within the treatment or the control group can be defined by using the index variable, which is shown in equation 3.5. We will be using a matched control group, which essentially is the US S&P 500 but matched by using the observable covariates. When defining the control group, we will also be using a dummy.

$$Index: 1 = Matched\ Treatment\ Group, 0 = Matched\ Control\ Group \quad (3.5)$$

In summary, the DiD estimator (3.6) is defined as a dummy variable which represents both of the dummy variables mentioned above. The product of these two dummies is thus the DiD estimator (Wooldridge, 2007). Given that both criteria of the DiD are fulfilled, namely if the date is after 1st of November (D = 1) and the security is within the treatment group, the DiD is equal to 1 (1 × 1 = 1).

$$DiD = D(MiFID) \times D(Index) \quad (3.6)$$

When performing the DiD analysis, we will as mentioned use the OLS framework with the liquidity measurement metrics as the dependent variable. More specifically, we will use the DiD dummy, index, MiFID and control variables (θ_i) to isolate the effect transparency has on market liquidity (3.7).

$$L = \beta_0 + \beta_1 DiD_i + \beta_2 Index_i + \beta_3 MiFID_i + \beta_\gamma \theta_i + \varepsilon_{it} \tag{3.7}$$

3.2.1 Interpreting the DiD Analysis

Given that the introduction of MiFID – and thus increased transparency – has a causal effect on liquidity, this would be expressed through the DiD coefficient. By using the DiD model to map the hypotheses stated earlier, we are able to identify possible causal relationships between increased transparency, mechanisms and the effect on liquidity. The DiD estimator will thus be used to validate the presumed dimension-specific liquidity effects for the four different hypotheses.

4. Variables

In this section of the thesis we will present the variables which will be used to perform the empirical analysis through the methods presented in section 3. Firstly, we will present the dependent variables which will be used to measure market liquidity. Secondly, we will introduce the explanatory variables which will be used to estimate liquidity. These variables will be calculated for a treatment group and a control group. Consequently, we will also present the method for sampling the dataset.

4.1 Dependent Variables

As mentioned in the literature review, liquidity is complex and multifaceted. Inspired by Sarr and Lybek (2002), we will use the five distinct characteristics of a liquid market; *tightness, immediacy, depth, breadth and resiliency*. As our four supplementary hypotheses show, the complexity of liquidity implies that some dimensions of stock liquidity may decrease while others increase. By using the five dimensions of market liquidity, we are better able to capture the effect transparency has on the different dimensions of stock market liquidity. In this section of the thesis, we will present measurable dimension-specific liquidity metrics, followed by a summary of these dependent variables.

4.1.1 Tightness

Of the many liquidity measures presented by Sarr and Lybek (2002), one of the simplest and most common liquidity measures is the bid-ask spread. According to the authors, the bid-ask spread reflects order-processing costs, asymmetric information costs, inventory-carrying costs, and oligopolistic market structure costs. In addition, the bid and ask prices are available for most investors and reflects the highest price an investor is willing to pay for a security and the lowest price a seller would sell the security, respectively.

We will in this thesis be using the absolute value of the bid-ask spread (3.8), as the goal is to measure the changes in the size and not the direction of the spread. However, it is reasonable to believe that a high stock price often yields a higher absolute spread compared to a low stock price. The percentage spread adjusts for the fact that a given spread will be less costly for higher priced stocks (Sarr & Lybek, 2002). This is done by dividing the bid-ask spread by the respective stock closing price (3.9). Here, P_A is the ask price and P_B is the bid price.

$$Spread = |(P_A - P_B)| \quad (3.8)$$

$$Spread\ Percentage = \frac{|(P_A - P_B)|}{Daily\ Close\ Price} \quad (3.9)$$

Bid-Ask-Spread Percentage

When measuring tightness, we will be using the bid-ask-spread percentage. In order to calculate the spread percentage, we will be using daily closing, bid and ask prices gathered for each security per trading day. This yields a bid-ask-spread percentage value for each stock, each trading day. The higher the spread percentage, the lower the market liquidity.

4.1.2 Immediacy

Immediacy says something about the market efficiency in terms of how fast new orders can be executed (Sarr & Lybek, 2002). A market with poor immediacy is often associated with difficulties in executing orders, and often leads to high price movements once the order gets executed (Broto & Lamas, 2016). The daily trading range (3.10) is the difference between the highest and lowest price of the security within a trading day. For the same reasons we use the bid-ask-spread percentage, we will be using the relative daily range, more specifically the range relative to the daily closing price (3.11)

$$Daily\ Range = Highest\ trading\ price - Lowest\ trading\ price \quad (3.10)$$

$$Daily\ Range\ Percentage = \frac{Daily\ Range}{Closing\ Price} \quad (3.11)$$

Daily Range Percentage

As a measure of market immediacy, we will be using the daily range percentage (3.11). This is computed using the daily high and low prices in addition to the daily closing price. This data is gathered for each security, each trading day. A high daily range percentage indicates large intraday price spikes, thus indicating poorer market immediacy.

4.1.3 Breadth and Depth

According to Sarr and Lybek (2002, p. 11), deep markets "tend to foster breadth since large orders can be divided into several smaller orders to minimize the impact on transaction prices". As previously mentioned, depth refers to the abundancy of orders above and below the current trading price (Sarr & Lybek, 2002). The trading volume (3.12) refers to the number of Euros that is traded on the different securities, and thus a higher volume is indicative of a deeper and more liquid market.

$$V = \sum P_i * Q_i \tag{3.12}$$

$V = Currency\ volume\ traded$

$P_i = Price\ of\ the\ i\ trade\ during\ a\ specified\ period$

$Q_i = Quantity\ of\ the\ i\ trade\ during\ a\ specified\ period$

Sarr and Lybek (2002) note that the measure of trading volume is more informative if it is related to the outstanding volume of the respective asset, which implicitly yields the turnover rate (3.13). As a liquidity measure, the turnover rate indicates how many times the outstanding number of instruments has changed hands (Sarr & Lybek, 2002).

$$Tn = \frac{V}{S * P} \tag{3.13}$$

$V = Currency\ volume\ traded$

$S = outstanding\ stock\ of\ the\ asset$

$P = average\ price\ of\ the\ i\ trades$

In addition to the volume and turnover rates, Lybek and Sarr (2002) suggest the Hui-Heubel liquidity ratio as a measure of market breadth. This ratio is calculated as the price impact per currency unit of trading volume. As can be seen in the equation for L_{HH} (3.14), the denominator is the turnover rate presented above. Assets that are more liquid will have a lower Hui-Heubel liquidity ratio than less liquid assets (Sarr & Lybek, 2002). The authors also note that other volume measures may be used in the denominator depending on data availability. In this thesis, we will be using the volume to measure the depth of the market, while using the Hui-Heubel liquidity ratio to measure the market breadth.

$$L_{HH} = \frac{\frac{P_{\max} - P_{min}}{P_{min}}}{\frac{V}{S \times \overline{P}}} \tag{3.14}$$

P_{max} : $Highest\ daily\ price\ over\ the\ past\ 5\ days$

P_{min} : $Lowest\ daily\ price\ over\ the\ past\ 5\ days$

V : $Total\ euro\ volume\ traded\ the\ last\ 5\ days$

S : $The\ number\ of\ instruments\ outstanding$

$\bar{P}$: $The\ average\ closing\ price\ of\ the\ instrument\ over\ a\ 5-day\ period$

Volume and the Hui-Heubel Liquidity Ratio

The volume can be directly extracted from Eikon and does therefore not require any further computation. For the Hui-Heubel liquidity ratio, we will be computing the metric by using the highest and lowest closing prices during a window of five days. Furthermore, we will be using the volume, the number of shares outstanding and the average closing price for the five consecutive trading days.

The calculation of the Hui-Heubel liquidity ratio is done in R by defining the dataset as groups of trading weeks (5 trading days) for each individual stock. This liquidity ratio will therefore be computed once every week and returns one ratio for each stock each trading week. For volume, the liquidity metric is withdrawn for each stock per trading day.

4.1.4 Resiliency

Volume and prices often fluctuate heavily around the time where new relevant market information is released (Fama, Fisher, Jensen, & Roll, 1969). Bernstein (1987) argues that "measures of liquidity when no information is hitting a stock must be more relevant than measures of liquidity when new information leads to new equilibrium values". Hasbrouck and Schwartz's (1988) Market Efficiency Coefficient (MEC) states that price movements are continuous in liquid markets, and thus permanent price changes in the instrument should lead to minimal movements in a resilient market (Sarr & Lybek, 2002). As equation 3.15 shows, the coefficient measures liquidity by comparing short- and long-period volatility in logarithmic returns.

$$MEC = \frac{Var(R_S)^*}{Var(R_S)} = \frac{Var(R_L)}{T*Var(R_S)} \tag{3.15}$$

Here, T is the number of short periods in each long period, while $Var(R_S)$ and $Var(R_L)$ are short- and long-period log return variances, respectively. According to Bernstein (1987), the short-term price action tends to be more random as there is no new information hitting the stock, while longer-term price fluctuations tend to be information driven as new information changes the equilibrium value of the stock. By comparing long and short-period variances, the

Market Efficiency Coefficient deals with the separation between liquidity when new information is hitting the stock and liquidity when there is no new information (Bernstein, 1987).

According to Sarr and Lybek (2002), resilient markets tend to have a Market Efficiency Coefficient close to but slightly below the value one, as some unexplained short-term volatility is still expected. For a less resilient market however, the volatility between periods of different equilibrium prices would be greater, yielding a ratio substantially below one (Sarr & Lybek, 2002). This is because lower price volatility in general increases price continuity, which in other words argues for a more resilient market (Bernstein, 1987).

Market Efficiency Coefficient

We will use the Market Efficiency Coefficient to measure market resiliency, using daily log return for the short-period volatility and monthly log return for the long-period volatility. We are assuming that there are in average 20 trading days each month, and thus the value for T in equation 3.15 will be equal to 20. The long-period volatility is constant and equal to the monthly volatility, while the short-period volatility is calculated by using a rolling window of 20 trading days. The ratio will therefore yield one single value for the Market Efficiency Coefficient for each stock per trading day.

4.1.5 General Liquidity Measure

The previous liquidity measures are chosen to measure the five dimensions of liquidity. In addition to the presented metrics, we will also include one metric which measures the overall market liquidity. This liquidity measure will thus work as a complementary metric to validate the net dimension-specific liquidity effects presented earlier. Amihud (2002) proposes an illiquidity measure calculated as the daily ratio of absolute stock return of a stock to its dollar volume averaged over some period *y*:

$$ILLIQ_{iy} = \frac{1}{D_{iy}} \sum_{t=1}^{Diy} \frac{|R_{iyd}|}{VOLD_{iyd}} \tag{3.16}$$

By comparing the stock's daily return to the volume over the same period, Amihud´s Illiquidity ratio provides a measure of the price impact from one dollar of trading volume without the need for microstructure data required by more sophisticated illiquidity measures

(Amihud, 2002). This enables the ILLIQ measure to be calculated for long time series data, where such microstructure data may not be available (Amihud, 2002).

Bernstein (1987) argues that to effectively measure liquidity, we must separate between market moves caused by noise and those caused by fundamental factors. Market noise is price movement caused by random shifts in supply and demand for the security, whereas fundamental price shifts are a result of information-driven changes in supply and demand for the security (Bernstein, 1987). Bernstein (1987) argues that for the stock market and market maker, it is desirable to minimize the impact of the former while allowing the latter to freely impact prices. According to the author, a popular measure of liquidity is the ratio of dollar volume of trading by the average absolute percentage change in price. This is similar to Amihud´s Illiquidity ratio presented earlier. However, a major problem with this measure is that trade size has been shown to be uncorrelated with price impact, as demonstrated in Marsh and Rock (as cited in Bernstein (1987)). According to Bernstein (1987), this implies that larger stocks, where average transaction size tends to be larger, will have a larger ratio even if they are no more liquid than a smaller stock. Thus, he argues, the ratio may reflect differences in trade sizes rather than liquidity.

Amihud´s Illiquidity Ratio

Amihud (2002) suggests that market liquidity can be measured by calculating the average of the daily illiquidity ratios for all stocks. Thus, this thesis will use the average daily stock-specific illiquidity ratio as the measure for general market liquidity.

4.1.6 Overview of Dependent Variables

For the analysis, we will use each of the five presented dimension-specific liquidity measures, in addition to the general liquidity measure. The data needed to compute the metrics is gathered from the Eikon Terminal. Table 2 presents the different metrics´ effect on their corresponding liquidity dimensions, and thus also their effect on market liquidity. Amihud´s Illiquidity ratio is also included in the table, as this metric supplements the dimension-specific liquidity measures.

		Increase in Metric		Decrease in Metric	
Liquidity Metric	**Liquidity Dimension**	**Effect on Dimension**	**Effect on Liquidity**	**Effect on Dimension**	**Effect on Liquidity**
Bid-Ask Spread	Tightness	Loose	Less Liquid (-)	Tight	More Liquid (+)
Daily Range Percentage	Immediacy	Poor Immediacy	Less Liquid (-)	High Immediacy	More Liquid (+)
Hui-Heubel Liquidity Ratio	Breadth	Broad	More Liquid (+)	Thin	Less Liquid (-)
Volume	Depth	Deep	More Liquid (+)	Shallow	Less Liquid (-)
Market Efficiency Coefficient	Resiliency	Resilient	More Liquid (+)	Non-resilient	Less Liquid (-)
Amihud´s Illiquidity Ratio	-	-	Less Liquid (-)	-	More Liquid (+)

Table 2: Dependent Variables

The signs presented in column four and six of the table indicate the effect on liquidity from each metric increasing or decreasing, respectively. Positive sign refers to increased liquidity, while negative indicates decreased liquidity.

The general level of market liquidity can be expressed through two measures. Firstly, the net effect of the five liquidity dimensions may give an indication about the aggregate effect on general market liquidity. Secondly, Amihud´s Illiquidity ratio is the chosen measure for capturing general market liquidity. The sum of these two methods will thus be used to evaluate whether market liquidity increases or decreases. The reason for adding Amihud´s Illiquidity ratio is to account for the dimension-specific correlations. As presented in Table 3, the Market Efficiency Coefficient (MEC) correlates negatively (-0,52) with the daily range percentage. Elaborated, given an increase in the Market Efficiency Coefficient (indicating increased resiliency and liquidity), the range is expected to decrease (indicating increased immediacy and liquidity). In addition, deep markets tend to foster broad markets (Sarr & Lybek, 2002). This correlation is observable through the negative correlation between volume and the Hui-Heubel liquidity ratio (LHH).

Correlation Matrix

	bid_ask_percentage	range_percentage	volume	MEC	LHH	Market_illiq
bid_ask_percentage	1.00	0.21	-0.18	-0.16	-0.04	0.28
range_percentage	0.21	1.00	0.16	-0.52	0.02	0.07
volume	-0.18	0.16	1.00	-0.09	-0.56	-0.03
MEC	-0.16	-0.52	-0.09	1.00	-0.01	-0.11
LHH	-0.04	0.02	-0.56	-0.01	1.00	-0.11
Market_illiq	0.28	0.07	-0.03	-0.11	-0.11	1.00

Table 3: Correlation Matrix

4.2 Explanatory variables

In this thesis, there are mainly one explanatory variable which is of interest, namely whether MiFID has been implemented for the security in question. The other chosen explanatory variables seek to capture as many dimensions of a company´s characteristics as possible. Inspired by the literature review we will be using some of the control variables which prior research has found to be important determinants of market liquidity. In this thesis, we will thus be using the company’s industry type, market capitalization, relative company size and the number of days being listed on an exchange. The definition of these control variables can be found in the appendix (A2: Explanatory Variables).

4.3 Treatment and Control Group

The presented variables will be gathered for a treatment group and a control group. The treatment group is defined as the securities which MiFID is implemented on, while the control group consist of the securities for which the directive is not implemented. The empirical study will separate the measures from the group who receives the treatment and the measures from the group who does not. By dividing the data between two separate groups, we are able to compare the post-implementation liquidity levels for the two groups, and thus analyze the effect of increased transparency on liquidity.

4.3.1 Treatment Group

The purpose of this thesis is to see whether the official MiFID implementation on the 1st of November has impacted stock market liquidity in the EU. Thus, the treatment group will be comprised of EU stocks, more specifically stocks within the Euro STOXX 600 index. This index is derived from STOXX Europe Total Market Index (TMI) and consists of the largest 600 European companies.

4.3.2 Control Group

The control group for the empirical study is comprised of stocks from the US S&P 500 index (SPX). This index is comprised of the largest 500 listed companies in the US and is used as the counterpart to the European Euro STOXX 600 Index. This is because the Euro STOXX 600 represents the largest 600 companies within Europe, and the control group should therefore also be large in terms of market cap. Furthermore, we consider the US market to be the closest peer to the EU market in terms of size and financial market infrastructure.

However, there is a broad range of factors differing the two indices from each other, which may also imply that there are inherent differences in terms of liquidity. For example, firm characteristics such as the industry types, the range of firm sizes, and the average firm age may differ between the indices. In addition, the National Market Systems (NMS) was introduced in the US the same year as MiFID was implemented in the EU (2007). However, a report from the European Capital Markets Institute (2007) compared the two regulations and argues that the NMS is not a regulation which actively increases market transparency. Thus, we expect most of the differences between the two indexes to be due to inherent firm-specific characteristics, and that the NMS will not interfere with the estimation of transparency effects from MiFID.

Although the control group accounts for the size and MiFID criteria, the stocks within STOXX and S&P itself may be different. Hence, when selecting stocks for the treatment and control groups, we may face the problem of selection bias. This is because differences in market liquidity in Europe and US after the implementation of MiFID may be due to the differences in observable covariates rather than the MiFID regulation (Figure 2). In order to account for these observable covariates, we will perform Nearest Neighbor (NN) Matching by computing a propensity score for each security. This is done because the difference between the treated and untreated stocks should be minimized (Angrist & Pischke, 2011).

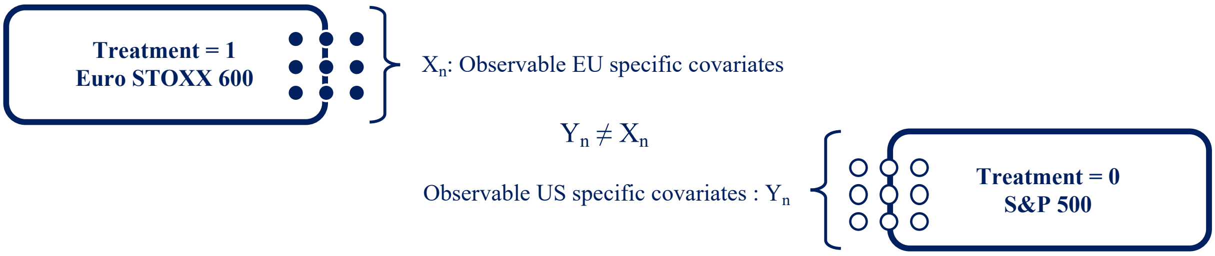

Figure 2: Differences in Observable Index-Specific Covariates

4.3.3 Propensity Score Matching (PSM) Model

According to Caliendo and Kopeinig (2005), Propensity Score Matching (PSM) is one of several popular methods to estimate causal treatment effects. This method is well-suited when performing event studies where there is a likelihood for selection bias, and therefore an endogeneity problem (Caliendo & Kopeinig, 2005). The PSM model assumes that two securities have the same propensity score given the same covariate vector X (Rosenbaum & Rubin, 1983). As we are using the US S&P 500 index portfolio as a peer for the European Euro STOXX 600, it is reasonable to account for observable covariates which affect stock market liquidity. More specifically, the firm-specific characteristics which lies within the two portfolios should be accounted for.

The PSM model seeks to pair two securities which have similar pre-treatment characteristics, and from this create an “untreated-proxy” which will act as a control group for the treated securities. The proxy should act similarly to the treated security, given that the proxy was treated (Pan & Bai, 2021). This enables the empirical analysis to interpret the results in a more causal manner (Pan & Bai, 2021).

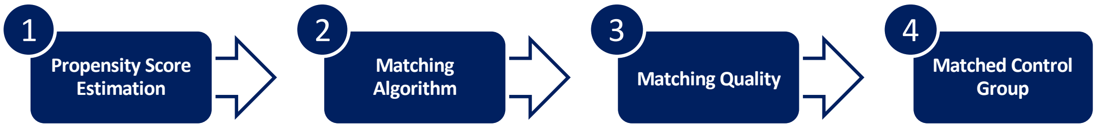

Figure 3: Propensity Score Matching Process

When performing the PSM, we will first estimate the propensity scores, which are then used in the matching algorithm. After this, the matching quality (assumptions) will be evaluated before the final treatment and control groups are presented.

Propensity Score Calculation

When isolating the MiFID effect, it is important that the treatment group and the control group has the same observed covariates. In summary, the propensity score is an estimated value which identifies the securities´ observable covariates (characteristics). The propensity score is estimated using logistic regression. The logistic regression (3.17) predicts the probability that an event occurs, and the propensity score would usually estimate the probability of a stock being treated given the observable covariates. This ensures that the subsequent propensity score matching yields groups that are as similar as possible, with the only difference being the treatment. This allows for a causal interpretation of the effects of treatment.

However, the PSM model assumes that the treatment is randomly assigned. In our case, the treatment is an EU-specific directive, and the treatment is thus not random but entirely dependent on the geographical region where the stock is listed. However, the desired circumstances can be artificially created. By adjusting for all characteristics that differ between securities in the EU and the US, we alleviate differences stemming from geographical location and ensure that the two groups are as similar as possible. Consequently, we would expect the stocks in the treatment and control groups to react similarly if both were given the treatment.

Given two securities with the same covariate vector, the propensity score should be equal for both securities, and thus have equal probability of being treated. In our case, the propensity score is essentially an estimation of the probability of a single stock being in the treatment group. As only the EU stocks are treated by MiFID, the index variable suits well as the response variable. Thus, we will use the logistic regression (3.17) to estimate the probability of a stock being a constituent of Euro STOXX 600.

$$PS = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i \quad (3.17)$$

$PS: Propensity\ Score$

β_0 : $Intercept$

β_i : $Regression\ Coefficient$

X_i : $Observable\ covariates$

The logistic regression will be performed by using the "index" variable as the binary variable. The binary variable is equal to 1 if stock i is subject to Euro STOXX 600, and the value 0 if it is subject to the US S&P 500. We seek to use the observable firm-specific characteristics of the companies as the explanatory variables (X_i). The covariate vector seeks to identify the probability of being subject to the European Euro STOXX 600.

When choosing the explanatory variables for estimating the propensity score, it is important to only include variables which influence the outcome variable (propensity score) simultaneously (Caliendo & Kopeinig, 2005). The chosen explanatory variables seek to capture as many dimensions of a company´s characteristics as possible. In this thesis, we will thus be using the company's industry type (GICS), relative size, market capitalization, and the number of days being listed on an exchange. These explanatory variables will thus be used to estimate each security´s propensity score. This is done by using a logistic regression model (3.18).

$$PS = \beta_0 + \beta_1 GICS_{1:N} + \beta_2 Size_{L,M,S} + \beta_3 IPO_i \quad (3.18)$$

GICS: Table 4 shows that each industry is fairly represented in both portfolios, and we therefore have a good basis on matching the securities. However, the European securities are heavily in the "Industrials" and "Financials" sector which represents approximately 21 % of the securities each, for a total of 42 %. The same sectors only represent 29% of the total number of securities within SPX.

	S&P		STOXX	
Gics	N: Numer of Firms	P: % of Population	N: Numer of Firms	P: % of Population
Communication Services	13	3.892216	32	8.510638
Consumer Discretionary	48	14.371258	31	8.244681
Consumer Staples	27	8.083832	25	6.648936
Energy	23	6.886228	22	5.851064
Financials	49	14.670659	80	21.276596
Health Care	35	10.479042	23	6.117021
Industrials	48	14.371258	80	21.276596
Information Technology	41	12.275449	15	3.989362
Materials	16	4.790419	33	8.776596
Real Estate	12	3.592814	10	2.659575
Utilities	22	6.586826	25	6.648936

Table 4: Overview of GICS divided by index

Size: The size of the firms is a relative percentile computation. Because of the relative size categorization, the size variable should not cause any conflict concerning the possibility of finding a suitable "match" based on firm size.

	S&P		STOXX	
Gics	N: Numer of Firms	P: % of Population	N: Numer of Firms	P: % of Population
Large	125	37.42515	139	36.96809
Medium	111	33.23353	123	32.71277
Small	98	29.34132	114	30.31915

Table 5: Overview of company size divided by index

IPO: The mean number of days between the official MiFID implementation date and the IPO is somewhat similar for both groups. Although there are differences between the values, we expect this to have minimal impact. This is supported when comparing the minimum and maximum days the security has gone since the IPO.

Number of Days between IPO and 01-11-2007		
	S&P	STOXX
Mean	10859	9032
Standard Deviation	8030	9803
Minimum	50	9
Maximum	36912	37507

Table 6: Summary Statistics of IPO divided by index

Matching Algorithm (Nearest Neighbor Matching)

The propensity score computed in the previous section will be used to match the stock within Euro STOXX 600 with the untreated stocks within the US S&P 500. We will be using the Nearest Neighbor (NN) matching algorithm in order to perform the matching of propensity scores. This method is one of the simplest forms of matching algorithms and performs the matching by minimizing the difference between the estimated propensity scores (3.19) (Stuart, 2010). The treated and untreated securities are both randomly ordered, and the NN model matches the first treated security to the untreated security with the lowest corresponding $C(P_j)$ (Thavaneswaran & Lix, 2008).

$$C(P_j) = \min_j |P_i - P_j| \tag{3.19}$$

$C(P_j)$: $Group\ of\ control\ securities\ j\ matched\ to\ treated\ securities\ I$

P_i: $Estimated\ propensity\ score\ for\ treated\ securities\ i$

P_j: $Estimated\ propensity\ score\ for\ untreated\ securities\ j$

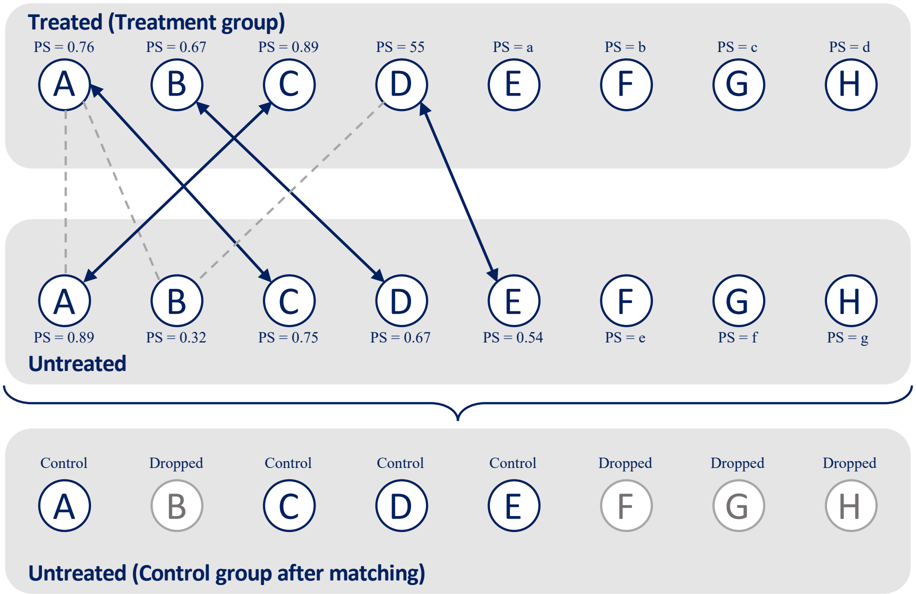

Figure 4: Nearest Neighbor Matching Method

Assumptions

In summary, the propensity score estimated above estimates the probability of a security being assigned to the treatment group, conditional on the covariate vector. In our case, this vector is a list of observable firm-specific characteristics, namely size, market cap, IPO and GICS. This method is based on two assumptions for *strong ignorability* in the treatment group (Rosenbaum & Rubin, 1983).

According to Rosenbaum and Rubin (1983), the first assumption states that *the treatment z and the response variable are conditionally independent given X.* This assumption requires that the propensity score (response variable) is independent of the treatment (Rosenbaum & Rubin, 1983). The propensity score is in this thesis estimated based on whether a security is subject to the European Euro STOXX 600. Since we are controlling for the pre-treatment variables, this assumption is considered fulfilled. Furthermore, the assumption also requires that the response variable is conditional on the pre-treatment characteristics (Rosenbaum & Rubin, 1983). We are using four explanatory variables to estimate the propensity score, and from TABLE, these explanatory variables are significant on a 10% significance level.

	Dependent variable:
	DiD
gicsConsumer Discretionary	-1.384***
	(0.408)
gicsConsumer Staples	-0.833*
	(0.442)
gicsEnergy	-0.871*
	(0.451)
gicsFinancials	-0.458
	(0.381)
gicsHealth Care	-1.332***
	(0.430)
gicsIndustrials	-0.339
	(0.387)
gicsInformation Technology	-1.903***
	(0.450)
gicsMaterials	-0.139
	(0.454)
gicsReal Estate	-1.093**
	(0.547)
gicsUtilities	-0.739*
	(0.448)
sizeMedium	-0.231
	(0.223)
sizeSmall	-0.248
	(0.238)
mcap	-0.000*
	(0.000)
IPO	-0.00003***
	(0.00001)
Constant	1.409***
	(0.401)
Observations	710
Log Likelihood	-461.588
Akaike Inf. Crit.	953.177
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 7: Propensity Score Model

The second assumption states that t*here lies a common support between the treatment and control group* (Rosenbaum & Rubin, 1983). According to Rosenbaum and Rubin (1983), this assumption refers to the broad range of available data, and for each explanatory variable X, there should be both a treated and untreated observation. As Figure 5 shows, the matched control group (Treatment = 0) and the treatment group (Treatment = 1) seem to have a somewhat similar distribution considering the size.

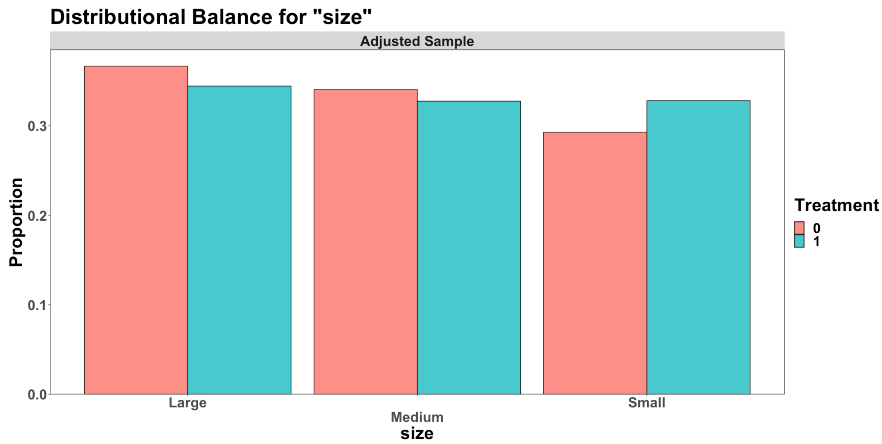

Figure 5: Matched and Unmatched Distribution for Size

When looking at different industry types (Figure 6), most of the industries are similarly represented within the matched control group (dummy equal to 0), except for the industrial, financial and consumer discretionary sectors. This is expected because of the lack of data for these industries within the SPX portfolio.

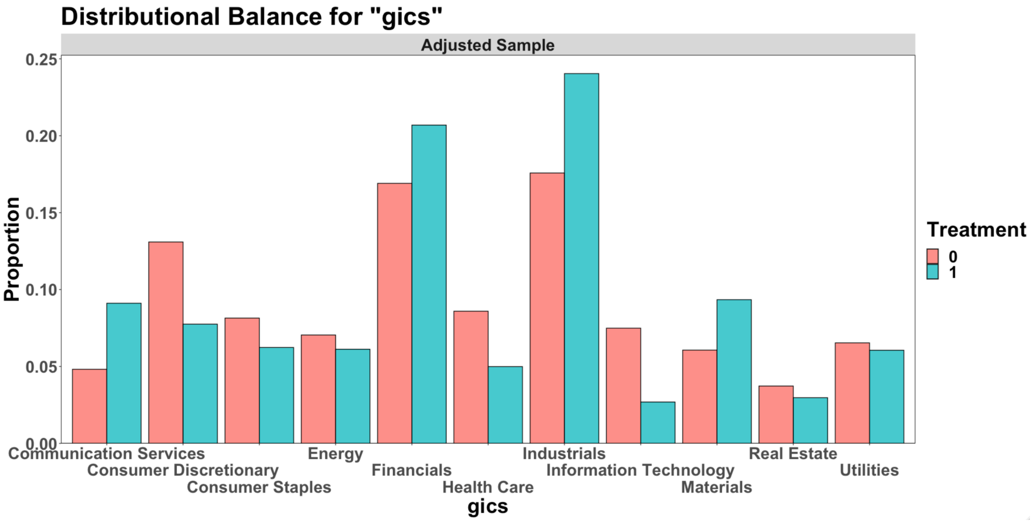

Figure 6: Matched and Unmatched Distribution for GICS

From the density plot for the company age (Figure 7), it is observable that there are fewer "old" companies within the treatment group (STOXX). This is expected from the initial table of summary for the IPO variable (Table 6). Furthermore, the American securities seem to consist of larger companies in terms of market capitalization (Figure 8).

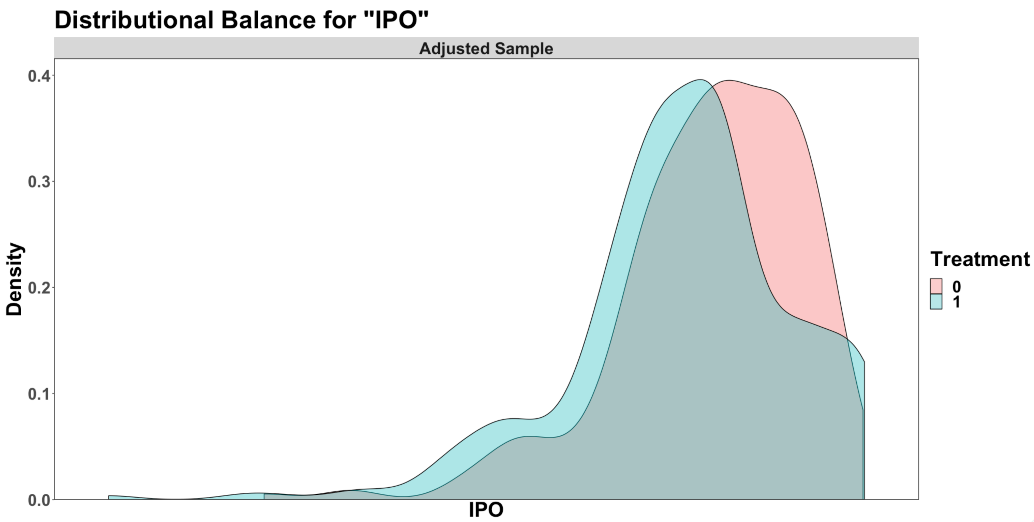

Figure 7: Matched and Unmatched Distribution for IPO

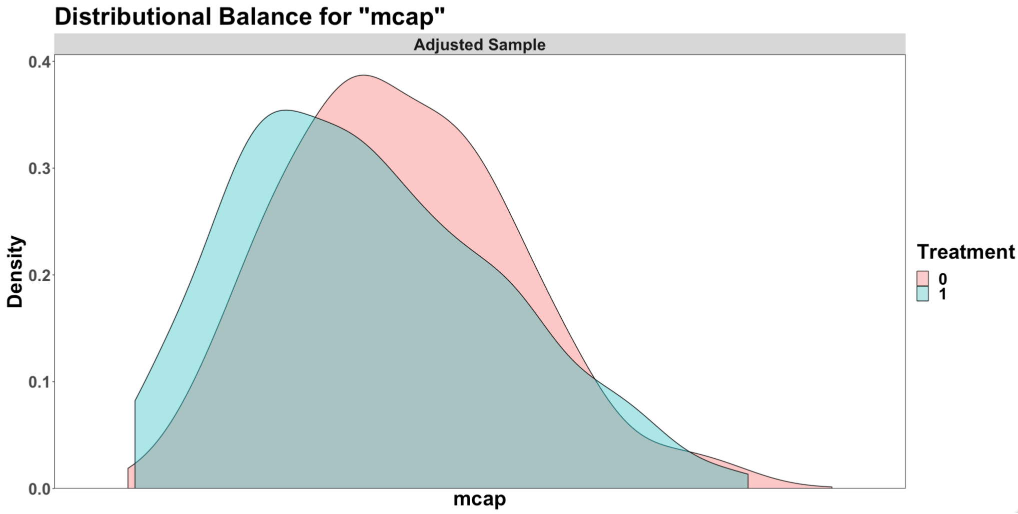

Figure 8: Matched and Unmatched Distribution for Market Capitalization

A general review of the distribution of the variables indicate that the second assumption is fulfilled. seem to be fulfilling the assumption, not a strong and clear conclusion, but enough to be able to use the matched control group as a better suited control compared to the raw S&P 500 index.

Matched Control Group

The control group is withdrawn by using the US S&P 500 as basis. This portfolio of 500 historical constituents is then matched against the treatment group (Euro STOXX 600). The matching is performed by using the estimated propensity scores, and by randomly ordering the stocks, matching the two portfolios by using the Nearest Neighbor matching method without replacement. Because of the lack of data, especially the industry type, the treatment- and matched control group decreases in size. More specifically, the sample is reduced to consisting of 334 securities within both the control and treatment groups.

	Without Replacement		With Replacement	
	T-test (P-Value): 2.2e-16		T-test (P-Value): 8.204e-08	
Index	Number of stocks	Mean Propensity Score	Number of stocks	Mean Propensity Score
SPX	334	0.6357501	180	0.5957896
STOXX	334	0.4550392	376	0.5133441

Table 8: Propensity Score Distribution With and Without Replacement

The mean propensity score for both methods are different, and both t-tests suggest that there is a significant difference in the average propensity score for the treatment and control group (B2: Propensity Score (T-test)). The difference in propensity score is lower when allowing for replacement (Table 8). We will however perform the matching by restricting replacement in order to have a broader dataset, and therefore randomly ordering the securities when performing the matching.

5. Data Structure

As MiFID was officially introduced on the 1st of November 2007, we will need the historical constituents of the two indexes (STOXX 600 and S&P 500) to capture the directive´s effect on stock market liquidity. In practical terms, we will use the constituents for the 1st of January 2011. This is because the constituents in 2011 have "survived" the financial crisis in 2008. Thus, the data sampling would be less affected by missing values, which consequently strengthens the initial data sampling. Furthermore, we remove securities from European countries not part of the EU in the period from one year prior to and one year after the implementation date. This is done as MiFID is an EU directive, and to avoid any complications regarding potential special rules applying for countries that are part of the European Economic Area (EEA) but not the EU.

After removing the aforementioned countries, the initial dataset consists of 528 securities from STOXX and 500 securities from SPX. The initial raw data is gathered from the Eikon Terminal for all 1,028 securities and a daily trading window between the 1st of January 2004 to the 1st of January 2011. The data consists of 2,629,624 observations for each imported variable (17 variables excluding computed metrics), which form the fundamental dataset upon which further analyses will be performed. The initial dataset is reduced when performing the PSM model, resulting in a reduction of 166 securities for the control group and 194 securities for the treatment group. Consequently, the PSM model returns a dataset consisting of 668 securities equally distributed between the two groups (334 securities for each group).

	Initial	Matched	
	Number of Securities	Number of Securities	Difference
Control Group	500	334	166
Treatment Group	528	334	194
Total	1028	668	340

Table 9: Summary of Control and Treatment Group for Matched and Unmatched Sample

When performing the empirical study, we will sort the group into two periods and two groups. This is done because the data can be divided based on two main conditions, namely time and index (group). The event study seeks to examine changes following the implementation of MiFID, and we will thus be gathering data for 3 years before and after the implementation date (1st of November 2007).

	Data Type		Summary Statistics (Euro STOXX 600)			Summary Statistics (S&P 500)		
	Type	Frequency	Max	Min	Average	Max	Min	Average
Volume	Log	Daily	20.703533	0	14.010217	21.337238	6.907755	14.109248
Bid-Ask Spread Percentage	Log	Daily	4.597632	-12.269042	-6.561981	-0.098695	-11.495806	-7.062919
Range Percentage	Log	Daily	0.763863	-9.764411	-3.770972	0.962421	-8.178919	-3.788575
Hui-Heubel´s Liquidity Ratio	Log	Weekly	16.649238	-5.548068	4.109695	12.035502	-0.941181	4.351933
Market Efficiency Coefficient	Log	Daily	6.560383	-6.644466	-2.540301	4.131453	-6.437966	-2.485543
Amihuds´s Illiquidity Ratio	Log	Monthly	-14.154811	-17.68692	-15.916897	-17.844879	-22.024451	-19.912892

Table 10: Summary Statistics for the Initial Sample Divided by Index

When computing the metrics, some variables are scaled especially high, while other variables measure as low as 10^(-10). In order to interpret the results (coefficients), we scale the variables by using a log-transformation (Table 10).

There are some potential limitations regarding the data sampling of our study. During the timeframe of our data sampling (2004 – 2011), the global financial crisis erupted (2007 – 2008). The financial crisis could naturally be expected to affect stock market liquidity, as many companies are likely to be struggling and the financial markets likely experience increased volatility and fear. However, a study performed by Halil & Engkuchik (2017) showed that there is no causal linkage between four financial crises (the Thai crisis, the Hong Kong crisis, the Russian crisis, and the Brazilian crisis) and stock market liquidity. In this thesis, the financial crisis is therefore not considered a strong limitation for our empirical study. Nevertheless, a potential solution to alleviate any effects from the crisis is to control for the year-specific fixed effects by using a categorical control variable for the different years.

5.1 Univariate Analysis

Before performing the empirical analysis, we will present the changes in each liquidity metric, split between one week, two weeks, one month, three months, 6 months and 12 months pre and post MiFID. The variables are solely based upon the EU securities and thus the treatment group.

	BAS	Range	Volume	LHH	MEC	ILLIQ
Pre 1w	-6.8287121	-3.7757723	14.2926694	4.0742512	-2.4849549	-14.893926
Post 1w	-6.7803303	-3.5656842	14.2652598	4.3333269	-2.5010876	NA
Difference (1w)	0.0483818	0.2100882	-0.0274096	0.2590756	-0.0161326	NA
Pre 2w	-6.8065543	-3.7970929	14.2803220	4.0107749	-2.5347528	-14.893926
Post 2w	-6.8214784	-3.5081865	14.3198664	4.2369897	-2.5729484	NA
Difference (2w)	-0.0149240	0.2889064	0.0395444	0.2262149	-0.0381956	NA
Pre 1m	-6.8101425	-3.8112814	14.2848959	4.0048856	-2.5875899	-14.893926
Post 1m	-6.8079349	-3.4740186	14.3402604	4.2188466	-2.7000656	NA
Difference (1m)	0.0022075	0.3372629	0.0553645	0.2139611	-0.1124757	NA
Pre 3m	-6.7723997	-3.7150365	14.3562997	4.0621002	-2.8002161	-15.067623
Post 3m	-6.7438621	-3.4518001	14.3523565	4.2434021	-2.9252492	-16.543324
Difference (3m)	0.0285377	0.2632364	-0.0039432	0.1813019	-0.1250331	-1.475701
Pre 6m	-6.7723997	-3.7150365	14.3562997	4.0621002	-2.8002161	-15.067623
Post 6m	-6.7438621	-3.4518001	14.3523565	4.2434021	-2.9252492	-16.543324
Difference (6m)	0.0285377	0.2632364	-0.0039432	0.1813019	-0.1250331	-1.475701
Pre 12m	-6.7723997	-3.7150365	14.3562997	4.0621002	-2.8002161	-15.067623
Post 12m	-6.7438621	-3.4518001	14.3523565	4.2434021	-2.9252492	-16.543324
Difference (12m)	0.0285377	0.2632364	-0.0039432	0.1813019	-0.1250331	-1.475701

Table 11: Univariate Analysis

The table summarizes the changes in liquidity for different periods by measuring the difference in liquidity pre and post MiFID (2007-11-01).

The univariate analysis (Table 11) supports the hypotheses of a positive liquidity effect of increased transparency. Most liquidity variables point in the direction of increased market liquidity when measuring the post-treatment variables against the pre-treatment variables. However, it is yet hard to distinguish whether the effect is due to MiFID or a general increase in market liquidity after 1st of November 2007.

6. Results

In this section, we will interpret the results from the empirical analysis. Furthermore, we will evaluate whether the DiD models´ assumptions can be considered as fulfilled, which is critical for being able to interpret the results causally. Each method in this section is followed by a statistical significance evaluation, while the economic plausibility of the results will be presented at the end of this section using the statistical interpretations of each model. For each analysis, we perform one regression for each metric, with pre and post treatment windows of 6 months.

6.1 OLS Regression

The OLS Regression (Table 12) is performed upon each of the six liquidity metrics by using the historical constituents (528 stocks) of the Euro STOXX 600 index. As Table 12 shows, most coefficients seem to be statistically significant. The variable of interest is the dummy variable "MiFID", which is statistically significant at a 1% significance level for each of the liquidity metrics.

	Dependent variable:					
	MEC (Resiliency) (1)	range_percentage (Immediacy) (2)	LHH (Breadth) (3)	bid_ask_percentage (Tightness) (4)	volume (Depth) (5)	Market_illiq (General) (6)
MiFID	-0.408***	0.250***	0.237***	0.044***	-0.080***	-1.561***
	(0.007)	(0.005)	(0.019)	(0.008)	(0.016)	(0.009)
sizeMedium	0.014	-0.015**	0.275***	-0.097***	0.085***	0.0003
	(0.010)	(0.006)	(0.026)	(0.011)	(0.022)	(0.012)
sizeSmall	0.060***	-0.019**	0.003	-0.186***	0.456***	-0.001
	(0.014)	(0.009)	(0.036)	(0.016)	(0.032)	(0.018)
gicsConsumer Discretionary	-0.057***	0.176***	0.166***	-0.348***	-0.143***	-0.0001
	(0.012)	(0.008)	(0.032)	(0.014)	(0.028)	(0.015)
gicsConsumer Staples	-0.241***	-0.011	0.235***	-0.282***	-0.244***	-0.001
	(0.013)	(0.008)	(0.035)	(0.014)	(0.029)	(0.016)
gicsEnergy	0.009	0.155***	0.064*	-0.366***	0.065**	-0.001
	(0.013)	(0.009)	(0.034)	(0.015)	(0.030)	(0.017)
gicsFinancials	0.172***	0.067***	0.995***	-0.013	-0.846***	0.002
	(0.010)	(0.007)	(0.027)	(0.012)	(0.023)	(0.013)
gicsHealth Care	-0.131***	0.056***	0.573***	0.116***	-0.472***	-0.001
	(0.013)	(0.009)	(0.035)	(0.014)	(0.030)	(0.017)
gicsIndustrials	-0.110***	0.181***	0.008	-0.210***	0.151***	-0.001
	(0.010)	(0.007)	(0.027)	(0.012)	(0.023)	(0.013)
gicsInformation Technology	-0.030**	0.138***	-0.372***	-0.360***	0.271***	-0.002
	(0.015)	(0.010)	(0.039)	(0.017)	(0.034)	(0.019)
gicsMaterials	-0.031***	0.241***	0.593***	-0.168***	-0.419***	-0.002
	(0.012)	(0.008)	(0.031)	(0.013)	(0.027)	(0.015)
gicsReal Estate	-0.113***	0.250***	0.747***	-0.077***	-0.375***	-0.003
	(0.017)	(0.011)	(0.048)	(0.020)	(0.040)	(0.022)
gicsUtilities	-0.080***	-0.039***	-0.015	-0.271***	0.111***	0.001
	(0.013)	(0.008)	(0.034)	(0.016)	(0.029)	(0.016)
IPO	-0.025***	-0.015***	0.043***	0.011***	-0.034***	0.0003
	(0.002)	(0.001)	(0.005)	(0.002)	(0.005)	(0.003)
mcap	0.089***	-0.051***	0.139***	-0.369***	0.966***	-0.001
	(0.005)	(0.003)	(0.013)	(0.006)	(0.011)	(0.006)
year2008	-0.388***	0.147***	-0.087***	0.071***	0.170***	0.338***
	(0.007)	(0.005)	(0.020)	(0.009)	(0.017)	(0.009)
Constant	-4.269***	-2.625***	0.121	1.890***	-7.838***	-14.968***
	(0.124)	(0.082)	(0.327)	(0.144)	(0.286)	(0.159)
Observations	74,503	94,940	80,520	84,674	95,001	30,437
Log Likelihood	-74,780.270	-67,432.760	-163,376.700	-102,696.200	-186,729.700	-24,582.260
Akaike Inf. Crit.	149,594.500	134,899.500	326,787.400	205,426.400	373,493.400	49,198.510
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 12: OLS Regression (T= 6 months pre and post MiFID)

The question of whether the introduction of MiFID has increased stock market liquidity can be answered by observing the coefficient for MiFID. As all the variables are logged, the coefficients can be interpreted in percentage terms. As Table 13 shows, all liquidity dimensions indicate a reduction in market liquidity. More specifically, the Market Efficiency Coefficient decreases by 40,8%, range increases by 25%, the Hui-Heubel liquidity ratio increases by 23,7 %, the spread increases by 4,4% and the volume decreases by 8%. This indicates a looser, shallower and narrower market with lower resiliency and immediacy after the MiFID implementation, implying a loss of liquidity.

OLS Regression			
Liquidity Metric	**MiFID Coefficient**	**Effect on Liquidity**	**Liquidity Dimension**
Bid-Ask Spread	+	Less Liquid (-)	Tightness
Daily Range Percentage	+	Less Liquid (-)	Immediacy
LHH	+	Less Liquid (-)	Breadth
Volume	-	Less Liquid (-)	Depth
MEC	-	Less Liquid (-)	Resiliency
Net Liquidity Effect		**Less Liquid (-)**	
ILLIQ	**-**	**More Liquid (+)**	**General**

Table 13: Summary Table for the OLS Regression

The table summarizes the coefficient signs and presents the corresponding dimension-specific liquidity effects. An increase (+) in coefficient for the Bid-Ask Spread indicates a “Less Liquid (-)” market for the “Tightness” dimension. The Net Liquidity Effect is the summary of the five dimensions and shall be read complementary to the ILLIQ variable.

On the other hand, the coefficient for Amihud´s Illiquidity ratio (ILLIQ) is negative, indicating that general stock market liquidity has increased. In summary, liquidity as measured by the five liquidity dimensions decreases while Amihud´s Illiquidity ratio indicates an increase in liquidity. This contradiction highlights the importance of using several different liquidity measures, as the effect on liquidity may differ depending on how liquidity is measured. However, the OLS regression only measures the difference in liquidity levels pre and post treatment for EU stocks. Without a control group, we cannot infer whether the effect is due to MiFID or other factors. Due to these considerations, it is difficult to conclusively say whether liquidity has increased or decreased, and it is even harder to identify a potential causal relationship between increased transparency and liquidity.

6.2 Difference-in-Difference

The DiD model is performed upon the matched treatment and control group, which are matched through a pair-to-pair matching as described earlier. The treatment and control groups consist of 334 stocks each. For each stock, we have six dependent variables. The data is narrowed down to a period of 6 months pre and post treatment for a total of 12 months. Table 14 shows the results from the DiD analysis. The DiD estimator is statistically significant for each of the variables. This is similar to the significance of the MiFID coefficient from the multiple OLS-regression.

Results

	Dependent variable:					
	MEC (Resiliency) (1)	range_percentage (Immediacy) (2)	LHH (Breadth) (3)	bid_ask_percentage (Tightness) (4)	volume (Depth) (5)	Market_illiq (General) (6)
DiD	0.114^{***}	0.042^{***}	-0.042^{***}	-0.101^{***}	0.038^{***}	-2.327^{***}
	(0.007)	(0.005)	(0.015)	(0.008)	(0.014)	(0.011)
MiFID	-0.528^{***}	0.206^{***}	0.269^{***}	0.164^{***}	-0.100^{***}	0.397^{***}
	(0.006)	(0.004)	(0.013)	(0.006)	(0.012)	(0.009)
indexSTOXX	-0.186^{***}	0.049^{***}	-0.257^{***}	0.183^{***}	0.013	5.819^{***}
	(0.005)	(0.004)	(0.011)	(0.006)	(0.010)	(0.007)
gicsConsumer Discretionary	-0.172^{***}	0.254^{***}	-0.174^{***}	-0.080^{***}	-0.086^{***}	0.001
	(0.009)	(0.006)	(0.019)	(0.009)	(0.018)	(0.013)
gicsConsumer Staples	-0.217^{***}	-0.089^{***}	-0.063^{***}	-0.135^{***}	-0.415^{***}	-0.001
	(0.010)	(0.007)	(0.021)	(0.010)	(0.019)	(0.014)
gicsEnergy	-0.032^{***}	0.254^{***}	0.234^{***}	0.032^{***}	-0.352^{***}	-0.0004
	(0.010)	(0.007)	(0.021)	(0.011)	(0.020)	(0.014)
gicsFinancials	0.171^{***}	0.132^{***}	0.779^{***}	0.080^{***}	-0.845^{***}	0.001
	(0.008)	(0.005)	(0.017)	(0.009)	(0.016)	(0.012)
gicsHealth Care	-0.102^{***}	-0.024^{***}	0.268^{***}	0.076^{***}	-0.603^{***}	0.0004
	(0.010)	(0.006)	(0.020)	(0.010)	(0.019)	(0.014)
gicsIndustrials	-0.182^{***}	0.167^{***}	0.060^{***}	-0.036^{***}	-0.375^{***}	-0.001
	(0.008)	(0.005)	(0.017)	(0.008)	(0.016)	(0.012)
gicsInformation Technology	-0.162^{***}	0.220^{***}	-0.645^{***}	-0.109^{***}	0.530^{***}	0.001
	(0.010)	(0.007)	(0.022)	(0.010)	(0.020)	(0.014)
gicsMaterials	-0.094^{***}	0.229^{***}	0.399^{***}	-0.039^{***}	-0.461^{***}	-0.001
	(0.010)	(0.006)	(0.020)	(0.010)	(0.019)	(0.014)
gicsReal Estate	-0.017	0.292^{***}	1.068^{***}	0.211^{***}	-0.811^{***}	-0.001
	(0.013)	(0.008)	(0.026)	(0.013)	(0.025)	(0.018)
gicsUtilities	-0.251^{***}	-0.046^{***}	0.028	-0.094^{***}	-0.256^{***}	0.0004
	(0.010)	(0.007)	(0.020)	(0.011)	(0.019)	(0.014)
sizeMedium	-0.066^{***}	0.068^{***}	-0.221^{***}	0.315^{***}	-1.017^{***}	-0.0002
	(0.004)	(0.003)	(0.009)	(0.005)	(0.009)	(0.006)
sizeSmall	-0.103^{***}	0.100^{***}	-0.515^{***}	0.512^{***}	-1.561^{***}	0.0001
	(0.005)	(0.003)	(0.009)	(0.005)	(0.009)	(0.006)
IPO	-0.026^{***}	-0.039^{***}	0.028^{***}	0.005^{***}	-0.045^{***}	0.001
	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)
year2008	-0.376^{***}	0.150^{***}	-0.090^{***}	0.038^{***}	0.151^{***}	0.858^{***}
	(0.006)	(0.004)	(0.011)	(0.006)	(0.011)	(0.008)
Constant	-1.892^{***}	-3.721^{***}	4.153^{***}	-7.286^{***}	15.793^{***}	-20.811^{***}
	(0.017)	(0.011)	(0.035)	(0.018)	(0.033)	(0.024)
Observations	131,767	168,649	148,411	158,890	168,710	61,021
R^2	0.285	0.172	0.099	0.104	0.199	0.940
Adjusted R^2	0.285	0.172	0.098	0.104	0.199	0.940
Residual Std. Error	0.657 (df = 131749)	0.494 (df = 168631)	1.440 (df = 148393)	0.746 (df = 158872)	1.446 (df = 168692)	0.625 (df = 61003)
F Statistic	$3,095.843^{***}$ (df = 17; 131749)	$2,054.856^{***}$ (df = 17; 168631)	954.554^{***} (df = 17; 148393)	$1,084.102^{***}$ (df = 17; 158872)	$2,466.654^{***}$ (df = 17; 168692)	$55,844.820^{***}$ (df = 17; 61003)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 14: DiD Regression for Matched Treatment and Control Group

The variables of interest are the DiD Estimator (DiD), treatment variable (MiFID) and the group variable (indexSTOXX). The year-fixed effect is significant for each liquidity metric and accounts for potential liquidity changes due to the financial crisis.

As all of the six regressions presented are log-level regressions, the coefficient represents a percentage change in the dependent variable. As regression 1 shows, the post-treatment Market Efficiency Coefficient increases by approximately 11,4%, significant at the 1% significance level. The increase in the Market Efficiency Coefficient implies a decrease in short-period volatility relative to long-period volatility, indicating an increase in liquidity in the form of higher market resiliency.

This relationship is supported by three other liquidity dimensions, namely market depth, breadth, and tightness. The spread decreases by 10,1% implying a reduction in transaction cost, indicating increased market liquidity as measured by tightness. Furthermore, the volume increases by 3,8% post-treatment, implying a deeper and more liquid market. In addition, the Hui-Heubel liquidity ratio decreases by 4,2% indicating a broader and thus more liquid market. Amihud´s illiquidity ratio decreases by 232,7% after the implementation of MiFID for the treatment group, suggesting an increase in general market liquidity.

However, the daily range percentage increases by 4,2 %, significant at the 1% significance level. Thus, liquidity as measured by immediacy decreases after the implementation of MiFID. The signs of the coefficients are summarized in Table 15. In summary, four out of five dimensions as well as the general illiquidity measure suggest an increase in liquidity.

DiD Analysis					
Liquidity Metric	**DiD Coefficient**	**Effect on Liquidity**	**Liquidity Dimension**	**Significance Level**	**Coefficient**
Bid-Ask Spread	-	More Liquid (+)	Tightness	p < 1%	0,101
Daily Range Percentage	+	Less Liquid (-)	Immediacy	p < 1%	0,42
LHH	-	More Liquid (+)	Breadth	p < 1%	0,042
Volume	+	More Liquid (+)	Depth	p < 1%	0,038
MEC	+	More Liquid (+)	Resiliency	p < 1%	0,114
Net Liquidity Effect		**More Liquid (+)**			
ILLIQ	-	**More liquid (+)**	**General**	p < 1%	2,327

Table 15: Summary Statistics for the 6m Pre and Post Treatment DiD Regression

The DiD analysis indicates that increased transparency causes increased market liquidity on aggregate. However, the analysis also shows that an increase in liquidity from one dimension may not necessarily imply an increase in other liquidity dimensions.

DiD Analysis		Results Effect on Liquidity´s Five Dimensions			
Liquidity Metric	**Effect on Liquidity**	**MM Competition**	**MM Freeloading**	**Trader Adaption**	**LO Aversion**
Bid-Ask Spread	More Liquid (+)	+	-	+	-
Daily Range Percentage	Less Liquid (-)	?/+	?	?	?
LHH	More Liquid (+)	=/+	-	=/+	=/-
Volume	More Liquid (+)	+	-	+	-
MEC	More Liquid (+)	+	+	+	-
Net Liquidity Effect	**Increase**	**Increase**	**Decrease**	**Increase**	**Decrease**

Table 16: Net Liquidity Effect Applied upon the Four Hypotheses

The green fields indicate that the liquidity effect from the regression is consistent with the expected dimension-specific liquidity effect. Red otherwise.

Table 16 summarizes the observed effects from the DiD analysis and compares them to the expected effects from our four hypotheses. As the table shows, our findings are highly consistent with two mechanisms, namely *Market Maker Competition and Trader Adaption*. It is yet hard to distinguish the effect between the two hypotheses.

6.2.1 Parallel Trends & Other Assumptions

In the DiD model, there are several assumptions that need to hold for the results to be interpreted as causal (Fredriksson & Magalhaes, 2019). The most important assumption is the "parallel trends" assumption (i). In addition to the parallel trends, the DiD model has two other assumptions. The stable unit assumption (ii) implies that there are no spill-over effects between the control- and treatment groups. If the stable unit assumption does not hold, the effect of increased transparency cannot be identified. Furthermore, the model assumes that the control variables are exogenous (iii). This implies that the control variables should not be affected by whether MiFID has been implemented, as the coefficient would then be biased (Rahendran, 2019).

The latter two assumptions (ii, iii) can be considered as fulfilled. The Stable unit assumption assumes that the model equation is correct. In our model equation, we are using firm-specific characteristics in addition to the treatment variable, the group variable, and the interaction between the latter two variables. The variables can also be considered as exogenous, implying that the error term is equal to zero. The exogenous variable assumption is considered fulfilled, as our DiD model includes a constant term (Albouy, 2004).

As mentioned, the parallel trends assumption is the most crucial assumption in order to interpret the results as causal. This assumption states that the trends for the control and treatment groups are the same before the treatment. The control group is sampled by using the PSM model, and firm-specific characteristics are thus accounted for. By using a matched control group, the likelihood of fulfilling the parallel trend assumption is higher (Ryan et al. 2018).

Several statistical tests have been proposed for evaluating whether the parallel trends assumption is fulfilled. However, these methods have received much criticism (Kahn-Lang & Lang, 2018). This is because the only group which can be observed as treated is the treatment group, and the parallel trends assumption is therefore fundamentally untestable (Fredriksson & Magalhaes, 2019). We will therefore be performing a graphical analysis for deciding whether the parallel trends assumption holds. When evaluating the pre-treatment trends, we are defining the pre-treatment period as the 6 months prior to treatment. The pre-treatment period is thus the period from the 1st of May 2007 to the 1st of November 2007. The evaluation of the parallel trends assumption will be performed upon each of the liquidity metrics.

Evaluation of Parallel Trends Assumption

From appendix (C3: Parallel Trends (Matched STOXX and SPX)), it is observable that some of the metrics are fulfilling the parallel trends assumption while other metrics have more deviations from what is defined as equally trending time series before the treatment. For the Market Efficiency Coefficient and the daily range percentage, the treatment and control groups are similar in terms of the level and trends for the whole six-month period prior to treatment. Thus, the parallel trends assumption can be considered as fulfilled for the Market Efficiency Coefficient and the daily range percentage.

For the bid-ask spread there is a large initial difference that later converges towards a similar level around September 2007. It is thus doubtful whether the parallel trends assumption holds for the pre-treatment bid-ask spread. For the volume, both groups experience an initial increase followed by a dip from the middle of August 2007. However, the difference between the two groups is not constant, as the levels first converge before diverging. Because of these reasons, it is doubtful whether the parallel trends assumption holds for the spread and volume.

For Amihud´s Illiquidity ratio, the pre-treatment levels diverge before later converging slightly. It is also noticeable that the difference in level between the groups is larger for this measure than for the previous measures. Although this difference does not reject the assumption by itself, it is important to mention that the parallel trends assumption is more likely to hold if the levels are similar to begin with (Mckenzie, 2020). For the Hui-Heubel liquidity ratio, the trends are initially similar, but later diverge before converging again. Thus, it is also doubtful whether the parallel trends assumption holds for Amihud´s Illiquidity Ratio and the Hui-Heubel Liquidity Ratio.

6.3 Staggered Difference-in-Difference

Although the official implementation date of MiFID is the 1st of November 2007, the actual implementation date for several European countries differ from the official date. This might be because the directive takes time and affects countries differently. To capture the transparency effect on the stock market liquidity, it is therefore important to account for the difference in implementation dates (Table 17).

Implementation of MiFID overview			
Country	Index	Date	Number of Stocks
Belgium	STOXX	2006-07-01	18
Italy	STOXX	2007-11-01	35
United Kingdom	STOXX	2007-11-01	165
Greece	STOXX	2007-11-01	12
France	STOXX	2007-11-01	80
Netherlands	STOXX	2007-11-01	30
Germany	STOXX	2007-11-01	58
Sweden	STOXX	2007-11-01	35
Austria	STOXX	2007-11-01	11
Portugal	STOXX	2007-11-01	10
Denmark	STOXX	2007-11-01	19
Finland	STOXX	2007-11-01	19
Spain	STOXX	2007-12-21	36
United States of America	SPX	NA	499

Table 17: Summary of the Official Implementation Dates for the Countries Represented in this Thesis

By performing the DiD model upon the "early" treated country and using the remaining non-treated EU securities as the control group, we will be able to account for the different implementation dates. This requires the use of a Staggered Difference-in-Difference model. This model is essentially the regular DiD model, but accounts for multiple treatment dates. Table 18 shows two countries of special interest, namely Belgium and Spain. The former implemented MiFID on the 1st of July 2006, while the latter implemented it on the 21st of December 2007. We will therefore perform a staggered DiD with these two countries in addition to the remaining countries which implemented MiFID on the official implementation date.

Treatment Group	Control Group	Treatment (Pre/Post)
Belgium	Matched Control Group (SPX)	01.07.2006
Belgium	Matched Control Group (STOXX)	01.07.2006
Spain	Matched Control Group (SPX)	21.12.2007
STOXX Without Belgium and Spain	Matched Control Group (SPX)	01.11.2007

Table 18: Summary of Dates used in the Staggered DiD Analysis

6.3.1 Belgium

Belgium implemented MiFID more than a year prior to the official implementation date. We will therefore use the stocks traded within Belgium as the treatment group and use the Belgian implementation date (the 1st of July 2006) as a dummy for whether or not the stock has been treated. For the control group, we will use two scenarios. The first scenario uses the US stocks as the basis for the matched control group, while the second uses the non-treated EU stocks.

Both cases use the PSM model described earlier to match the securities. The reason for performing the DiD with two different control groups is to account for the observable covariates which lie within the stock-specific characteristics. It is reasonable to believe that the stocks in the Euro STOXX 600 will be a better match for the Belgian securities compared to the stocks in SPX. This is because factors such as the implementation of NMS in the US can be taken out of consideration when matching Belgian securities against European securities. Furthermore, when using the yet non-treated EU securities as the basis for the matched control group for Belgium, we can remove other index-specific differences. This is likely to improve empirical quality, and thereby the chance of interpretating the results as causal. The results still have country-specific differences, but these are reduced by using control variables such as size, GICS, market capitalization and IPO.

	Belgium against SPX	Belgium against STOXX
	T-test (P-Value): 0.6385	T-test (P-Value): 0.9953
	Mean Propensity Score	Mean Propensity Score
Treatment	0.1580005	0.0804841
Control	0.1395449	0.0804308

Table 19: Propensity Score Table for Belgium

From Table 19, the mean propensity scores for the treatment and control group are close for both of the scenarios. However, it is noticeable that the p-value from the t-test for mean differences increases for the scenario which uses Euro STOXX 600 as the basis for the matched control group. This argues for a more precise matching when using the “late” implemented European stocks as the basis for the PSM model.

Interpretation (Belgium and Europe)

	Results					
	Dependent variable:					
	MEC (Resiliency) (1)	range_percentage (Immediacy) (2)	LHH (Breadth) (3)	bid_ask_percentage (Tightness) (4)	volume (Depth) (5)	Market_illiq (General) (6)
DiD	0.018	-0.001	-0.059	-0.016	-0.090	-0.053
	(0.040)	(0.028)	(0.073)	(0.037)	(0.084)	(0.084)
MiFID	0.180***	-0.146***	-0.010	-0.043	-0.084	0.846***
	(0.028)	(0.020)	(0.049)	(0.027)	(0.060)	(0.060)
belgium	0.176***	-0.283***	0.646***	-0.170***	-1.775***	0.0003
	(0.030)	(0.021)	(0.056)	(0.028)	(0.064)	(0.060)
gicsConsumer Staples	0.024	0.092*		0.578***	0.103	0.018
	(0.066)	(0.047)		(0.059)	(0.141)	(0.139)
gicsFinancials	1.235***	-0.347***	2.456***	0.469***	-2.305***	-0.005
	(0.042)	(0.030)	(0.074)	(0.038)	(0.089)	(0.088)
gicsHealth Care	0.709***	0.023	-0.513***	0.261***	0.177	-0.014
	(0.053)	(0.038)	(0.086)	(0.047)	(0.113)	(0.112)
gicsMaterials	0.601***	0.304***	-1.079***	0.071*	0.370***	0.019
	(0.046)	(0.033)	(0.076)	(0.041)	(0.098)	(0.097)
sizeMedium	-0.234***	-0.310***	1.476***	0.421***	-2.150***	-0.015
	(0.027)	(0.019)	(0.053)	(0.028)	(0.057)	(0.057)
sizeSmall	-0.568***	-0.179***	0.815***	1.000***	-2.730***	0.018
	(0.031)	(0.022)	(0.058)	(0.028)	(0.065)	(0.064)
IPO_bel	-0.00003***	0.00000***	-0.0001***	0.00002***	0.00004***	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Constant	-2.522***	-3.663***	3.948***	-7.072***	15.975***	-16.403***
	(0.047)	(0.033)	(0.082)	(0.042)	(0.099)	(0.097)
Observations	5,192	6,518	5,023	5,807	6,552	3,017
R^2	0.349	0.200	0.546	0.247	0.414	0.112
Adjusted R^2	0.348	0.199	0.545	0.246	0.413	0.109
Residual Std. Error	0.715 (df = 5181)	0.568 (df = 6507)	1.289 (df = 5013)	0.705 (df = 5796)	1.702 (df = 6541)	1.148 (df = 3006)
F Statistic	277.834*** (df = 10; 5181)	162.446*** (df = 10; 6507)	669.382*** (df = 9; 5013)	190.187*** (df = 10; 5796)	461.805*** (df = 10; 6541)	37.822*** (df = 10; 3006)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 20: DiD Regression for Belgium and European Control Group

Belgium & STOXX					
Liquidity Metric	**DiD Coefficient**	**Effect on Liquidity**	**Liquidity Dimension**	**Significance Level**	**Coefficient**
Bid-Ask Spread	-	More Liquid (+)	Tightness	p > 10%	0,016
Daily Range Percentage	-	More Liquid (+)	Immediacy	p > 10%	0,001
LHH	-	More Liquid (+)	Breadth	p > 10%	0,059
Volume	-	Less Liquid (-)	Depth	p > 10%	0,090
MEC	+	More Liquid (+)	Resiliency	p > 10%	0,018
Net Liquidity Effect		**More Liquid (+)**			
ILLIQ	-	**More liquid (+)**	**General**	p > 10%	0,053

Table 21: Summary Statistics for the DiD Regression on Belgium and the European Control

When comparing Belgian stocks against the matched stocks within EU, none of the DiD coefficients are significant. This implies that for Belgian stocks, the implementation of MiFID did not significantly affect liquidity compared to non-treated EU countries. This possibly indicates that even though the directive may affect liquidity for the EU market in general, this may not apply to all countries. One possible explanation is that countries with less transparent and less liquid markets prior to MiFID will experience a greater effect, as the directive induces greater changes in these countries´ markets. Thus, if the Belgian market is highly transparent and liquid prior to MiFID, the implementation of the directive may not have a significant effect on this market. Another possible explanation is that MiFID may have had spillover effects before being officially implemented. As the directive was drafted and publicized in 2004, it was already known that MiFID would be implemented long before the official implementation date. It is thus possible that some markets experienced anticipatory changes to transparency or liquidity prior to the official implementation. If the latter explanation is correct, using a non-EU control group should yield different results.

Interpretation (Belgium and USA)

Results

	Dependent variable:					
	MEC (Resiliency) (1)	range_percentage (Immediacy) (2)	LHH (Breadth) (3)	bid_ask_percentage (Tightness) (4)	volume (Depth) (5)	Market_illiq (General) (6)
DiD	0.172***	-0.048*	-0.018	-0.106***	-0.036	0.961***
	(0.038)	(0.026)	(0.043)	(0.037)	(0.059)	(0.068)
MiFID	0.027	-0.099***	-0.051*	0.047*	-0.138***	-0.168***
	(0.027)	(0.019)	(0.029)	(0.026)	(0.043)	(0.049)
belgium	-0.449***	-0.133***	1.264***	0.798***	-2.248***	4.031***
	(0.028)	(0.019)	(0.031)	(0.027)	(0.043)	(0.050)
gicsConsumer Staples	-0.432***	0.106**		0.679***	-0.552***	0.000
	(0.060)	(0.042)		(0.059)	(0.095)	(0.107)
gicsFinancials	1.041***	-0.325***	1.614***	0.238***	-1.936***	0.000
	(0.033)	(0.023)	(0.035)	(0.031)	(0.051)	(0.058)
gicsHealth Care	-0.149***	-0.016	0.479***	0.463***	-0.618***	-0.000
	(0.043)	(0.030)	(0.045)	(0.041)	(0.068)	(0.077)
gicsMaterials	-0.262***	0.520***	-0.369***	0.535***	0.192***	0.000
	(0.042)	(0.029)	(0.043)	(0.040)	(0.065)	(0.074)
sizeMedium	0.055**	-0.228***	-0.024	0.121***	-0.593***	-0.000
	(0.025)	(0.017)	(0.030)	(0.026)	(0.039)	(0.044)
sizeSmall	-0.288***	-0.092***	-0.085***	0.683***	-1.568***	-0.000
	(0.026)	(0.018)	(0.029)	(0.025)	(0.041)	(0.047)
IPO_bel	-0.00004***	0.00001***	-0.00004***	0.00001***	0.00005***	0.000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Constant	-1.703***	-3.914***	3.817***	-7.812***	15.508***	-20.421***
	(0.038)	(0.027)	(0.041)	(0.037)	(0.060)	(0.070)
Observations	5,003	6,295	5,056	6,072	6,327	2,939
R^2	0.506	0.214	0.583	0.347	0.610	0.861
Adjusted R^2	0.505	0.212	0.583	0.346	0.610	0.860
Residual Std. Error	0.668 (df = 4992)	0.521 (df = 6284)	0.756 (df = 5046)	0.718 (df = 6061)	1.174 (df = 6316)	0.909 (df = 2928)
F Statistic	510.817*** (df = 10; 4992)	170.730*** (df = 10; 6284)	784.872*** (df = 9; 5046)	321.765*** (df = 10; 6061)	988.950*** (df = 10; 6316)	1,812.405*** (df = 10; 2928)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 22: DiD Regression for Belgium and US Control Group

Belgium & SPX					
Liquidity Metric	**DiD Coefficient**	**Effect on Liquidity**	**Liquidity Dimension**	**Significance Level**	**Coefficient**
Bid-Ask Spread	-	More Liquid (+)	Tightness	p < 1%	0,106
Daily Range Percentage	-	More Liquid (+)	Immediacy	p > 10%	0,057
LHH	-	More Liquid (+)	Breadth	p > 10%	0,018
Volume	-	Less Liquid (-)	Depth	p > 10%	0,036
MEC	+	More Liquid (+)	Resiliency	p < 1%	0,172
Net Liquidity Effect		**More Liquid (+)**			
ILLIQ	+	**Less Liquid (-)**	**General**	p < 1%	0,961

Table 23: Summary Statistics for the DiD Regression on Belgium and the US Control Group

When using the US securities as basis for the control group, several liquidity metrics are significant. More specifically, the coefficients for the Market Efficiency Coefficient, bid-ask spread and Amihud´s Illiquidity ratio are significant at the 1% significance level, while the daily range percentage coefficient is significant at the 10% significance level. A narrower spread and range in addition to the increased Market Efficiency Coefficient indicate an increase in market liquidity, while Amihud´s Illiquidity ratio indicates reduced market liquidity. The results also indicate a reduction in volume and the Hui-Heubel liquidity ratio, but these are not significant. On aggregate, the liquidity dimensions suggest an increase in liquidity, while the general liquidity measure suggests the opposite. This may be due to there being an actual reduction in volume despite the lack of significance to support this in our findings. Alternatively, there may be factors other than the spread increasing the magnitude of absolute returns, thus causing an increase in Amihud´s Illiquidity ratio.

Contrary to the previous DiD regression, these results indicate a significant effect on liquidity. If the Belgian market was already transparent and liquid to such a degree that MiFID was irrelevant, we would expect the results from using US stocks as a control to still be insignificant. As this is not the case, it supports the explanation that the knowledge of MiFID may have had effects on EU stock markets before the directive was implemented. This has implications for the choice of control group. Generally, it would be preferable to use EU stocks in the control group as the security-specific differences are likely to be smaller than when using US stocks as a control. However, if there are spillover effects, there may have been gradual changes in transparency and liquidity in the EU control group prior to the treatment date. This would make it difficult to isolate the effect of MiFID. Due to the likelihood of spillover effects, we will therefore use US stocks for the control group in the subsequent analyses.

6.3.2 Spain

When performing the DiD analysis on Spain, we will use a matched control group withdrawn from the US S&P 500. This is because other EU countries have already implemented MiFID, and the EU control group would therefore already have been treated.

Interpretation

Results						
	Dependent variable:					
	MEC (Resiliency) (1)	range_percentage (Immediacy) (2)	LHH (Breadth) (3)	bid_ask_percentage (Tightness) (4)	volume (Depth) (5)	Market_illiq (General) (6)
DiD	0.171***	0.047***	-0.020	-0.006	-0.010	-2.252***
	(0.025)	(0.017)	(0.031)	(0.024)	(0.035)	(0.037)
MiFID	-0.273***	-0.191***	0.613***	0.262***	-0.421***	0.550***
	(0.060)	(0.034)	(0.062)	(0.048)	(0.070)	(0.058)
spain	-0.197***	-0.043***	-0.918***	0.122***	0.827***	5.608***
	(0.018)	(0.012)	(0.022)	(0.017)	(0.024)	(0.024)
gicsConsumer Discretionary	-0.116***	0.267***	-1.052***	0.347***	-0.628***	-0.001
	(0.040)	(0.026)	(0.048)	(0.038)	(0.055)	(0.057)
gicsConsumer Staples	-0.080*	-0.011	-0.131**	0.379***	-1.798***	-0.006
	(0.044)	(0.029)	(0.052)	(0.041)	(0.060)	(0.062)
gicsEnergy	0.235***	0.209***	-0.257***	0.349***	-1.132***	-0.003
	(0.042)	(0.028)	(0.051)	(0.040)	(0.058)	(0.060)
gicsFinancials	0.332***	0.128***	-0.290***	0.702***	-0.781***	-0.010
	(0.036)	(0.024)	(0.043)	(0.034)	(0.049)	(0.051)
gicsHealth Care	0.200***	0.063**	-0.350***	0.677***	-1.249***	-0.005
	(0.041)	(0.027)	(0.049)	(0.038)	(0.056)	(0.057)
gicsIndustrials	0.010	0.227***	0.273***	0.371***	-1.635***	-0.002
	(0.037)	(0.024)	(0.045)	(0.034)	(0.050)	(0.052)
gicsInformation Technology	0.183***	-0.176***	-0.548***	0.242***	-1.311***	-0.003
	(0.060)	(0.039)	(0.072)	(0.056)	(0.083)	(0.090)
gicsMaterials	-0.161***	0.462***	-1.199***	0.438***	-0.175***	-0.002
	(0.049)	(0.032)	(0.059)	(0.046)	(0.067)	(0.070)
gicsUtilities	0.244***	0.012	0.111**	0.336***	-1.753***	-0.004
	(0.037)	(0.024)	(0.045)	(0.035)	(0.051)	(0.054)
sizeMedium	-0.167***	0.071***	-0.510***	0.330***	-0.523***	0.005
	(0.017)	(0.012)	(0.022)	(0.016)	(0.024)	(0.025)
sizeSmall	-0.206***	0.172***	-0.242***	0.334***	-1.509***	0.006
	(0.020)	(0.013)	(0.024)	(0.018)	(0.027)	(0.028)
IPO_Sp	-0.00005***	-0.00000*	-0.00004***	-0.00001***	0.0001***	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
year2008	-0.403***	0.417***	-0.434***	-0.153***	0.411***	0.873***
	(0.059)	(0.033)	(0.061)	(0.047)	(0.069)	(0.057)
Constant	-2.308***	-3.943***	5.202***	-7.641***	15.608***	-20.959***
	(0.036)	(0.024)	(0.043)	(0.034)	(0.050)	(0.050)
Observations	11,590	14,749	14,197	14,748	14,749	5,078
R^2	0.212	0.121	0.319	0.133	0.391	0.935
Adjusted R^2	0.211	0.120	0.318	0.132	0.390	0.935
Residual Std. Error	0.680 (df = 11573)	0.504 (df = 14732)	0.919 (df = 14180)	0.721 (df = 14731)	1.057 (df = 14732)	0.641 (df = 5061)
F Statistic	194.776*** (df = 16; 11573)	126.169*** (df = 16; 14732)	415.346*** (df = 16; 14180)	140.996*** (df = 16; 14731)	590.846*** (df = 16; 14732)	4,547.405*** (df = 16; 5061)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 24: DiD Regression for Spain and the US Control Group

Spain & SPX					
Liquidity Metric	**DiD Coefficient**	**Effect on Liquidity**	**Liquidity Dimension**	**Significance Level**	**Coefficient**
Bid-Ask Spread	-	More Liquid (+)	Tightness	p > 10%	0,006
Daily Range Percentage	+	Less Liquid (-)	Immediacy	p < 1%	0,047
LHH	-	More Liquid (+)	Breadth	p > 10%	0,020
Volume	-	Less Liquid (-)	Depth	p > 10%	0,010
MEC	+	More Liquid (+)	Resiliency	p < 1%	0,171
Net Liquidity Effect		**More Liquid (+)**			
ILLIQ	-	**More Liquid (+)**	**General**	p < 1%	2,252

Table 25: Summary Statistics for the DiD Regression on Spain and the US Control

As with the DiD analysis for Spain and the matched control group, the coefficients for the Market Efficiency Coefficient, daily range percentage and Amihud´s Illiquidty ratio are all significant at the 1% significance level while the Hui-Heubel liquidity ratio, bid-ask spread and volume coefficients are insignificant at 10% significance level. The increased range and Market Efficiency Coefficient indicate two contrasting effects, as the former indicates lower immediacy while the latter indicates increased resiliency. When isolating the significant coefficients, only two dimensions are significant and indicate opposite results. It is thus hard to determine whether liquidity has increased or decreased on aggregate. However, when including all dimensions, three of five dimensions indicate an increase in liquidity. This result is supported by the coefficient for Amihud´s Illiquidity ratio, which decreases by 225,2%, significant at the 1 % significance level. This indicates increased general market liquidity.

As mentioned, Spain was late to implement MiFID compared to other EU countries. Much of the EU market would therefore already been affected by MiFID, and it is reasonable to believe that this may have had spillover effects to the Spanish market prior to the country's implementation of the directive. Given this, the transparency effect on liquidity may be hard to be identify at this point.

6.3.3 Excluding Belgium and Spain

The DiD analysis performed on the remaining EU countries is in practice performed similarly to the regular DiD model. The reason for using the model again while controlling for Belgium and Spain is that we are removing variables which reduce the chance of fulfilling the parallel trends assumption. If increased transparency has a significant causal effect on stock market liquidity, Belgium could potentially distort the results. The reasoning is that including Belgium may decrease the statistical effect because liquidity for the treatment group is affected before the official implementation date. Furthermore, the coefficients would be biased.

Interpretation

Results

	Dependent variable:					
	MEC (Resiliency) (1)	range_percentage (Immediacy) (2)	LHH (Breadth) (3)	bid_ask_percentage (Tightness) (4)	volume (Depth) (5)	Market_illiq (General) (6)
DiD	0.097^{***}	0.035^{***}	-0.048^{***}	-0.102^{***}	0.038^{***}	-2.356^{***}
	(0.006)	(0.004)	(0.011)	(0.006)	(0.010)	(0.009)
MiFID	-0.538^{***}	0.215^{***}	0.278^{***}	0.163^{***}	-0.098^{***}	0.290^{***}
	(0.005)	(0.003)	(0.008)	(0.005)	(0.008)	(0.007)
indexSTOXX	-0.152^{***}	0.017^{***}	-0.129^{***}	0.107^{***}	0.175^{***}	5.820^{***}
	(0.004)	(0.003)	(0.008)	(0.004)	(0.007)	(0.006)
gicsConsumer Discretionary	-0.195^{***}	0.228^{***}	-0.102^{***}	-0.109^{***}	-0.251^{***}	0.001
	(0.007)	(0.005)	(0.013)	(0.007)	(0.012)	(0.010)
gicsConsumer Staples	-0.314^{***}	-0.088^{***}	-0.035^{***}	-0.098^{***}	-0.391^{***}	-0.001
	(0.008)	(0.005)	(0.013)	(0.007)	(0.013)	(0.011)
gicsEnergy	-0.134^{***}	0.306^{***}	0.339^{***}	0.068^{***}	-0.373^{***}	-0.001
	(0.008)	(0.006)	(0.014)	(0.008)	(0.014)	(0.012)
gicsFinancials	0.069^{***}	0.186^{***}	0.702^{***}	0.091^{***}	-0.622^{***}	-0.001
	(0.007)	(0.004)	(0.012)	(0.007)	(0.011)	(0.009)
gicsHealth Care	-0.184^{***}	0.047^{***}	0.228^{***}	0.101^{***}	-0.485^{***}	0.0003
	(0.008)	(0.005)	(0.014)	(0.008)	(0.013)	(0.011)
gicsIndustrials	-0.300^{***}	0.131^{***}	0.195^{***}	-0.017^{***}	-0.500^{***}	-0.001
	(0.006)	(0.004)	(0.011)	(0.006)	(0.011)	(0.009)
gicsInformation Technology	-0.250^{***}	0.229^{***}	-0.405^{***}	-0.097^{***}	0.373^{***}	0.002
	(0.008)	(0.006)	(0.015)	(0.008)	(0.014)	(0.012)
gicsMaterials	-0.242^{***}	0.244^{***}	0.405^{***}	0.022^{***}	-0.333^{***}	-0.001
	(0.008)	(0.005)	(0.013)	(0.007)	(0.013)	(0.011)
gicsReal Estate	-0.017	0.320^{***}	1.036^{***}	0.181^{***}	-0.608^{***}	-0.001
	(0.010)	(0.007)	(0.017)	(0.010)	(0.017)	(0.014)
gicsUtilities	-0.383^{***}	-0.044^{***}	0.256^{***}	-0.020^{**}	-0.364^{***}	-0.001
	(0.008)	(0.005)	(0.014)	(0.008)	(0.014)	(0.012)
sizeMedium	-0.054^{***}	0.087^{***}	-0.210^{***}	0.256^{***}	-0.897^{***}	-0.002
	(0.004)	(0.002)	(0.006)	(0.004)	(0.006)	(0.005)
sizeSmall	-0.103^{***}	0.111^{***}	-0.596^{***}	0.461^{***}	-1.344^{***}	0.001
	(0.004)	(0.002)	(0.006)	(0.004)	(0.006)	(0.005)
IPO	-0.014^{***}	-0.050^{***}	0.022^{***}	-0.010^{***}	-0.066^{***}	0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
year2008	-0.353^{***}	0.149^{***}	-0.079^{***}	0.042^{***}	0.133^{***}	1.049^{***}
	(0.004)	(0.003)	(0.008)	(0.004)	(0.007)	(0.007)
Constant	-1.916^{***}	-3.612^{***}	4.071^{***}	-7.099^{***}	15.775^{***}	-20.818^{***}
	(0.014)	(0.009)	(0.024)	(0.014)	(0.023)	(0.020)
Observations	198,406	254,391	233,911	244,151	254,450	95,486
R^2	0.300	0.177	0.113	0.091	0.196	0.926
Adjusted R^2	0.300	0.177	0.113	0.091	0.196	0.926
Residual Std. Error	0.649 (df = 198388)	0.492 (df = 254373)	1.209 (df = 233893)	0.715 (df = 244133)	1.220 (df = 254432)	0.636 (df = 95468)
F Statistic	$4,999.067^{***}$ (df = 17; 198388)	$3,228.565^{***}$ (df = 17; 254373)	$1,760.838^{***}$ (df = 17; 233893)	$1,441.583^{***}$ (df = 17; 244133)	$3,657.009^{***}$ (df = 17; 254432)	$70,215.380^{***}$ (df = 17; 95468)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 26: DiD Regression for the remaining EU Securities (Excluding Belgium & Spain) and the US Control Group

Excluding Belgium & Spain					
Liquidity Metric	**DiD Coefficient**	**Effect on Liquidity**	**Liquidity Dimension**	**Significance Level**	**Coefficient**
Bid-Ask Spread	-	More Liquid (+)	Tightness	p < 1%	0,102
Daily Range Percentage	+	Less Liquid (-)	Immediacy	p < 1%	0,035
LHH	-	More Liquid (+)	Breadth	p < 1%	0,048
Volume	+	More Liquid (+)	Depth	p < 1%	0,038
MEC	+	More Liquid (+)	Resiliency	p < 1%	0,097
Net Liquidity Effect		**More Liquid (+)**			
ILLIQ	-	**More Liquid (+)**	**General**	p < 1%	2,356

Table 27: Summary Statistics of the DiD Analysis for the Remaining European Countries

As opposed to previous DiD regressions, the coefficients are now statistically significant at the 1% level for all liquidity metrics. Increased daily range percentage suggest reduced immediacy, and thereby reduced liquidity. However, the coefficients for the spread, Hui-Heubel liquidity ratio, volume and Market Efficiency Coefficient suggest increased liquidity in the form of a tighter, broader, deeper, and more resilient market, respectively. This divergence may be due to other factors increasing the daily range. If the increased range is accompanied by increased absolute returns, volume may outweigh this effect in the case of Amihud´s Illiquidity ratio. When using the five dimensions of liquidity, three out of five dimensions indicate higher market liquidity. This is also supported by the reduction in the general market liquidity measure.

6.4 Summary of Staggered DiD

We have in total presented five DiD analyses, each performed with six liquidity metrics. It is therefore pertinent to discuss how the results of different analyses should be weighted. The regular DiD model includes two countries which have implemented MiFID on different dates compared to most of the European countries in the treatment group. This is accounted for when performing the staggered DiD model. Thus, when comparing the sample from the regular DiD model to the sample from the staggered DiD model where the differing dates were accounted for, the staggered DiD is seemingly a more “correct” model. However, whether the preferred DiD model is based upon the sample excluding Belgium and Spain, or one of the samples only using Belgium or Spain, is yet hard to distinguish. As Belgium is the first country in the sample to implement MiFID, it is also the country best suited for measurements of the effects on liquidity. However, by only using Belgium, we are facing a tradeoff between these benefits and the issue of having an adequate sample size. Because of these considerations, each of the staggered DiD models will be weighted equally.

Table 28 presents a summary of each DiD model performed within the Staggered DiD analysis where any coefficients were found significant. The bid-ask spread decreases in all the significant models, indicating a tighter market with lower transaction costs. The Market Efficiency Coefficient increases in all the models, indicating that the short-period volatility is more consistent with the long-period volatility thus implying a more resilient market. These findings point to increased liquidity. Supporting increased liquidity, volume and the Hui-Heubel liquidity ratio coefficients are also significant, but only for the DiD model excluding Spain and Belgium. These metrics indicates a deeper and broader market respectively. Contrary to these findings, the daily range increases in most of the models, indicating reduced immediacy. However, this is the only dimension indicating lower liquidity. Because of this, it is reasonable to believe that increased transparency has caused an increase in market liquidity. This is supported by the decrease in Amihud´s Illiquidity ratio, which indicates a more liquid market.

The mechanisms behind the increase in liquidity are however unclear. We will thus perform a wholistic interpretation of the coefficient signs to evaluate the four hypotheses presented earlier.

	Significant Coefficient Sign			Average Coefficient Sign		
Liquidity Metric	**Belgium & SPX**	**Spain & SPX**	**Excluding SPN & BEL**	**Summary**	**Effect on Liquidity**	**Liquidity Dimension**
Bid-Ask Spread	-	Insignificant	-	-	More Liquid (+)	**Tightness**
Daily Range Percentage	-	+	+	+	Less Liquid (-)	**Immediacy**
LHH	Insignificant	Insignificant	-	-	More Liquid (+)	**Breadth**
Volume	Insignificant	Insignificant	+	+	More Liquid (+)	**Depth**
MEC	+	+	+	+	More Liquid (+)	**Resiliency**
Net Liquidity Effect					**More Liquid (+)**	
ILLIQ	+	-	-	-	**More Liquid (+)**	

Table 28: Summary of the Significant Coefficients

7. Conclusion

Staggered DiD Analysis		Results Effect on Liquidity´s Five Dimensions			
Liquidity Metric	**Effect on Liquidity**	**MM Competition**	**MM Freeloading**	**Trader Adaption**	**LO Aversion**
Bid-Ask Spread	More Liquid (+)	+	-	+	-
Daily Range Percentage	Less Liquid (-)	?/+	?	?	?
LHH	More Liquid (+)	=/+	-	=/+	=/-
Volume	More Liquid (+)	+	-	+	-
MEC	More Liquid (+)	+	+	+	-
Net Liquidity Effect	**More Liquid (+)**	**Increase**	**Decrease**	**Increase**	**Decrease**

Table 29: The net liquidity effects summarized for the corresponding hypotheses

A key goal of the MiFID regulatory framework was to increase transparency in equity markets across the EU. This thesis has examined the introduction of MiFID as a "shock" to transparency to analyze causal effects of increased transparency on different liquidity dimensions. We find evidence for a significant effect on liquidity from the implementation of MiFID, implying that market transparency is an important determinant of market liquidity. More specifically, we find a significant increase in four out of five liquidity dimensions, with only immediacy being negatively affected. Our general measure of market liquidity also indicates an increase in liquidity on aggregate. These findings suggest that increased transparency causes an increase in liquidity, resulting in a tighter, deeper, broader, and more resilient market. However, the findings also suggest that increased transparency may cause immediacy to decrease.

As such, these findings provide evidence for a positive effect from increased transparency on the liquidity of equity markets, but that the increased liquidity comes at the expense of a reduction in immediacy. These findings are highly consistent with two of our hypotheses, namely the *Market Maker Competition* and *Trader Adaption* hypotheses. However, as both these hypotheses have similar effects on the liquidity dimensions, it is difficult to discern which effects may be attributable to each mechanism. Considering that there is a substantial focus of MiFID on fostering competition between different trading venues and market makers, it is likely that the positive liquidity effects at least partly stem from competition between market makers, where spreads are reduced by these actors to attract order flow. The *Market Maker Competition Hypothesis* argues that increased transparency enables the reduction in spreads by lowering the risk for market makers, and this benefit is captured by traders due to market maker competition. The reduction in spreads is thus the direct response from market makers to an increase in transparency, while the effects on other dimensions of liquidity in the *Market Maker Hypothesis* are arguably secondary effects. Although we are not able to reach a firm conclusion, we argue that these considerations give support to the *Market Maker Competition Hypothesis* as the explanation for the increased tightness observed.

As mentioned, the positive effects are also highly consistent with the *Trader Adaption Hypothesis*. According to this hypothesis, traders respond to increased transparency by reducing their order sizes and more actively managing their orders. This consequently reduces their price impact, thereby improving depth, resiliency, and tightness. As such, the primary effect of the *Trader Adaption Hypothesis* is arguably the reduction in price impact stemming from smaller order sizes. It is implicit that price impact is dependent on both the order size and the spread, and thus a reduction in the average order size is likely to reduce price impact even if spreads are held equal. As previously argued, increased depth will often also imply increased breadth (Sarr & Lybek, 2002). Once again, we are not able to firmly conclude that these mechanisms cause the observed effects. It is however reasonable to expect that each group of market participants has its own response to changes in transparency, given that their roles in the market differ. By extension, it is reasonable that there is at least one dominant mechanism for each of the two groups of market participants, representing the optimal response for that group. Considering this, we argue that there is support for the *Trader Adaption Hypothesis* as a likely explanation for the increased breadth and depth observed. The increased resiliency is likely to be attributable to both mechanisms, where market maker competition mainly narrows spreads and trader adaption mainly reduces average trade size.

Perhaps unsurprisingly considering the complexity of liquidity measurement, we find transparency to have a multifaceted effect on liquidity. We find evidence for a positive liquidity effect in which increased transparency leads to a more liquid market. However, we find that there is a trade-off, where a more transparent market gains liquidity in the form of tightness, breadth, depth, and resiliency at the expense of immediacy. Based on these findings, we argue that transparency has a positive effect on the *magnitude* of liquidity, but also changes the *nature* of liquidity since different dimensions are unequally affected. This implies that the consideration of whether increased transparency is desirable depends on which dimensions of liquidity are deemed more important. However, it should be emphasized that the findings are subject to uncertainty, particularly as it is doubtful whether the parallel trends assumption is fulfilled for some metrics. Furthermore, the discussion regarding which mechanisms explain the effects observed is largely an economic interpretation. Although some of our findings support the *Market Maker Competition* and *Trader Adaption* hypotheses, they are not adequately tested to conclusively say that these mechanisms cause the observed effects. As such, a possible avenue for future research is to examine which of the market maker- and trader-focused mechanisms have the greatest effect on the different dimensions of liquidity.

7.1 Limitations

A major limitation in our analysis is the fact that the treatment (MiFID) is not randomly assigned. Although we argue that this problem is mitigated by accounting for firm-specific characteristics, it is likely that we have not accounted for all possible characteristics that differ between EU and US stocks. The initial sampling can therefore not be considered as good as random, and we thus have the potential problem of selection bias.

Another important limitation is the doubt whether the parallel trends assumption is fulfilled. If this assumption does not hold, it restricts the possibility of interpretating the results as causal, thus limiting the empirical results found in this thesis. Because of the lack of statistical tests to conclusively reject the assumption, we are restricted to only performing a visual analysis of the trends to evaluate if they are parallel. The evaluation of whether the assumption holds is thus a subjective evaluation.

In addition, there are two other important limitations, namely the lack of breadth in the represented countries and the number of missing values. When performing the staggered DiD analysis, it is preferred to have several countries with different implementation dates. In our study, we are restricted to only dividing the group into three groups, namely Belgium, Spain, and the remaining countries. The optimal solution would be to have different implementation dates for more of the EU countries, as this would strengthen the staggered DiD analysis. Concerning the data sampling, the sample period is between 2004 and 2011. Because of this, the sampling of data for some stocks are missing.

In this thesis, we have used a six-month period pre and post treatment as our timeframe. We have restricted the analysis to this timeframe as this enables us to get a better matched control group based on the firm-specific characteristics and a higher likelihood of fulfilling the Parallel Trends Assumption. Additionally, given an efficient market, we expect any liquidity effect to manifest rather quickly after the implementation of MiFID. However, if there are liquidity effects that manifest over a longer time, our analysis may not capture these. Thus, performing the analysis for a timeframe of for example 2 and 4 years before and after the MiFID implementation date might reveal additional effects.

Lastly, we have been interfering with the data by using R to automatically remove the outliers for all liquidity metrics, thus removing data in the upper and lower 99^{th} percentiles of our data set. This may lead to increased selection bias.

References

Akramov, K. T. (2015, June 04). *Regression, Causality and Identification Issues.* Retrieved from IFPRI, Washington DC: https://www.resakss-asia.org/files/events/attachments/Session4-%20Regression%2C%20Causality%20and%20Identification%20Issues.pdf

Albouy, D. (2004). Program Evaluation and the Difference in Difference Estimator. *Economics 131*, pp. 1-5.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*, pp. 31-56.

Amihud, Y., & Mendelson, H. (1986). Asset Pricing and the Bid-Ask Spread. *Journal of Financial Economics 17*, pp. 223-249.

Amihud, Y., Mendelson, H., & Pedersen, L. H. (2012). *Market Liquidity : Asset Pricing, Risk, and Crises.* Cambridge University Press.

Angrist, J. D., & Pischke, J.-S. (2011, May 01). Mostly Harmless Econometrics: An Empiricist's Companion. *Statistical papers (Berlin, Germany), Vol.52 (2)*, p. 503.

Apergis, N., Artikis, P. G., & Kyriazis, D. (2015). Does stock market liquidity explain real economic activity? New evidence from two large European stock markets. *Journal of International Financial Markets, Institutions & Money 38*, pp. 42-64.

Arbel, A., Carvell, S., & Strebel, P. (1983). Giraffes, Institutions and Neglected Firms. *Financial Analyst Journal, vol. 39*, pp. 57-63.

Bernstein, P. L. (1987). Liquidity, Stock Markets, and Market Makers. *Financial Management Association, Vol 16, No. 2*, pp. 54-62.

Bloomfield, R., & O'Hara, M. (1999). Market Transparency: Who Wins and Who Loses. *The Review of Financial Studies, v.12, n.1*, pp. 5-35.

Bloomfield, R., & O'Hara, M. (2000, November 23). Can transparent markets survive? *Journal of Financial Economics 55*, pp. 425-549.

Boehmer, E., Saar, G., & Yu, L. (2005, April). Lifting the Veil: An Analysis of Pre-trade Transparency at the NYSE. *The Journal of Finance, Vol. 60, No. 2*, pp. 783-815.

Booth, J. R., & Chua, L. (1996). Ownership dispersion, costly information, and IPO underpricing. *Journal of Financial Economics 41*, pp. 291-310.

Brau, J. C., & Fawcett, S. E. (2006, February). Initial Public Offerings: An Analysis of Theory and Practice. *The Journal of Finance, Vol. LXI, No. 1*, pp. 399-435.

Broto, C., & Lamas, M. (2016, June). Measuring market liquidity in US fixed income markets: A new synthetic indicator. *Financial Stability, Vol. 14, Issue 1.* , pp. 15-22.

Buse, L., Ganea, M., & Circiumaru, D. (2021, March). *USING LINEAR REGRESSION IN THE ANALYSIS OF FINANCIAL-ECONOMIC PERFORMANCES*. Retrieved from University of Craiova: https://core.ac.uk/download/pdf/6239921.pdf

Caliendo, M., & Kopeinig, S. (2005, May). *Some Practical Guidance for the Implementation of Propensity Score Matching.* Retrieved from University of Cologne: Discussion Paper No. 1588: http://ftp.iza.org/dp1588.pdf

Camilleri, S., & Galea, F. (2019, April 15). The determinants of securities trading activity: evidence from four European equity markets. *University of Malta - Banking and Finance Department*.

Chordia, T., Huh, S.-W., & Subrahmanyam, A. (2007). The Cross-Section of Expected Trading Activity. *The Review of Financial Studies v 20, n 3*, pp. 709-737.

Chordia, T., Roll, R., & Subrahmanyam, A. (2001, April). Market Liquidity And Trading Activity. *The Journal of Finance (New York), Vol. 56(2)*, pp. 501-530. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.35.3257&rep=rep1&type=pdf

Cooper, K. S., Groth, J. C., & Avera, W. E. (1985). Liquidity, Exchange Listing, and Common Stock Performance. *Journal of Economics and Business, 0148-6195*, pp. 19-33.

European Commission. (2004, April 21). DIRECTIVE 2004/39/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL. *Official Journal of the European Union*.

European Commission. (2006, September 02). COMMISSION DIRECTIVE 2006/73/EC. *Official Journal of the European Union*.

European Commission. (2006, September 02). COMMISSION REGULATION (EC) No 1287/2006. *Official Journal of the European Union*.

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969, February). The Adjustment of Stock Prices to New Information. *International Economic Review, Vol. 10, No.1*.

Foucault, T., Pagano, M., & Röell, A. (2013). *Market Liquidity : Theory, Evidence, and Policy.* Oxford University Press, Incorporated.

Fredriksson, A., & Magalhaes, G. D. (2019, August 8). *Impact evaluation usingDifference-in-Differences.* Retrieved from Researchgate: https://www.researchgate.net/publication/337247210_Impact_evaluation_using_Difference-in-Differences

Gemmill, G. (1996, December). Transparency and Liquidity: A Study of Block Trades on the London Stock Exchange under Different Publication Rules. *The journal of Finance, Vol.LI, No. 5*, pp. 1765-1790.

Goldberg, J. (2015, November). What drives liquidity? Identifying shocks to market makers' supply of liquidity and their role in economic fluctuations.

Halil, K. D., & Engkuchik, N. S. (2017, June 02). The effect of financial crises on stock market liquidity across global markets. *Investment management & financial innovations, Vol.14 (2)*, pp. 38-50. Retrieved from https://bibsys-almaprimo.hosted.exlibrisgroup.com/primo-explore/fulldisplay?docid=TN_cdi_doaj_primary_oai_doaj_org_article_9e932e2c7b3046838fd3ae64166344c2&context=PC&vid=NHHB&lang=no_NO&search_scope=default_scope&adaptor=primo_central_multiple_fe&tab=def

Hasbrouck, J., & Schwartz, R. A. (1988). Liquidity and execution costs in equity markets. *Journal of Portfolio Management, 14, 3* , pp. 10-16.

HM Treasury. (2007). Explanatory memorandum to the Markets in Financial Instruments Directive (Consequential Amendments) Regulations 2007. *No. 2932*.

Jacoby, G., Fowler, D. J., & Gottesman, A. A. (2000). The capital asset pricing model and the liquidity e!ect: A theoretical approach. *Journal of Financial Markets 3*, pp. 69-81.

Kahn-Lang, A., & Lang, K. (2018, October 18). The Promise and Pitfalls of Differences-in-Differences: Reflections on 16 and Pregnant and Other Applications. *Harvard Kennedy School, Harvard University & Department of Economics, Boston University*.

Lannoo, K. (2007, July). *MiFID and Reg NMS A test-case for 'substituted compliance'?* Retrieved from ECMI Policy Brief: https://www.ceps.eu/wp-content/uploads/2009/08/1522.pdf

Leigtner, J. E. (2012). *Solving the Omitted Variables Problem of Regression Analysis Using the Relative Vertical Position of Observations*. Retrieved from Advances in Decision Sciences: https://doi.org/10.1155/2012/728980

London Economics. (2010, October). *Report prepared for the City of London Corporation.* Retrieved from London Economics: https://londoneconomics.co.uk/wp-content/uploads/2011/09/12-Understanding-the-Impact-of-MiFID-in-the-Context-of-National-and-Global-Regulatory-Innovations.pdf

London Economics. (2010). *Understanding the Impact of MiFID.* London: City of London Corporation.

Madhavan, A., Porter, D., & Weaver, D. (2005). Should securities markets be transparent? *Journal of Financial Markets 8*, pp. 266-288.

Mantecon, T., & Poon, P. (2009). An analysis of the liquidity benefits provided by secondary markets. *Journal of Banking and Finance, Vol. 33 (2)*, pp. 335–346.

Mckenzie, D. (2020, January 21). *Revisiting the Difference-in-Differences Parallel Trends Assumption: Part I Pre-Trend Testing*. Retrieved from World Bank Blogs: https://blogs.worldbank.org/impactevaluations/revisiting-difference-differences-parallel-trends-assumption-part-i-pre-trend

Merton, R. C. (1987, July). A Simple Model of Capital Market Equilibrium with Incomplete Information. *The Journal of Finance, Vol.42, No.3*, pp. 483-510.

Pagano, M., & Röell, A. (1996, June). Transparency and Liquidity: A Comparison of Auction and Dealer Markets with Informed Trading. *The Journal of Finance, Vol.51, No.2*, pp. 579-611.

Pan, W., & Bai, H. (2021, March). *Propensity Score Analysis: Concepts and Issues.* Retrieved from http://people.duke.edu/~wp40/sample_files/chapter%201.pdf

Peterson, P. P. (1989, Summer). *Event Studies: A Review of Issues and methodology.* Retrieved from Florida State University: https://www.jstor.org/stable/40472954?seq=1

Pischke, J.-S. (2019, September 27). *Difference-in-Difference.* Retrieved from London School of Economics: http://econ.lse.ac.uk/staff/spischke/ec533/did.pdf

PwC. (2015). *Global financial markets liquidity study.*

Rahendran, P. (2019, March 29). *Causal Inference using Difference in Differences, Causal Impact, and Synthetic Control*. Retrieved from Towards Data Science: https://towardsdatascience.com/causal-inference-using-difference-in-differences-causal-impact-and-synthetic-control-f8639c408268

Ricketts, D., & Agini , S. (2019, December 19). *Financial News London*. Retrieved from Brexit to spark Mifid III, warns former MEP Swinburne: https://www.fnlondon.com/articles/brexit-to-spark-mifid-iii-warns-former-mep-swinburne-20191216

Rosenbaum, P. R., & Rubin, D. B. (1983, April). The central role of the propensity score in observational studies for causal effects. *Biometrika, Volume 70, Issue 1*, pp. 41-55.

Sarr, A., & Lybek, T. (2002). *IMF Working Paper.* International Monetary Fund.

Stuart, E. A. (2010, February). *Matching methods for causal inference: A review and a look forward.* Retrieved from National Institute of Health: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2943670/pdf/nihms200640.pdf

Thavaneswaran, A., & Lix, l. (2008, April 22). *Propensity Score Matching in Observational Studies.* Retrieved from https://www.umanitoba.ca/faculties/health_sciences/medicine/units/chs/departmental_units/mchp/protocol/media/propensity_score_matching.pdf

Wooldridge, I. (2007, July 31). *Difference-in-Differences Estimation.* Retrieved from https://www.nber.org/sites/default/files/2021-03/lect_10_diffindiffs_0.pdf

Appendix A: Data

A1: Data Structure

There have been used several data frames in this thesis. This is because we have been performing several DiD analyses based on different filters and characteristics. More specifically, 5 data frames for 5 DiD analyses; *General (EU & USA), Belgium & EU, Belgium & USA, Spain & USA, EU excluding Spain and Belgium & USA.* These data are used as different filters for the same set of variables. The treatment and control group are sampled by using the PSM model for the same range of observable security-specific characteristics.

A2: Explanatory Variables

Following paragraphs represents the univariate analysis for the treatment group. A descriptive evaluation of the directions the liquidity development.

Bid-ask spread percentage decreases for all periods except for the 2 week pre and post measurement. This indicates that the post MiFID stock market has lower transaction costs compared to the same period before MiFID. Furthermore indicating a higher market liquidity, regarding the *tightness* dimension.

Daily Range percentage is decreasing for all periods, indicating a stronger market immediacy. Thus, a more liquid stock market. The measurement values for the periods between 3 and 12 months pre and post MiFID is however equal, which is the results from missing values.

Volume has increased for each period. A clear indication for a deeper market with higher market liquidity. Deep markets tend to foster broad markets, and is supported by an increased **LHH** for the same periods.

MEC is both decreasing and increasing. Short-term decreases indicating a lower resiliency, while increasing in the long-term (3 to 12 months) and referring to a more resilient and liquid market.

ILLIQ have several missing values for the post-MiFID metrics. But has in general increased, thus indicating a lower market liquidity.

Explanatory Variables			
Variable	**Description**	**Computation**	**Source**
MiFID	The Main explanatory variable. This indicates whether the current observation is pre or past treatment.	MiFID = 1: After 01.11.2007 MiFID = 0: Before 01.11.2007	MiFID Report
Index	Index defines whether the observation is within STOXX or SPX.	Used as a categorical variable.	Eikon Terminal
GICS	The Global Industry Classification Standard (GICS) is a four-step hierarchical industry classification system.	Using the above tiered 11 sectors to categorize each securities corresponding sector. Used as a categorical variable.	Eikon Terminal
Mcap	The market capitalization of each security at 01.11.2007	Measured in USD and is a numerical variable.	Eikon Terminal
Size	The relative firm size of each security. Computed as the firm specific size relative to the corresponding index.	Using the upper, middle and lower 33,33% percentile of the index market cap to identify the respective categories: Large, medium and smal.	Eikon Terminal
IPO	The age and maturity of the firms.	Computed as the number of days from IPO to MiFID = 1.	Eikon Terminal

Table 30: Overview of Explanatory Variables

A3: Dependent Variables

Market Liquidity Metrics	Required data	Source
Bid-Ask Spread Percentage	Bid close Ask close	EIKON - Datastream
Daily Range Percentage	Daily High Daily Low	EIKON - Datastream
Volume	Volume	EIKON - Datastream
Hui-Heubel´s liquidity ratio	Daily High, Daily Low Volume, VWAP	EIKON - Datastream
Market Efficiency Coefficient (MEC)	Daily close price	EIKON - Datastream
Amihuds´s Illiquidity Measure	Daily close price Volume	EIKON - Datastream

Table 31: Overview of Dependent Variables

Appendix B: Matching Algorithm

We have chosen the Nearest Neighbor (NN) Matching Algorithm to create the treatment and control groups. The NN model can either accept "replacement" or "without replacement". In the former case, one security can be matched against several other securities, while in the latter, only a one-to-one pair. When allowing for replacements, the model faces a trade-off between bias and variance. The quality of the matching increases and bias decreases. Allowing for replacement is of "particular interest with data where the propensity score distribution is very different in the treatment and the control group" (Caliendo and Kopeinig). However, given a somewhat equal distribution of the propensity scores, one should choose a matching method without replacement. This method should however be applied upon a randomly ordered data (Caliendo and Kopeinig).

B1: Propensity Score for Matched and Unmatched Sample

The histogram presents the probability of a stock being assigned to STOXX. The left hand side is for the US stocks, while the right hand side is for the EU stocks.

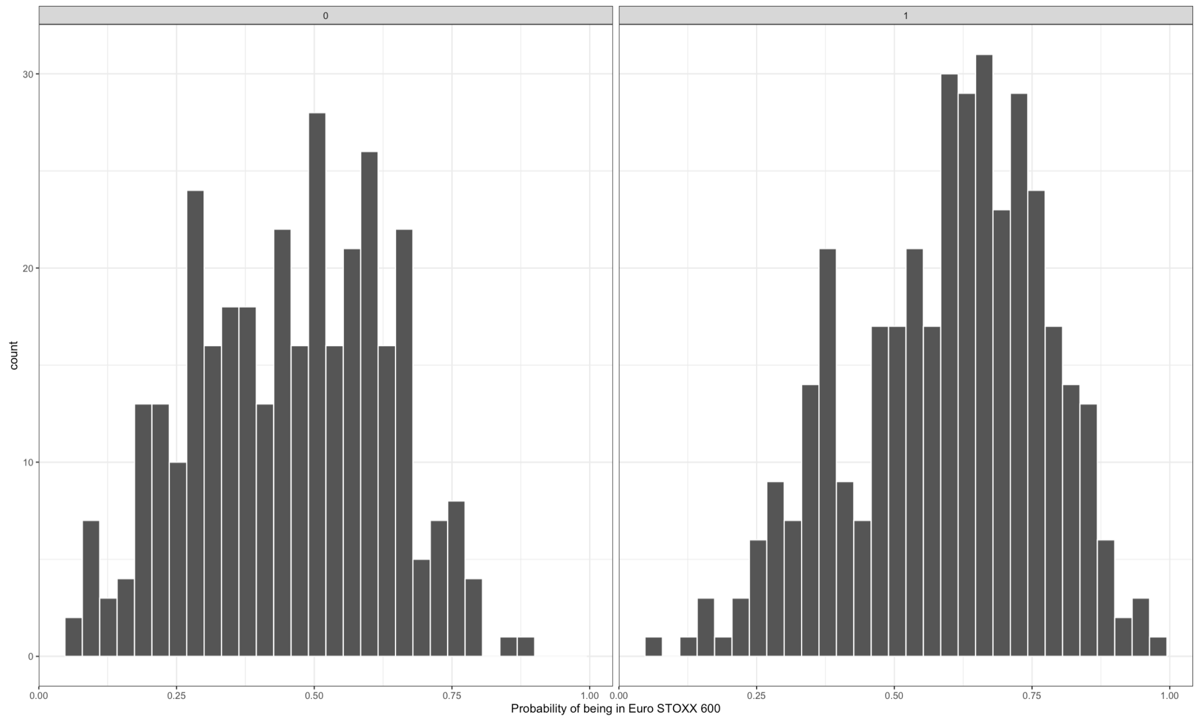

Figure 9: Histogram of the Distribution of Propensity Score

B2: Propensity Score (T-test)

The following tests is a statistical test performed to evaluate the difference in mean propensity score. A p value below 5 % can be considered as enough statistical evidence for rejecting the null hypothesis: *True Difference in means is equal to 0*. Given a rejection, one would assume that the difference in mean propensity score is statistically different from 0.

```
	Welch Two Sample t-test

data:  prop_EU$PScores and prop_US$PScores
t = 14.819, df = 637.16, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.1567653 0.2046564
sample estimates:
mean of x mean of y
0.6357501 0.4550392
```

Figure 10: T-test for Prospensity Score (EU & SPX) Without Replacement

```
	Welch Two Sample t-test

data:  prop_EU_2$PScores and prop_US_2$PScores
t = 5.4698, df = 378.54, p-value = 8.204e-08
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.05280837 0.11208259
sample estimates:
mean of x mean of y
0.5957896 0.5133441
```

Figure 11: T-test for Prospensity Score (EU & SPX) With Replacement

Appendix C: Difference-in-Difference

C1: Staggered Difference-in-Difference

The Staggered DiD is performed by creating date-specific groups. The DiD model is then applied upon each of these groups. The interpretation of the different DiD models are therefore a relative evaluation based on the number of periods before and after the implementation.

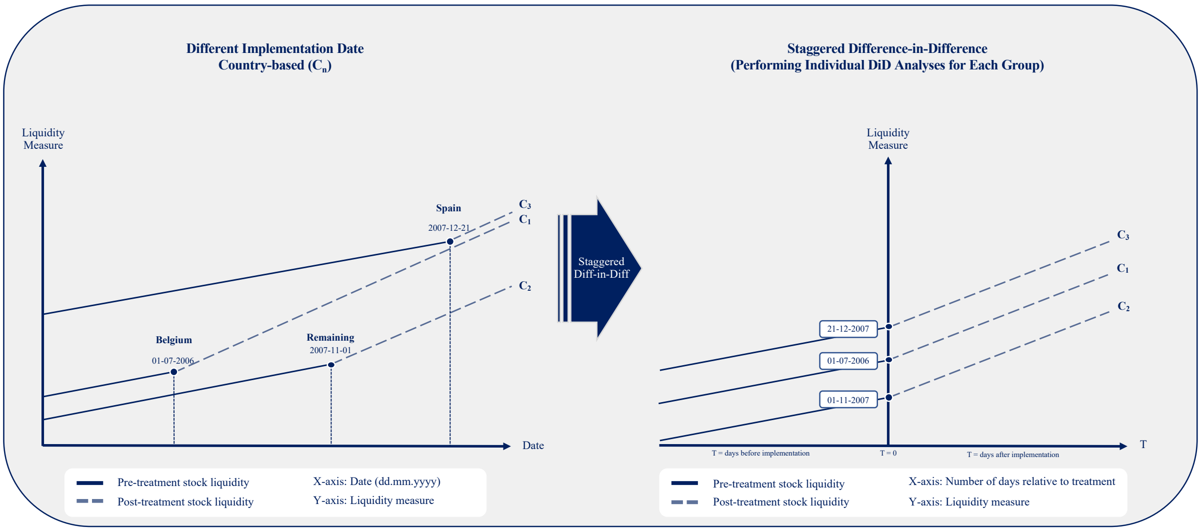

Figure 12: Visualization of Staggered DiD

C2: Summary of Parallel Trends Evaluations

The Summary of the Parallel Trends Assumption is presented. The green marks indicate a fulfillment of the assumption, while red indicates a rejection of the assumption. Furthermore, the yellow fields indicate our doubts for fulfilling the assumption. The graphical presentation of the trends can be found in the following sections for Appendix D.

Parallel Trends Assumption					
	DiD Analysis	Staggered DiD Analysis			
Liquidity Metric	EU & US	Belgium & EU	Belgium & US	Spain & US	Excluding SPN & BEL
Bid-Ask Spread Percentage	Doubt	Doubt	Yes	No	No
Daily Range Percentage	Yes	Yes	No	Yes	Yes
LHH	No	No	No	Yes	Doubt
Volume	Doubt	Yes	Yes	No	Yes
Market Efficiency Coefficient	Yes	Yes	Yes	No	Yes
Amihud`s Illiquidity Ratio	No	Yes	No	Yes	No

Yes | No | Doubt

Table 32: Summary of Parallel Trends

C3: Parallel Trends (Matched STOXX and SPX)

The following plots presents the historical trends for the six liquidity metrics used to evaluate the parallel trends assumption. There may be differences in the level of liquidity between the European and US markets, but this difference should stay constant between the two groups. This is because “observable and unobservable factors may cause the level of the outcome variable to differ between the treatment and control” (Fredriksson & Magalhaes, 2019). However, as suggested by Kahn-Lane and Lang (2018), the parallel trends assumption is more likely to be fulfilled if the pre-treatment levels are more similar.

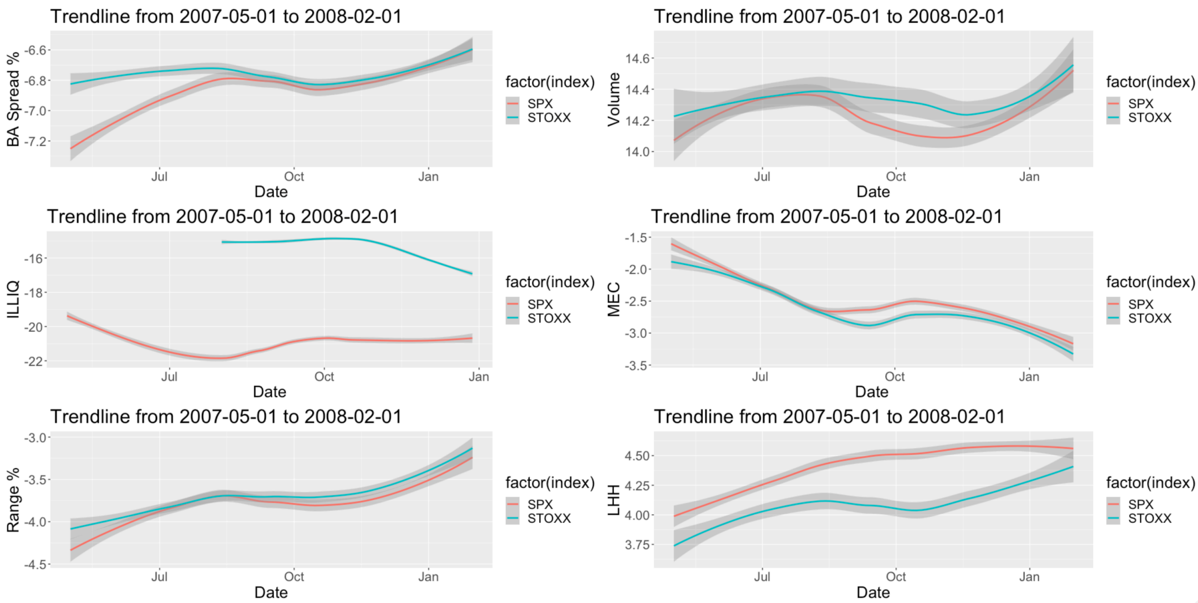

Figure 13: Graphical Summary of Liquidity Trends for STOXX & SPX

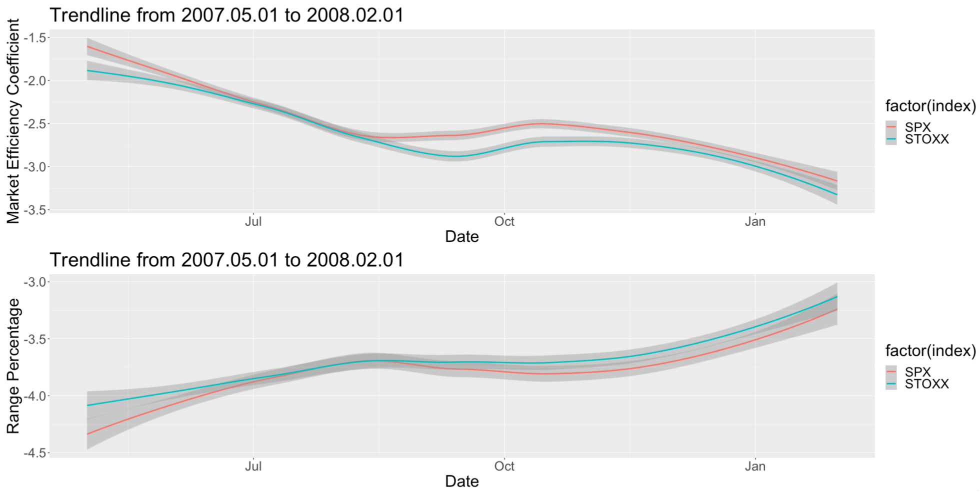

Figure 14: Trend development (Market Efficiency Coefficient & Daily Range Percentage)

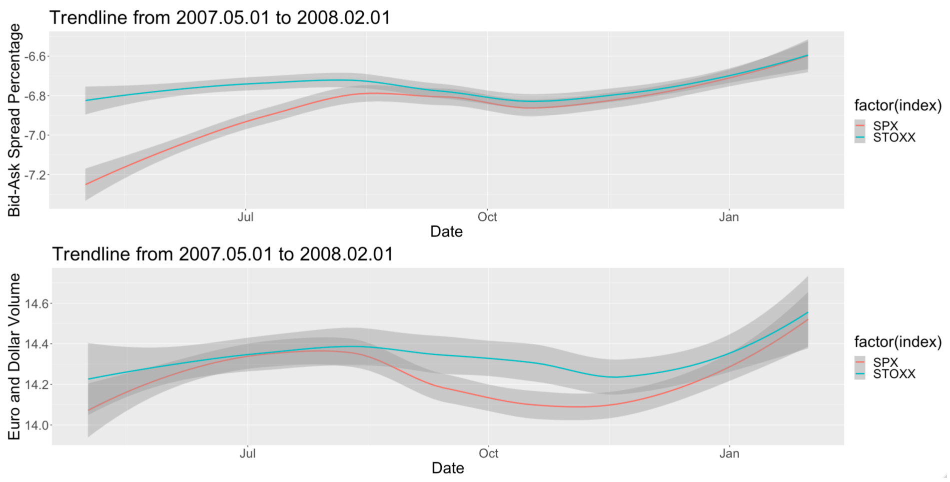

Figure 15: Trend Development (Bid-Ask Spread Percentage & Volume)

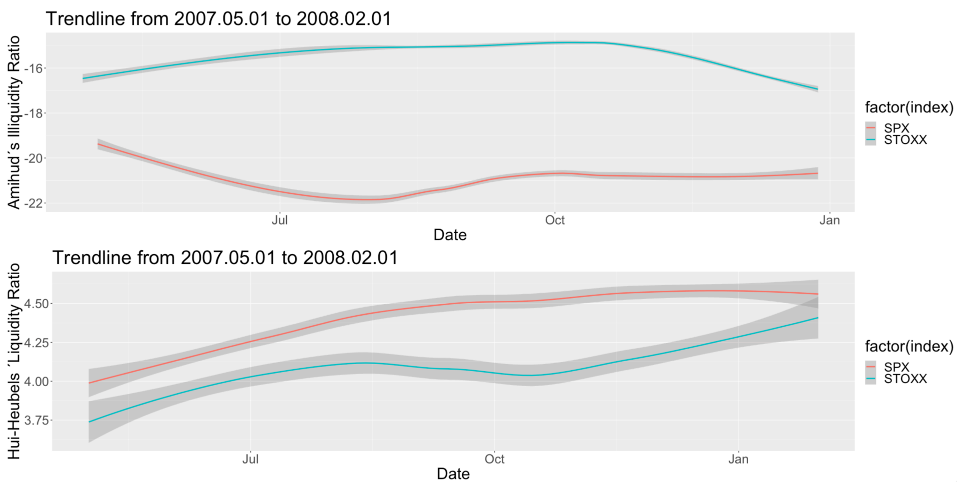

Figure 16: Trend Development (Amihud´s Illiquidity ratio & Hui Heubel Liquidity ratio)

C4: Parallel Trends (Belgium & Europe)

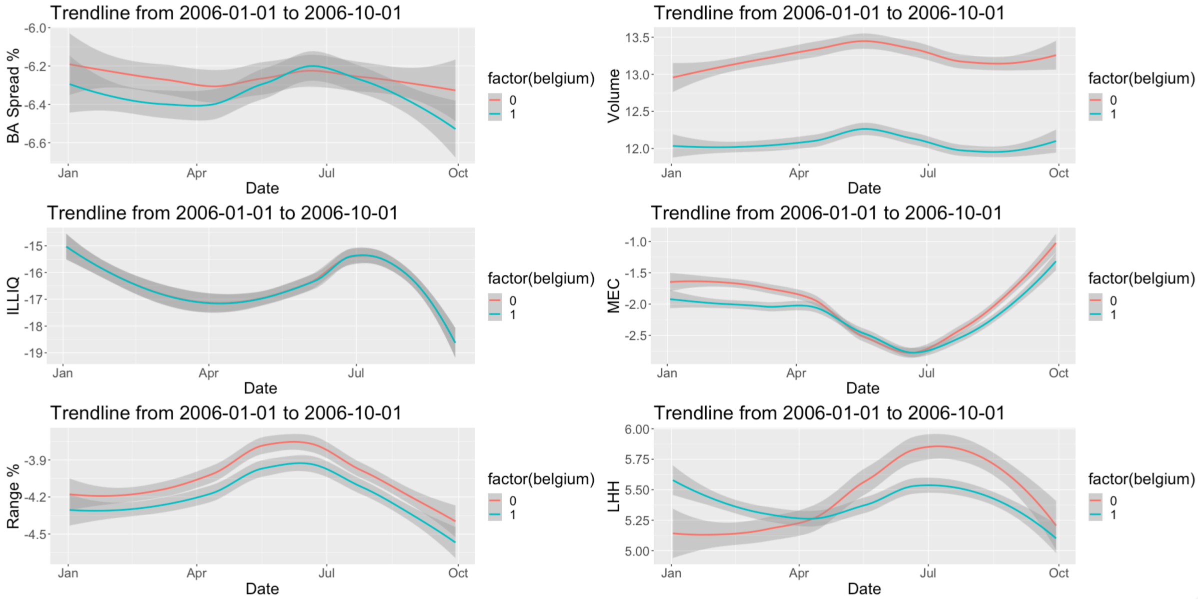

Figure 17: Summary of the Trend Development for Matched Belgium and STOXX

C5: Parallel Trends (Belgium & US)

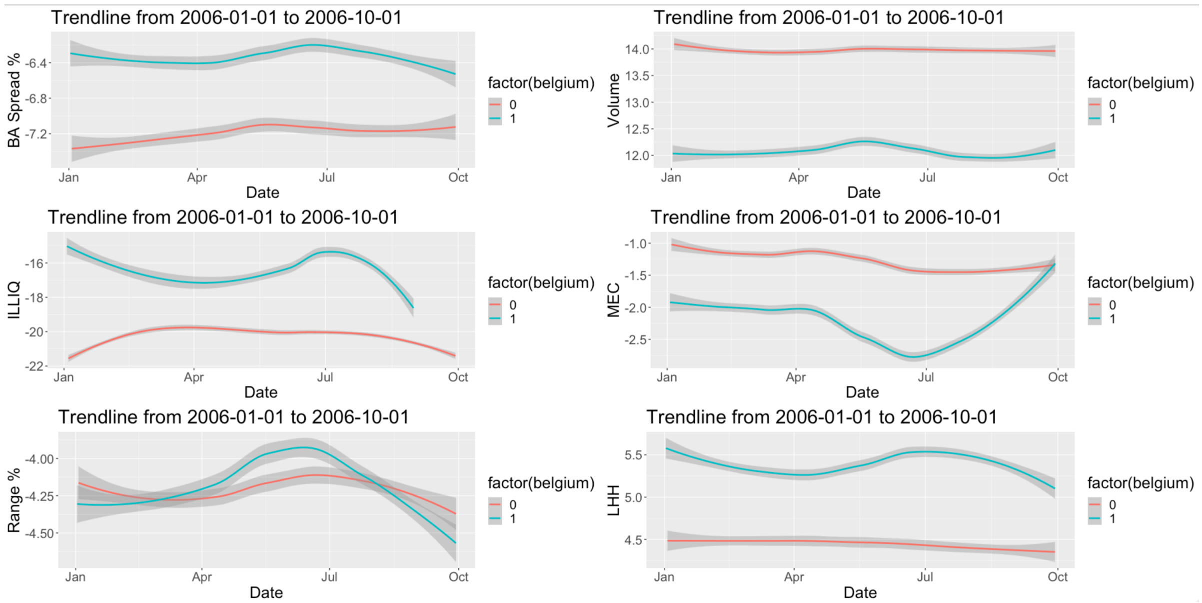

Figure 18: Summary of the Trend Development for Matched Belgium and SPX

C6: Parallel Trends (Spain & US)

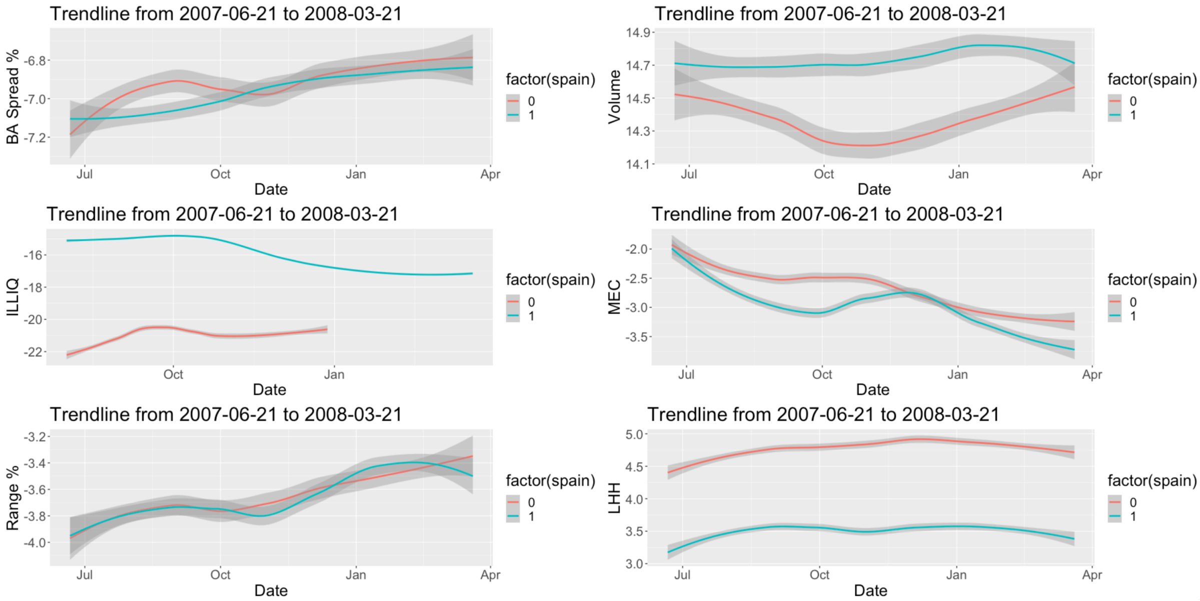

Figure 19: Summary of the Trend Development for Matched Spain and SPX

C7: Parallel Trends (EU ex. Spain and Belgium & US)

Figure 20: Summary of the Trend Development for Matched STOXX (ex. Spain & Belgium) and SPX