Three essays on securities market transparency and design

Author:
Krug, Juliane

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THREE ESSAYS ON SECURITIES MARKET TRANSPARENCY AND DESIGN

Juliane Dorothea KRUG
M.Sc.

A thesis in fulfilment of the requirements of the degree of

Doctor of Philosophy

School of Banking and Finance
UNSW Business School
University of New South Wales

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Abbreviation for degree as give in the University calendar	:	**Ph.D**
Faculty	:	**School of Banking and Finance**
School	:	**UNSW Business School**
Thesis Title	:	**Three essays on securities market transparency and design**

This dissertation focuses on exogenous regulatory changes, which allow us to provide quantitative causal evidence on th impact of pre-and post-trade transparency and alternative order books on market quality.

First, we study how increasing informational asymmetry due to declining broker ID disclosure affects market liquidity fo individual and institutional investors and their trading behaviour at the trading level and on an order level, respectively We investigate three unique policy changes regarding broker ID disclosure conducted on the Helsinki stock market. W find that transaction costs overall improve with an enhanced level of information disclosure. The reintroduction of ex-pos broker identities improved transaction costs by over 36.8bps at market level and 15.6bps for buyer-initiated orders. Overal market volume declined by 0.1% when ex-post broker identities were removed and increased by 0.02% when ex-pos identities were reintroduced.

Second, we explore how trading via systematic internaliser (SI), investment firms dealing on their own account outside regulated market and are a counterparty, not a trading venue, relates to overall market quality. We are the first to provid quantitative causal results, showing that on an aggregate level, SI trading, driven by limit-order SI trading, seems t improve market quality by enhancing competition in the limit order book. Limit-order SI trading lowers transaction cost significantly. Autocorrelation and variance-ratio improve at a highly significant level. The findings are essential to evaluat SI trading on a quantitative basis, allowing regulators to evaluate decisions and provide a foundation for future discussion on internalised trading.

Last, we examine the level of informed trading in SI and periodic call auction trading and how it drives price discovery o the lit trading venues. Both forms of trading offer less pre-trade transparency than the central-limit-order book but ar much more transparent than dark pools. Literature has yet failed to quantify how those forms of trading contribute to pric discovery. We show the level of informed trading depends on the liquidity of the individual security. For constituents o the FTSE 100 index, periodic auction trading is the most informed form of trading after CLOB trading, whereas SI limit order trading is the least informative.

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Abstract

Regulatory authorities rely on well-founded theoretical and quantitative research from academics and practitioners' experiences to evaluate market systems and make superior decisions. Regulators and stock exchanges worldwide constantly debate the optimal level of transparency to support price discovery and serve the needs of all stakeholders.

This dissertation focuses on exogenous regulatory changes in Finland and the United Kingdom, which allow us to provide quantitative causal evidence on the impact of pre-and post-trade transparency and alternative order books on market liquidity, efficiency, and price discovery.

First, we study how increasing informational asymmetry due to declining broker ID disclosure affects market liquidity for individual and institutional investors and their trading behaviour, respectively.

Unlike virtually all market microstructure research that is, of necessity, restricted to actual trades, we study the underlying orders prior to their disguise in the form of trades to examine trading cost implications for institutional investors and households as well as order direction separately. We investigate three unique policy changes regarding broker ID disclosure, conducted on the Finnish NASDAQ OMX Helsinki stock market in March 2006, June 2008, and April 2009. We find for all participants that transaction costs substantially improve with an enhanced level of information disclosure. The reintroduction of ex-post broker identities in 2009 improved transaction costs by over 36.8bps at market level and 15.6bps for buyer-initiated orders. Overall market trade volume declined by 0.1% and the respective trade count by 0.2% when ex-post broker identities were removed in 2008. Trade volume increased by 0.02% and trade count by 0.05% in 2009 when ex-post identities were reintroduced. Institutional as well as individual investors adapt their trading behaviour to the level of broker ID disclosure. The reintroduction of broker ID disclosure shows that institutional investors submit significantly larger orders for less liquid securities.

Second, we explore the question, how trading via systematic internaliser relates to overall market quality.

The already fragmented European market shifted when trading via systematic internaliser (SI) jumped by over 14% in January 2018, when the Markets in Financial Regulation and the Markets in Financial Instruments Directive and Markets' (MiFIR/MiFID II) ambitious regulatory changes to increase transparency and efficiency came into effect. SI are investment firms dealing on their own account outside a regulated market and are, in fact, a counterparty, not a trading venue. The concept of semi-opaque counterparty trading was not new; however, it now captured

the previously opaque broker-crossing-network trading. We are the first to provide quantitative causal results, showing that on an aggregate level, SI trading, driven by limit-order SI trading, seems to improve market quality by enhancing competition in the limit order book. Limit-order SI trading lowers effective and quoted spread 3.6bps each. Realised spread and price impact drop by 9.1bps and 6.2bps, respectively. Autocorrelation and variance-ratio improve at a highly significant level. SI trading executed at the mid-point, similar to dark pool trading executed at the mid-point, presents insignificant or weak significant coefficients for transaction costs and contradictive findings for informational efficiency. The findings are essential to evaluate SI trading on a quantitative basis, allowing regulators to evaluate decisions and provide a foundation for future discussions on internalised trading.

Last, we examine the level of informed trading in systematic internaliser and periodic call auction trading and how it drives price discovery on the lit trading venues.

The European Securities and Market Authority, and other regulators worldwide expressed for a decade concerns on the potential harm of opaque trading on price discovery, also recent literature shows that those concerns might not be valid. In Europe, MiFIR/MiFID II addressed those concerns, introducing comprehensive regulation to shift OTC and dark trading to less opaque venues. New forms of trading gained market share: Trading via systematic internaliser and periodic auctions. Both offer less pre-trade transparency than the central-limit-order-book but are much more transparent than dark pools. Neither regulatory nor academic literature has yet quantified how those forms of trading contribute to price discovery. Driven by different levels of transparency and market structure, the respective impact on informed and uninformed traders' segmentation drives price discovery on an aggregate level. We show the level of informed trading in periodic auctions, systematic internaliser trading at the mid-point and away from the mid-point depends on the liquidity of the individual security. For constituents of the FTSE 100 index, periodic auction trading is the most informed form of trading after CLOB trading, whereas SI trading away from the mid-point is the least informative. We close a significant gap in the literature and provide a foundation for regulators to evaluate introduced regulations and to discuss future market design.

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List of Abbreviations

AFME	Association for Financial Markets in Europe
AMF	Authorité des marches financiers
APA	Authorised Publication Arrangement
ATS	Alternative Trading System
Aquis	Aquis Exchange PLC (MTF)
Cboe	Cboe Europe Equities
Cboe BXE	Cboe Europe Equities BXE MTF (lit &/ dark)
Cboe CXE	Cboe Europe Equities CXE MTF (lit &/ dark)
DiD	Difference-in-Difference
DVC	Double volume cap
DVCM	Double volume cap mechanism
EBBO	Europe-wide best bid offer, referring here to the mid-point of the best bid and ask price on any lit order book in Europe
ELP	Electronic Liquidity Provider
ESMA	European Securities and Markets Authority
ETF	Exchange-Traded Fund
EU	European Union
FBA	Frequent Batch Auctions
FTSE	Financial Times Stock Exchange Group
Instinet Blockmatch	Instinet BlockMatch MTF, operated by Instinet Europe Ltd.
LIS	Large-in-Scale
LSE	London Stock Exchange
MiFID I	Markets in Financial Instruments Directive – Directive 2004/39/EC of the European Parliament and of the Council
MiFID II	Markets in Financial Instruments Directive (recast) – Directive 2014/65/EU of the European Parliament and of the Council
MiFIR	Markets in Financial Instruments Regulation – Regulation 600/2014 of the European Parliament and of the Council

MTF	Multilateral Trading Facility - Multilateral system, operated by a market operator or qualifying investment firm. It connects multiple third-party buying and selling clients in financial instruments
NBBO	National best bid offer, referring here to the mid-point of the best bid and ask price on the lit order books, of LSE, CBOE BXE, CBOE CXE, Turquoise and Aquis.
Obs.	Number of observations
OTC	Over-the-Counter
OTF	Organised Trading Facility – Introduced under MiFID II, a multilateral system that is not a RM or MTF. Third-party buying and selling interests in bonds, structured finance products, emission allowances or derivatives are able to interact in a way that results in a contract. Equities are not permitted for trading.
POSIT	ATS operated by ITG Inc.
RM	Regulated market
RTS	Regulatory technical standards
RTS 1	Commission Delegated Regulation (EU) 2017/587 on transparency requirements for trading venues and qualifying investment firms in respect of shares, depositary receipts, exchange-traded funds, certificates and other similar financial instruments and on transaction execution obligations in respect of certain shares on a trading venue or by a Systematic Internaliser
RTS 11	Commission Delegated Regulation (EU) 2017/588 of 14 July 2016 supplementing Directive 2014/65/EU of the European Parliament and of the Council with regard to regulatory technical standards on the tick size regime for shares, depositary receipts and exchange-traded funds
SI	A Systemic Internaliser is defined as a qualifying investment firm which, on an organised, frequent systematic and substantial basis, deals on own account when executing client orders outside a Regulated Market, a Multilateral Trading Facility or an Organised trading Facility without operating a multilateral system
SORT	Smart Order Routing Technology
Std. Dev.	Standard deviation
Turquoise	Turquoise MTF
UK	United Kingdom

CHAPTER 1: INTRODUCTION

Regulators and stock exchanges worldwide express concerns around the optimal level of transparency to support price discovery and serve the needs of all stakeholders. The individual design of an order book in the form of tick size, access fees, transparency, speed, and matching engine determines the overall market efficiency, liquidity, and price discovery in fragmented and complex markets. With growing competition and customer-focused trading systems, regulatory authorities rely on founded theoretical and quantitative research from academics as well as experiences from practitioners to evaluate markets systems and come to superior decisions.

This dissertation focuses on major regulatory changes in Finland and the United Kingdom, which allow us to provide quantitative causal evidence on the impact of pre-and post-trade transparency and alternative order books on market liquidity, efficiency, and price discovery.

In the following three chapters, we each exploit natural experiments with different methodologies to answer three questions:

(i) *How does an increasing informational asymmetry, due to declining broker identity information disclosure, affect market liquidity for individual and institutional investors and their trading behaviour, respectively?*

The level of trade information disclosure pre-and post-trade is an essential question in an exchange's design and competition with increasingly fragmented markets. Literature shows that broker identities (henceforth IDs) are informative, and market participants can infer price information, which supports price discovery. Pham et al. (2016) show for the Korean stock exchange that the disclosure of the broker IDs post-trade led to an increase in trade volume and a decline in realised spread. A superior level of counterparty information disclosure benefits liquidity since the fear of better-informed investors, and therefore adverse selection risk is lowered. Uninformed participants have the opportunity to copycat supposedly informed participants with a market converging to informational efficiency with the beliefs of both parties converging.

In Chapter 2, we investigate three unique regulatory changes appearing on the Finnish stock market, NASDAQ OMX Helsinki, between 2006 and 2009. During the first event, the market switched from a fully transparent market where all information on broker IDs was disclosed in real-time in the limit order book before the trade to post-trade broker information disclosure. In 2008 the market became completely opaque. In 2009 these changes were partly reversed, and for all securities, except for the top five traded stocks, broker information disclosure was reintroduced post-trade. Hence, the third event allows one to construct a natural control group based on the five most highly traded stocks. Thus, we are able to present detailed findings for different levels of broker ID disclosure, allowing a broader understanding and comparison of the underlying mechanisms.

We can provide unique and robust results by relying on two data sets. First, we use Thomson-Reuters-Tick-History data to provide a comprehensive picture of the consequences for market liquidity, resilience, and transaction costs of these three policy changes for the complete market. Second, we examine the effect of different levels of broker information disclosure on liquidity parameters of the underlying orders derived from the Euroclear database for the Finnish OMX Helsinki market. The quality of the underlying Euroclear data set allows us to rebuild the actual orders of each investor, which provides an improved and rare picture of the impacts on market liquidity and transaction costs of the switch from pre-trade broker transparency to post-trade transparency to total opacity and back to post-trade transparency. The data set includes information about the actual investors, the brokers and even about their nature, e.g., households, institutional and accordingly about the counterparty side.

We contribute to literature, by elaborating the impact of these well-known events on the Finnish Stock exchange on the market's liquidity based on orders, distinguishing between trade direction as well as individual and institutional investors, which captures the impacts in an improved and more realistic way than the common approach. By distinguishing between individual and institutional investors, this paper can narrow down the true impact of broker ID transparency on different market participants and their reactions.

(ii) How does trading via systematic internaliser, firms that deal on their own account by executing client orders outside of regulated trading venues, relate to overall market quality?

The Markets in Financial Regulation and the Markets in Financial Instruments Directive and Markets (henceforth MiFIR/MiFID II) defines a systematic internaliser (henceforth SI) as a firm that deals on its own account by executing client orders outside of regulated trading venues. A SI is a counterparty in the form of an (investment) bank or electronic liquidity provider, not a trading venue. Regular trading venues differ from a SI as they offer multilateral trading, whereas a SI provides only bilateral trading. SI compete with regulated markets and multilateral trading facilities. Under MiFIR/MiFID II regulations, a SI must provide a certain level of pre-trade transparency by publishing quotes for liquid equity instruments up to the average order size and disclose executed trades in real-time. Orders above-average market size do not require disclosure at order submission.

Therefore, a SI does not match the pre-trade transparency of central limit-order books (henceforth CLOB) but is more transparent than dark pool or over-the-counter (henceforth OTC) trading.

Academic literature focuses on more prominent forms of non-lit market trading, such as dark pools, automated non-transparent venues, or opaque order types on lit exchanges. When the European Securities and Markets Authority (henceforth ESMA) introduced MiFIR/MiFID II on 3rd January 2018, the trade volume market share of internalised trading in the United Kingdom (henceforth the UK) jumped by 14.2 percentile points to 18.1%. The closure of broker-crossing networks led to a jump in SI market share. As of 2021, SI presents a sizeable market share of around 14 to 15% for securities within the FTSE 100 index despite SI now being subject to the tick size reform. Still, there is no research on the relationship between market quality and SI.

Chapter 3 provides first insights and causal evidence on the impact of internalised trading on market quality overall. We can overcome not only issues regarding data availability on SI trading but endogeneity issues in the methodology. We rely on the shift in SI trade share as an instrumental variable in a two-stage least squares (henceforth 2SLS) regression.

We demonstrate that by distinguishing between SI trading via limit-orders and at the mid-point, one can determine how the lit trading venue's transaction costs and informational efficiency are impacted. SI trading, driven by limit-order SI trading, seems to improve market quality by enhancing competition in the limit order book. The concept of a semi-opaque counterparty capturing the previously opaque OTC trading and adding new trading opportunities for dark pool and lit venue trading seems, in general, a success. Those findings are essential to evaluate this type of trading on a quantitative basis which allows regulators to evaluate decisions and provides a foundation for future discussions on internalised trading.

(iii) What level of informed trading can be expected in systematic internaliser and periodic call auction trading and how does it drive price discovery on the lit trading venues?

MiFIR/MiFID II came into effect on 3rd January 2018 to promote overall transparency and a robust price formation process due to ESMA's concerns that the growing share of trade execution outside of CLOBs could harm the overall market quality, investor trust, and the price discovery process. The new regulation shifted the focus to two forms of order flow: systematic internaliser and frequent periodic call auctions.

Both forms of trading gained market share and attention due to unrelated regulatory changes, which forced traders to move trade execution from opaque to alternative venues. Trading via broker-crossing networks (henceforth BCNs) needed to be reclassified and redirected as BCNs were closed under MIFIR/MiFID II, resulting in a significant increase in the market share of SI. ESMA introduced the Double Volume Cap Mechanism (henceforth DVCM) to mitigate the extensive use of pre-trade transparency waivers, explicitly stating those waivers could harm price discovery. The DVCM sets a threshold on the use of the reference price and negotiated price waiver, which triggers a suspension for trading under those waivers for the respective security. When a suspension is triggered, data shows that trading not only shifts from dark pools to CLOBs but also to periodic auctions.

Literature and practitioners agree that the price discovery process is driven by the respective CLOBs. So far, there is no empirical work on whether and how periodic auction and SI trading contribute to price discovery.

Our study presented in Chapter 4 focuses on the contribution of periodic auction and SI trading to price discovery by determining the respective quantitative level of informed trading. In contrast to a CLOB, SI must not disclose real-time pre-transparency information for above-market sized orders. The potential opacity might attract market participants who would like to ensure execution at a certain price or/and might not want to immediately disclose their potentially superior information for large orders. SI are not affected by any pre-trade transparency waiver suspensions. Similar to SI, periodic auctions could attract informed participants. The order books only display the potential auction price in real-time, but not the complete quote information as published in the CLOB. The actual auction mechanism could be favoured by less informed and potentially slower market participants, as they might receive a competitive price without the need to compete for speed or the fear of being exploited.

The issue of how market segmentation across different forms of trading drives price discovery and how venues provide timely and informative prices is extremely relevant not only for market participant’s pricing and hedging purposes but also for regulatory authorities’ supervisory activities.

The subsequent Chapters 2 to 4 examine the above questions and provide each an overview on related literature, methodology and findings. Chapter 5 concludes our overall results and discusses potential policy implications.

CHAPTER 2: WHO BENEFITS FROM BROKER ID DISCLOSURE?

2.1 INTRODUCTION

Transparency may relate to various levels of information availability, which impact the market in different ways. Information disclosure about trades and prices after trade execution is referred to as post-trade transparency, whereas information related to upcoming trades is referred to as pre-trade transparency.[1] Some markets disclose full information even in real-time, mostly for a fee, whereas others release trade information with a certain delay or not at all. The speed of information availability overall is essential. Pre-trade transparency may lead to information about execution risks by customers adapting their orders to the liquidity supply when observing the quotes. Besides, the visibility of incoming orders improves liquidity as dealers' rents are reduced; uninformed investors benefit from this situation. The visibility of quotes can also help to distinguish between informed and uninformed traders, which improves price discovery and decreases spreads. The disclosure of the trade's actual investor and broker pre- or post-trade increases the value of every other given information as the observer can relate background information and known strategies of a broker or investor to actual trades. The transparency allows not only the possibility to change one's strategy in a much faster way according to newly gained information, which relates to improved price discovery, but can also affect implementation shortfall costs due to the market moving against a trader splitting up a sizable order. Hence, broker ID information is likely to be price relevant irrespective of whether it is either pre-trade or post-trade transparency.

The question we address is how does an increasing informational asymmetry due to declining broker ID information disclosure affect market liquidity? Specifically, how does the changing market environment influence the transaction costs of individual orders of institutional and household investors, and to what extent do these investor types adapt their trading behaviour? Conflicting findings in previous literature do not allow one to provide soundly founded recommendations to exchanges and regulators. We are able to provide comprehensive results from a different angle, allowing us to make improved inferences about the impact of these central decisions.

We investigate three unique regulation changes appearing on the Finnish stock market,

[1] Admati and Pfleiderer (2001), on the other side, refer to the announcement of intentions in advance.

NASDAQ OMX Helsinki, on 13th March 2006, 2nd June 2008, and 14th April 2009. During the first event, the market switched from a fully transparent market where all information on broker IDs was disclosed in real-time in the limit order book prior to the trade to post-trade broker information disclosure. In 2008 the market became completely opaque. In 2009 these changes were partly reversed, and for all securities, except for the top 5 traded stocks, broker information disclosure was reintroduced post-trade.[2] Hence, the third event allows one to construct a natural control group based on the five most highly traded stocks. Thus, we are able to present detailed findings for different levels of broker ID disclosure, allowing a broader understanding and comparison of the underlying mechanisms.

We present conclusive results showing that transaction costs decrease with enhanced broker information disclosure for both types of market participants. Liquidity is positively associated with decreased informational asymmetry; however, institutional and individual investors react differently but submit more orders on average.

We find that the switch from pre- to post-trade broker ID disclosure leads to a decrease of the daily relative effective spread, as one measure for transaction costs, by 9.5basis points (henceforth bps) at a 1% significance level at market level.[3]

Institutional investors who submit sell-orders experience an increase of 33.4bps per sell order, whereas the measure drops by 21.0bps for buyer-initiated orders. Those results are mainly driven by trading in illiquid securities. Buyer-initiated orders by individual investors present a highly significant drop in price impact up to 40.6bps across all securities.

As a consequence of the switch to opacity in 2008, the relative effective spread for orders of institutional investors increases further by 1.9bps, whereas for individual investors, the relative effective spread per order remains unaffected. However, the relative realised spread for buyer-initiated orders submitted by individual investors drops by 3.0bps, complemented by a decline in price impact of 6.4bps. On a market level, we observe all transaction cost measures increasing. The effective spread widens by 24.2bps at a 1% significance, which is driven by the impact on illiquid securities.

The difference-in-difference (henceforth DiD) analysis for the third event on a market level confirms the previous findings, as the daily relative effective spread for the treatment group falls over 36.8bps more than for the control group. The results on a market level are consistent with our findings for orders submitted by an individual as well as an institutional investor: The

[2] This information was supplied to Peter Swan in a series of emails at the time from NASDAQ's then Chief Economist, Frank Hathaway.

[3] Henceforth bps.

effective spread for buyer-initiated orders submitted by individuals tightens on average by 25.2bps for securities within the treatment group in comparison to the control group, while institutional investors do not experience a change in transaction costs at the order level. The results for buyer-initiated orders of individual investors show further a drop in realised spread by 11.9bps and 43.1bps in price impact, respectively. Those results are consistent across all security groups for orders submitted by individuals.

Institutional investors do not experience a reduction in transaction costs by the reintroduction of broker ID transparency post-trade, unrelated to the order direction or the liquidity of the security. These results on a market-wide level stand in contrast to the results presented in Pham et al. (2016) for the reintroduction of post-trade broker ID disclosure on the Korean Stock Exchange. Frino et al. (2010) find that trades have a higher price impact when the relevant broker information are disclosed to the public. In contrast, our analyses show that price impact increases on a market level when the exchange implemented opacity in 2008 and tightens in 2009. Seller-initiated orders by institutional investors experience an increase of 5.1bps in 2008.

Furthermore, the same parameter for institutional investors shows a drop of 3.4bps a year later. We find inconsistent changes in market liquidity measures. The regulation change in 2006 led to a significant jump in market depth; our results show a drop in 2008. While neither on-market volume nor trade count are significantly changing, those measures are consistently dropping when the market became opaque in 2008. On order-level, illiquid securities are not impacted, whereas seller-initiated orders overall present an increase in trade count.

In 2009, when post-trade transparency was reintroduced for all securities except for the top 5 most highly traded stocks, we find that individual investors decrease their order volume by 0.2% for buyer-initiated orders. Institutional investors increase their order volume for illiquid securities. On a market level, only illiquid securities present a significant incline in liquidity measures compared to the control group. The DiD analysis does not show any significant change for liquid securities within the treatment group. These findings are important as they indicate that individual household investors are not simply ‘noise traders’ but respond to altering levels of information provided on the identity of traders and, additionally, are more responsive on the buy-side of the market. The number of daily submitted orders increases. In contrast, in. 2006, institutional traders increase their sell-order size with an increasing level of opacity. However, they reduce splitting up buyer-initiated orders for illiquid securities, hence are less careful about disguising their intentions. We confirm those findings with our second experiment in 2008. Our findings indicate a relatively small 0.21% decrease in the average number of trades per buy-order for illiquid securities for the policy change in 2006 and a further 0.05% decrease in 2008. Accordingly, in 2009 when the market became more transparent, we observe a jump of 0.13% in the volume of institutional buy-orders and 0.15% for seller-initiated orders. Especially for less liquid securities within the treatment group, the number of trades within an order increases, confirming the observations due to the first two regulatory changes. Institutional traders submit significantly more orders of illiquid securities daily when the market switched to ex-post broker identities in 2006 but do not change their order submission frequency in 2008 when the market became opaque. However, the third (transparency) event in 2009 seems to operate in the same direction; across all investor types and securities, the number of daily order submissions jumps significantly compared to the control group. The result could relate to Gallagher et al. (2013), where price efficiency, measured by lower spreads, is improving when more institutional investors execute swing trades simultaneously. In our case, the overall trading volume of institutional investors does not increase with a declining level of transparency. However, the number of trades within an order falls significantly. The third event shows that institutional investors submit significantly larger orders for less liquid securities for which broker ID transparency is reintroduced. The higher number of daily order submissions could indicate that institutional investors change trade direction more often when the market becomes more transparent. By doing so, institutional investors can hold on to their informational advantage for longer.

The findings are supported by Pham et al.'s (2016) results for the Korean event. Liquidity declines with a decreasing level of broker ID disclosure while transaction costs increase. Publicly displayed broker IDs provides information about the investor's intentions, leading to an improved price discovery from the order flow.[4] Our study shows that each regulation change towards total opacity led to a decline in market liquidity for individual and institutional investors. Our findings should be included in ongoing discussions concerning broker information disclosure and the impact of market transparency on market quality, not only within the academic literature but also in debates of regulators and the conceptual construction of exchanges.

We approach our study using two data sets: First, we use Thomson-Reuters-Tick-History data to provide a comprehensive picture of the consequences for market liquidity, resilience and transaction costs of these three policy changes for the complete market.[5] Second, this study is the first to examine the effect of different levels of broker information disclosure on liquidity parameters of underlying orders derived from the Euroclear database for the Finnish OMX Helsinki market. The quality of the underlying Euroclear data set allows the rebuild of each investor's actual orders, which provides an improved and rare picture of the impacts on market

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[4] NASDAQ OMX Helsinki is an order-driven market; hence our conclusion refers to limit-order markets rather than dealer markets. It is expected that the impact of transparency on market quality will be the same overall, but as we need to distinguish between different market structures, we expect different mechanisms which lead to changed market quality.

[5] The data was processed by the Market Quality Dashboard by the CMCRC. Henceforth, we refer to Thomson-Reuters-Tick-History as TRTH, the Market Quality Dashboard as MQD.

liquidity and transaction costs of the switch from pre-trade broker transparency to post-trade transparency to total opacity and back to post-trade transparency. The data set includes information about the actual investors, the brokers and even about their nature, e.g. households, institutional and accordingly about the counterparty side. To our knowledge, this study is the first to elaborate the impact of these well-known events on the Finnish Stock exchange on the market's liquidity on the basis of orders, distinguishing between trade direction as well as individual and institutional investors, which captures the impacts in an improved and more realistic way than the common approach. By distinguishing between individual and institutional investors, this study can narrow down the true impact of broker ID transparency on different market participants and their reactions.

Bloomfield and O'Hara (1999) show that trade disclosure leads to enhanced informational efficiency in trade prices and widens spreads. Market makers do no longer need to compete for order flow in order to acquire information. Hence, trade disclosure benefits market makers at the expense of informed and liquidity traders who do not time their trading. We find that broker ID disclosure narrows spreads significantly, which does not stand in contrast to the findings by Bloomfield and O'Hara (1999). Rindi (2008) presents a theoretical analysis of two possible consequences of pre-trade transparency. Transparency leads either to decreased or increased liquidity. Identifying the counterparty by uninformed traders leads overall to enhanced confidence about the market and its risk. Under these circumstances, uninformed traders are willing to provide liquidity, which results in increased market liquidity. It is important to know whether the information about the market participant's identity is free and publicly available or its acquisition is costly. The costlier the information, the higher the proportion of uninformed traders. It can be expected that any change lowering the transparency level of trades will lead to a reduced number of informed traders.

Consequently, trading costs increase due to enhanced adverse selection and less competition between traders as only a few have information, and hence, liquidity decreases.[6] Our study supports these conclusions, showing a positive relationship between increased liquidity and enhanced transparency. Following Rindi (2008), we assume that individual traders feel more comfortable providing liquidity when broker ID information are disclosed.

Collin-Dufresne and Fos (2015) argue that standard adverse selection measures are not robust to informed trading by strategic traders with long-lived information who can choose when and how to trade. The authors identify informed traders by studying Schedule 13D filers. They

[6] See also Foucault et al. (2007), who present a similar model where the uniformed benefit of a higher level of market transparency, as they can observe the order placement of informed investors.

find that insiders predominantly use limit orders and improve any adverse selection measures. This results in an asymmetric relation between buyer- and seller-initiated orders, with higher measures for price impact for buyer-initiated transactions on days of informed trading, suggesting that major purchases are made. On the same days, realised spread is on average lower, but more for buyer-initiated trades. The findings show that liquidity providers will have smaller rents on days of informed trading, especially when acting as the counterparty for buyer-initiated trades since the measure stands for the revenue of liquidity providers (see Hendershott et al. (2011)). Collin-Dufresne and Fos (2015) conclude that the asymmetry between buyer- and seller-initiated measures of adverse selection might be a signal for the presence of strategic traders, using both market and limit orders. We do not find significantly different coefficients for the price impact of buyer- and seller-initiated orders.

The level of market transparency is an essential question in an exchange's design and competition with increasingly fragmented markets. Broker IDs have shown to be informative, such that market participants can infer price information and thus price stocks more accurately.[7] Pham et al. (2016) present strong evidence that the disclosure of the broker identity post-trade not only improved their measure of market liquidity, namely the trade volume, which increased significantly, while the realised spread declined. They interpret this as a sign of higher competition between market makers. They also present significant results showing that the enhanced post-trade transparency increases the informational content of trades by analysing the efficiency improvement using measures based on alterations to volatility ratios. The more traditional measure of liquidity, namely the effective spread, rose due to the much greater rate of information release. Overall, their analysis of the Korean Stock Exchange in 1996 shows that when broker IDs were revealed at the close of the morning and afternoon trading sessions, there were significant market quality improvements. Their findings support the model of Pagano and Roell (1996), where the bid-ask spread is widened as a protection against adverse selection resulting from greater transparency. Hence, an increased level of information concerning the counterparty benefits liquidity since the fear of better-informed investors is lowered.[8] Besides, uninformed participants and have the opportunity to copycat supposedly informed participants

[7] Linnainmaa and Saar (2012).

[8] These conclusions go along with Biais (1993). The implicit bid-ask spread of noise traders is tighter in an auction than a dealer market due to higher transparency. Therefore, these traders can observe and learn from and about other market participant's trades what leads to less risk for themselves. Thus, they are willing to trade with a lower spread. Yin (2005) extends this analysis by introducing the idea that quote transparency leads to competitive pressure since the costs for information acquisition are lowered. When investors must pay for opacity in an opaque market, he concludes that the spread is smaller in the more transparent market.

with a market converging to informational efficiency with the beliefs of both parties converging. In contrast to Pham et al. (2016), we find that effective spreads narrow significantly when broker ID disclosure was reintroduced and increase steadily with transparency. In accordance with the findings for the Korean Stock exchange, we observe a positive relationship between liquidity and improving transparency. Bessembinder et al. (2006) develop a theoretical model and test its implications on institutional trades in bonds. They find that trade execution costs fall by 50% for bonds eligible for a more transparent reporting system and 20% for not eligible bonds. According to the authors, the results reflect a liquidity externality by which better pricing information regarding a subset of bonds improves valuation and execution cost monitoring for related bonds.

The literature presents conflicting arguments on how the market reacts to informational efficiency. While Grossman and Stiglitz (1980) state that a competitive equilibrium is not compatible with informational efficient markets and argue that a market would thin, Ou-Yang and Wu (2017) claim an informed trader always has a superior level of information resulting in potentially increased trading volume overall.[9] This conclusion conforms with Chau and Vayanos (2008), who find that an informed trader's profit does not converge to zero, continuous exposure to other participants, and driving a steady-state market (informational) efficiency. To conclude, the interest of exchanges in broker information transparency does not only result from its obvious impact on transaction costs and overall market quality. In addition, trading volume, a critical element in competitive outcomes, is affected.

Based on previous research, we base our analysis on the following hypotheses:

H1: Liquidity is positively associated with enhanced broker ID information disclosure.

Based on Pham et al. (2016), the decreased information symmetry encourages individual investors to provide liquidity. Presumably, uninformed investors become quasi-informed and incorporate the information in their orders. As Rindi (2008) points out, there is a possibility that informed investors reduce their liquidity provision since rents decrease with enhanced information disclosure and uninformed copying their strategies.

H2: A decreased level of broker ID information disclosure leads to increased transaction costs.

We expect that the effective spread measures narrow with increasing transparency and accordingly lower informational asymmetry. This impact will be visible on the market level and on an investor's order itself. Following Foucault (2013), the disclosure of broker IDs balances out

[9] Ou-Yang and Wu (2017) claim that the trading volume of informed traders has a positive limiting value. The error term of the variance of the informed's signal is converging to zero with increased market efficiency.

asymmetric information and improves price discovery, leading to lower transaction costs.[10] Quasi-informed household investors will increase their trading activities and support a faster price discovery. While the impact on a market level is well studied, we expect that the transaction costs for individual orders as an accurate measurement to determine the magnitude of impact for the investor himself will increase. Furthermore:

H3: Not only institutional investors adapt their order submission to a changing market environment, but so do household investors.

As potentially superior and informed traders, institutional investors adapt their order submission characteristics to the level of broker ID information disclosure. In an opaque market, uninformed participants can only infer information from trade size, price and direction and cannot copy strategies easily, allowing higher rents for informed since price discovery is slowed down. Informed investors carefully split up orders to minimise implementation shortfall costs and to avoid unnecessary information disclosure. Therefore, we expect in a transparent market smaller orders or increased order splitting by institutional investors. Research on the Finnish stock market has shown that individual investors trade at an inferior level in relation to institutional investors and foreign investors. In contrast, other studies provide evidence that households can exhibit superior trading performance and cannot per se be categorised as noise traders. However, we expect that both types of investors actively adapt their trading behaviour following the regulatory changes to minimise the risk of losses or exposure.

This chapter is organised as follows. Chapter 2.2 discusses previous findings in literature, Chapter 2.3 explains the underlying data of the study as well as the 2.3 analysed policy changes. Chapter 2.4 presents our methodology. Chapter 2.5 shows our univariate analysis followed by Chapter 2.6 with a comprehensive presentation of our multivariate analysis. A summary concludes the results in Chapter 2.7.

2.2 LITERATURE REVIEW

Findings by Linnainmaa and Saar (2012) suggest that broker IDs are informative for other market participants. Information related to trading motivation can be inferred from the identity of an investor or broker. Market participants can combine order flow and trade size with the investor's or broker's identity and infer underlying information. This leads to changes in their

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[10] Frino et al. (2010) show that improved transparency leads to a significantly higher price impact for sequences of trades from the same broker. Such sequences improve price discovery by imparting new information and reducing information asymmetry.

trading behaviour, and hence the degree of information efficiency relates to the market's quality.[11]

Frino et al. (2010) present similar findings for broker ID transparency at the Australian Stock Exchange. Consecutive buyer-/seller-initiated trades by the same broker have an above-average price impact when the broker identity is available. The magnitude of impact is even more significant for securities with higher estimated adverse selection costs and the first half-hour of a trading day. Overall, that implies that trades with disclosed broker information have more informational value and lead to higher market efficiency.

In the last experiment of our study, the treatment group is exposed to similar changes examined by Pham et al. (2016) since broker identities are provided ex-post. The authors find strong evidence that the disclosure of broker ID information on the Korea Exchange positively affects trading activity, market efficiency, and liquidity. Eom et al. (2007) support these findings for the same exchange, concluding that market quality is increasing with the introduction of pre-trade transparency. On the other hand, Comerton-Forde et al. (2005) study the impact of broker ID disclosure on three different exchanges and find a negative relationship between liquidity and enhanced broker ID disclosure, but in the case of the Korean exchange event, there appears to be confusion over the dating of events (see Pham et al. (2016)). Our events enable us to examine the effect of three different kinds of transparency changes, whereas most studies investigate only one type of change, mainly pre-trade transparency in other than limit order markets.[12]

Meling (2021) studies the impact of the switch from post-trade broker ID disclosure to opacity and a subsequent reversal on market quality on the Oslo Stock Exchange. Based on a regression discontinuity model, the author finds that opacity is overall improving liquidity and transaction costs, which stands in contrast to our findings. The significant increase in trading volume can be attributed to institutional investors, whereas individual investors in his sample do not change their trading behaviour. Given the finding of higher volume with opacity, it seems surprising that the Oslo Exchange switched back to transparency after a relatively short interval. Based on the behaviour of NASDAQ OMX, one would have expected opacity to be retained if the exchange believed that volume was higher and the market more liquid.

As described in the Glosten-Milgrom (1985) model, liquidity demands result from these two types of traders. Kyle (1985) presents a model focusing on asymmetric information. Orders are combined so that the market maker cannot distinguish between the orders of informed or uninformed investors. However, the market maker knows that a uniformed investor submits on

[11] Please see also Beneviste et al. (1992) and Chakravarty (2001) who came to similar conclusions in their analyses.

[12] As Beneviste et al. (1992), Desgranges and Foucault (2005) and Green et al. (2007).

an aggregate level a regular distributed order of a zero mean and random variance. In contrast, the better-informed trader submits an order with a mean of μ, and a variance of σ_v^2, as he has information about the true value of the security. The market maker observes an aggregated order, not knowing about the securities true price v, but infers it from the order flow. The relation between the equilibrium price and the order flow is assumed to be linear, where the price is equal to the true value plus the influence of the order flow. This influence, the slope of the order flow, is Kyle's λ, which is a measure of price pressure exerted per unit of the order, in other terms the price impact. Within a deep market, order size is not as relevant as it does not drive the price as much as it would in a market that lacks market depth. If a market is deep, Kyle's λ is small. Thus, the market depth can be measured as the inverse of Kyle's λ. The market depth, liquidity, is proportional to the share of liquidity demand by noise traders. Therefore, volume and liquidity are positively correlated.[13]

This leads to the conclusion that enhanced transparency in the form of the disclosure of broker IDs leads to decreased asymmetric information, which gives uninformed traders the confidence to make more valid conclusions from the order flow. Price discovery improves, which enables higher liquidity demand by uniformed, which triggers more informed trading. As a result, a higher level of transparency goes along with a higher trading volume and liquidity. Besides, the improved liquidity leads to a faster implementation of information in the security's price. Hence, not only price discovery improves, but also transaction costs are lowered. Foucault (2013) shows that bid and ask prices are determined with a top-up to protect the price setters against adverse selection costs. With decreased adverse selection through the disclosure of broker information, traders are willing to buy at higher and sell at a lower price if they believe the price is closer to the security's actual value. The disclosure of broker ID's balances out asymmetric information, and the improved price discovery leads to lower transaction costs. Flood et al. (1999) agree with these arguments but point out the possibility that increased transparency can also widen spreads. Market participants are less willing to provide liquidity at the beginning of trading and to compete for order flow since no information is yet available. This trend vanishes over time. Further, while in an opaque market, both informed and uninformed pay higher half spreads, with increasing transparency, these costs of a trading shift towards the informed participants.[14]

[13] See Johnson (2008), Foster and Viswanathan (1990) and Admati and Pfleiderer (1988). Ou-Yang and Wu (2017) relax Kyle's (1985) assumption that an informed receives information only at the beginning of a trading day. The insider receives information continuously, and therefore also noise traders can copycat through the day if information efficiency is improved. Aspects of market efficiency and liquidity will be impacted more intensely and differently.

[14] Fong et al. (2011) find for the Australian ASX that the disclosure of broker IDs to the brokers but not to non-broker traders let to increased splitting of orders across brokers to increase their information content.

A broad literature addresses the relationship and the mechanisms of post-trade transparency and market efficiency and liquidity, but few base their conclusions on real-world events. Boehmer et al. (2005) find for the NYSE that the introduction of the real-time order book feed in 2002 led to significant lower trading costs. In contrast, Madhavan et al. (2005) analyse the introduction of pre-trade transparency at the Toronto Stock Exchange. They show that the pre-trade disclosure leads to increased volatility as well as execution costs. The impact was observable for the floor traded stocks but not for stocks under their Computer-Aided Trading System. Simaan et al. (2003) analysed the introduction of pre-trade anonymity of quotes and trades placed by liquidity providers. The authors argue that transparency enables traders to quote wider spreads. Participants setting narrower quotes can be identified as potentially informed. Hence, spreads will be narrower in an anonymous environment. Consistent with their analysis, they provide empirical evidence based on NASDAQ data.

Pagano and Roell (1996) find a positive and significant impact of trade information reports on market efficiency. Baruch (2004) supports these results as his theoretical model considers a situation where smart limit-order traders and specialists supply liquidity and shows that an open limit order book positively affects liquidity. Gemmill (1996) does not find any significant changes in liquidity or price discovery speed when the London Stock Exchange implemented post-trade transparency for large block trades. Hendershott and Jones (2005) find the switch to an undisclosed order book for very liquid ETF in Island led to a decrease in share in trading activity, and price discovery worsens. Trading costs rise in Island but decline on other trading venues. Madhavan et al. (2005), on the other hand, infer from their model that greater order book transparency harms liquidity. Furthermore, the changes also affect the order placement behaviour of investors who split large orders into several trades to prevent a fast revelation of trading intentions. Implantation shortfall costs, the cumulative price impact of large, split up orders, are supposed to increase with an improved transparency.[15]

2.3 MARKET, MARKET DESIGN DECISIONS AND DATA

NASDAQ OMX Helsinki is a significant part of the global portfolio, being home to important companies of the technology sector like Nokia. NASDAQ acquired the Helsinki Security Exchange within OMX AB in 2008. NASDAQ OMX is a conglomerate of Nordic exchanges that includes exchanges from Sweden, Iceland, Denmark, Copenhagen, the Baltic countries and Finland. NASDAQ OMX comprises 2,400 companies with a market value of over US $ 8.5 trillion. The OMX Helsinki trades from 10:00 a.m. through 6:30 p.m. via a centralised

[15] Van Kervel and Menkveld (2015).

pure limit order book market with relatively simple trading rules and a transparent market design.

Our analysis about the impact of different stages of broker ID disclosure is based on three events, where new regulations regarding the transparency of broker information were implemented. Prior to the investigated event on the 13th March 2006, OMX Helsinki reported broker information pre-trade and can be considered fully transparent. With the implementation of the new regulation, broker information were available post-trade. On 2nd June 2008, the market became completely opaque. This decision was partly reversed on 14th April 2009, when for all securities, apart from the top 5 traded stocks, post-trade broker ID disclosure was reintroduced. For the top 5 securities, Nokia, Fortum, Stora Enso, UPM and Sampo, the market remained opaque. We refer to this policy change as the third event.[16]

We base our study on two data sets. First, we use end-of-day security-level metrics computed from TRTH data to analyse the impact of the regulatory changes overall on market quality and liquidity. Transaction costs and resilience metrics were computed with the Market quality dashboard developed and managed by Capital Markets CRC.[17] Thomson-Reuters provides un-manipulated trade and quote records data for all major markets since 1996. For NASDAQ OMX Helsinki, we find complete intraday times-and-sales data, with time stamps at the millisecond level, allowing a comprehensive analysis. All securities classified as equity by Thomson-Reuters, which were traded at least 90% of the days pre-and-post the event within the event horizons, were included in the analysis. The metrics for each security were extracted from the Market quality dashboard and included in our event study. For the first event study, analysing the switch from pre- to post-trade transparency, 97 securities fulfil our criteria. For the second analysed regulation implementation,126 securities remain in our data set. 111 securities are included in the last DiD analysis studying the partial reintroduction of post-trade transparency.

Euroclear Finland Ltd provides our second data set. The book-entry system of OMXH holds the official record of the shareholdings and all trades and consists of information on investor identity, location, date, stock, transaction type, price and volume. The dataset is a copy of the book-entry system records and is reliable given that it is the only official certificate of share ownership. Each investor account has been assigned an anonymous number for privacy reasons.

[16] According to information supplied by the NASDAQ Chief Economist at the time, Frank Hathaway, the reversal was instigated by domestic brokers concerned about the fall in trade volume following complete broker opacity whereas the brokers in the five largest stocks operating out of London preferred opacity. The new rules were designed to meet the requirements of both domestic and London brokers.

[17] The Capital Markets Cooperative Research Centre (CMCRC) provides through the Market Quality Dashboard (MQD) a high-level description of enhanced data analytics for exchanges, regulators, and academics. A unique ETL (Extract, transform and load) workflow engine allows data management automation and the computation of various market quality metrics based on any kind of market data.

Therefore, with negligible exceptions, it is possible to construct the precise composition and value of a particular investor's portfolio at a given date. A valuable characteristic of this data set is that it allows the classification of all holdings and transactions by the investor type. The book-entry system records the compulsory registration for every investor on the OMXH and allocates a unique investor type identification code for each investor which does not alter. Based on this unique identification code, trades can be sorted by investor type, and trade packages can be constructed. The unique data set allows observing comprehensive trade information and both counterparties to each trade, investor (type), broker (type), and even the related account number of the investor. Investors are categorised into six investor categories: individuals (resident in Finland), financial institutions (registered in Finland), foreign investors, government, not-for-profit organisations, and non-financial institutions. NASDAQ OMX Helsinki trades roughly 150 securities throughout our analysis period. Our final data set contains 171 securities over the complete horizon from 1st July 2004 until 30th December 2009. After applying certain criteria as to liquidity to the data, we remain with the same securities for each event study as for the first data set.[18]

2.4 METHODOLOGY

The TRTH data processed with the MQD of the CMCRC is used to analyse the overall impact of the regulatory changes. The second data set from Euroclear provides account information allowing to study the consequences for institutional investors and households. For both, we compute similar metrics, however, the methodologies differ.

For both data sets, we ignore securities that are not traded in the relevant period either before or after an event. Our benchmark and analysis horizon are each 21 trading days pre and post the event.[19]

Thomson-Reuters-Tick-History/Market Quality Dashboard data

All included metrics for all securities of Nasdaq OMXH were extracted from the MQD. We analyse the impact on market liquidity through liquidity measures, measures for transaction costs, and resilience. As liquidity measures, we include the trade volume, trade count and value of a security. These are defined as the sum of the relevant parameter across all on-market trades. A trade is classified as on-market if it occurs within the trading hours and is flagged as on-market. We include the relative effective, realised spread, price impact, implementation shortfall costs

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[18] We require that a security is traded at least on 90% of the days within the pre-and post-event horizon.

[19] In addition, we tested our results for an event horizon of 21 and 63 trading days. The magnitude of the coefficients varies slightly, however the significance and impact direction are always the same.

and quoted depth as measures of transaction costs. The relative or percentage effective spread represents the actual round-trip trading costs for a liquidity demander. It is computed as the difference between the trade price and the prevailing mid-point price, defined as the average of the best bid and ask price, scaled by the mid-point price, multiplied by the trade direction. The dummy variable for the trade direction equals -1 if the trade is seller-initiated and 1 otherwise. We express all spread measures in bps, therefore multiplied by 100. We compute the relative realised spread as the trade price minus the mid-point price 10 minutes later, times two and the trade direction, which is inferred from the Lee-Ready algorithm. The value is scaled by the initial prevailing mid-point price and expressed in bps. The measure can be interpreted as the revenue earned for the liquidity provider. The relative price impact is computed as the difference between the relative effective and realised spread, measuring the subsequent price change following a transaction, an indicator regarding the amount of private information within a trade. Our quoted depth measure is computed as the sum of the daily time-weighted depth of the best ask and bid. Implementation shortfall costs are defined as opportunity plus the execution costs of a trade, also referred to as a measure of institutional trading costs.[20] The explicit costs incur with the usual order-processing, settlement costs in the form of fees or commissions. However, implicit costs depend on the order book, on the spread between the best bid and ask price. The implementation shortfall costs are based on the liquidity premium as the difference between the mid-point and the bid (ask) price for sell (buy) orders and the adverse price movement. Further, they include the adverse price movement, which is especially relevant for larger orders. The trading costs then increase as the difference between the best bid or ask price and the average order execution price. The market impact costs are redistributed to liquidity suppliers. The measure is the sum of the market impact in bps for a given euro transaction volume, describing the performance loss due to liquidity costs. We include intraday volatility, multiplied by 10,000 as a measure of resilience. We compute this measure as the standard deviation of the 5 minutes log-returns of the mid-point throughout the trading day. The variance-ratio measures the linearity of the variance of the mid-point price returns in a certain data interval, in our case 1 and 5 minute(s). An efficient market has an expected variance of close to 1, as the variance of mid-point price returns in t (5) minutes is expected to be close to k times the variance of the mid-point price return over x (1) minutes. Hence, our measure follows Lo and Mac Kinlay (1988) and implies a test for the random walk hypothesis.

[20] See Malinova et al. (2018).

We include these measures as dependent variables in following fixed-effect model for the first and the second event:

$$y_{i,d} = \beta_1 event_d + \beta_2 trend_{i,d} + \beta_3 VIX_d + \sum_{k=1}^{K=5} \theta_k weekday_k + \sum_{i=2}^{I=n} \gamma_i D_i + \varepsilon_{i,d} \tag{1}$$

where $y_{i,d}$ of security i on day d acts as the dependent market quality variable. $event_d$ is a dummy variable equal to 1 post the analysed event and 0 before. We include a time variable, $trend_{i,d}$, to correct trends as our event horizons are extensive. $\theta_k weekday_k$ is a weekday specific dummy variable allowing for weekday and stock-fixed effects. Accordingly, $\gamma_i D_i$ allows us to include stock-fixed effects. VIX_d refers to the daily European Volatility index as there is not specific on for Finland or Scandinavia. It includes the 50 most liquid securities traded in Europe, and only a minimal fraction are actually from Scandinavia. Standard errors are clustered by security.[21]

The nature of the third event allows one to include a DiD measure as the top 5 traded stocks are not affected by the new regulation and act as a control group. Therefore, we implement a dummy variable, $treatment_i$, equal to 1 if the security is affected by the regulations, or 0 otherwise. The DiD measure is a dummy variable computed as the product of $treatment_i$ and $event_d$ for each security on a daily basis. Again, standard errors are clustered by security. We estimate the following model for the third event:

$$y_{i,d} = \beta_1 event_d + \beta_2 treatment_i + \beta_3 DID_{i,d} + \beta_4 VIX_d + \sum_{k=1}^{K=5} \theta_k \, weekday_k + \sum_{i=2}^{I=n} \gamma_i D_i + \varepsilon_{i,d} \tag{2}$$

Euroclear data set

Most available trade data sets do not provide information about the brokers and investors on both sides of the market. The Euroclear data set provides account information such as the investor ID and allows one to recreate the underlying orders. The dataset provides a fully transparent overview of trades, including the actual account numbers taking part and the broker. This allows us to consolidate the data to reflect the underlying, split up orders of an investor. This leads improved understanding of the investor’s trading behaviour and better visualisation of the impact of their trades. All analyses are computed separately for orders overall as well as for seller- and buyer-initiated orders. Further, we distinguish the type of investor, e.g., individual investors, or households, and institutional investors.

We construct the underlying order in two steps. First, we consolidate trade sequences of the same investor, in the same direction, of the same security if the time difference between two

[21] Chang and Fong (2000) document that the trade size itself has relevant informational content. We ran additional regressions for trade size. Also, the coefficients for volume are indeed significant, this does not change the magnitude or significance for the coefficient of the event dummy variable.

trades is less than five trading days. In a second step, we analyse whether investors perform minor trades in the opposite direction between larger trades. If a trade's/order's volume between two orders in the opposite direction is less than 5% of the combined volume of the previous and the following trade, we consider this trade minor and not relevant. We then rerun the first to combine trades if minor trades in between were removed. With this method, we can construct the underlying orders and evaluate the impact of broker information policy changes directly on the actual order, even if the trader tries to disguise his intention by making small reversals. To our knowledge, this study is the first to investigate these issues from this point of view. Putniņš and Barbara (2020) use a similar approach to analyse how the transaction costs for orders of institutional traders are affected by different types of high frequency and algorithmic traders. The study shows that toxic traders trade with the institutional order flow rather than against it. This behaviour can reduce liquidity provision by institutional traders but also enhance price discovery. The advantage of their and our approach is that it allows us to measure trading costs for an investor himself very accurately. The discrepancy in the magnitude of impact between results on the market and an order level can be observed in our findings.

We use similar market liquidity measures as used in the baseline dataset, liquidity measures, and transaction cost measures. However, all these measures are computed based on the actual orders, not on a conventional daily trade base.

We evaluate the impact of the different regulations on trading activity and market liquidity. We estimate the impact with a fixed-effects regression model, as in the following, for the first two events:

$$y_{i,t,d} = \beta_1 event_d + \beta_2 trend_{i,t,d} + \sum_{k=1}^{K=5} \theta_k\, weekday_k + \sum_{i=2}^{I=n} \eta_{i,t,d}\, investor_{i,t,d} + \sum_{i=2}^{I=n} \gamma_i D_i + \varepsilon_{i,t,d} \tag{3}$$

where we include a market quality determinant $y_{i,t,d}$, as for instance the logarithmised total order volume of order t, security i on date d, as the dependent variable. A dummy variable $event_d$, equals 0 prior and 1 post the event. We control for the first weekday of the order and the investor of the order, further we include stock-fixed effects. Standard errors are clustered by security.[22] We do not control for the investor type, when analysing individual and institutional investors separately. In addition, we estimate the same kind of model for the logarithmised number of trades within an order as well as its duration. The order volume, value, the number of trades within an order are the sum of the relevant parameters after the orders are constructed. Further, we compute the number of daily issued order per security (and direction) as the sum of all orders issued on the

[22] By clustering the standard errors by firm, we account for both heteroscedasticity and correlation within stocks.

relevant day. The order duration is the number of hours (within trading hours) it takes to execute an order fully.

Furthermore, we investigate the impact of the policy changes on transaction costs. We compute the relative effective spread of an order as the difference of the volume-weighted order price and the first mid-point price of the order scaled by the first mid-point price, times the order direction.[23] In addition, we evaluate the impact on the relative realised spread by the difference between the last mid-point price and the volume-weighted order price scaled by the volume-weighted order price, multiplied by the order direction. We further compute the relative market impact as the difference between the last and first mid-point price scaled by the first mid-point price. The relative price impact is measured by the difference between the last and first order price, scaled by the first order price. Van Kervel and Menkfeld (2016) use this measure as a proxy for institutional implementation shortfall.[24] The values are multiplied by 10,000 and are therefore expressed in bps. For instance, we estimate the relative price impact of an order using the following fixed-effect model for events one and two when evaluating the overall effect regardless of the type of investor following specification (3).

For the third event, we follow the same approach as in the TRTH data set and estimate a model including a DiD analysis:

$$y_{i,t,d} = \beta_1\, event_d + \beta_2 treatment_i + DID_{i,d} + \sum_{k=1}^{K=5} \theta_k\, weekday_k + \sum_{i=2}^{I=n} \eta_{i,t,d}\, investor_{itd} + \varepsilon_{i,t,d} \qquad (5)$$

where $y_{i,t,d}$ acts again as the dependent variable and we control for the first weekday of the order issue, as well as for the investor type if we do not distinguish our analysis by the type. We cluster standard errors by security.

Combining these two approaches, we achieve a comprehensive picture and an improved understanding of the impact of the three policy changes on market quality and trading activity.

2.5 UNIVARIATE ANALYSIS

Tables 1, 2, and 3 each present an overview of the relevant determinant's mean and standard deviation before and after the event within each of the three sample horizons. The Wilcoxon Rank-

[23] Putniņš and Barbara (2020) refer to the same measure as implementation shortfall costs for an order. The authors use that measure to show that some high-frequency traders appear toxic to institutional investors, while others seem beneficial.

[24] By contrast, Bikker et al. (2004) compute the implementation shortfall for pension funds as $IS_{i,t}^{B} = log\left(P_{i,t}^{exe}/P_{i,t}^{pt}\right) - log\left(M_{i,t}^{exe}/M_{i,t}^{pt}\right)$ with $P_{i,t}^{exe}$and $P_{i,t}^{pt}$ as the execution and pre-trade stock price of stock i at day t, $M_{i,t}^{exe}$ and $M_{i,t}^{pt}$ are determined accordingly.

sum test tests whether the two samples derive from the same distribution. Each table refers in Panel A to the market liquidity parameters derived from the TRTH data/MQD data set, presenting daily parameters. Panel B presents the market liquidity parameter per order for individual investors only derived from the Euroclear data set, while Panel C refers to the same parameters for institutional investors.

The switch from pre-trade to post-trade broker information disclosure on 13th March 2006 leads to significantly higher transaction costs market-wide, as shown in Table 1, Panel A. All t-tests for transaction cost metrics show that the mean transaction costs increase post the regulatory changes. The mean relative effective spread widens about 14.5bps, with a mean increase of market-wide price impact by 8.8bps. The mean variance-ratio increases at a 1% significance level, indicating that the informational efficiency worsens. While all transaction cost measures present an increase, our results do not show a significant change in market liquidity in the form of on-market or off-market trading or market depth. We observe a minimal but highly significant increase in on-market trade count only. Given that the volume remains constant, this might indicate overall a smaller trade size.

Table 1: Switch from pre- to post-trade broker ID disclosure - Univariate Analysis

The table below presents the mean and median for the main parameters used in this study for the first analysed event on 13th March 2006, when the exchange implemented a new regulation, switching to post-trade disclosure. Before that date, NASDAQ OMX Helsinki disclosed broker information prior to trade execution. Our analysis covers a horizon prior to and post of 21 trading days and includes 126 securities. We distinguish between measures for transaction costs, resilience, and liquidity. These were computed on base of two data sets. First, the mean daily transaction costs, resilience and liquidity parameters prior to and post the event as well as their standard deviation, presented in Panel A, were derived by using TRTH data. The relative effective spread is computed as the difference between the trade price and the prevailing mid-point price, divided by the mid-point price, times two. The relative realised spread is defined as the difference between the trade price and the mid-point price 10 minutes after the trade, divided by the initial mid-point price, multiplied by two. Accordingly, price impact is computed as the difference between effective and realised spread. These measures are expressed in bps. Implementation shortfall costs capture the execution as well as the opportunity costs. The intraday volatility is computed using 5 min intervals, measuring the intraday mid-point price return volatility, multiplied by 10,000. The on-market trade volume is defined as the sum of the volume traded within trading hours and on the main market.[25] Accordingly, the on-market trade count is computed. The off-market volume refers to trading outside trading hours as well as any trading not on the main lit order book. We define the variance-ratio in accordance with the methodology of Lo and MacKinlay (1988), testing whether the security prices follow a random walk as a measure for informational efficiency. Panels B as well as C show the mean and the standard deviation for market liquidity parameters computed with the Euroclear data set, which provides additional information as the actual account numbers of the trading participants. Trades are consolidated to simulate the underlying order of an investor, e.g. sequences of trades in the same direction of the same investor are combined, if the time difference between trades is less than 5 days. Minor trades in the opposite direction than the previous and following trade of the same investor were deleted. Hence, we are able to analyse the impact specifically

[25] When performing the t-test on the logarithmised daily on-market trading volume, we find a decrease in the mean of 0.1% at a 10% significance level. The original coefficient shows no significant difference in the mean.

for orders, distinguishing between buyer- and seller-initiated orders. Further, Panel B presents the findings exclusively for individual investors, while Panel C shows the findings for institutional investors only. We present the summary statistics for the number of trades within an order, as well as the order volume and value. We computed the execution time of an order before and after the new regulation came into force. In addition, the number of daily submitted orders is included. We compute various transaction cost measures on base of the underlying order. The relative effective spread is computed as the difference of the volume-weighted order price and the first mid-point price of the order, scaled by the first mid-point price, times the order direction and 10,000, e.g. $\left(\frac{VWAP_{i,t}-mid-point_{i,t,first}}{mid-point_{i,t,first}}\right) * direction * 10{,}000$. The relative realised spread is computed by the difference of the last mid-point price and the volume-weighted order price scaled by the volume-weighted order price. Again, we multiply by order direction and convert the value in bps. Further, we compute the relative market impact as the difference between the last and first mid-point price scaled by the first mid-point price. The relative price impact is measured by the difference between the last and first order price, scaled by the first order price. Van Kervel and Menkfeld (2016) use this measure as a proxy for institutional implementation shortfall costs. Both of measures are multiplied by order direction and 10,000. Please refer to the methodology chapter for further information. In addition, we capture the number of daily issued orders pre- and post the event. Finally, we test the differences of the summary statistics prior to and post the event for significance. The Wilcoxon Rank-sum test refers to the hypothesis that the two samples of each event derive from the same distribution. ***, **, * denotes statistical significance at 1%, 5% and 10%.

	Prior-Event			Post-Event			Analyses of differences	
	Obs.	Mean	Std. dev.	Obs.	Mean	Std. Dev.	T-Test	Wilcoxon Rank-sum
Panel A: Liquidity and efficiency determinants on a daily base derived from TRTH data								
On-market volume (‘000)	5,658	382.00	2,709.00	5,729	435.46	2,689.00	52.60	-1.44
On-market count (‘000)	5,658	0.20	0.59	5,729	0.25	0.68	0.05***	-2.23**
Off-market volume (‘000)	5,658	340.44	2,055.00	5,729	372.23	2,031.00	31.79	-0.58
Rel. effective spread	5,658	63.47	74.10	5,729	77.96	95.00	14.48***	-9.14***
Rel. realised spread	5,658	46.77	70.55	5,729	52.38	86.73	5.61***	-1.70*
Rel. price impact	5,658	16.70	55.59	5,729	25.58	75.77	8.87***	-9.57***
Implementation shortfall	5,658	33.02	37.48	5,729	40.39	48.14	7.37***	-8.80***
Intraday volatility	5,658	153.10	119.60	5,729	208.80	158.90	55.77***	-22.70***
Quoted Depth (Ask)	5,658	38,345	100,184	5,729	35,598	94,430	-2,747.02	5.47***
Quoted Depth (Bid)	5,658	35,913	96,539	5,729	34,050	92,235	-1,863.37	5.50***
Variance ratio (1-5 min)	5,658	1.17	0.20	5,729	1.19	0.20	0.02***	-5.07***
Panel B: Liquidity determinants per order derived from Euroclear data for individual investors only								
No of trades	77,600	1.91	2.38	29,760	1.56	2.36	-0.35***	42.59***
Order volume	77,600	1,365	4,420	29,760	1,465	6,172	99.15***	32.71***
Order value	77,600	17,882	68,653	29,760	26,318	101,729	8,436.12***	-22.52***
Execution time (hrs)	77,600	6.97	29.84	29,760	7.88	33.89	0.90***	14.27***
Rel. effective spread	77,600	45.81	87.89	29,760	70.41	91.93	24.59***	-81.23***
Rel. realised spread	77,600	-14.66	55.26	29,760	-36.74	61.17	-22.07***	89.68***
Rel. market impact	77,600	31.16	125.60	29,760	27.76	116.20	-3.39***	13.62***
Rel. price impact	77,600	30.70	124.80	29,760	27.58	116.40	-3.12***	15.76***
Daily no of issues p. sec	77,600	398.70	588.00	29,760	85.32	119.40	-313.34***	82.60***
Panel C: Liquidity determinants per order derived from Euroclear data for institutional investors only								
No of trades	59,322	6.87	8.04	17,253	11.36	11.41	4.48***	-39.72***
Order volume	59,322	9,576	18,507	17,253	17,413	26,537	7,836.24***	-40.45***
Order value	59,322	155,107	292,143	17,253	300,142	425,376	14,034.40***	-48.68***
Execution time (hrs)	59,322	8.01	27.82	17,253	25.27	44.94	17.26***	-85.19***
Rel. effective spread	59,322	24.45	62.13	17,253	81.79	117.9	57.33***	-88.71***
Rel. realised spread	59,322	2.16	28.82	17,253	1.82	58.43	-0.34	20.21***
Rel. market impact	59,322	28.73	81.25	17,253	90.32	156.7	61.58***	-27.64**
Rel. price impact	59,322	26.38	81.95	17,253	91.58	156.8	65.19***	-53.67***
Daily no of issues p. sec	59,322	715.70	734.30	17,253	73.50	74.21	-642.20***	141.18***

Panel B and C refer to our analysis for individual and institutional investors using the underlying order. Individual investors seem more confident, submitting significantly larger orders, combined with larger trades. The mean transaction costs, measured by relative realised spread and price impact per order, drop by over 22.1bps and 3.4bps, respectively, at a 1% significance level. Post the event, individual investors submit on average more than 313 orders per security less per day. In combination with an overall increased order value and volume, this finding is conform with the findings of Panel A that on a market level, trading activity is not or minimally impacted. The same can be shown for institutional investors: Our results show a highly significant increase in the mean order volume of over 7,836 while the mean daily number of submissions falls by over 642 post the event. Those findings are combined with a jump in price impact of over 61.6bps after the event. The relative effective spread per order increases by 57.3bps. Overall, the switch from pre- to post-trade transparency seems to increase transaction costs, while orders become significantly larger but order submission drops.

The second investigated policy change occurred on 2nd June 2008. Nasdaq OMX Helsinki discontinued broker ID disclosure post-trade. As shown in Table 2, Panel A, we observe a significant drop in the mean daily off-market trade volume, whereas the lit market seems unaffected. Panels B and C however, present a significant drop for both investor types regarding the mean order size and the mean number of daily order submissions. The mean order volume of individual investors falls by 214 at a 1% significance level and 152 for institutional investors. For both, the mean daily number of order submissions drops by over 300 at a 1% significance level. In contrast to the findings for institutional investors, the mean transaction costs at an order level drop for individual investors between 3.3bps and 8.3bps. Institutional investors, however, experience a slight but significant increase in transactions costs. Since institutional investors drive the market, on a market level, transaction costs increase.

Table 2: Switch from post-trade broker ID disclosure to opacity - Univariate Analysis

Table 2 presents the univariate analysis for the second event on 2nd June 2008. Until this date, the relevant broker information were disclosed post-trade to the public. NASDAQ OMX Helsinki decided to stop displaying any broker information, leading to total opacity. The sample period before and after includes 63 trading days. We require securities to be traded at least 90% of the trading days before and post the event. We remain with 102 securities. We distinguish between measures for transaction costs, resilience and liquidity. These were computed on base of two data sets. The mean daily transaction costs, resilience, and liquidity parameters prior to and post the event and their standard deviation, presented in Panel A, were derived by using TRTH data. The relative effective spread is computed as the difference between the trade price and the prevailing mid-point price, divided by the mid-point price, times two. The relative realised spread is defined as the difference between the trade price and the mid-point price 10 minutes after the trade, divided by the initial mid-point price, multiplied by two. Accordingly, price impact is computed as the difference between effective and realised spread. These measures are expressed in bps. Implementation shortfall costs capture the execution as well as the opportunity costs. The intraday volatility is computed using 5 min intervals, measuring the intraday mid-point price return volatility, multiplied by 10,000. The on-market trade volume (count) is defined as the sum of the volume traded (the number of trades) within trading hours and on the main market. Accordingly, the off-market trade volume refers to any trading occurring either outside trading hours or not in the main lit order book. We define the variance-ratio in accordance with the methodology of Lo and MacKinlay (1988), testing whether the security prices follow a random walk as a measure for informational efficiency. Panels B, as well as C, show the mean for market liquidity parameters and the standard deviation computed with the Euroclear data set, which provides additional information as the actual account numbers of the trading participants. Trades are consolidated to simulate the underlying order of an investor, e.g. sequences of trades in the same direction of the same investor are combined if the time difference between trades is less than 5 days. Minor trades in the opposite direction than the previous and following trade of the same investor were deleted. Hence, we are able to analyse the impact specifically for orders, distinguishing between buyer- and seller-initiated orders. Panel B presents the findings exclusively for individual investors, while Panel C shows the findings for institutional investors only. We present the summary statistics for the number of trades within an order, as well as the order volume and value. We computed the execution time of an order before and after the new regulation came into force. In addition, the number of daily submitted orders is included. We compute various transaction cost measures on the basis of the underlying order. The relative effective spread is computed as the difference of the volume-weighted order price and the first mid-point price of the order, scaled by the first mid-point price, times the order direction and 10,000, e.g. $\left(\frac{\mathrm{VWAP}_{i,t}-\text{mid-point}_{i,t,\mathrm{first}}}{\text{mid-point}_{i,t,\mathrm{first}}}\right) * direction * 10{,}000$. The relative realised spread is computed by the difference of the last mid-point price and the volume-weighted order price scaled by the volume-weighted order price. Again, we multiply by order direction and convert the value in bps. Further, we compute the relative market impact as the difference between the last and first mid-point price scaled by the first mid-point price. The relative price impact is measured by the difference between the last and first order price, scaled by the first order price. Van Kervel and Menkfeld (2016) use this measure as a proxy for institutional implementation shortfall. Both measures are multiplied by order direction and 10,000. Please refer to the methodology chapter for further information. In addition, we capture the number of daily issued orders pre-and post the event. Finally, we test the differences of the summary statistics prior to and post the event for significance. The Wilcoxon Rank-sum test refers to the hypothesis that the two samples of each event derive from the same distribution. ***, **, * denotes statistical significance at 1%, 5% and 10%.

	Prior-Event			Post-Event			Analyses of differences	
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	T-Test	Wilcoxon Rank-sum
Panel A: Liquidity and efficiency determinants on a daily base derived from TRTH data								
On-market volume ('000)	5,448	643.56	3,620.00	5,432	590.72	2,940.00	-52.83	3.42***
On-market count ('000)	5,448	0.61	1.61	5,432	0.59	1.46	-0.27	2.79***
Off-market volume ('000)	5,448	113.99	549.11	5,432	46.26	184.44	67.73***	29.51***
Rel. effective spread	5,448	109.50	152.60	5,432	128.40	174.60	18.83***	-7.67***
Rel. realised spread	5,448	86.78	146.30	5,432	105.50	163.90	18.83***	-5.18***
Rel. price impact	5,448	23.60	68.29	5,432	24.33	77.85	0.72	-0.83
Implementation shortfall	5,448	58.84	79.43	5,432	72.28	94.11	13.44***	-8.65***
Intraday volatility	5,448	222.90	156.30	5,432	267.50	210.30	44.62***	-12.73***
Quoted Depth (Ask)	5,448	28,510	74,206	5,432	25,594	72,541	2,961.21**	6.20***
Quoted Depth (Bid)	5,448	27,503	76,404	5,432	22,749	65,574	-4,753.68	7.43***
Variance ratio (1-5 min)	5,354	1.21	0.22	5,326	1.21	0.22	-0.01*	2.89***
Panel B: Liquidity determinants per order derived from Euroclear data for individual investors only								
No of trades	184,887	2.85	3.46	138,935	2.51	3.19	-0.33***	42.60***
Order volume	184,887	1,966	4,218	138,935	1,752	4,046	-214.14***	33.01***
Order value	184,887	34,913	75,866	138,935	28,810	69,098	-6,102.56***	51.13***
Execution time (hrs)	184,887	5.15	9.47	138,935	3.96	8.51	-1.19***	37.87***
Rel. effective spread	184,887	36.87	46.48	138,935	33.23	43.48	-3.64***	3.62***
Rel. realised spread	184,887	6.89	25.42	138,935	3.57	23.73	-3.32***	46.66***
Rel. market impact	184,887	42.34	70.38	138,935	34.08	64.28	-8.25***	33.13***
Rel. price impact	184,887	41.62	69.74	138,935	33.41	63.62	-8.20***	34.06***
Daily no of issues p sec	184,887	1,334.00	1,521.00	138,935	1,003.00	1,174.00	-330.56***	51.61***
Panel C: Liquidity determinants per order derived from Euroclear data for institutional investors only								
No of trades	563,499	4.65	4.59	464,811	4.51	4.50	-0.13***	14.06***
Order volume	563,499	4,065	6,125	464,811	3,913	5,956	-152.59***	6.11***
Order value	563,499	76,082	110,411	464,811	66,893	101,604	-9,189.00***	40.18
Execution time (hrs)	563,499	0.64	3.43	464,811	0.66	3.46	0.02***	-9.14***
Rel. effective spread	563,499	10.19	18.98	464,811	11.55	20.63	1.35***	-52.40***
Rel. realised spread	563,499	2.02	11.70	464,811	2.37	12.76	0.35***	-2.35**
Rel. market impact	563,499	12.72	28.00	464,811	14.40	30.39	1.68***	-21.55***
Rel. price impact	563,499	10.77	27.96	464,811	12.35	30.26	1.57***	-18.82***
Daily no of issues p sec	563,499	1,570.00	1,509.00	464,811	1,261.00	1,167.00	-309.20***	86.41***

The third event allows to build a control group and analyse the impact of the policy change as a natural experiment. For the top 5 securities, Nokia, Fortum, Stora Enso, UPM and Sampo, the market remained opaque, hence these were unaffected by the reversed policy. For securities within the treatment group, broker information disclosure was reintroduced on the 14th April 2009. The results for the univariate analysis are presented in Table 3.

A detailed comparison between the development of the treatment and control group using a DiD approach is presented in Tables 10 to 12. Liquidity in the form of market volume/trade count or order volume/size for institutional and individual investors is consistently stronger, decreasing for the control group compared to the treatment group. Illiquid securities seem to be impacted the most. For example, the mean order volume of institutional investors for securities within the control group falls by 414 over the event. In contrast, securities considered illiquid present an order volume drop of 57. The difference is even more significant for institutional investors.

Table 3: Switch from post-trade broker ID disclosure to opacity - Univariate Analysis
The following table shows the summary statistics of the main parameters used in this study for the third analysed event on 14th April 2009. For all securities but the top 5 traded stocks, following their yearly trading volume, the regulations introduced on 2nd June 2008 were reversed. Hence, the market remained opaque for the top traded securities, while post-trade broker ID disclosure was reintroduced for the remaining securities. Our analysis covers a horizon prior and post of 63 trading days. Our data set includes 102 securities traded on at least 90% of the trading days before and after the event. The top 5 traded securities act as a control group, including the following securities: Nokia, Fortum, Stora Enso, UPM and Sampo. We analyse the difference in the impact compared to the control group for a) liquid securities and b) illiquid securities, for which post-trade broker ID disclosure was reintroduced. The 'liquid treatment' group included the top 6-10 traded securities in accordance with their yearly trading volume. Those are Telia, Outokumpu Oyj, Nordea Bank, Neste, Metso Oyj. The remaining 92 securities affected by the regulatory changes are referred to as 'illiquid'. Please note that Sampo is not included in the analyses in Panels B and C, e.g. the Euroclear data set, due to data availability.

We distinguish between measures for transaction costs, resilience and liquidity. The mean and median daily transaction costs, resilience and liquidity parameters prior to and post the event, presented in Panel A, were derived using TRTH data, using the Market Quality Dashboard (CMCRC) to compute the metrics. The relative effective spread is computed as the difference between the trade price and the prevailing mid-point price, divided by the mid-point price, times two. The relative realised spread is defined as the difference between the trade price and the mid-point price 10 minutes after the trade, divided by the initial mid-point price, multiplied by two. Accordingly, the price impact is computed as the difference between effective and realised spread. These measures are expressed in bps. Implementation shortfall costs capture the execution as well as the opportunity costs. The intraday volatility is computed using 5 min intervals, measuring the intraday mid-point price return volatility, which is multiplied by 10,000. The on-market trade volume (count) is defined as the sum of the volume traded (number of trades executed) within continuous trading hours in the central limit order book. Accordingly, the off-market trade volume refers to any trades either executed outside of trading hours or not on the main lit order book. We define the variance-ratio following the methodology of Lo and MacKinlay (1988), testing whether the security prices follow a random walk as a measure for informational efficiency. Panel B and C show the mean and standard deviation for market liquidity parameters computed with the Euroclear data set, which provides additional information as the actual account numbers of the trading participants. Trades are consolidated to simulate the underlying order of an investor, e.g. sequences of trades in the same direction of the same investor are combined if the time difference between trades is less than 5 days. Minor trades in the opposite direction than the previous and following trade of the same investor were deleted. Hence, we can analyse the impact specifically for orders, distinguishing between buyer- and seller-initiated orders.

Further, Panel B presents the findings exclusively for individual investors, while Panel C shows the results for institutional investors only. Following, we present the summary statistics for the number of trades within an order and the order volume and value. We computed the execution time of an order before and after the new regulation came into force. Besides, the number of daily submitted orders is included. We compute various transaction cost measures based on the underlying order. The relative effective spread is computed as the difference of the volume-weighted order price and the first mid-point price of the order, scaled by the first mid-point price, times the order direction and 10,000, e.g. $\left(\frac{\mathrm{VWAP}_{i,t}-\mathrm{mid{-}point}_{i,t,first}}{\mathrm{mid{-}point}_{i,t,first}}\right) * direction * 10{,}000$. The relative realised spread is computed by the difference of the last mid-point price and the volume-weighted order price scaled by the volume-weighted order price. Again, we multiply by order direction and convert the value in bps. We compute the relative market impact as the difference between the last and first mid-point price scaled by the first mid-point price. The relative price impact is measured by the difference between the last and first order price, scaled by the first order price. Van Kervel and Menkfeld (2016) use this measure as a proxy for institutional implementation shortfall. Both measures are multiplied by order direction and 10,000. Please refer to the methodology chapter for further information. In addition, we capture the number of daily issued orders pre-and-post the event. Finally, we test the differences of the summary statistics before and after the event for significance. The Wilcoxon Rank-sum test refers to the hypothesis that the two samples of each event derive from the same distribution. ***, **, * denotes statistical significance at 1%, 5% and 10%.

	Group	Prior-Event			Post-Event			Analyses of differences	
		Obs.	Mean	Std .Dev.	Obs.	Mean	Std .Dev.	T-Test	Wilcoxon Rank-sum
Panel A: Liquidity efficiency determinants on a daily base derived from TRTH data									
On-market volume ('000)	Control	315	8,212.00	10,680.00	315	6,316.00	8,086.00	-1,896.00***	3.06***
	Liquid	315	1,700.00	1,038.00	315	1,248.00	662.48	-452.22***	6.67***
	Illiquid	4,706	129.04	290.59	4,781	111.23	243.06	-17.81***	-2.59***
On-market count ('000)	Control	315	4.63	3.69	315	4.03	3.18	-0.60**	2.96**
	Liquid	315	1.83	1.10	315	1.67	1.10	-0.16 *	2.09**
	Illiquid	4,706	0.22	0.53	4,781	0.21	0.47	0.01	-4.67***
Off-market volume ('000)	Control	315	69.81	129.68	315	82.93	199.37	13.12	0.69
	Liquid	315	317.92	641.77	315	326.96	1,096.00	9.04	2.04**
	Illiquid	4,706	74.58	1,179.00	4,781	47.58	324.49	27.00	-0.79
Rel. effective spread	Control	315	14.75	7.04	315	12.63	6.18	-2.12***	5.19***
	Liquid	315	18.17	5.23	315	15.09	4.91	-3.08***	8.25***
	Illiquid	4,706	203.80	295.30	4,781	158.00	200.50	-45.80***	7.57***
Rel. realised spread	Control	315	4.10	6.86	315	3.26	5.71	-0.84*	1.33
	Liquid	315	5.00	11.19	315	4.99	9.20	-0.01	-1.16
	Illiquid	4,706	163.20	280.90	4,781	124.40	184.80	-38.80***	3.55***
Rel. price impact	Control	315	10.65	7.81	315	9.37	7.08	-1.28**	2.29**
	Liquid	315	13.17	10.69	315	10.11	9.31	-3.06	-0.28
	Illiquid	4,706	40.64	201.10	4,781	33.61	160.50	-7.03*	2.45**
Implemen-tation shortfall	Control	315	8.83	3.79	315	7.72	3.43	-1.11***	5.33
	Liquid	315	11.48	3.82	315	9.64	3.59	-1.84***	7.57***
	Illiquid	4,706	110.30	154.60	4,781	85.21	104.30	-25.09***	7.69***
Intraday volatility	Control	315	311.50	85.91	315	254.90	83.50	-56.60***	8.66***
	Liquid	315	331.93	110.4	315	249.37	87.76	-82.56***	9.72***
	Illiquid	4,706	331.80	329.50	4,781	283.10	302.10	-48.71***	10.87***
Ask depth	Control	315	70,725.00	58,595.00	315	72,636.00	53,372.00	1,911.00	-2.24**
	Liquid	315	74,922.00	76,399.00	315	93,196.00	98,764.00	18,274.00***	-1.87*
	Illiquid	4,706	9,685.00	18,259.00	4,781	9,767.00	17,402.00	82.00	-3.43
Bid depth	Control	315	69,982.00	58,373.00	315	70,217.00	52,104.00	235.00	-2.31**
	Liquid	315	63,364.00	61,102.00	315	82,693.00	84,282.00	19,328.00***	-2.20**
	Illiquid	4,706	18,929.00	264,064.00	4,781	12,944.00	158,270.00	-5,984.46	-5.60***
Variance ratio (1-5 min)	Control	315	1.30	0.21	315	1.25	0.19	-0.05***	3.19***
	Liquid	315	1.24	0.20	315	1.24	0.20	-0.00	-0.22
	Illiquid	4,576	1.20	0.24	4,648	1.21	0.23	-0.01	-1.72*

	Group	Prior-Event			Post-Event			Analyses of differences	
		Obs.	Mean	Std .Dev.	Obs.	Mean	Std .Dev.	T-Test	Wilcoxon Rank-sum
Panel B: Liquidity determinants derived from Euroclear data for individual investors only									
No of trades/order	Control	113,527	4.07	9.67	72,979	3.69	10.57	-0.38***	25.36***
	Liquid	43,223	2.87	4.98	37,691	2.48	3.99	-0.39***	23.53***
	Illiquid	88,905	2.14	5.12	98,433	1.85	4.46	-0.29***	44.78***
Order volume	Control	113,527	4,127.34	14,124.34	72,979	3,712.54	122.37	-414.80***	-5.08***
	Liquid	43,223	1,137.13	3,273.32	37,691	885.70	238.54	-251.43***	21.66***
	Illiquid	88,905	1,358.10	14,451.82	98,433	1,300.71	3,384.34	-57.39***	14.90***
Order value	Control	113,527	31,219.32	69,937.55	72,979	32,975.65	68,637.82	1,756.33***	-23.94***
	Liquid	43,223	8,783.35	12,986.23	37,691	8,782.56	13,208.65	-0.79	0.37
	Illiquid	88,905	5,777.45	9,959.05	98,433	5,121.14	8,944.65	-656.31***	14.56***
Order execution time in hrs	Control	113,527	18.54	37.84	72,979	14.32	31.94	-4.22***	8.03***
	Liquid	43,223	47.30	100.05	37,691	32.22	82.15	-15.08***	20.45***
	Illiquid	88,905	24.93	78.20	98,433	15.34	55.93	-9.59***	41.44***
Rel. effective spread/order	Control	113,527	84.30	140.64	72,979	60.38	112.35	-23.92***	50.27***
	Liquid	43,223	126.9	215.98	37,691	84.67	173.12	-42.23***	47.79***
	Illiquid	88,905	127.1	334.55	98,433	97.04	284.84	-30.06***	34.30***
Rel. realised Spread/ order	Control	113,527	33.07	73.44	72,979	22.60	59.08	-10.47***	-6.82***
	Liquid	43,223	52.38	108.66	37,691	33.96	89.32	-18.42***	-6.92***
	Illiquid	88,905	26.21	203.35	98,433	10.62	178.05	-15.59***	42.34***
Rel. market impact/order	Control	113,527	129.14	231.73	72,979	91.18	184.96	-37.96***	23.25***
	Liquid	43,223	196.07	347.54	37,691	128.24	276.54	-67.83***	24.55***
	Illiquid	88,905	166.44	539.95	98,433	117.12	460.62	-49.32***	42.36***
Rel. price impact/order	Control	113,527	127.49	231.05	72,979	90.18	184.25	-37.31***	23.13***
	Liquid	43,223	195.07	346.57	37,691	127.43	275.79	-67.64***	25.12***
	Illiquid	88,905	165.04	538.56	98,433	116.36	460.66	-48.68***	42.66***
Daily no of issues p sec	Control	113,527	2,887.45	3,616.34	72,979	2,061.78	2,219.75	-825.67***	73.44***
	Liquid	43,223	826.45	319.93	37,691	751.17	293.13	-75.28***	29.76***
	Illiquid	88,905	243.56	238.14	98,433	223.35	223.55	-20.21***	40.83***
No of trades/order	Control	200,628	7.77	22.07	161,711	7.77	25.24	-0.00	8.20***
	Liquid	44,679	6.11	13.79	38,119	5.87	13.23	-0.24**	4.94***
	Illiquid	114,985	5.54	20.81	106,404	5.48	13.93	-0.06	4.95***
Order volume	Control	200,628	11,343.45	27,102.34	161,711	8,682.32	19,748.83	-2,660.13***	40.45***
	Liquid	44,679	2,725.45	6,911.74	38,119	2,283.95	5,620.54	-441.50***	23.39***
	Illiquid	114,985	2,580.35	53,565.84	106,404	2,713.65	109,383.12	133.30	20.51***
Order value	Control	200,628	78,359.45	111,644.92	161,711	71,835.21	104,885.65	-6,524.24***	16.01***
	Liquid	44,679	18,201.21	19,035.44	38,119	18,735.56	19,585.81	533.35***	-2.32**
	Illiquid	114,985	13,586.34	15,671.24	106,404	13,330.64	15,525.27	-392.70**	6.32***
Order execution time in hrs	Control	200,628	0.56	4.505.54	161,711	0.62	4.64	0.06***	2.80***
	Liquid	44,679	1.42	10.93	38,119	1.47	10.51	0.05	4.44***
	Illiquid	114,985	4.63	28.85	106,404	4.20	24.92	0.43***	-5.91***
Rel. effective spread/order	Control	200,628	14.32	30.32	161,711	12.81	29.21	-1.51***	56.09***
	Liquid	44,679	19.73	49.09	38,119	16.67	45.48	-3.06***	34.93***
	Illiquid	114,985	31.50	84.23	106,404	28.77	82.06	-2.73***	21.84***
Rel. realised Spread/ order	Control	200,628	4.50	18.23	161,711	4.03	17.52	-0.47***	7.20***
	Liquid	44,679	6.75	28.75	38,119	5.59	25.97	-1.16***	-0.42
	Illiquid	114,985	7.63	51.08	106,404	6.96	49.15	-0.67***	-2.38***
Rel. market impact/order	Control	200,628	19.27	45.61	161,711	17.31	43.79	-1.96***	25.32***
	Liquid	44,679	27.10	74.35	38,119	22.65	65.40	-4.44***	13.35***
	Illiquid	114,985	41.31	128.0	106,404	37.57	120.6	-3.73***	8.49***
Rel. price impact/order	Control	200,628	15.55	45.31	161,711	14.07	43.62	-1.47***	16.92***
	Liquid	44,679	24.38	74.51	38,119	20.16	65.66	-4.22***	12.23***
	Illiquid	114,985	37.98	128.5	106,404	33.97	119.87	-4.01***	9.00***
Daily no of issues p sec	Control	200,628	2,420.12	2,850	161,711	1,906.12	1,908.86	-514.00***	81.76***
	Liquid	44,679	771.32	293.55	38,119	724.92	286.51	-46.40 ***	26.93***
	Illiquid	114,985	316.31	190.82	106,404	297.73	204.42	-18.58***	61.93***

Mean transaction costs decrease overall on the market as well as an order level. The most significant drop at the market-level is for illiquid securities, for which post-trade transparency is reintroduced. We find that the mean relative effective spread drops by 45.8bps in contrast to securities within the control group, for which we observe a drop of 2.1bps. On-market trade volume declines by 17 for illiquid securities, whereas the top 5 traded stocks experience a mean daily drop of over 1895. The results show the largest decline in transaction costs for liquid securities impacted by the regulatory changes for individual investors. The order volume and number of daily order submissions. The number of daily order submissions drops for both investor types and all security groups over the event. Only a quantitative analysis can determine the distinct differences across those security groups. An appropriate and detailed multivariate analysis of the impact on market liquidity by the three events is given in the following chapter.

2.6 MULTIVARIATE ANALYSIS

Our study provides a unique approach to address the controversial findings in previous literature. For each event, we first analyse the impact by using a fixed-effect regression model based on TRTH data, relying on daily liquidity, transaction costs, and resilience metrics. Second, we present our findings based on the Euroclear data set. We reconstructed the underlying orders of each investor and computed all determinants based on these orders. Further, the data set allows us to distinguish between individual and institutional investors. In addition, we show the impact on buyer- and seller-initiated orders separately.

2.6.1 Switch from pre- to post-trade broker ID disclosure on 13th March 2006

Tables 4 to 6 present the regression coefficients for the first investigated event. Table 4 shows the relevant daily parameters regarding market liquidity derived from TRTH/MQD.

Table 4: Switch from pre- to post-trade broker ID disclosure - Impact on Market Liquidity

The table below presents the regression coefficient estimates for the first analysed event on 13th March 2006. Before this date, Nasdaq OMX Helsinki disclosed broker ID information prior to trade execution. The newly implemented policy allowed information disclosure only post-trade. Our analysis covers a horizon prior to and post of 63 trading days and includes 126 securities.

We distinguish between measures for transaction costs, resilience, and liquidity. The relative effective spread is computed as the difference between the trade price and the prevailing mid-point price, divided by the mid-point price, times two. The relative realised spread is defined as the difference between the trade price and the mid-point price 10 minutes after the trade, divided by the initial mid-point price, multiplied by two. The price impact is computed as the difference between effective and realised spread. These measures are expressed in bps. Implementation shortfall costs capture the execution as well as the opportunity costs. The intraday volatility is computed using 5 min intervals, multiplied by 10,000, measuring the intraday mid-point price return volatility. The on-market trade volume (count) is defined as the sum of the volume traded (number of trades executed) within continuous trading hours on the central limit order book. Accordingly, the off-market trade volume refers to the total volume traded either outside of trading hours or not on the main lit order book. We define the variance-ratio in accordance with the methodology of Lo and MacKinlay (1988), testing whether the security prices follow a random walk as a measure for informational efficiency. We use a 1 to 5 minute/s return ratio. We run the fixed-effect regression model according to specification (1).

We cluster the standard errors by security and included stock as well as weekday fixed-effects. The t-statistics are presented in parentheses. ***, **, * denotes statistical significance at 1%, 5% and 10%.

	Rel. Effective Spread	Rel. Realised Spread	Rel. Price impact	Implementation shortfall	Intraday volatility	Log On-market Volume	Log On-market Count	Log Off-market Volume	Log Ask Depth	Log Bid Depth
Panel A: Complete market										
Event	-9.48***	-9.87***	1.58	-4.82***	-54.70***	-0.00	-0.01	0.13	0.15***	0.07**
	(-4.36)	(-4.57)	(0.93)	(-4.59)	(-8.89)	(-0.07)	(-1.15)	(0.87)	(4.49)	(2.55)
Obs.	11,477	11,477	11,477	11,477	11,477	11,477	11,477	11,477	11,477	11,477
Adj. R^2	0.54	0.40	0.21	0.57	0.18	0.80	0.79	0.72	0.76	0.79
Panel B: Top 5 traded securities										
Event	-1.09***	-0.64	-0.46	-0.58***	-50.21***	0.01	0.01	0.001	0.38***	0.25**
	(-6.88)	(-1.23)	(-0.91)	(-8.25)	(-4.70)	(1.04)	(0.55)	(1.04)	(4.71)	(3.39)
Obs.	630	630	630	630	630	630	630	630	630	630
Adj. R^2	0.55	0.07	0.042	0.57	0.24	0.82	0.74	0.82	0.84	0.83
Panel C: Top 10 traded securities										
Event	-1.66***	-0.19	-1.33**	-0.79***	-59.88***	-0.01	-0.01	-0.37	0.28***	0.18***
	(-3.54)	(-0.48)	(-2.36)	(-3.97)	(-4.66)	(-0.48)	(-0.42)	(-0.99)	(5.00)	(3.73)
Obs.	1,260	1,260	1,260	1,260	1,260	1,260	1,260	1,260	1,260	1,260
Adj. R^2	0.67	0.10	0.13	0.80	0.30	0.81	0.85	0.87	0.86	0.87
Panel D: Illiquid securities										
Event	-10.53***	-11.10***	1.90	-5.36***	-54.11***	-0.00	-0.01	0.19	0.14***	0.06*
	(-4.38)	(-4.65)	(1.01)	(-4.63)	(-7.99)	(-0.01)	(-1.11)	(1.19)	(3.64)	(1.91)
Obs.	10,217	10,217	10,217	10,217	10,217	10,217	10,217	10,217	10,217	10,217
Adj. R^2	0.51	0.37	0.21	0.53	0.18	0.73	0.73	0.69	0.57	0.62

Our highly significant results show a decline in the daily transaction costs. The relative effective spread drops overall by over 9.5bps at a 1% significance level, driven by the most illiquid securities, which experience a decline of over 10.5bps. The more liquid the security, the smaller the impact, however highly statistically significant. The relative released spread drops by 11.1bps for illiquid securities, which drives the findings market-wide as the top 10 traded securities are not impacted. The findings for implementation shortfall costs conform with the results for the relative effective spread. Across all securities, we observe a drop in intraday volatility. Market liquidity in the form of on-market trade count and volume and off-market volume does not change over the event on a market level. Bid as well as ask depth is across the whole sample significantly improving. The most significant change can be observed for the top 5 traded stocks, where ask depth is improving by 38% at a 1% significance level. For less liquid securities, ask depth is growing by 14.

Our study deepens the understanding of different levels of broker ID information disclosure in Table 5 by analysing the impact separately for individual and institutional investors.

While the first should benefit from broker ID disclosure in general, the latter might benefit from a reduced availability of information. To clarify, how exactly these investors adapt to the new regulations, we use the Euroclear data set and base our study on the actual orders the individual investor submits. We distinguish between buyer- and seller-initiated orders, allowing a comprehensive picture. Table 5 shows that significantly more orders for the top 10 traded stocks are submitted.

While illiquid securities are not significantly impacted, overall 288% more orders of top 10 traded securities are submitted on a daily basis. Especially significant are the results for sell orders, for which order submission increases by 143%. Those findings derive equally by increased order submission by individual and institutional investors. Institutional investors submit 20% smaller buy orders for illiquid securities post the event. Since the order volume remains constant, and the number of trades per order decreases, we suggest trade size increases on average. Institutional investors seem to feel more confident trading illiquid securities. Further, sell order volume of institutional investors increases by 34% at a 1% significance level. We observe a different result for individual investors trading the top 10 traded securities: Buy order volume increases by 20% at a 10% significance level and the number of trades per order overall jumps by 9% at a 5% significance level.

Table 5: Switch from pre- to post-trade broker ID disclosure - Impact on Liquidity measures households and institutional investors

Prior 13th March 2006, Nasdaq OMX Helsinki disclosed broker ID information prior to trade execution. The newly implemented policy allowed information disclosure only post-trade. Our analysis covers a horizon prior to and post of 63 trading days and includes 126 securities. Trades are consolidated to simulate the underlying order of an investor, e.g., sequences of trades in the same direction of the same investor are combined if the time difference between trades is less than 5 days. Minor trades in the opposite direction than the previous and following trade of the same investor were deleted. We are able to analyse the impact not only on overall market quality but specifically on issued orders. We run basic fixed-effect regression with various determinants as the number of trades within an order, the order volume as well as the order value as the dependent variable. Further, we analyse the order execution time and the number of daily submitted orders per security. We run fixed-effect models as the following one.

$$y_{i,t,d} = \beta_1 event_d + \beta_2 treatment_{i,t} + \sum_{k=1}^{K=5} \theta_k\, weekday_k + \sum_{i=2}^{I=n} \eta_{itd}\, investor_{i,t,d} + \sum_{i=2}^{I=n} \gamma_i D_i + \varepsilon_{i,t,d}$$

where the $y_{i,t,d}$ is computed per order t and security i on day d, $event_d$ equals 0 prior to the event and 1 post the event. The standard errors are clustered by security. Further, we control for the weekday of the first trade's execution as well as the investor in Panel A, D and G. In Panels B and C, E and F, H and I; the latter is not applicable. Panels A, D and G present the regression coefficients when the type of investor is disregarded and only distinguish between seller- and buyer-initiated orders. We show joint and separated findings for liquid (top 10 traded securities) and illiquid (other than the top 10 traded) securities.[26] Panels B, E and H show the findings for individual investors only, again presenting the overall effect as well as the impact on buyer- and seller-initiated orders. Panel C, F and I present the relevant results for institutional investors. The t-statistics are presented in parentheses. ***, **, * denotes statistical significance at 1%, 5% and 10%.

[26] The top 10 traded securities include Nokia, Fortum, Stora Enso, UPM and Sampo. Those securities are the top 5 traded securities in accordance with their yearly trading volume and exempted by the regulatory changes. These are followed by Telia, Outokumpu Oyj, Nordea Bank, Neste, Metso Oyj.

	Log Order volume	Log Order volume	Log Order volume	Log No of trades per order	Log No of trades per order	Log No of trades per order	Log Daily No of issued orders	Log Daily No of issued orders	Log Daily No of issued orders
Order type	Any	Buy	Sell	Any	Buy	Sell	Any	Buy	Sell
Panel A: Impact on Liquidity measures									
Event	0.06	-0.01	0.14**	-0.02	-0.07**	0.03	167.71***	88.39**	77.85***
	(1.16)	(-0.07)	(2.39)	(-0.76)	(-2.37)	(1.35)	(2.79)	(2.36)	(2.77)
Obs.	183,935	88,800	95,135	183,935	88,800	95,135	183,935	88,800	95,135
Adj. R^2	0.36	0.36	0.36	0.31	0.30	0.32	0.66	0.65	0.65
Panel B: Impact on Liquidity measures for orders of individual investors only									
Event	0.06*	0.05	0.08	0.02	0.00	0.04*	137.84**	76.87*	61.13**
	(1.74)	(0.83)	(1.52)	(1.47)	(0.23)	(1.79)	(2.18)	(1.74)	(2.07)
Obs.	107,360	50,099	57,21	107,36	50,099	57,261	107,360	50,099	57,261
Adj. R^2	0.11	0.15	0.12	0.06	0.06	0.05	0.60	0.60	0.61
Panel C: Impact on Liquidity measures for orders of institutional investors only									
Event	0.19	0.03	0.34***	-0.01	-0.11*	0.09**	210.47***	98.54***	110.78***
	(1.45)	(0.17)	(3.19)	(-0.17)	(-1.72)	(2.14)	(3.79)	(3.11)	(4.300)
Obs.	76,572	38,695	37,868	76,572	38,695	37,868	76,572	38,69	37,86
Adj. R^2	0.15	0.14	0.15	0.05	0.05	0.06	0.68	0.68	0.68
Panel D: Impact on Liquidity measures for the top 10 traded securities only									
Event	0.10	0.04	0.17	-0.00	-0.05	0.04	288.46**	145.20*	143.06***
	(0.93)	(0.25)	(1.77)	(-0.07)	(-0.81)	(0.87)	(3.13)	(2.33)	(4.12)
Obs.	96,778	45,284	51,494	96,778	45,284	51,494	96,778	45,284	51,494
Adj. R^2	0.31	0.29	0.33	0.26	0.22	0.29	0.66	0.66	0.65
Panel E: Impact on Liquidity measures for the top 10 traded securities and orders of individual investors only									
Event	0.16	0.22*	0.13	0.09**	0.10**	0.09*	347.30**	178.76*	172.07***
	(1.87)	(1.97)	(1.23)	(3.46)	(2.61)	(2.07)	(3.32)	(2.11)	(4.22)
Obs.	43,705	18,412	25,293	43,705	18,412	25,293	43,705	18,412	25,293
Adj. R^2	0.03	0.06	0.02	0.09	0.08	0.06	0.65	0.64	0.65
Panel F: Impact on Liquidity measures for the top 10 traded securities and for orders of institutional investors only									
Event	0.31	0.12	0.50**	0.04	-0.05	0.14*	243.16**	116.12*	125.37**
	(1.52)	(0.43)	(3.14)	(0.61)	(-0.45)	(2.02)	(2.71)	(2.30)	(3.25)
Obs.	53,073	26,872	26,201	53,073	26,872	26,201	53,073	26,872	26,201
Adj. R^2	0.091	0.09	0.09	0.05	0.04	0.05	0.67	0.67	0.66
Panel G: Impact on Liquidity measures other than the top 10 (e.g., Illiquid) traded securities only									
Event	0.03	-0.06	0.16*	-0.024	-0.09***	0.05*	14.12	14.45	-2.37
	(0.58)	(-0.97)	(1.70)	(-1.51)	(-4.03)	(1.74)	(0.43)	(0.53)	(-0.11)
Obs.	87,157	43,516	43,641	87,157	43,516	43,641	87,157	43,516	43,641
Adj. R^2	0.266	0.26	0.27	0.39	0.39	0.31	0.55	0.54	0.57
Panel H: Impact on Liquidity measures for other than the top 10 (e.g., Illiquid) traded securities and orders of individual investors only									
Event	0.01	-0.03	0.05	-0.02	-0.05*	0.05	7.80	14.85	-8.04
	(0.34)	(-0.42)	(0.78)	(-1.45)	(-1.80)	(0.13)	(0.20)	(0.45)	(-0.54)
Obs.	63,655	31,687	31,968	63,655	31,687	31,968	63,655	31,687	31,968
Adj. R^2	0.16	0.17	0.17	0.04	0.04	0.05	0.54	0.55	0.56
Panel I: Impact on Liquidity measures for other than the top 10 (e.g., Illiquid) traded securities and for orders of institutional investors only									
Event	0.03	-0.11	0.16	-0.044	-0.21***	0.10	27.27	11.93	12.90
	(0.31)	(-1.09)	(1.36)	(-0.94)	(-4.08)	(1.59)	(1.21)	(0.85)	(1.38)
Obs.	23,499	11,823	11,667	23,499	11,823	11,667	23,499	11,823	11,667
Adj. R^2	0.08	0.06	0.10	0.06	0.05	0.07	0.56	0.59	0.59

Table 6 shows that the superior order liquidity for seller-initiated orders by institutional investors is accompanied by a significant increase in transaction costs. Overall, the effective spread per seller-initiated orders by institutional investors increases by 33.4bps overall, driven by both liquid and illiquid securities for which transaction costs increase by 20.8bps at a 5% significance level and 44.3bps at a 1% significance level, respectively.

Those results drive the findings overall. Sell orders of individual investors are not impacted at a significant level. We observe the opposite for buyer-initiated orders, where transactions costs drop by 42.9bps overall for illiquid securities. Orders by institutional investors are affected the most. At the same time, price impact per order is dropping overall by 41.2bps at a 1% significance level. The finding is mainly driven by less liquid securities, for which price impact drops by 49.9bps. The relative realised spread per buyer-initiated orders in illiquid securities for institutional investors falls by over 9.4bps at a 1% significance level.

The first event leads to lower transaction costs on a market level when switching from pre- to post-trade broker ID disclosure. At the order level, we observe the opposite for seller-initiated orders by institutional investors. The changes in transaction costs on a market level seem mainly driven by buyer-initiated orders.

Literature usually assigns more informational value to buyer-initiated orders and trades than seller-initiated. We find that consistently across both investor types, that the informational content of seller-initiated orders increases, whereas the price impact of buyer-initiated orders falls. The switch from pre- to post-trade transparency allows market participants to still infer information from other sources that the order flow. It seems that the regulation impacts seller-initiated orders more, increasing the transaction costs as a result of more information asymmetry.

Table 6: Switch from pre- to post-trade broker ID disclosure - Impact on transaction costs for households and institutional investors

The following table presents the coefficient estimates of the fixed-effect regression concerning the transaction costs based on the underlying order for the first event on 13th March 2006, when NASDAQ OMXH changed the regulations from full pre-trade transparency to post-trade broker information disclosure. To analyse the impact of the regulatory changes specifically for individual and institutional investors, we compute the underlying order of each investor using the Euroclear data set, which provides account information. The event study covers a horizon of 26 trading days before and after. After removing securities not traded at least 90% of the trading days in both event horizons, we remain with 126 securities for our analysis. Trades are consolidated to simulate the underlying order of an investor, e.g. sequences of trades in the same direction of the same investor are combined if the time difference between trades is less than 5 days. Minor trades in the opposite direction than the previous and following trade of the same investor were deleted.

As one measure for transaction costs, we use the relative effective spread computed on the base of the underlying order as the difference of the volume-weighted order price and the first mid-point price of the order t scaled by the first mid-point price times the order direction and 10,000. We run the following model in Panel A: $\left(\frac{VWAP_{i,t,d} - \text{mid-point}_{i,t,d,first}}{\text{mid-point}_{i,t,d,first}}\right)_{i,t} * direction * 10{,}000 = \beta_1 event_d + \sum_{k=1}^{K=5} \theta_k \, weekday_k + \varepsilon_{i,t,d}$, where the relative effective spread of the order t of security i acts as the dependent variable. $event_d$ equals 0 prior to the event, and 1 post the event. We cluster the standard errors by security and control for the security, the weekday of the first trade's execution as well as the investor in Panel A. In Panels B and C, the latter is not applicable. Accordingly, the other models for market quality determinant $y_{i,t,d}$ are designed. The relative realised spread is computed by the difference of the last mid-point price and the volume-weighted order price scaled by the volume-weighted order price. We multiply by order direction and convert the value in bps. We further compute the relative market impact as the difference between the last and first mid-point price scaled by the first mid-point price. The relative Price impact is measured by the difference between the last and first-order price, scaled by the first-order price. Van Kervel and Menkfeld (2016) use this measure as a proxy for institutional implementation shortfall. Both of these measures are multiplied by order direction and 10,000.

Further, we control for the security, the weekday of the first trade's execution as well as the investor in Panels A, D and G. In Panels B and C, E and F, H and I, the latter is not applicable. Panels A, D and G report the regression coefficients when the type of investor is disregarded and only distinguishes between seller- and buyer-initiated orders. We show joint and separated findings for liquid (top 10 traded securities) and illiquid (other than the top 10 traded) securities.[27] Panels B, E and H show the findings for individual investors only, again presenting the overall effect as well as the impact on buyer- and seller-initiated orders. Accordingly, Panels C, F and I present the results for institutional investors. The t-statistics are presented in parentheses. ***, **, * denotes statistical significance at 1%, 5% and 10%.

[27] The top 10 traded securities include Nokia, Fortum, Stora Enso, UPM and Sampo. Those securities are the top 5 traded securities in accordance with their yearly trading volume and exempted by the regulatory changes. These are followed by Telia, Outokumpu Oyj, Nordea Bank, Neste, Metso Oyj.

	Rel. Effective Spread	Rel. Effective Spread	Rel. Effective Spread	Rel. Realised Spread	Rel. Realised Spread	Rel. Realised Spread	Rel. Price impact	Rel. Price impact	Rel. Price impact
Order type	Any	Buy	Sell	Any	Buy	Sell	Any	Buy	Sell
Panel A: Impact on transaction costs									
Event	-3.16	-24.50*	15.68***	-2.87**	-10.19**	0.96	-6.84*	-41.22***	19.29***
	(-0.66)	(-1.74)	(2.89)	(-2.06)	(-2.42)	(0.38)	(-1.79)	(-3.59)	(2.75)
Obs.	183,935	88,800	95,135	183,935	88,800	95,135	183,935	88,800	95,135
Adj. R^2	0.16	0.13	0.19	0.13	0.11	0.15	0.06	0.08	0.09
Panel B: Impact on transaction costs for orders of individual investors only									
Event	-7.74	-26.04	6.51	-2.19	-8.01	-0.90	-10.94***	-40.63***	6.94
	(-1.49)	(-1.52)	(0.98)	(-0.97)	(-1.26)	(-0.27)	(-2.92)	(-3.10)	(0.95)
Obs.	107,360	50,099	57,261	107,360	50,099	57,261	107,360	50,099	57,261
Adj. R^2	0.13	0.11	0.16	0.15	0.13	0.16	0.04	0.08	0.06
Panel C: Impact on transaction costs for orders of institutional investors only									
Event	7.17*	-21.00**	33.39***	-0.49	-8.42***	5.93**	7.76*	-33.05***	45.13***
	(1.83)	(-2.16)	(5.03)	(-0.45)	(-6.25)	(2.57)	(1.71)	(-2.67)	(4.46)
Obs.	76,572	38,695	37,868	76,572	38,695	37,868	76,572	38,695	37,868
Adj. R^2	0.21	0.19	0.25	0.02	0.03	0.04	0.17	0.16	0.19
Panel D: Impact on transaction costs for the top 10 traded securities									
Event	2.19	-5.31	10.84**	-2.36	-12.04**	1.265	-3.48	-27.78*	12.41**
	(0.37)	(-0.30)	(2.74)	(-1.80)	(-3.12)	(0.66)	(-0.74)	(-2.25)	(2.48)
Obs.	96,778	45,284	51,494	96,778	45,284	51,494	96,778	45,284	51,494
Adj. R^2	0.18	0.15	0.23	0.14	0.12	0.18	0.07	0.07	0.09
Panel E: Impact on transaction costs for orders for the top 10 traded securities of individual investors only									
Event	-0.25	0.66	5.08	-0.28	-10.25	2.451	-4.72	-23.37*	6.98
	(-0.04)	(0.03)	(1.23)	(-0.11)	(-1.51)	(0.77)	(-1.45)	(-2.03)	(1.61)
Obs.	43,705	18,412	25,293	43,705	18,412	25,293	43,705	18,412	25,293
Adj. R^2	0.12	0.10	0.20	0.17	0.16	0.23	0.022	0.04	0.04
Panel F: Impact on transaction costs for orders for the top 10 traded securities of institutional investors only									
Event	6.56	-11.11	20.75**	-0.74	-6.93***	2.97	6.59	-20.12	27.29**
	(1.49)	(-1.03)	(3.39)	(-1.08)	(-9.72)	(1.80)	(1.35)	(-1.54)	(3.16)
Obs.	53,073	26,872	26,201	53,073	26,872	26,201	53,073	26,872	26,201
Adj. R^2	0.22	0.19	0.25	0.00	0.01	0.01	0.18	0.17	0.20
Panel G: Impact on transaction costs for other than the top 10 (e.g. Illiquid) securities									
Event	-8.55	-42.89***	23.14**	-2.17	-4.70	1.53	-8.77**	-49.97***	31.11***
	(-1.63)	(-2.99)	(2.16)	(-0.81)	(-0.70)	(0.29)	(-2.09)	(-3.28)	(2.69)
Obs.	87,157	43,516	43,641	87,157	43,516	43,641	87,157	43,516	43,641
Adj. R^2	0.13	0.12	0.16	0.15	0.12	0.17	0.05	0.06	0.08
Panel H: Impact on transaction costs for other than for the top 10 (e.g. Illiquid) traded securities for orders of individual investors only									
Event	-13.15**	-43.65**	12.48	-4.38	-3.35	-4.04	-16.32***	-46.89**	12.03
	(-2.46)	(-2.46)	(0.99)	(-1.11)	(-0.37)	(-0.58)	(-3.23)	(-2.53)	(0.98)
Obs.	63,655	31,687	31,968	63,655	31,687	31,968	63,655	31,687	31,968
Adj. R^2	0.12	0.12	0.14	0.16	0.14	0.19	0.03	0.07	0.06
Panel I: Impact on transaction costs for other than for the top 10 (e.g. Illiquid) traded securities for orders of institutional investors only									
Event	2.01	-40.99***	44.26***	0.24	-9.39***	10.22***	2.14	-59.34***	55.06***
	(0.31)	(-4.33)	(4.56)	(0.10)	(-3.25)	(2.71)	(0.28)	(-4.62)	(4.71)
Obs.	23,499	11,823	11,667	23,499	11,823	11,667	23,499	11,823	11,667
Adj. R^2	0.16	0.14	0.21	0.03	0.03	0.05	0.11	0.11	0.16

2.6.2 Switch from post-trade broker ID disclosure to opacity on 2nd June 2008

The regression coefficients in Tables 7 to 9 present our findings regarding the change from post-trade broker ID disclosure to total opacity in June 2008. Table 7 relates to the impact on market-level.

Table 7: Switch from post-trade broker ID disclosure to opacity - Impact on Market Liquidity

Table 7 presents the regression coefficients for the second event on 2nd June 2008. Until this date, the relevant broker information for any trade sides was disclosed post-trade to the public. NASDAQ OMX Helsinki decided to stop displaying any broker information, leading to total opacity. The sample period before and after includes 63 trading days. We require securities to be traded at least 90% of the trading days prior to and post the event. We remain with 102 securities.

We distinguish between measures of transaction costs, resilience as well as liquidity using TRTH data. The relative effective spread is computed as the difference between the trade price and the prevailing mid-point price, divided by the mid-point price, times two. The relative realised spread is defined as the difference between the trade price and the mid-point price 10 minutes after the trade, divided by the initial mid-point price multiplied by two. Accordingly, the price impact is computed as the difference between effective and realised spread. These measures are expressed in bps. Implementation shortfall costs capture the execution as well as the opportunity costs. The intraday volatility is computed using 5 min intervals, multiplied by 10,000, measuring the intraday mid-point price return volatility, multiplied by 10,000. The on-market trade volume (count) is defined as the sum of the volume traded (trades executed) within continuous trading hours on the central limit order book. Accordingly, the off-market trade volume refers to any trades executed either outside of trading hours or not on the lit order book. We define the variance-ratio following the methodology of Lo and MacKinlay (1988), testing whether the security prices follow a random walk as a measure for informational efficiency. We use a 1 to 5 minute/s return ratio. We run the following fixed-effect regression model to analyse the impact on the market quality determinant $y_{i,t,d}$

$$y_{i,t,d} = \beta_1 event_d + \beta_2 trend_{i,d} + \beta_3 VIX_d + \sum_{k=1}^{K=5} \theta_k weekday_k + \sum_{i=2}^{I=n} \gamma_i D_i + \varepsilon_{i,t,d}$$

where $y_{i,t,d}$ is computed per security i and day d, $event_d$ equals 0 prior to the event and 1 post the event and $trend_d$ refers to time trend as 1, 2, 3, …, 43. We cluster the standard errors by security and included stock- as well as weekday-fixed effects. The t-statistics are presented in parentheses. Panel A presents the findings covering the complete sample. Panels B, C and D distinguish further as stated. ***, **, * denotes statistical significance at 1%, 5% and 10%.

	Rel. Effective Spread	Rel. Realised Spread	Rel. Price impact	Implemen-tation shortfall	Intraday volatility	Log On-market Volume	Log On-market Count	Log Off-market Volume	Log Ask Depth	Log Bid Depth
Panel A: Complete market										
Event	24.24***	21.56***	7.94**	14.25***	71.08***	-0.12***	-0.02***	-2.83***	-0.16***	-0.14***
	(3.76)	(3.33)	(2.46)	(3.87)	(6.86)	(-3.53)	(-3.25)	(-11.51)	(-3.79)	(-3.17)
Obs.	10,793	10,793	10,793	10,793	10,793	10,793	10,793	10,793	10,793	10,793
Adj. R^2	0.69	0.58	0.06	0.73	0.16	0.82	0.85	0.65	0.75	0.77
Panel B: Top 5 traded securities										
Event	1.17	0.73***	0.45	0.64	54.56***	-0.91***	0.02*	-0.83**	-0.02	0.03
	(1.62)	(6.66)	(0.66)	(1.68)	(9.34)	(-4.77)	(2.37)	(-3.16)	(-0.32)	(0.46)
Obs.	630	630	630	630	630	630	630	630	630	630
Adj. R^2	0.85	0.05	0.27	0.86	0.29	0.90	0.820	0.781	0.871	0.868
Panel C: Top 10 traded securities										
Event	0.66	0.84	-0.29	0.35	57.81***	-0.23***	-0.03***	-1.00**	-0.06	-0.02
	(1.42)	(0.840)	(-0.26)	(1.44)	(9.79)	(-9.79)	(-4.35)	(-2.88)	(-1.28)	(-0.44)
Obs.	1,270	1,270	1,270	1,270	1,270	1,270	1,270	1,270	1,270	1,270
Adj. R^2	0.76	0.07	0.20	0.88	0.25	0.76	0.88	0.79	0.91	0.91
Panel D: Illiquid securities										
Event	26.94***	23.84***	6.15	15.83***	72.56***	0.01	0.01	-3.04***	-0.18***	-0.16***
	(3.75)	(3.30)	(1.62)	(3.86)	(6.22)	(0.20)	(0.79)	(-11.49)	(-3.75)	(-3.23)
Obs.	9,610	9,610	9,610	9,61	9,610	9,610	9,610	9,610	9,610	9,610
Adj. R^2	0.61	0.50	0.04	0.66	0.15	0.74	0.78	0.59	0.57	0.61

We observe a consistent and highly significant increase in transaction costs. The daily relative effective spread widens by about 24.2bps at a 1% significance level; the relative realised spread jumps about 21.6bps. Both results are driven by less liquid securities, while the top 10 traded securities are not or minimally impacted.

Further, the implementation shortfall costs jump by nearly 14.2bps. We observe an increase in price impact by over 7.9bps at a 5% significance level. In contrast, our liquidity measures show a small but significant drop. The daily on-market volume falls about 0.12% at a 1% significance level, on-market trade count decreases for the top 10 traded securities by 0.02%. Off-market volume drops on a market level by 2.83%, driven by less liquid securities. Our results show a decrease of 0.16% for the depth at the best ask and 0.13% for the market depth at the best bid, respectively. Overall, intraday volatility is increasing significantly across all securities, the most for less liquid securities. Tables 8 and 9 provide a detailed insight into how the switch to complete broker ID anonymity impacts the trading behaviour on an order-level. In line with the findings presented in Table 7, we cannot observe a significant impact regarding the logarithmic order volume overall. However, we find that buyer-initiated orders, especially submitted by individual investors, are negatively impacted by the switch to opacity. Overall, the results show that order volume falls about 0.09% for buyer-initiated orders at a 1% significance level, driven by orders of individual investors involving the top 10 traded securities. Seller-initiated orders, on the other hand, increase by 0.11% for individual investors. We find the trend for the number of trades within orders: Panel G shows that the number of trades for the top 10 traded securities for buyer-initiated orders drops by 0.05% at a 1% significance level, driven by the impact of institutional investors. The number of trades within seller-initiated orders increases by 0.1% for individual investors and 0.05% for institutional investors, respectively, at a 5% significance level. The number of daily order submissions is not significantly impacted overall. Only the number of buyer-initiated orders for the top 10 traded stocks for individual investors drops by 356% at a 10% significance level, whereas the number of seller-initiated order submissions of the top 10 trades of institutional investors increases by 198% at a 10% significance level.

As presented in Table 9, we observe an increase in transaction costs in the form of relative effective spread by 1.6bps at a 5% significance level, which is driven by the jump in transaction costs for seller-initiated orders the impact on orders submitted by institutional traders. In fact, Panel B shows that the relative realised spread for orders submitted by individual investors droops by 1.6bps at a 1% significance level overall, however, driven by buyer-initiated orders. For those, the price impact drops by 6.4bps. Therefore, analysing the impact across all securities shows that transaction costs for seller-initiated orders by institutional trader's increase, whereas transaction costs and informativeness of buyer-initiated orders submitted by individual investors drop. When splitting the sample into the top 10 and less liquid securities, Panels D and G show that only fewer liquid securities are actually affected. Orders relating to less liquid securities experience an increase in transaction costs by 3.5bps at a 1% significance level. Panel I indicates that institutional investors experience a jump in transaction costs for orders of any direction; Panel H shows that individual investors experience a significant increase in transaction costs for seller-initiated orders only. The relative realised spread as well as price impact for buyer-initiated orders drop. Similarly, Panel E indicates that individual investors experience an overall drop of 2.9bps in relative effective spread, 1.8bps in relative realised spread and 4.9bps, respectively. In contrast, Panel F shows that institutional investors' transaction costs for sell orders increase 2.3bps in effective spread and 3.3bps in price informativeness. Therefore, the switch to broker ID opacity leads to a drop in transaction costs for individual investors trading liquid securities and the opposite for less liquid securities. Institutional investors experience an increase in transaction costs overall, especially for seller-initiated orders and less liquid securities.

Table 8: Switch from post-trade broker ID disclosure to opacity - Impact on Liquidity measures individual and institutional investors

Following Table 8 presents the coefficient estimates of the fixed-effect regression concerning the market liquidity measures on the basis of the underlying order for the second event on 2nd June 2008.

Until this date, the relevant broker information for any side of a trade were disclosed post-trade to the public. NASDAQ OMX Helsinki decided to stop displaying any broker information, leading to total opacity. The sample period before and after includes 63 trading days. Securities are required to be traded at least 90% of the trading days prior to and post the event. We remain with 102 securities. To analyse the impact of the event specifically for institutional and individual investors, we compute the underlying order of each investor using the Euroclear data set, which provides account information. Trades are consolidated to simulate the underlying order of an investor, e.g., sequences of trades in the same direction of the same investor are combined if the time difference between trades is less than five days. Minor trades in the opposite direction than the previous and following trade of the same investor were deleted. We are able to analyse the impact not only on overall market quality but specifically on issued orders. We run basic fixed-effect regression with various determinants as the number of trades within an order, the order volume as well as the order value as the dependent variable. We analyse the order execution time and the number of daily submitted orders per security. We run fixed-effect models as the following one for Panel A:

$$Log(Volume_{i,t,d}) = \beta_1 Event_d + \sum_{k=1}^{K=5} \theta_k \, weekday_k + \sum_{i=2}^{I=n} \eta_{i,t,d} \, investor_{i,t,d} + \varepsilon_{i,t,d}$$

where $y_{i,t,d}$, as for instance, the logarithmised order volume, is computed per order t and security i on day d and acts as the dependent variable. $event_d$ equals 0 prior to the event and 1 post the event. It measures the difference in the impact of the new regulations between the control and treatment group. The standard errors are clustered by security. Further, we control for the security, the weekday of the first trade's execution, as well as the investor in Panels A, D and G. In Panels B and C, E and F, H and I, the latter is not applicable. Panels A, D and G present the regression coefficients when the type of investor is disregarded and only distinguishes between seller- and buyer-initiated orders. We show joint and separated findings for liquid (top 10 traded securities) and illiquid (other than the top 10 traded) securities.[28] Panels B, E and H show the findings for individual investors only, again presenting the overall effect as well as the impact on buyer- and seller-initiated orders. Accordingly, Panels C, F and I present the results for institutional investors. The t-statistics are presented in parentheses. ***, **, * denotes statistical significance at 1%, 5% and 10%.

[28] The top 10 traded securities include Nokia, Fortum, Stora Enso, UPM and Sampo. Those securities are the top 5 traded securities in accordance with their yearly trading volume and exempted by the regulatory changes. These are followed by Telia, Outokumpu Oyj, Nordea Bank, Neste, Metso Oyj.

	Log Order volume	Log Order volume	Log Order volume	Log No of trades per order	Log No of trades per order	Log No of trades per order	Log Daily No of issued orders	Log Daily No of issued orders	Log Daily No of issued orders
Order type	Any	Buy	Sell	Any	Buy	Sell	Any	Buy	Sell
Panel A: Impact on Liquidity measures									
Event	-0.04	-0.10***	0.04	0.01	-0.05**	0.07***	380.54	187.36	195.628
	(-1.29)	(-3.18)	(1.10)	(0.40)	(-2.45)	(3.51)	(1.29)	(1.12)	(1.453)
Obs.	1,352,132	710,519	641,613	1,352,132	710,519	641,613	1,352,132	710,519	641,613
Adj. R^2	0.30	0.31	0.28	0.09	0.11	0.07	0.76	0.72	0.79
Panel B: Impact on Liquidity measures for orders of individual investors only									
Event	-0.05	-0.17***	0.12**	0.01	-0.07**	0.11**	169.61	38.22	123.37
	(-1.42)	(-3.06)	(2.35)	(0.24)	(-2.30)	(2.39)	(0.65)	(0.24)	(1.08)
Obs.	323,822	187,605	136,217	323,822	187,605	136,217	323,822	187,605	136,217
Adj. R^2	0.15	0.15	0.17	0.10	0.10	0.11	0.76	0.70	0.80
Panel C: Impact on Liquidity measures for orders of institutional investors only									
Event	-0.03	-0.07*	0.01	0.01	-0.04*	0.05**	452.11	243.95	217.13
	(-0.94)	(-1.83)	(0.26)	(0.33)	(-1.68)	(2.38)	(1.49)	(1.44)	(1.56)
Obs.	1,028,310	522,914	505,396	1,028,310	522,914	505,396	1,028,310	522,914	505,396
Adj. R^2	0.28	0.27	0.28	0.02	0.02	0.02	0.77	0.73	0.79
Panel D: Impact on Liquidity measures for the Top 10 traded securities only									
Event	-0.05	-0.12*	0.03	0.01	-0.05	0.08**	695.90	123.40	162.23
	(-1.46)	(-2.44)	(0.91)	(0.55)	(-1.38)	(2.62)	(1.70)	(1.21)	(1.97)
Obs.	809,371	421,638	387,733	809,371	421,638	387,733	809,371	421,638	387,733
Adj. R^2	0.24	0.26	0.22	0.05	0.06	0.03	0.70	0.37	0.40
Panel E: Impact on Liquidity measures for the Top 10 traded securities and orders of individual investors only									
Event	-0.07	-0.23*	0.17*	-0.01	-0.10	0.14	529.55	-356.02*	-13.47
	(-1.89)	(-2.33)	(2.28)	(-0.04)	(-1.54)	(1.37)	(1.12)	(-2.28)	(-0.19)
Obs.	152,535	87,099	65,436	152,535	87,099	65,436	152,535	87,099	65,436
Adj. R^2	0.10	0.10	0.16	0.04	0.04	0.05	0.67	0.35	0.36
Panel F: Impact on Liquidity measures for the Top 10 traded securities and for orders of institutional investors only									
Event	-0.04	-0.09	0.01	0.02	-0.03	0.07*	735.05	239.72	198.65*
	(-0.988)	(-1.53)	(0.04)	(0.59)	(-0.94)	(2.29)	(1.86)	(1.93)	(2.14)
Obs.	656,836	334,539	322,297	656,836	334,539	322,297	656,836	334,539	322,297
Adj. R^2	0.22	0.22	0.22	0.02	0.02	0.02	0.71	0.38	0.41
Panel G: Impact on Liquidity measures other than the Top 10 traded securities only									
Event	-0.01	-0.07	0.06	-0.01	-0.05***	0.04*	-73.98	-55.94	-15.25
	(-0.15)	(-1.37)	(1.08)	(-0.73)	(-3.56)	(1.89)	(-1.05)	(-1.09)	(-0.73)
Obs.	542,761	288,881	253,880	542,761	288,881	253,880	542,761	288,881	253,880
Adj. R^2	0.12	0.140	0.09	0.10	0.12	0.07	0.32	0.29	0.44
Panel H: Impact on Liquidity measures for other than the Top 10 traded securities and orders of individual investors only									
Event	-0.05	-0.13	0.07	0.01	-0.05	0.09*	-132.06	-98.85	-29.56
	(-0.65)	(-1.58)	(0.88)	(0.29)	(-1.33)	(1.79)	(-1.04)	(-0.99)	(-1.10)
Obs.	171,287	100,506	70,781	171,287	100,506	70,781	171,287	100,506	70,781
Adj. R^2	0.12	0.14	0.10	0.07	0.09	0.07	0.36	0.36	0.51
Panel I: Impact on Liquidity measures for other than the Top 10 traded securities and for orders of institutional investors only									
Event	0.01	-0.03	0.05	-0.02	-0.05***	0.01	-37.87	-24.73	-8.54
	(0.22)	(-0.54)	(0.87)	(-1.22)	(-3.13)	(0.68)	(-0.81)	(-0.95)	(-0.45)
Obs.	371,474	188,375	183,099	371,474	188,375	183,099	371,474	188,375	183,099
Adj. R^2	0.07	0.067	0.07	0.01	0.01	0.01	0.30	0.26	0.39

Table 9: Switch from post-trade broker ID disclosure to opacity - Impact on transaction costs for individual and institutional investors

The following table presents the fixed-effect regression coefficient estimates concerning the transaction costs based on the underlying order for the second event on 2nd June 2008. Until this date, the relevant broker information for any trade sides was disclosed post-trade to the public. NASDAQ OMX Helsinki decided to stop displaying any broker information, leading to total opacity. Around the event, five trading days were excluded. The sample period before and after includes 125 trading days from 20th November 2007 and lasts till 2nd December 2008. We require securities to be traded at least 90% of the trading days prior to and post the event. We remain with 102 securities. To analyse the impact of the event specifically for institutional and individual investors, we compute the underlying order of each investor using the Euroclear data set, which provides account information. Trades are consolidated to simulate the underlying order of an investor, e.g., sequences of trades in the same direction of the same investor are combined if the time difference between trades is less than five days. Minor trades in the opposite direction than the previous and following trade of the same investor were deleted. The relative effective spread of an order is computed on the base of the underlying order as the difference of the volume-weighted order price and the first mid-point price of the order scaled by the first mid-point price, times the order direction and 10,000. We run the following model in Panel A:

$$\left(\frac{VWAP_{i,t,d} - midquote_{i,t,d,first}}{midquote_{i,t,d,first}}\right)_{it} * direction * 10{,}000 = \beta_1 event_d + \sum_{k=1}^{K=5} \theta_k\, weekday_k + \sum_{i=2}^{I=n} \eta_{i,t,d}\, investor_{i,t,d} + \varepsilon_{i,t,d}$$

where the relative effective spread of the order t of security i acts as the dependent variable. $event_d$ equals 0 before the event and 1 post the event, and $trend_d$ refers to a trend as $1,2,3...D$ to adjust for trend related changes in the dependent variable. We cluster the standard errors by security and control for the security, the weekday of the first trade's execution, and the investor in Panel A. In Panels B and C, the latter is not applicable. Accordingly, the other models are designed, where the other market quality determinants act as the dependent variable $y_{i,t,d}$. The relative realised spread is computed by the difference of the last mid-point price and the volume-weighted order price scaled by the volume-weighted order price. Again, we multiply by order direction and convert the value in bps. We further compute the relative market impact as the difference between the last and first mid-point price scaled by the first mid-point price. The relative price impact is measured by the difference between the last and first order price, scaled by the first order price. Van Kervel and Menkfeld (2016) use this measure as a proxy for institutional implementation shortfall. Both of these measures are multiplied by order direction and 10,000.

Panel A, D and G present the regression coefficients when the type of investor is disregarded and only distinguishes between seller- and buyer-initiated orders. We show joint and separated findings for liquid (top 10 traded securities) and illiquid (other than the top 10 traded) securities. Panels B, E and H show the findings for individual investors only, again presenting the overall effect and the impact on buyer- and seller-initiated orders. Accordingly, Panel C, F and I present the results for institutional investors. The t-statistics are presented in parentheses. ***, **, * denotes statistical significance at 1%, 5% and 10%.

	Rel. Effective Spread	Rel. Effective Spread	Rel. Effective Spread	Rel. Realised Spread	Rel. Realised Spread	Rel. Realised Spread	Rel. Price impact	Rel. Price impact	Rel. Price impact
Order type	Any	Buy	Sell	Any	Buy	Sell	Any	Buy	Sell
Panel A: Impact on transaction costs									
Event	1.65**	-0.15	5.29**	0.08	-0.73**	1.73**	1.08	-1.27	6.90**
	(2.61)	(-0.238)	(2.62)	(0.53)	(-2.57)	(2.11)	(1.48)	(-1.53)	(2.29)
Obs.	1,352,132	710,519	641,613	1,352,132	710,519	641,613	1,352,132	710,519	641,613
Adj. R^2	0.18	0.184	0.23	0.03	0.05	0.09	0.08	0.03	0.16
Panel B: Impact on transaction costs for orders of individual investors only									
Event	0.92	-2.73	10.67	-1.60***	-3.03***	2.62	-2.41	-6.42**	12.57
	(0.61)	(-1.54)	(1.64)	(-3.38)	(-2.93)	(0.88)	(-1.43)	(-2.57)	(1.25)
Obs.	323,822	187,605	136,217	323,822	187,605	136,217	323,822	187,605	136,217
Adj. R^2	0.05	0.13	0.05	0.08	0.14	0.08	0.02	0.04	0.05
Panel C: Impact on transaction costs for orders of institutional investors only									
Event	1.87***	0.77**	3.67***	0.60***	0.07	1.42***	2.11***	0.51	5.12***
	(4.13)	(2.30)	(4.42)	(4.56)	(0.52)	(5.64)	(3.73)	(1.22)	(4.40)
Obs.	1,028,310	522,914	505,396	1,028,310	522,914	505,396	1,028,310	522,914	505,396
Adj. R^2	0.13	0.13	0.13	0.01	0.01	0.01	0.06	0.05	0.07
Panel D: Impact on transaction costs for the top 10 traded securities									
Event	0.38	-0.99	3.48	0.05	-0.69	1.61	0.09	-1.86	5.33
	(0.81)	(-0.91)	(1.25)	(0.31)	(-1.56)	(1.26)	(0.15)	(-1.30)	(1.20)
Obs.	809,371	421,638	387,733	809,371	421,638	387,733	809,371	421,638	387,733
Adj. R^2	0.13	0.08	0.21	0.05	0.01	0.14	0.12	0.05	0.21
Panel E: Impact on transaction costs for orders for the top 10 traded securities of individual investors only									
Event	-2.99**	-6.59	8.19	-1.77**	-3.62	3.78	-4.93**	-9.69	13.87
	(-2.66)	(-1.51)	(0.62)	(-3.76)	(-1.53)	(0.59)	(-2.89)	(-1.61)	(0.64)
Obs.	152,535	87,099	65,436	152,535	87,099	65,436	152,535	87,099	65,436
Adj. R^2	0.01	0.01	0.04	0.01	0.01	0.04	0.01	0.01	0.04
Panel F: Impact on transaction costs for orders for the top 10 traded securities of institutional investors only									
Event	1.13*	0.36	2.37**	0.48**	0.04	1.10***	1.22	0.07	3.34**
	(2.25)	(0.75)	(2.87)	(3.15)	(0.20)	(4.39)	(1.97)	(0.11)	(2.93)
Obs.	656,836	334,539	322,297	656,836	334,539	322,297	656,836	334,539	322,297
Adj. R^2	0.02	0.03	0.02	0.01	0.01	0.01	0.01	0.02	0.01
Panel G: Impact on transaction costs for other than the top 10 (e.g. 'Illiquid') securities									
Event	3.49***	1.05	7.99***	0.13	-0.80***	1.93**	2.49***	-0.48	9.26***
	(5.84)	(1.26)	(5.68)	(0.400)	(-2.83)	(2.02)	(2.86)	(-0.52)	(3.29)
Obs.	542,761	288,881	253,880	542,76	288,881	253,880	542,761	288,881	253,880
Adj. R^2	0.19	0.22	0.21	0.03	0.08	0.06	0.04	0.02	0.11
Panel H: Impact on transaction costs for other than the top 10 (e.g. 'Illiquid') securities for orders of individual investors only									
Event	4.17***	0.42	12.71***	-1.46*	-2.55***	1.59	-0.34	-3.76*	11.34
	(2.79)	(0.23)	(2.82)	(-1.88)	(-3.42)	(0.54)	(-0.15)	(-1.75)	(1.31)
Obs.	171,287	100,506	70,781	171,287	100,506	70,781	171,287	100,506	70,781
Adj. R^2	0.09	0.19	0.06	0.10	0.16	0.09	0.03	0.07	0.06
Panel I: Impact on transaction costs for other than the top 10 (e.g. 'Illiquid') securities for orders of institutional investors only									
Event	3.17***	1.49***	5.91***	0.82***	0.14	1.97***	3.68***	1.31**	8.18***
	(8.19)	(3.75)	(9.88)	(4.24)	(0.65)	(5.75)	(9.24)	(2.47)	(10.29)
Obs.	371,474	188,375	183,099	371,474	188,375	183,099	371,474	188,375	183,099
Adj. R^2	0.17	0.17	0.16	0.01	0.01	0.02	0.06	0.05	0.074

2.6.3 Partial switch from opacity to post-trade broker ID disclosure on 14th April 2009

The final event allows us to perform a DiD analysis, as the top traded stocks are not impacted by the reversed regulations originally introduced in 2008. These top stocks, Nokia, Fortum, Stora Enso, UPM, and Sampo, act as a control group. Hence, we can observe how the reintroduction of the disclosure of broker information post-trade affects the securities in contrast to securities for which broker information are not revealed.

Our focus lies on the DiD dummy variable, which is the product of binary dummy variables for the event horizon and the security group.

We investigate the impact on daily market liquidity measures as presented in Table 10. We find overall highly significant coefficients for the DiD variable. The relative effective spread tightens about 36.8bps at a 1% significance level more for the treatment group than the control group when post-trade broker ID disclosure was reintroduced. In comparison, the DiD coefficient for the implementation shortfall costs decreases by 30bps more over the event for the treatment group.

The relative realised spread declines by 36.2bps for treated securities in contrast to the control group. Moreover, the relative price impact falls about 8.7bps.

While intraday volatility and market depth are not changing, on-market volume, trade count, and off-market volume equally increase by about 0.02% at a 1% significance level. Panels B and C show that those results are solely driven by the impact of the regulatory changes on illiquid securities. At a market level, we observe highly significant drops in transaction cost and a small but significant increase in liquidity for illiquid securities versus the control group. In comparison, the relative effective spread drops by 39.4bps at a 1% significance level, the relative realised spread by 34.1bps. On-market volume and trade count increase by 0.02 and 0.05%, respectively.

Tables 11 and 12 break those results up and give insight into the impact on individual and institutional investor’s trading behaviour and how their trading costs are affected.

Panel A in Table 11 shows that the order volume and well as trade count declines for buyer-initiated orders by 0.07% and 0.03%, respectively but increases for seller-initiated orders by about 0.1% and 0.03%, respectively. The order volume of liquid securities is not changing; however trade count of buyer-initiated orders decreases by 0.7% and increases by 0.04% for seller-initiated orders. The order volume of illiquid securities increases for seller-initiated orders by 0.15% at a 1% significance level. In accordance, the number of trades within an order is increasing by 0.4%. When breaking the analysis up by investor type, we observe quite contrary results. Panel B shows that individual investors reduce buyer-initiated orders, especially for more liquid securities by 0.3% at a 5% significance level and increase the order volume for seller-initiated orders containing illiquid securities 0.14% at a 10% level. The number of trades per order increases overall by 0.1% for seller-initiated orders, whereas order volume for buyer-initiated orders drops across all securities at a 1% significance level. Institutional investors increase their order size, especially for illiquid securities. As presented in Panel C, order volume is increased by 0.14% at a 5% significance level and the number of trades by 0.03% at a 1% significance level for illiquid securities in comparison to the control group. In contrast, the volume of seller-initiated orders of liquid securities is reduced by 0.02% and the number of trades within buyer-initiated orders reduced by 0.07%. Consistently, the regulatory changes lead to an overall increase in the number of daily order submissions, regardless of investor type and order direction. Individual investors submit 551% more buyer-initiated and 240% more seller-initiated orders at a 1% significance level. Panel C shows that institutional investors increase their order submission overall by 480% at a 1% significance level. While the results for individual investors seem to be driven by mainly liquid securities as presented in Panel B, for institutional investors, the DiD coefficients for illiquid securities are highly significant. The order execution time decreases for buyer-initiated orders of individual investors only.

Turning to the impact on the transaction costs at the order level as presented in Table 12, the results show that only buyer-initiated orders are affected. For individual investors (Panel B), the respective relative effective spread drops by 43.3bps at a 5% significance level compared to the control group for orders involving liquid securities and 17.9bps at a 5% significance level for illiquid securities, respectively. Relative to that, we find a drop in the relative realised spread for buyer-initiated orders for liquid securities within the treatment group of 18.0bps and a respective decline in price impact of 72.7bps, both at a 5% significance level. Overall, the decline in transaction costs for illiquid securities in comparison to the control group is smaller than for liquid securities. The transaction costs for institutional investors are overall not significantly affected. Solely the price impact for seller-initiated orders drops by 3.4bps at a 5% significance level.

Table 10: Switch from opacity to post-trade broker ID disclosure - Impact on Market Liquidity

The following table presents the regression coefficient estimates for the third analysed event on 14th April 2009. For all securities but the top5 traded stocks, NASDAQ OMX Helsinki reversed the regulations introduced on 2nd June 2008. Hence, the market remained opaque for the top traded securities, while post-trade broker ID disclosure was reintroduced for the remaining securities.

Our analysis excludes 5 trading days prior to and post the event date and covers a horizon of 125 trading days before and after the event, hence from 2nd October 2008 till 16th October 2009. Our data set includes 102 securities traded on at least 90% of the trading days before and after the event. The control group consists of the following securities: Nokia, Fortum, Stora Enso, UPM and Sampo. We distinguish between measures of resilience, transaction costs, and liquidity derived by using TRTH data. The relative effective spread is computed as the difference between the trade price and the prevailing mid-point price, divided by the mid-point price, times two. The relative realised spread is defined as the difference between the trade price and the mid-point price 10 minutes after the trade, divided by the initial mid-point price, multiplied by two. Accordingly, price impact is computed as the difference between effective and realised spread. These measures are expressed in bps. Implementation shortfall costs capture the execution as well as the opportunity costs. The intraday volatility is computed using 5 min intervals, multiplied by 10,000, measuring the intraday mid-point price return volatility. The (on-market) trade volume is defined as the sum of the volume traded within continuous trading hours on the central limit order book. Accordingly, the on-market trade count is computed. We define the variance-ratio following the methodology of Lo and MacKinlay (1988), testing whether the security prices follow a random walk as a measure for informational efficiency. We use a 1 to 5 minute/s return ratio. We run the following fixed-effect regression model for the analysis of the impact of the event on any market quality determinant:

$$y_{i,t,d} = \beta_1 event_d + \beta_2 treatment_i + \beta_3 DID_{i,d} + \beta_4 VIX_d + \sum_{k=1}^{K=5} \theta_k weekday_k + \sum_{i=2}^{I=n} \gamma_i D_i + \varepsilon_{i,t,d}$$

where $y_{i,t,d}$ is computed per security i and day d, $event_d$ equals 0 prior to the event and 1 post the event and $trend_d$ refers to time trend as 1, 2, 3, …, 43. We cluster the standard errors by security and included stock- as well as weekday-fixed effects. The t-statistics are presented in parentheses. ***, **, * denotes statistical significance at 1%, 5% and 10%.

	Rel. Effective Spread	Rel. Realised Spread	Rel. Price impact	Imple-mentation shortfall	Intraday volatility	Log On-market Volume	Log On-market Count	Log Off-market Volume	Ask Depth	Bid Depth
Panel A: Complete market										
DiD	-36.83***	-36.422***	-8.71*	-20.46***	5.66	0.02***	0.05***	0.02***	0.01	0.07
	(-4.34)	(-4.39)	(-1.86)	(-4.20)	(0.51)	(3.94)	(4.79)	(3.94)	(0.20)	(1.66)
Obs.	10,747	10,747	10,747	10,747	10,747	10,747	10,747	10,747	10,747	10,747
Adj. R^2	0.03	0.03	0.01	0.04	0.01	0.15	0.12	0.03	0.18	0.18
Panel B: Top 5 traded securities vs other than the top 10 traded (e.g., 'Illiquid') securities										
DiD	-39.38***	-34.05***	-7.57*	-21.86***	7.73	0.02***	0.06***	0.28	0.01	0.08
	(-4.35)	(-3.49)	(-1.67)	(-4.21)	(0.67)	(4.10)	(4.89)	(0.75)	(0.16)	(1.63)
Obs.	10,117	10,117	10,117	10,117	10,117	10,117	10,117	10,117	10,117	10,117
Adj. R^2	0.05	0.03	0.01	0.05	0.01	0.19	0.15	0.03	0.24	0.24
Panel C: Top 5 traded securities vs top 6-10 traded securities										
DiD	-0.89	0.72	-0.65	-0.71	-25.89	-0.01	-0.01	-0.57	0.06	0.09
	(-0.90)	(1.07)	(-1.23)	(-1.30)	(-1.66)	(-1.29)	(-0.16)	(-1.29)	(0.66)	(0.82)
Obs.	1,260	1,260	1,260	1,260	1,260	1,260	1,260	1,260	1,260	1,260
Adj. R^2	0.10	0.013	0.03	0.12	0.14	0.41	0.31	0.02	0.01	0.02

Table 11: Switch from opacity to post-trade broker ID disclosure - Impact on Liquidity measures for individual and institutional investors and liquid and illiquid securities

The following table presents the regression coefficient estimates for the third analysed event on 14th April 2009. For all securities but the Top5 traded stocks, NASDAQ OMX Helsinki reversed the regulations introduced on 2nd June 2008. Hence, the market remained opaque for the top traded securities, while post-trade broker ID disclosure was reintroduced for the remaining securities.

Our analysis excludes 5 trading days prior to and post the event date and covers a horizon of 125 trading days before and after the event, hence from 2nd October 2008 till 16th October 2009. Our data set includes 102 securities that are traded on at least 90% of the trading days before and after the event. The control group includes the following securities: Nokia, Fortum, Stora Enso, UPM, and Sampo. However, our data set did not provide sufficient trades for Sampo; hence the security is not included. Trades are consolidated to simulate the underlying order of an investor, e.g., sequences following securities of trades in the same direction of the same investor are combined if the time difference between trades is less than 5 days. Minor trades in the opposite direction than the previous and following trade of the same investor were deleted. We are able to analyse the impact not only on overall market liquidity but specifically on issued orders. We run a fixed-effect regression with various determinants as the number of trades within an order, the order volume as well as the order value as the dependent variable. Further, we analyse the order implementation time and the number of daily issued orders per security. We run fixed-effect regression models as the following one:

$$y_{i,t,d} = \beta_1 event_d + \beta_2 treatment_{i,t} + \beta_3 DID_{i,t,d} + \sum_{k=1}^{K=5} \theta_k\, weekday_k + \sum_{i=2}^{I=n} \eta_{i,t,d}\, investor_{i,t,d} + \varepsilon_{i,t,d}$$

where $y_{i,t,d}$ is computed per order t and security i on day d, $event_d$ equals 0 prior to the event and 1 post the event and $treatment_{i,t}$ refers to a dummy variable, equal to 0 for the top5 traded securities acting as a control group, and 1 for the remaining securities, which were affected by the policy change. $DID_{i,t,d}$ is the product of $event_d$ and $treatment_{i,t}$. It measures the difference in the impact of the new regulations between the control and treatment group. We included investor-fixed effects for models run in Panel A, not in Panel B and C. Further, we control for the weekday of order submission and cluster standard errors by security.

In addition to the difference-in-difference analysis between the control and treatment group, we distinguish within the treatment group by liquid vs illiquid securities to gain insight which securities are driving the results. We determine the 5 most liquid securities within the treatment group in the same way the top 5 traded securities were determined, by the highest total trading volume in the previous year. We refer to those as the Liquid group. All remaining securities are considered illiquid.

Panel A presents the regression coefficients when disregarding the type of investor and only distinguishing between seller- and buyer-initiated orders. Panel B shows the findings for individual investors merely, again presenting the overall effect as well as the impact on buyer- and seller-initiated orders. Accordingly, Panel C shows the results for institutional investors. Within those Panels we present the findings not only for securities affected versus unaffected securities (e.g. top 5 traded securities). We further perform the same analysis for the control group versus 'liquid' and versus 'illiquid' securities within the treatment group. The 'liquid treatment' group includes the top 6-10 traded securities in accordance with their yearly trading volume. Those are Telia, Outokumpu Oyj, Nordea Bank, Neste, and Metso Oyj. Accordingly, the remaining securities construct the 'illiquid treatment group'. The t-statistics are presented in parentheses. Across all Panels, we present the difference-in-difference coefficients (DiD) only for brevity. ***, **, * denotes statistical significance at 1%, 5% and 10%.

	Liquid group	Log Order volume	Log Order volume	Log Order volume	Log No of trades per order	Log No of trades per order	Log No of trades per order	Log Daily No of issued orders	Log Daily No of issued orders	Log Daily No of issued orders	Order execution time (hrs)	Order execution time (hrs)	Order execution time (hrs)
Order type		Both	Buy	Sell	Both	Buy	Sell	Both	Buy	Sell	Both	Buy	Sell
Panel A: Impact on Liquidity measures													
DiD	N/A	0.02	-0.07**	0.11***	-0.01	-0.03**	0.04***	573.30**	407.79***	176.55**	-4.59***	-7.06***	-3.09
		(0.51)	(-2.39)	(2.99)	(-0.49)	(-2.45)	(2.78)	(2.59)	(2.90)	(2.42)	(-3.03)	(-3.36)	(-0.85)
Obs.		1,121,284	710,908	488,523	1,121,284	632,761	488,523	1,121,284	632,76	488,523	1,121,284	632,761	488,523
Adj. R^2		0.23	0.21	0.21	0.12	0.14	0.09	0.21	0.20	0.21	0.06	0.04	0.06
DiD	Yes	-0.07	-0.15	0.05	-0.02**	-0.07***	0.04*	557.88*	383.07*	171.89*	-4.11***	-5.54***	-0.79
		(-0.89)	(-1.83)	(0.53)	(-2.77)	(-5.59)	(2.12)	(2.29)	(2.39)	(2.13)	(-7.057)	(-8.38)	(-0.24)
Obs.		712,557	399,609	312,948	712,557	399,609	312,948	712,557	399,609	312,948	712,557	399,609	312,948
Adj. R^2		0.19	0.23	0.13	0.08	0.10	0.04	0.08	0.08	0.08	0.11	0.09	0.15
DiD	No	0.06**	0.01	0.14***	0.01	-0.01	0.04**	596.89***	431.68***	183.98**	-3.27**	-5.29***	-1.49
		(2.43)	(0.52)	(3.82)	(0.66)	(-1.23)	(2.27)	(2.75)	(3.17)	(2.55)	(-2.16)	(-2.96)	(-0.46)
Obs.		957,572	534,823	422,749	422,749	957,572	534,823	422,749	957,572	534,823	422,749	957,572	534,823
Adj. R^2		0.23	0.24	0.22	0.14	0.15	0.10	0.20	0.21	0.20	0.05	0.04	0.05
Panel B: Impact on Market liquidity measures for orders of individual investors only													
DiD	N/A	-0.13*	-0.22**	0.09	-0.02	-0.06***	0.11**	760.99**	551.57***	240.34**	-8.02***	-12.01***	-2.60
		(-1.95)	(-2.50)	(1.36)	(-0.90)	(-4.88)	(2.34)	(2.41)	(2.75)	(2.43)	(-3.04)	(-4.06)	(-0.22)
Obs.		454,758	292,108	162,650	454,758	292,108	162,650	454,758	292,108	162,650	454,758	292,108	162,650
Adj. R^2		0.08	0.06	0.14	0.05	0.04	0.09	0.22	0.22	0.23	0.01	0.02	0.01
DiD	Yes	-0.22**	-0.32**	0.02	-0.02	-0.07***	0.09	749.19*	543.89*	227.25*	-10.87	-8.80***	1.23
		(-3.08)	(-3.60)	(0.20)	(-1.04)	(-5.82)	(1.79)	(2.17)	(2.41)	(2.09)	(-1.98)	(-13.01)	(0.09)
Obs.		267,420	172,643	94,777	267,420	172,643	94,777	267,420	172,643	94,777	267,420	172,643	94,777
Adj. R^2		0.06	0.05	0.08	0.02	0.01	0.03	0.10	0.10	0.10	0.04	0.04	0.03
DiD	No	-0.09	-0.17*	0.13*	-0.01	-0.05***	0.13**	-503.657	-153.58	-311.405*	-5.373**	-9.389***	3.143
		(-1.29)	(-1.89)	(1.95)	(-0.0)	(-4.23)	(2.50)	(-1.54)	(-0.82)	(-1.89)	(-2.13)	(-3.85)	(0.30)
Obs.		373,844	236,605	137,239	373,844	236,605	137,239	167,209	98,203	69,006	373,844	236,605	137,239
Adj. R^2		0.08	0.06	0.15	0.07	0.05	0.12	0.36	0.40	0.32	0.01	0.02	0.01
Panel C: Impact on Market liquidity measures for orders of institutional investors only													
DiD	N/A	0.10*	0.07	0.13**	0.02*	-0.01	0.04***	480.05***	316.69***	160.45**	-0.31	-0.32	-0.53
		(1.81)	(1.35)	(2.12)	(1.99)	(-0.08)	(5.53)	(2.67)	(2.91)	(2.41)	(-1.16)	(-0.91)	(-1.39)
Obs.		666,526	340,653	325,873	666,526	340,653	325,873	666,526	340,653	325,873	666,526	340,653	325,873
Adj. R^2		0.18	0.18	0.19	0.02	0.01	0.02	0.19	0.19	0.19	0.01	0.01	0.01
DiD	Yes	0.01	-0.06	-0.02**	0.08	-0.07***	0.09	466.01*	278.88*	159.97*	0.01	-0.03	0.13
		(0.08)	(-0.46)	(-2.77)	(0.73)	(-5.82)	(1.79)	(2.34)	(2.19)	(2.19)	(0.03)	(-0.21)	(0.30)
Obs.		445,137	226,966	712,557	445,137	226,966	218,171	445,137	226,966	218,171	445,137	226,966	218,171
Adj. R^2		0.08	0.08	0.08	0.02	0.01	0.03	0.07	0.07	0.07	0.01	0.01	0.01

	Liquid group	Log Order volume	Log Order volume	Log Order volume	Log No of trades per order	Log No of trades per order	Log No of trades per order	Log Daily No of issued orders	Log Daily No of issued orders	Log Daily No of issued orders	Order execution time (hrs)	Order execution time (hrs)	Order execution time (hrs)
Order type		Both	Buy	Sell	Both	Buy	Sell	Both	Buy	Sell	Both	Buy	Sell
DiD	No	0.14**	0.13***	0.15**	0.03***	0.02	0.04***	494.68***	336.07***	164.89**	-0.48	-0.48	-0.85
		(2.62)	(2.66)	(2.37)	(2.75)	(0.99)	(2.82)	(2.76)	(3.12)	(2.47)	(-1.11)	(-0.90)	(-1.35)
Obs.		583,728	298,218	285,510	583,728	298,218	285,510	583,728	298,218	285,510	583,728	298,218	285,510
Adj. R^2		0.19	0.18	0.20	0.02	0.02	0.01	0.19	0.18	0.19	0.01	0.01	0.01

Table 12: Switch from opacity to post-trade broker ID disclosure - Impact on transaction costs for individual and institutional investors and liquid and illiquid securities

The following table presents the regression coefficient estimates for the third analysed event on 14th April 2009. For all securities but the Top5 traded stocks, NASDAQ OMX Helsinki reversed the regulations introduced on 2nd June 2008. Hence, the market remained opaque for the top traded securities, while post-trade broker ID disclosure was reintroduced for the remaining securities.

Our analysis covers a horizon of 63 trading days before and after the event. Our data set includes 102 securities that are traded on at least 90% of the trading days before and after the event. The control group consists of the following securities: Nokia, Fortum, Stora Enso, UPM and Sampo. To analyse the impact of the regulatory changes specifically for institutional and individual investors, we compute the underlying order of each investor using the Euroclear data set, which provides account information. Our data set did not provide sufficient data for Sampo. Hence the security is not included. Trades are consolidated to simulate the underlying order of an investor, e.g. sequences following securities of trades in the same direction of the same investor are combined if the time difference between trades is less than 5 days. Minor trades in the opposite direction than the previous and following trade of the same investor were deleted. As one measure for transaction costs, we use the relative effective spread computed on the base of the underlying order as the difference of the volume-weighted order price and the first mid-point price of the order scaled by the first mid-point price, times the order direction and 10,000. We run the following model in Panel A:

$$\left(\frac{\mathrm{VWAP_{i,t,d}} - \mathrm{mid{-}point_{i,t,d,first}}}{\mathrm{mid{-}point_{i,t,d,first}}}\right)_{it} * direction * 10{,}000 = \beta_1 event_d + \beta_2 treatment_i + DID_{i,t} + \sum_{k=1}^{K=5} \theta_k\, weekday_k + \sum_{i=2}^{I=n} \eta_{i,t,d}\, investor_{i,t,d} + \varepsilon_{i,t,d},$$

where the relative effective spread of the order t of security i acts as the dependent variable. $event_d$ equals 0 prior to the event and 1 post the event. We cluster the standard errors by security and control for the security, the weekday of the first trade's execution as well as the investor in Panel A. In Panels B and C, the latter is not applicable. Accordingly, we design the model for any other market quality determinant $y_{i,t,d}$. The relative realised spread is computed by the difference of the last mid-point price and the volume-weighted order price scaled by the volume-weighted order price. Again, we multiply by order direction and convert the value in bps. We further compute the relative market impact as the difference between the last and first mid-point price scaled by the first mid-point price. The relative price impact is measured by the difference between the last and first order price, scaled by the first order price. Van Kervel and Menkfeld (2016) use this measure as a proxy for institutional implementation shortfall. Both of these measures are multiplied by order direction and 10,000.

In addition to the difference-in-difference analysis between the control and treatment group, we distinguish within the treatment group by liquid vs illiquid securities to gain insight which securities are driving the results. We determine the 5 most liquid securities within the treatment group in the same way the top 5 traded securities were determined, by the highest total trading volume in the previous year. We refer to those as the Liquid group. All remaining securities are considered illiquid.

Panel A presents the regression coefficients when disregarding the type of investor and only distinguishing between seller- and buyer-initiated orders. Panel B shows the findings for individual investors only, again presenting the overall effect as well as the impact on buyer- and seller-initiated orders. Accordingly, Panel C presents the results for institutional investors. Within those Panels, we present the findings not only for securities affected versus unaffected securities (e.g. top 5 traded securities). We further perform the same analysis for the control group versus 'liquid' and versus 'illiquid' securities within the treatment group. The 'liquid treatment' group includes the top 6-10 traded securities in accordance with their yearly trading volume. Those are Telia, Outokumpu Oyj, Nordea Bank, Neste, and Metso Oyj. Accordingly, the remaining securities construct the 'illiquid treatment group'. The t-statistics are presented in parentheses. Across all Panels we present the difference-in-difference (DiD) coefficients only for brevity.

***, **, * denotes statistical significance at 1%, 5% and 10%.

	Liquid group	Rel. Effective Spread	Rel. Effective Spread	Rel. Effective Spread	Rel. Realised Spread	Rel. Realised Spread	Rel. Realised Spread	Rel. Market Impact	Rel. Market Impact	Rel. Market Impact	Rel. Price Impact	Rel. Price Impact	Rel. Price Impact
Order type		Both	Buy	Sell	Both	Buy	Sell	Both	Buy	Sell	Both	Buy	Sell
Panel A: Impact on Liquidity measures													
DiD	N/A	-8.43*	-15.58**	-1.18	-4.87**	-6.47**	-3.12	-14.53**	-25.88**	-3.32	-14.78**	-26.08**	-3.76
		(-1.99)	(-2.52)	(-0.13)	(-2.23)	(-2.24)	(-0.62)	(-2.08)	(-2.38)	(-0.24)	(-2.13)	(-2.43)	(-0.27)
Obs.		1,121,284	632,761	488,523	1,121,284	632,761	488,523	1,121,284	632,761	488,523	1,121,284	632,761	488,523
Adj. R^2		0.06	0.05	0.07	0.02	0.01	0.03	0.05	0.03	0.07	0.05	0.04	0.07
DiD	Yes	-13.76**	-27.37*	0.53	-6.03**	-11.26**	0.48	-22.31**	-45.95*	0.54	-22.42**	-45.73*	0.07
		(-3.08)	(-2.47)	(0.07)	(-3.14)	(-2.71)	(0.12)	(-2.97)	(-2.45)	(0.05)	(-3.06)	(-2.44)	(0.01)
Obs.		712,557	399,609	312,948	712,557	399,609	312,948	712,557	399,609	312,948	712,557	399,609	312,948
Adj. R^2		0.12	0.08	0.17	0.08	0.04	0.14	0.11	0.07	0.18	0.11	0.08	0.18
DiD	No	-6.28**	-10.53**	-0.26	-3.74	-3.671*	-3.82	-10.71	-16.41*	-3.91	-10.99	-16.78**	-4.34
		(-2.50)	(-2.05)	(-0.03)	(-1.48)	(-1.685)	(-0.67)	(-1.31)	(-1.97)	(-0.25)	(-1.35)	(-2.02)	(-0.27)
Obs.		957,572	534,823	422,604	422,604	957,572	534,823	422,749	957,572	534,823	422,749	957,572	534,823
Adj. R^2		0.06	0.05	0.10	0.01	0.01	0.03	0.04	0.03	0.06	0.04	0.03	0.06
Panel B: Impact on Market liquidity measures for orders of individual investors only													
DiD	N/A	-9.52	-25.27***	18.19	-7.22	-11.99***	3.15	-18.01	-43.23***	26.61	-17.74	‘-43.1***	26.82
		(-1.21)	(-2.96)	(0.59)	(-1.63)	(-2.70)	(0.19)	(-1.36)	(-2.75)	(0.55)	(-1.35)	(-2.76)	(0.62)
Obs.		454,758	292,108	162,650	454,758	292,108	162,650	454,758	292,108	162,650	454,758	292,108	162,650
Adj. R^2		0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DiD	Yes	-18.35*	-43.34**	19.81	-7.96	-18.04**	10.18	-29.95*	-73.10**	31.27	-29.83*	-72.73**	31.24
		(-2.24)	(-2.63)	(0.64)	(-1.96)	(-3.13)	(0.59)	(-2.11)	(-2.57)	(0.63)	(-2.11)	(-2.59)	(0.63)
Obs.		267,420	172,643	94,777	267,420	172,643	94,777	267,420	172,643	94,777	267,420	172,643	94,777
Adj. R^2		0.02	0.03	0.04	0.02	0.03	0.03	0.03	0.03	0.04	0.02	0.03	0.04
DiD	No	-6.15	-17.94**	18.27	-5.121	-7.57**	2.59	-11.38	-28.79**	27.88	-11.04	-28.73**	28.17
		(-0.63)	(-2.42)	(0.56)	(-0.998)	(-2.18)	(0.14)	(-0.73)	(-2.37)	(0.54)	(-0.71)	(-2.38)	(0.55)
Obs.		373,844	236,605	137,239	373,844	236,605	137,239	373,844	236,605	137,239	373,844	236,605	137,239
Adj. R^2		0.01	0.02	0.01	0.01	0.001	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Panel C: Impact on Market liquidity measures for orders of institutional investors only													
DiD	N/A	-1.13	-0.29	-1.98**	-0.32	-0.09	-0.56	-1.73	-0.81	-2.67	-2.37	-1.38	-3.48**
		(-0.94)	(-0.17)	(-2.09)	(-0.64)	(-0.12)	(-1.10)	(-0.99)	(-0.29)	(-1.61)	(-1.51)	(-0.54)	(-2.13)
Obs.		666,526	340,653	325,873	666,526	340,653	325,873	666,526	340,653	325,873	666,526	340,653	325,873
Adj. R^2		0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
DiD	Yes	-1.56	-1.98	-0.87	-0.69	-1.14	-0.17	-2.48	-3.56	-1.17	-2.74	-3.48	-1.85
		(-0.92)	(-1.17)	(-0.58)	(-1.21)	(-1.59)	(-0.87)	(-1.02)	(-1.32)	(-0.69)	(-1.30)	(-1.49)	(-1.33)
Obs.		445,137	226,966	218,171	445,137	226,966	218,171	445,137	226,966	218,171	445,137	226,966	218,171
Adj. R^2		0.01	0.01	0.01	0.02	0.03	0.01	0.03	0.04	0.03	0.04	0.05	0.03

	Liquid group	Rel. Effective Spread	Rel. Effective Spread	Rel. Effective Spread	Rel. Realised Spread	Rel. Realised Spread	Rel. Realised Spread	Rel. Market Impact	Rel. Market Impact	Rel. Market Impact	Rel. Price Impact	Rel. Price Impact	Rel. Price Impact
Order type		Both	Buy	Sell	Both	Buy	Sell	Both	Buy	Sell	Both	Buy	Sell
DiD	No	-1.23	0.08	-2.68*	-0.21	0.26	-0.72	-1.77	-0.12	-3.55	-2.53	-0.91	-4.39*
		(-0.78)	(0.05)	(-1.97)	(-0.35)	(0.28)	(-1.07)	(-0.81)	(-0.05)	(-1.51)	(-1.21)	(-0.30)	(-1.85)
Obs.		583,728	298,218	285,510	583,728	298,218	285,510	583,728	298,218	285,510	583,728	298,218	285,510
Adj. R^2		0.02	0.02	0.02	0.01	0.03	0.01	0.02	0.02	0.02	0.02	0.02	0.02

2.7 CONCLUSIONS

This study investigates three unique policy changes conducted at the Nasdaq OMX Helsinki. On 13th March 2006, Nasdaq OMX Helsinki switched from pre-trade broker ID disclosure to post-trade broker ID disclosure. On 2nd June 2008, the exchange decided not to disclose broker information anymore; hence the market became opaque. This decision was partly reversed on 14th April 2009. For all securities, except for the top 5 traded stocks, broker ID disclosure was reintroduced post-trade. Therefore, the last event allows us to conduct a DiD analysis, where the top traded stocks, Nokia, Fortum, Stora Enso, UPM, and Sampo, act as the control group. These multiple events allow us to analyse the relevance of broker ID disclosure for market liquidity and determine the impact for different investor types submitting an order in terms of their personal transaction costs and their reaction to the new market environment.

We base our analysis on two different data sets and introduce a different methodology than the previous literature: First, we analyse all policy changes on base of daily measures regarding transaction costs, market resilience and liquidity, using TRTH data. Second, we study the impact on these parameters using the Euroclear data set, which provides us with additional information regarding both trade sides, as the account numbers and the investor type. Trades are consolidated to simulate the underlying order of an investor, e.g., sequences following securities of trades in the same direction of the same investor are combined if the time difference between trades is less than 5 days. Minor trades in the opposite direction than the previous and following trade of the same investor were deleted. We can analyse the impact not only on overall market liquidity but specifically on issued orders. We run fixed-effect regressions for both data sets.

To our knowledge, this study is the first to demonstrate the impact of different stages of broker ID disclosure on the base of orders and in such an extensive way: Based on the underlying order, we not only show the impact of these policy changes on various determinants of market liquidity separately for buyer- and seller-initiated orders, furthermore, we distinguish between the type of investor, individual as well as institutional investors. Our results show that the usually used daily measures often do not match the impact on single orders and differ across investor types. Further, we can show how the market participants adapt their trading behaviour. Our study presents consistent results across different levels of broker ID information disclosure on NASDAQ OMX Helsinki.

Our results show that transaction costs decrease with enhanced broker information disclosure for both types of market participants, especially for buyer-initiated orders. Market liquidity is positively associated with decreased informational asymmetry. However, institutional and individual investors react differently but submit more orders on average.

We find that the switch from pre- to post-trade broker ID disclosure decreases the daily relative effective spread, as one measure for transaction costs, by 9.5bps at a 1% significance level at the market level.

Institutional investors submitting sell-orders experience a highly significant increase in transaction costs, measured by effective spread, of 33.4bps, whereas the same measure drops by 21.0bps for buyer-initiated orders. For liquid securities, only seller-initiated orders significantly impacted, whereas, for illiquid securities, orders in both directions are significantly changing. Buyer-initiated orders by individual investors present a highly significant drop in price impact up to 46.9bps across all securities.

As a consequence of the switch to opacity in 2008, the relative effective spread for orders of institutional investors increases further by 1.8bps, whereas for individual investors, the relative effective spread per order remains unaffected. The relative realised spread for buyer-initiated orders submitted by individual investors drops by 3.0bps, complemented by a decline in price impact of 6.4bps. On a market level, we observe all transaction cost measures increasing. The effective spread widens by 24.2bps at a 1% significance, which is driven by illiquid securities. The DiD analysis for the third event on a market level confirms the previous findings, as the daily relative effective spread on a market level for the treatment group falls over 36.8bps more than for the control group. The results on a market level are consistent with our findings for orders submitted by an individual as well as institutional investors: The effective spread for buyer-initiated orders submitted by individuals tightens on average by 25.2bps for securities within the treatment group in comparison to the control group, while institutional investors do not experience a change in transaction costs on order level.[29] Individual investors experience for buyer-initiated orders a drop in realised spread by 12.0bps and 43.1bps in price impact, respectively. Those results are consistent across all security groups for orders submitted by individuals.

Institutional investors do not experience reduced transaction costs by the reintroduction of broker ID transparency post-trade, unrelated to the order direction or the liquidity of the security. Our analyses show that price impact increases on a market level when the exchange implemented opacity in 2008 and tightens in 2009. Seller-initiated orders by institutional investors experience an increase of 5.1bps in 2008. The same measure for institutional investors shows a drop by 3.4bps

[29] The magnitude of impact on orders is much lower than on a market level, however still high. Other studies as Putniņš and Barbara (2020) refer to our measure 'Effective Spread of an order' as 'Implementation shortfall costs of an order'. The authors use that measure to show that some high-frequency traders appear toxic to institutional investors, while others seem beneficial. Toxic traders increase the transaction costs of one order by an institutional investor by over 10bps. Hence, the magnitude of change for a single order is found in different studies too.

a year later. We find inconsistent changes in market liquidity measures.[30] The regulation change in 2006 leads to a significant jump in market depth, followed by a drop when the market becomes opaque. On-market volume, as well as trade count, are dropping only in 2008 but not when the market switches to post-trade broker-ID disclosure.

In 2009, when post-trade transparency was reintroduced for all securities except for the top 5 most highly traded stocks, we find that individual investors decrease their order volume by 0.2% for buyer-initiated orders. Institutional investors increase their order volume when submitting orders of illiquid securities. On a market level, only illiquid securities present a significant jump in liquidity measures compared to the control group. Our results indicate that individual household investors are not simply ‘noise traders’ but respond to altering levels of information provided on the identity of traders and, additionally, are more responsive on the buy-side of the market. The number of daily submitted orders increases significantly in 2009. In 2006, institutional traders increase their sell-order size with an increasing level of anonymity. However, they reduce splitting up buyer-initiated orders for illiquid securities, hence are less careful about disguising their intentions. We confirm those findings with our second experiment in 2008. The results indicate a relatively small 0.2% decrease in the average number of trades per buy-order for illiquid securities for the policy change in 2008 and a further 0.05% decrease in 2008. Accordingly, in 2009 we find a jump of 0.13% in the volume an institutional buy-orders and 0.15% for seller-initiated orders. For illiquid securities within the treatment group, the number of trades per order increases significantly, confirming the results of the first two regulatory changes. Institutional traders submit significantly more orders of illiquid securities on a daily basis when the market switched to ex-post broker identities in 2006 but do not change their order submission frequency in 2008 when the market became opaque. In 2009 across all investor types and securities, the number of daily order submissions jumps significantly compared to the control group. The trading volume of institutional investors does not increase with a declining level of transparency. However, the number of trades within an order falls significantly. The third event shows that institutional investors submit significantly larger orders for less liquid securities when broker ID disclosure was reintroduced.

Our results show a consistently positive effect of increasing broker ID disclosure on transaction costs. We show that the intensity of the impact differs significantly between institutional and individual investors and depends on the order direction. The overall positive effect of broker ID disclosure for all market participants stands in contrast to previous literature and common assumptions, where only household investors benefit from transparency. Institutional traders submit smaller orders; however, they submit more frequently when the

[30] This finding is in accordance with results of Pham et al. (2016), Eom et al. (2007).

market becomes more transparent. Since their informational advantage is significantly reduced, they cannot implement orders as cheaply into the market as in an opaque market. To ensure that a certain level of informational advantage can still be exploited, these might need to trade more aggressively. Transaction costs decrease significantly. On the other hand, households do no longer rely solely on the order flow for information. The decreased informational asymmetry encourages individual traders to trade more frequently and contributes to the overall liquidity increase. The transaction costs decrease as the informational content, or the order flow decreases overall. This study shows that the decision to reverse the implementation of total opacity was correct and allows NASDAQ OMX Helsinki a superior position in a competitive market environment.

2.8 ROBUSTNESS TESTS

To show that the results in Chapter 2.6.3 are driven by the reintroduction of broker ID disclosure post-trade for securities within the treatment group, we run a regression with the same setup for an alternative date, 10th March 2009. Hence, both groups had the same broker ID disclosure conditions on that date as it lies before the actual reintroduction on 14th April 2009. Table 13 presents the results. All results are insignificant besides intraday volatility for liquid securities versus the control group, which decline at 0 at a 10% significance level. Hence, we can be certain that the event drives our findings on 14th April 2009.

Table 13: Switch from opacity to post-trade broker ID disclosure - Robustness Test: 10th March 2009
One can argue that the control and treatment group for the experiment in 2009 are heterogeneous. Therefore, we separated the treated securities, e.g., securities affected by the regulatory changes, into a liquid, top 6 – 10 traded securities, and illiquid securities and performed a DiD analysis for both. However, as a robustness test, we present the same analyses for a 'fake' event prior to the actual event. We have the same settings, e.g., the same data set and an event horizon of 63 trading days prior to and post the experiment. We simulate the changes for the 10th March 2009, as the 'fake event date'. The actual changes came into effect on 14th April 2009.The t-statistics are presented in parentheses. ***, **, * denotes statistical significance at 1%, 5% and 10%.

	Rel. Effective Spread	Rel. Realised Spread	Rel. Price impact	Imple-mentation shortfall	Intraday volatility	Log On-market Volume	Log On-market Count	Log Off-market Volume	Log Ask Depth	Log Bid Depth
Panel A: Complete market										
DiD	-8.97	0.06	-9.29	-4.87	-0.00	-0.01	0.02	0.49	-0.15	-0.06
	(-1.22)	(0.01)	(-1.56)	(-1.27)	(-2.27)	(-0.63)	(0.77)	(0.57)	(-1.62)	(-0.68)
Obs.	3,655	3,655	3,655	3,655	3,655	3,655	3,655	3,655	3,655	3,655
Adj. R^2	0.03	0.03	0.01	0.03	0.01	0.15	0.12	0.03	0.18	0.17
Panel B: Top 5 traded securities vs >Top10 traded securities										
DiD	-9.58	0.03	-9.57	-5.17	-0.00*	-0.01	0.01	0.45	-0.14	-0.07
	(-1.18)	(0.02)	(-1.49)	(-1.234)	(-3.29)	(-0.69)	(0.70)	(0.52)	(-1.61)	(-0.79)
Obs.	3,440	3,440	3,440	3,440	3,440	3,440	3,440	3,440	3,440	3,440
Adj. R^2	0.04	0.03	0.01	0.04	0.01	0.19	0.15	0.04	0.24	0.23
Panel C: Top 5 traded securities vs top 6-10 traded securities										
DiD	-0.89	3.19	-4.22	-0.89	0.00	-0.01	0.01	1.00	-0.18	0.04
	(-0.74)	(1.36)	(-1.67)	(-1.44)	(-0.62)	(-0.13)	(0.16)	(1.05)	(-1.61)	(0.43)
Obs.	430	430	430	430	430	430	430	430	430	430
Adj. R^2	0.04	0.01	0.02	0.06	0.05	0.41	0.35	0.03	0.01	0.02

CHAPTER 3: SHEDDING LIGHT ON SYSTEMATIC INTERNALISER TRADING

3.1 INTRODUCTION

The Markets in Financial Regulation and the Markets in Financial Instruments Directive and Markets determines a systematic internaliser as a firm that deals on its own account by executing client orders outside of regulated trading venues. A trading venue like the London Stock Exchange (henceforth LSE) differs from a systematic internaliser as it offers multilateral trading, whereas a SI provides bilateral trading only. A SI is a counterparty in the form of a bank or electronic liquidity provider (henceforth ELP), not a trading venue. Still, it competes with trading venues such as regulated markets, multilateral trading facilities. Under MiFIR/MiFID II regulations, a SI must provide a certain level of pre-trade transparency by publishing quotes for liquid equity instruments up to the average order size and disclose executed trades in real-time. Therefore, trading via SI does not match the pre-trade transparency of central limit-order books but is more transparent than dark pool or OTC trading.

Internalisation has long been overlooked by academic research, focussing on more prominent forms of non-lit market trading, such as dark pools, automated non-transparent venues, or opaque order types on lit exchanges. When MiFIR/MiFID II came into effect on 3rd January 2018, the trade volume market share of internalised trading in the United Kingdom jumped by 14.2 percentile points to 18.1%, see Table 14. The shift was driven by the closure of broker-crossing networks and may have been facilitated by an exemption from the introduced tick size reform. As of 2021, SI trading presents a sizeable market share of around 14 to 15% for securities within the FTSE 100 index despite SI now being subject to the tick size reform. Still, there is no research on the relationship between market quality and SI.

This study provides first insights and causal evidence on the impact of internalised trading on market quality overall. We can overcome not only issues regarding data availability on SI trading but potential endogeneity in the methodology. We demonstrate that by distinguishing between SI trading via limit-orders and at the mid-point, one can determine how the lit trading venue's transaction costs and informational efficiency are impacted.[31] Based on a sample of the FTSE 100 index and FTSE 250 index constituents, we find that SI trading executed within the spread but not at the prevailing mid-point is highly beneficial to the overall market quality, improving informational efficiency and transaction costs on lit trading venues significantly. This leads to the discussion as to whether the rather negative press prior to and post MiFIR/MiFID II and subsequent regulatory changes came into effect were justified.[32] Our results in Chapter 3.6 show that effective and quoted spread drop by a minimum of 3.6bps each if the market share of limit-order SI trading increases by 1%. The realised spread drops by 9.1bps and price impact by 6.2bps. Autocorrelation and variance-ratio improve at a highly significant level. SI trading at the mid-point, similar to dark pool trading executed at the mid-point, presents insignificant or weak significant coefficients for transaction costs and contradictive findings for informational efficiency. At an aggregate level, we find that SI trading is highly beneficial for informational efficiency and indicates tighter spreads at a low significance level. SI trading, driven by limit-order SI trading, seems to improve market quality by enhancing competition in the limit order book. The concept of a semi-opaque counterparty capturing the previously opaque OTC trading and adding new trading opportunities for dark pool and lit venue trading seems, in general, a success.[33] Those findings are essential to evaluate this type of trading on a quantitative basis which allows regulators to evaluate decisions and provides a foundation for future discussions on internalised trading.[34]

MiFIR/MiFID II is best-known for its enhanced reporting obligations, which aim to increase transparency and investor protection to regain trust in a system that lost reputation during the Global Financial Crisis. The reform aims to shift liquidity from dark pools and broker-crossing networks to lit markets by imposing the Double Volume Cap mechanism, which prevents the

[31] Foley and Putniņš (2016) show that it is possible to determine how market quality is impacted by distinguishing particular types of dark trading. The authors show that common dark mid-point trading venues indeed do not seem to impact lit market quality. Opaque two-sided trading venues, on the other hand, have a positive impact on market efficiency.

[32] SI received negative press from regulated markets on their exclusion from the tick size regime. The trading classified as SI trading within banks was previously classified as OTC trading, further distinguished as price-forming and non-price forming. This type of trading served a different clientele than the lit market and did not contribute to liquidity and market quality. The new tick size regime recognised that allowing trade execution at the prevailing European Best Bid and Offer (henceforth EBBO) on all venues is a crucial way to execute Large-in-Scale orders. Our research shows that SI trades executed at the mid-point, e.g., the EBBO, do not increase transaction costs and might rather be beneficial.

[33] SI are required to provide real-time quote updates. For large-in-scale orders however, transparency waivers are applied. A SI is an opaque venue for above market-size orders.

[34] As of June 2020, a SI needs to comply with the tick size regime, a move was strongly supported by major market players. Please see AFME, CBOE, and LSE (2018). There is no obvious jump in market share.

extensive usage of certain transparency waivers on dark pools and the closure of BCNs. As a response to a changing trading environment, the closing of broker-crossing networks, the potential loss of opaque trading opportunities due to the DVCM, trading via SI as well as the number of newly established SI grew even before the regulatory changes came into effect.[35] Under MiFIR/MiFID II, SI have the same reporting obligations as other venues; however, the internal handling, potential liquidity, and matching might not be as transparent as in regulated markets. SI have the same right as regulated venues to apply for transparency waivers if conditions are met. Conditions for these waivers, such as Large-In-Scale trades or illiquidity, are more often met than on lit venues, similar to trading in dark pools. MiFIR/MiFID II introduced a new tick-size regime for shares, depositary receipts, and exchange-traded funds. The framework forces trading venues to price financial instruments under the regime in the same price increments.[36] According to Article (henceforth Art.) 49 (1) MiFID II, the tick-size regime must be adopted by regulated markets. Art. 18 (5) MiFID II indicates that investment firms and market operators operating multilateral trading facilities (henceforth MTFs) must adopt the regime, while SI were exempted.

MiFIR/MiFID II intended to increase transparency by shifting trading to more transparent forms of trading. Table 14 shows the market share of lit trading increased on average by 4.78 percentile points with the introduction of MiFIR/MiFID II for securities within our sample.

SI trading presents the largest increase in market share with 14.50 percentile points (equivalent to a relative increase of over 407%), driven by limit-order SI trading, which jumps by 13.95 percentile points. Also, the market share of periodic auction trading increased by 0.56 percentile points after the regulation came into effect. While still small, in relative terms, the share grew by over 1,867%. Despite the aim to reduce dark pool trading, dark pool trading increased on average by 2.62 percentile points. The significant decrease in trading classified as other, such as OTC, off-market trading, is mainly driven by the closure of broker-crossing networks and a reclassification of certain OTC trading. The shift in SI trading is used as an instrumental variable in our two-stage least squares regression.

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[35] As of 1st March 2020, 68 active SIs are registered in the United Kingdom alone, 38 in Germany, 16 in France, 221 world-wide (head office count). Please see ESMA (2020).

[36] The annex of RTS 11 presents price ranges and liquidity bands that determine the relevant tick size. See appendix A.1. The tick-size regime was introduced to minimize the risk of continuously decreasing tick-sizes. A study by the French regulator (see AFME, CBOE, and LSE (2018)) on the impact of the new tick size regime stated that prior to MiFIR/MiFID II that too small tick sizes increase the risk of order book noise and price discovery.

Table 14: Development of market share over the implementation of MiFIR/MiFID II
We present the market share of the daily trade volume executed as continuous lit trading, periodic auction trading, systematic internaliser trading, and within dark pools for three months preceding (1st October 2017 - 2nd January 2018) MiFIR/MiFID II came into effect and the three months after (3rd January 2018 - 31st March 2018). The market shares are calculated on a daily basis, as the ratio of the total trade volume across all trades classified as the respective type and the total daily trading volume irrelevant of any type. The mean, median and standard deviation are calibrated from the daily observations. The last two columns report the significance of the difference in means in the form of a t-test as well as the significance in the difference of the variance with the Wilcoxon Rank-sum test. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

Trading via	Pre-regulation			Post-regulation			T-Test	Wilcoxon Rank-sum
	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median		
Continuous lit	33.41%	2.12%	38.72%	38.19%	4.33%	32.96%	+4.78***	3.96 ***
Dark pool	5.83%	1.53%	5.03%	8.45%	1.15%	7.95%	+2.62***	3.91 ***
Periodic auction	0.03%	0.13%	0.14%	0.60%	0.93%	0.84%	+0.56***	0.05***
Systematic internaliser	3.56%	1.54%	3.75%	18.06%	4.55%	18.34%	+14.50***	0.01***
SI–mid-point trading	0.92%	0.44%	0.73%	1.47%	0.55%	1.32%	+0.55***	0.00***.
SI–limit-order trading	2.64%	1.35%	2.52%	16.59%	4.76%	17.17%	+13.95***	0.42***
Other	57.17%	4.21%	58.31%	34.70%	3.24%	33.52%	-22.46***	3.41**

The rest of the chapter is organised as follows. Chapter 3.2 discusses related literature and leads subsequently to our hypotheses. The institutional setting of our experiment is described in Chapter 3.3. Chapter 3.4 describes our data set. Chapter 3.5 states our methodology, which is the foundation for the univariate and multivariate analyses presented in Chapter 3.6. Chapter 3.7 summarises our conclusions.

3.2 LITERATURE AND HYPOTHESES

SI trading specifically and the impact on aspects of market quality such as efficiency or price discovery have not been explicitly addressed in the literature. While there have been many significant publications regarding opaque trading, the focus was on classic dark pool trading or opaque order types in lit venues. Now that SI trading has become a significant competitor to traditional trading venues and its' impact on the market is widely discussed, we aim to shed new light on it. We rely on research on common types of dark trading, in particular, broker-crossing networks, to form our hypotheses.

Ferrarini and Recine (2006) point out in their assessment of SI trading under MiFID I the benefits of the diversity of choice for trading participants, by eliminating concentration rules and the introduction of SI, but mention that these serve a small group of participants only. However, since no market model would serve the needs of all market participants and treat all investors equally, it would be important to offer alternative trading systems. Critics of SI in 2007 focussed on the possibility that internalisation might reduce market quality. Liquidity, in form of limit-orders, would shift from other order books to SI, which in turn would reduce liquidity in more significant markets contributing to market quality. In addition, the lower degree of price transparency might impact price discovery negatively. In general, investment firms must disclose executed trade information under MiFID I, however, the actual means of order publication were not specified. Firms must only disclose quote information for products classified as liquid and a quote size up to average market size. Limit orders by equity investors must either improve on the SI's quotation or be disclosed to the market. The authors suspected that the pressure could improve bid-ask spreads. This stands in contrast to research on dark trading and market quality. Weaver (2011) finds for a sample of US securities that dark trades harm market quality. Nimalendran and Rai (2014) show that quoted spread and price impact jump after significant dark pool trading.

A shift in market fragmentation and increased competition drive market efficiency, which has been a popular and important topic of an extensive number of studies after MiFID I came into effect. Research shows that fragmentation, in general, leads to lower transaction costs and increases execution speed (see O'Hara and Ye (2011)). Buti et al. (2011) show that increased dark pool activity is related to enhanced liquidity on lit venues. Degryse et al. (2015) find that enhanced dark trading activity has a detrimental impact on liquidity, whereas increased fragmentation on lit trading venues improves liquidity. When the number of liquidity providers increases with growing fragmentation, those can bypass time priority, which ultimately leads to superior pricing and a drop in transaction costs (see Biais et al. (2000), Biais et al. (2010), Foucault and Menkveld (2008), Colliard and Foucault (2012)).

Informed traders usually trade on the same side of the order book leading ultimately to lower execution probabilities on opaque venues. Therefore, uninformed traders dominate dark pools or other forms of opaque trading, and lit markets experience relatively more informed trading (Zhu (2014)). Foley and Putniņš (2016) study the impact of dark trading on the Australian and Canadian stock exchanges. The study distinguishes one-sided dark trading, usually at the mid-point, from two-sided dark trading, which is more commonly known as limit-order trading. One-sided dark trading is characterised by one-sided liquidity either on the buy- or sell-side and a low execution probability. Further, due to zero spread, dark market-making strategies are non-existent. Trading intentions are observable since probing orders can infer the direction of the dark order imbalance.[37] Two-sided dark trading, on the other hand, is closer to a dark limit-order market, with liquidity on either side and overall better execution probability which is equivalent to the term 'limit-order trading' used in this study. The authors show that dark limit-orders are overall beneficial to market quality, lowering quoted, effective, and realised spread, reduce price impact and metrics of illiquidity, and improve informational efficiency. The research, however,

[37] To infer the direction of order imbalance, one can submit probing orders in either direction. The order with the faster execution signals the direction of order imbalance.

presents contradictive findings regarding the impact on market depth in Canada and Australia. In previous research of the authors, Foley and Putniņš (2014) show that minimum price improvement rules significantly lower the level of dark trading and widened spreads. The results indicate that the impact is more significant for securities that experienced a superior shift from two-sided to one-sided dark pool trading. Comerton-Forde et al. (2015) present similar findings for the Canadian market, showing that regulation around price improvement has a heterogeneous impact on dark pools.

Boulatov and George (2013) show that dark pools on a limit-order basis motivate informed traders to supply liquidity as they can trade in an opaque environment. The study finds increased aggressive informed trading, which in turn improves informational efficiency. Those findings in relation to Foley and Putniņš (2016) suggest that strong competition in dark limit-order venues has certain spill-over effects on the lit market since spreads need to narrow to be able to compete with the dark trading venues. Zhu (2014) finds that informed participants are less likely to use one-sided or mid-point matching dark venues due to a low execution probability since informed traders often cluster on one side. Therefore, adverse selection risk on competing lit order books increases which might harm liquidity overall, although price discovery induced by informed trading is beneficial. It seems to be important to consider the specific type of dark trading venue to explain the different findings the literature presents. Ready (2014) shows in a study on Liquidnet and ITG Posit that securities with a higher dark trade volume share present less adverse selection risk.

Buti et al. (2015) show that non-mid-point trading venues contribute to superior market quality. The authors analyse how dark trading can be used for jumping the queue ahead of transparent lit trading venues. Kwan et al. (2015) study the impact of tick size on dark trading. In accordance with Buti et al. (2015), they find that investors turn to opaque trading venues for better quotes when securities on lit venues are tick-constrained. Buti et al. (2011) find for the US market that a superior level of dark trading leads to tighter spreads, larger depth, and improves short-term volatility.

Bloomfield et al. (2015) argue in a theoretical setting that dark trading impacts investors' trading behaviour but at an aggregate level has only a moderate impact on liquidity. Similarly, Degryse et al. (2015) find for a sample of securities listed in the Netherlands that competition and market fragmentation overall improve market liquidity. The rise of new lit order books after MiFID I came into effect had a significant positive impact on the aggregate market quality; the impact of dark pools, however, was negligible. Nimalendran and Ray (2014) find for the US market that traders split orders between the dark and transparent venues by identifying informational linkages.

Foley and Putniņš (2015) were the first to provide evidence on the causal impact of dark trading by distinguishing different types of dark trading, offering an explanation why some studies do not find a significant impact of dark trading on market quality. This study extends the idea and uses a regulatory change as a natural experiment to offer insights into SI trading. The interest in SI trading after the implementation of MiFIR/MiFID II and ongoing critique led to further discussion among regulators and professional investors. While investors shared their practical experience and preferences, there has not been actual research into the impact of internalised trading on market quality. Therefore, the findings of this study can be used to validate recent regulatory changes and to provide a foundation and guidance for future decisions for policymakers. In addition, we fill a gap in academic research where comprehensive empirical research on internalised trading specifically has so far been neglected.

We show that internalised trading, as likely any form of trading, cannot be treated and evaluated on an aggregate level, such as opaque trading or dark pool trading.[38] The actual composition of 'opaque' trading needs to be clear when evaluating any impact on the aggregate market efficiency. Our research will address the following hypotheses:

H1: The relation between SI trading on an aggregate level and market liquidity depends on the ratio of limit-order and mid-point trading.

SI mid-point trading is not beneficial to market liquidity in the sense that it might lead to increasing order imbalances in the lit trading venue. This trend might be balanced out by increased liquidity provision as a SI itself acts as a market maker. The advantage of reduced adverse selection risk for the SI itself and the temporary exclusion to comply with the tick size regime regulated markets allows them to quote superior spreads and forces lit trading venues to provide tighter spreads (confined by the tick size regulation) which in turn should not be a disadvantage to overall market liquidity. This leads to our hypothesis:

H2: SI mid-point trading is neutral or harmful to market quality. SI mid-point trading reduces overall liquidity and subsequently cannot contribute to tighter spreads or price discovery. However, we would argue that SI still provide potentially tighter quotes, which in turn puts pressure on lit trading venues.

Based on existing literature and models we suggest:

H3: Market liquidity across lit trading venues improves with increased SI limit-order trading.

Foley and Putniņš (2016) find that two-sided dark trading is related to decreasing

[38] Foley and Putniņš (2015) come to a similar conclusion that it is necessary to distinguish between mid-point matched dark pool trading and two-sided dark pool trading to be able to determine the actual relationship and impact of dark pool trading on the consolidated market quality.

transaction costs while one-sided has no significant impact.[39] While classic European dark pools would mostly be categorised as one-sided trading venues, SI, operated by banks or ELPs, can execute at any price point within the spread. The impact on market liquidity is dependent on the ratio of dark mid-point and limit-order trading and their respective relationship to lit market liquidity. Mid-point and limit-order trading differ in terms of execution probability and their impact on order routing decisions and order flow spill-overs between venues. At any point in time, if a dark trading venue offers mid-point matching only, dark liquidity, measured as the number of unexecuted dark orders, can be available to either buyers or sellers depending on the order imbalance at the mid-point, but not to both. In case of a sell imbalance at the mid-point, only incoming buy orders will be executed immediately against the existing dark orders. Sell orders would either be placed in the queue at the mid-point or re-routed to another venue for immediate execution, depending on routing preferences and regulation. The opposite is true if there is a buy imbalance. In contrast, in a two-sided dark market, both buyers and sellers can instantly execute their trades against the resting dark liquidity as long as there are resting dark orders on both sides. If resting dark orders are present, an impatient buy or sell order will be routed to a mid-point dark market at a random time and has a probability of around 50% of immediate execution. In contrast, if routed to a two-sided dark market, the probability is 100%. Market orders which are not immediately executed in a one-sided dark venue will be routed to lit venues, which leads to increasing imbalances in the lit venue. Research shows that enhanced order imbalances on lit venues can harm lit market liquidity.[40] Mid-point trading venues execute mainly the balanced order flow, but rarely the trades creating the order imbalance. In turn, this reduces the profits of lit liquidity providers and increases inventory and adverse selection costs. A drop in the balanced order flow leads to wider spreads, as lit liquidity provider's profits otherwise would decline. Literature shows a correlation in the order flow direction, which refers to market participants clustering on one side of the order book. This behaviour is more harmful when considering order flow spill-overs from one-sided dark venues. If informed traders rely on the same information, they will act simultaneously and either buy or sell. That means that an informed market order is more likely routed to a mid-point dark venue if there is already an imbalance of the same (informed) direction. In turn, the probability of immediate execution at the mid-point drops below 50%, whereas the immediate execution probability of an uninformed order is 50%. Similarly, limit-orders of informed traders will be queued as they correlate with other informed orders willing to execute at the mid-point. Informed traders, in general, face longer execution times in mid-point dark venues than uninformed traders, see Zhu (2014). The unexecuted order

[39] One-sided trading is equivalent to the term mid-point trading in our study. By definition, mid-point trading should not move the market price.

[40] See Hendershott and Mendelson (2000).

imbalance moves to the lit order books, either by routing regulation or choice. That spill-over increased the adverse selection risk as to the concentration of informed traders on the lit venue increases. Adverse selection risk likely widens spreads and, in turn, harms market liquidity. However, price discovery might improve. Zhu (2014) shows in his model exactly this mechanism, demonstrating how mid-point trading likely decreases market liquidity by increasing adverse selection risk. SI operated by banks mainly replaced BCNs and serve the same purpose for the buy-side. SI operated by ELPs act as a market maker, similar to single dealer pools in the US, which acted as liquidity providers in multilateral venues before. These present different business models and buy-side clients decide on a case-by-case basis which serves their (client's) purpose, which determines which ultimately determines the share of mid-point and limit-order trading. Based on Zhu (2014), Figure 1 would indicate that an increased SI market share on an aggregate level should not harm market liquidity, as the share of mid-point trading makes up only 20% and decreases significantly on 3rd January 2018.

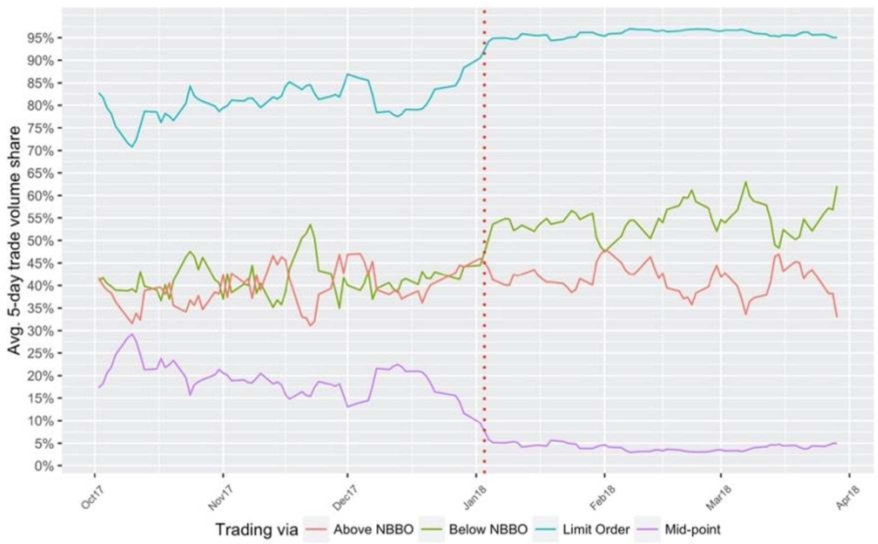

Figure 1: Trade volume share of limit and mid-point orders within systematic internaliser trading
The figure shows the 5-day average trade volume share of executed trades at the NBBO, below and above the NBBO and non-NBBO trades on an aggregate level within SI between 1st October 2017 and 31st March 2018. We refer to NBBO as the mid-point of the best bid and ask price on the main four lit order books in our sample. Our sample includes all securities within the FTSE 100 index and FTSE 250 index during that period. We recorded SI trades reported via the two largest Arranged Publication Arrangements (henceforth APA) of the UK, CBOE APA and TRADEcho. These are not the venue of execution, just the reporting venue. The vertical red dashed line refers to the 3rd January 2018, when MiFIR/MiFID II came into effect.

Figure 1 shows, SI limit-orders dominated before the regulatory changes, with a share of around 80%, which jumped to roughly 95% on 3rd January 2018. Roughly 42% of the trades before MiFID II were executed at a lower price/better price than the NBBO on the lit venues. Post MiFID II, that share increase to approximately 54%. Those numbers do not indicate whether those prices actually reflect a price improvement in comparison to a possible execution in a lit order book.[41]

Buy-side brokers use their respective smart-order-routing technology (SORT) to assess which market provides the best price, highest liquidity, least exposure and fast execution. While ‘best execution’ is the aim, individual client requests might be considered and drive decisions. Most major investment banks operate in-house SI post MiFIR/MiFID II. Usually, those are evaluated in the same way as external SI or other trading venues. However, potential direct transaction costs might play a factor. Similar to other venues, SI provide indicational quotes as required by the pre-trade transparency regulations. However, they are a counterparty and not a classic multilateral trading venue as an MTF, dark pool, or lit venue. Minimal adverse selection risk and the ability to quote more competitively provide them with an unusual advantage. Besides the differences, we suggest that the negative spill-over effects to lit trading venues, as described by Zhu (2014), exist. In addition, limit-order trading itself on SI should be seen as a further semi-opaque form of market fragmentation, which is likely beneficial to market liquidity in general. This is especially the case since, by the design of the tick size reform, SI will likely quote tighter spreads.

Foley and Putniņš (2016) argue that participants might anticipate trade intentions by observing order imbalances at the mid-point. Participants could submit smaller orders to test the market and unveil the direction of order imbalance and potential order implementation costs and time. This is a common strategy for classic dark pools. However, bilateral SI operators do not directly act as a venue, but a counterparty required by law to publish recent quotes. Whether a trade will occur depends on the relevant SI and SORT systems, and a direct execution might indicate information about other market participants’ intentions. Since the SI is the actual counterparty, the speed of execution might also be driven by the book of the SI itself. Similar to the broker itself, they might fill orders only partially and execution speed depends on in-house orders. Dark pools allowing two-sided trading do not easily give away information on trade intentions, as neither depth nor detailed prices and quantities are available pre-trade. Informed traders are likely more interested in other types of orders than mid-point trading if they focus on hiding information and execution probability.

Dark pools offering mid-point trading do not provide liquidity providers incentives as trading occurs with a zero spread, which might harm market liquidity on the lit trading venues. However, in an opaque limit-order market, informed traders are less concerned about revealing

[41] It is possible to calibrate an algorithm to proxy the magnitude of a possible price improvement by observing the prevalent and subsequent best trade price on a lit order book. The magnitude is the difference between the smaller of both lit trades and the SI trade times the trade volume. This is out of scope for this study.

any trade intentions and provide liquidity more actively (Boulatov and George (2013)). Doing so, they can undercut the spread in the lit venue, which in turn might support price discovery in general, which is supported by the results of Foley and Putniņš (2016).

Here, SI act as an extension in the number of liquidity providers, which should benefit liquidity in general, see Biais et al. (2000). Thus, we argue that Foley and Putniņš (2016) findings on the beneficial effects of two-sided dark pools to market liquidity are not transferrable to SI. SI fulfil a purpose for the buy-side, and the choice to trade with them lies on the broker side. Knowing its internal positions in either direction, provides awareness of the market and trade directions. Since SI can quote tighter spreads, they encourage more aggressive trading on the lit trading venues. Therefore, SI do not need to quote as aggressively as possible, just as much as is needed to take advantage of the temporary gap in the tick-sized regime. This is comparable to the beneficial results for limit-order dark pools, which encourage liquidity providers to provide superior quotes.[42] We do not disagree that market participants might be able to infer some information from trading with SI. In extreme market situations, it is likely they trade as the majority of the venues, and SI mid-point trading will be able to infer the direction of information, but to a lesser degree, that might not represent superior information. A participant with superior information might not trade with a SI as the first choice, as it is the SI itself who understands the intentions. We agree that an opaque limit-order trading venue might be the first choice. But the decision will ultimately be based on their internal SORT mechanism (which might favour superior quotes by SI), and cautious brokers might split orders to prevent information leakage.

We conclude, therefore, that a negative spill-over effect of SI mid-point trading could harm market liquidity. However, we do not see that SI trading, in general, will lower the number of liquidity providers in a meaningful way as they act as market makers themselves. Clients are unaware in any case of the nature of order matching within the SI engine. Therefore it will be unlikely they could infer more information from a mid-point trade than a limit-order trade executed with a SI.

3.3 INSTITUTIONAL SETTING

We exploit a natural experiment, which allows us to analyse the impact of trading via SI on market quality. The following chapter provides an overview of MiFIR/MiFID II and relevant regulatory changes to this study. Further, we discuss SI and the trading environment and markets in the UK.

[42] See Biais et al. (2010) and Buti et al. (2014).

3.3.1 MiFIR/MiFID II at a glance

MiFID I is a legislative framework instituted by the European Union (henceforth EU) to regulate financial markets and improve investor protection which came into effect on 1st November 2007. It introduced rules to create a more harmonised competitive and transparent trading environment across the EU. The framework focused on post-trade transparency to improve price discovery and enable clients to verify that their brokers comply with the best execution rules, to standardise post-trade transparency requirements for equity trading conducted on a trading venue, as well as enhance market data reporting to enable regulators to monitor and ensure the fair and orderly functioning of markets.

MiFID II and MiFIR resulted from a comprehensive revision of MiFID I by the EU and were agreed on 2nd July 2014. MiFIR/MiFID II extends the scope of MiFID I's regulatory requirements to equity products such as shares, depositary receipts, exchange-traded funds, certificates, other similar financial products, and non-equity products like bonds, structured products, emission allowances, and derivatives. Overall, MiFIR/MiFID II aims to enhance efficiency, resilience, and integrity by achieving greater transparency by introducing new provisions to enhance controls around preventing market abuse, increasing reporting obligations, and standardising practices across the EU.

MiFIR/MiFID II's transparency regime addresses pre-trade transparency, designed to provide market participants with a near real-time broadcast of basic trade data around firm quotes. A post-trade transparency regime was introduced to provide market participants with near-real-time reporting of basic trade data around executed trades. According to the Regulatory Technical Standards (RTS), the regulation requires a timebound publication of executed trades to an Arranged Publication Arrangement according to the Regulatory Technical Standards (henceforth RTS) to promote price transparency. EU MiFID II qualifying investment firms, their non-EU domiciled branches, and EU branches of non-EU MiFID II qualifying investment firms will be required to satisfy the MiFID II post-trade transparency and reporting obligations effective from 3rd January 2018. To shift specifically trading for derivates and bonds to regulated venues, organised trading facilities were created. Other implemented regulatory frameworks did not catch the eye of the public. MiFIR/MiFID II established a new tick-size regime so that every trading venue must price certain financial instruments in the same increments.[43] RTS 11 specifies the minimum tick-size regime in accordance with the instrument's liquidity and price level.

[43] Please see Art. 9 MiFID II and the Commission Delegated Regulation 2017/588 of 14 July 2016, in addition to the Directive 2014/65. EU of the European Parliament and the council regarding regulatory technical standards to the tick size regime (RTS 11), by European Commission (2017).

Instruments can switch between liquidity bands and price levels over time.[44] Please see Appendix A.1 for more information.

The tick-size regime refers to equity and equity-like instruments only and must be adopted by regulated markets, hence trading venues such as LSE or CBOE BXE. However, Art. 18 (5) implies that additional investment firms and market operators operating MTFs or OTFs must comply with the regime. SI are not subject to the requirement, which build the foundation for our experiment. Related to our research, Kwan et al. (2015) show that constrained securities experience higher dark pool activity. Dark trading is used to obtain better quotes, which is the basis of the natural experiment.

3.3.2 Systematic Internaliser

SI were introduced under MiFID I in 2007 and are commonly defined as 'an investment firms which, on an organised, frequent, systematic and substantial basis, deal on own account when executing client orders outside a regulated market, a MTF or an OTF without operating a multilateral system' under MiFID II.[45] The SI regime introduced under MiFIR/MiFID II extended the scope of SI eligible instruments from equity to equity-like instruments as depositary receipts, ETFs, certificates, and non-equity instruments such as derivates, bonds, structured finance products, and emission allowances. MiFID II introduced OTFs, which were added to the definition, and provided quantitative criteria to the term systemic. [46][47] Art. 4 (1) (1) MiFID II defines an investment firm as a legal person whose occupation of business is the provision of investment services or performance of investment activities. Most major international banks or electronic liquidity providers qualified for SI. The purpose of the expansion of the SI scope under MiFID II was to capture previously opaque OTC trading and to ensure that order flow

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[44] Our study, based on a UK sample, presents an average SI market share of 4.27% three months prior to the introduction of MiFID II, see Table 1. AMFE conducted research on the impact of SI trading under MiFID II on the French securities market showed that French blue chips and mid-cap securities experienced an increase in 74% of the cases and remained unchanged otherwise, whereas, for small-cap securities, the regime led to an increase for 21% and in 15% of the cases to a reduction. The study reported increased market depth and transaction costs overall for liquid securities.

[45] AMFE (2011) estimated between 2008 and 2010, the turnover share of real OTC trading, including SI and BCNs, was around 12%. SI trading experienced a peak after introduction in 2007 but experienced a rapid drop, from 14% to 2% market share. See The Trade (2020).

[46] Please see Deutsche Boerse (2018). The definition of SI is laid down in Art. 4 (1) (20) of MiFID II and specified in Commission Delegated Regulation (EU) No 2017/565 supplementing Directive 2014/65/EU of the European Parliament and of the Council.

[47] Commission Delegated Regulation (EU) No 2017/565 is supplemented by Directive 2014/65/EU of the European Parliament and the Council regarding organizational requirements and operating conditions for investment firms and defined terms for that Directive. Please see Emission Euts (2020).

internalisation would not affect price efficiency overall.

The main differences between a SI and classic trading venues are that trading venues deal with the client's capital, while SI deal on their own account and is thus also termed a principal trader. Based on that definition, a SI is a counterparty, whereas a trading venue is a facility. A SI is a single dealer, who cannot engage in matched principal trading, whereas a trading venue is a multilateral dealer platform that, if it is registered as an OTF, can engage in matched principal trading. ESMA advised the European Commission (henceforth EC) on the setting of quantitative criteria regarding the terms 'frequent', 'systematic', and 'substantial and takes into consideration the interlinks that might exist between the SI regime and the trading obligation for shares as defined under Art. 23 or MiFIR.[48]

For equity and equity-like instruments, 'frequent' and 'systematic' are defined as an investment firm executing at least 0.4% of the total number of transactions in a liquid financial instrument across any venue or OTC in the EU over the past six months via the firm's own account while executing client orders while dealing on average on a daily basis on own account. ESMA defines 'substantiality' if either the investment firm's OTC trade volume share in an instrument versus its total trading volume is larger than 15% or if it is 0.4% of the total trading in the European Union in the relevant instrument. A SI will not combine third-party buying and selling interests functionally the same way as a trading venue.[49] To determine whether an investment firm is "executing client orders" when dealing on its own account outside of trading venues, investment firms assess which of the two parties to the transactions acts in the capacity of executing client orders. This can be determined on a transaction-by-transaction basis or by type of transactions or type of counterparties. A SI operates a bilateral system, which prevents the investment firm from matching buying and selling orders in the way trading venues do. If a SI does so, it would no longer be considered a SI but would require authorisation to operate an MTF or OTF. A multi-dealer platform with multiple dealers interacting for the same financial instrument should not be considered a SI.[50]

[48] For brevity, this paper focuses on equity-like instruments. For more information regarding SI criteria for bonds, derivates, emission allowances, and structured finance products, please refer to Deutsche Boerse (2018).

[49] For equity-like instruments, the investment firm shall assess whether it meets the conditions mentioned quarterly based on data from the last six months. Newly issues instruments shall only be considered when historical data covers the period of at least three months. If those conditions are met, the investment firm shall comply within two months with all requirements set in Art. 13, 14, 15, and 16 of MiFIR. Please see also Deutsche Boerse (2018).

[50] This has been underlined in Recital 19 of the said Commission Delegated Regulation (EU) 2017/565 of 25th April 2016: "According to Directive 2014/65/EU, a SI should not be allowed to bring together third-party buying and selling interests in functionally the same way as a trading venue. A SI should not consist

SI are competing with trading venues over customers' order flow. To provide a level playing field, ESMA underlined that trading venues and SI using similar technology and systems should process transactions for post-trade publication at the same speed.[51] Consequently, ESMA expects that trading venues and investment firms, in particular SI, that use expedient systems publish transactions as close to real-time as technically possible. SI must provide public pre-trade quotes either by choice or on request either through a trading venue, an APA or the SI's web. Accordingly, post-trade information needs to be reported to an APA of choice. SI have the same right to offer pre- or/and post-trade transparency waiver for eligible trades as trading venues have.

3.3.3 Trading venues and trade types

MiFID I created a competitive environment for equity trading, introducing new trading venues known as MTFs and SI. While the LSE is still the dominant venue in the UK, the market share of MTFs nowadays is significant. CBOE Europe, combining CBOE BXE and CBOE CXE, has a total market share of 22.6% across Europe and 23.7% for London listed securities for displayed, hence lit continuous equity trading. 8.5% of London listed securities' lit equity trading is executed on Turquoise, 2.2% on Aquis.

The lit order books of MTFs are a direct competitor to LSE. However, MTFs provide diversified trading opportunities, offering to trade in dark pools and periodic auction books, competing against classic dark pools such as UBS Dark. 24.5% of opaque trading of London listed securities, comparable to dark pool trading, is executed on CBOE Europe, offering several dark order books. Turquoise has with 25.3% the largest market share, followed by Liquidnet with 16.7% and CBOE CXE with 13.9%, respectively.[52] Table 15 presents an overview of the trade types offered by each venue. Please note that SI trading is reported via LSE APA and CBOE APA but not executed on the venue.

Continuous lit trading refers to trading in central limit-order books with pre-trade transparency on the primary trading market or MTFs during continuous trading hours. Trading within the opening or closing auction is excluded. Market participants can observe updated quotes

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of an internal matching system that executes client orders on a multilateral basis, an activity that requires authorization as a multilateral trading facility. In this context, an internal matching system is a system for matching client orders that results in the investment firm undertaking matched principal transactions on a regular and not occasional basis. "In addition, if an investment qualifies as an MTF or OTF it would automatically need to comply with the tick-size regime.

[51] Real time post-trade transparency requirements, as expressed in Art. 6 and 10 of MiFIR and specified in Art. 14 of RTS 1.

[52] CBOE Europe offers on its online presence a comprehensive overview of historical daily market shares across all European venues, distinguishing by listing market. The market shares provided in this study areas of 23rd November 2017. Please see CBOE Europe (2017).

and executed trades.

Dark (pool) trading stands in contrast to lit trading. Opaque markets allow participants to execute trades without revealing their intentions. Since dark pools mostly match orders at the mid-point, participants might receive a better price than in more transparent markets, especially for large orders. However, the uncertainty of existing liquidity in a dark pool leads to subsequent risk of non or delayed execution. Dark order books, operated by a MTF, such as Turquoise or a classic dark pool as Liquidnet, benefited before MiFIR/MiFID II came into effect from the unlimited use of pre-trade transparency waivers under four scenarios. Visible large orders can face the risk of front-running and are likely executed at higher costs.

Table 15: Trade types across the trading venues
The table below provides an overview about the different types of trading each venue included in this study provides. Please note that SI trading is only reported via an APA but executed by an ELP acting as a SI or a bank via their own SI.

Venue	Continuous lit trading	Dark trading	Periodic auction trading	Systematic internaliser trading
LSE (TradEcho)	x	-	x	x
CBOE BXE	x	x	x	-
CBOE CXE	x	x	-	-
Turquoise	x	x	x	-
Aquis	x	-	-	-
Instinet BlockMatch	-	x	-	-
ITG Posit	-	x	x	-
Liquidnet	-	x	-	-
UBS Dark	-	x	-	-
Sigma X	-	-	x	-
CBOE APA	-	-	-	x

3.4 DATA

Our study relies pre-dominantly on Thomson Reuters (henceforth TR) DataScope tick data. The sample includes the constituents of the FTSE 100 index and FTSE 250 index between October 2017 and March 2018, which compromised approximately 355 of the most actively traded securities in the UK in the relevant horizon. By focussing on the International Securities Identification Number (ISIN) of those securities, we create a unique identifier, which allows us to map the venue-specific Reuters-Identification Codes (RIC) across all UK order books to the identifier. In total, we cover 3,098 venue/data stream-specific securities mapped to 355 identifiers. This includes TR DataScope data from streams reporting trading via continuous lit trading order books and periodic auction order books from LSE, CBOE BXE, CBOE CXE, and Aquis. Further, we include the stream for trade reporting of SI trading via CBOE APA and dark pool order books of BLINK MTF, CBOE BXE, CBOE CXE, Instinet Blockmatch, ITG Posit, Liquidnet, SIGMA X, Turquoise, and UBS Dark.

TR DataScope reports trades executed on dark pools as well as SI trading via CBOE APA via a consolidated stream. Extensive research and data manipulation allow us to allocate those trades to five dark pools and CBOE APA. The comprehensiveness of the data was verified with market data reported on CBOE Europe and Fidessa. All streams report first-level best bid and ask price and size and trades with an extensive set of qualifiers. CBOE APA reports trade data only. The historical market capitalisation of the relevant firms was collected from Bloomberg.

The study considers a horizon from 2nd October 2017 to 31st March 2018, hence roughly three months pre-and post-MiFIR/MiFID II came into effect. The three months period is chosen due to two market-relevant events. First, the implementation of the DVCM in mid-March 2018.[53] Second, the implementation of TRADEcho on 21st November 2017.[54] TRADEcho is operated by LSE and provides on-exchange off-book reporting, and is approved as an APA.[55] Both, the introduction of the DVCM as well as TRADEcho drive the trading environment and behaviour in the UK and need to be considered.

3.5 METHODOLOGY

This chapter provides an overview about the methodology and measures used to evaluate the impact of SI trading on market quality.

3.5.1 Liquidity and informational efficiency metrics

We incorporate a proxy for the degree of information asymmetry[56] of trades by calculation the price impact in the form of $Price\ Impact_{id} = Effective\ Spread_{id} - Realized\ Spread_{id}$. We include the daily quoted depth as another measure for liquidity. Quoted depth refers to the total daily volume available at the best bid and ask price on the relevant venue during continuous trading hours. The informational efficiency of prices is evaluated by autocorrelations, variance-ratios, and a HFT measure. Autocorrelations moving away from 0 indicate that quoted spreads deviate from stochastic random walk and exhibit short-term return predictability. The predictability is

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[53] The DVCM (Art. 5 of MiFIR) aims to limit the trading under the reference price waiver (Art. 4 (1)(a) of MiFIR) and the negotiated transaction waiver for liquid instruments (Art. 4 (1)(b)(i) of MiFIR) in equity instruments. Implementing such a mechanism is likely to significantly change the trading environment and might lead to a certain bias.

[54] Please see TRADEcho (2020) for an overview.

[55] This affected the tick data provided by TR DataScope. TR DataScope introduced new RICs specifically for off-market trades executed on-exchange in addition to the existing corresponding RICs for any security traded on LSE to translate the implementation of on-exchange off-market reporting into their tick data. Prior, on-exchange off-market trading was reported via the existing RIC for securities traded on LSE; those were discontinued for that kind of trading. However, the function was reintroduced on 18th April 2018, leading to a certain double reporting of on-exchange off-market trading, which required extensive data cleaning.

[56] See Bessembinder (2003).

mainly driven by partial price adjustment to certain information as over- and under-reaction (Anderson et al. (2013)). This behaviour is an indication of an informationally inefficient market. The measure is computed as the absolute value of first-order autocorrelations for each security on a daily basis at a 10-second frequency in accordance with Hendershott and Jones (2005). We calibrate $AutoCorr_{i,d} = |Corr(r_{k,\tau}, r_{k,\tau-1})|$, where $r_{k,\tau}$ is the τ^{th} mid-point return for a time period k over a day d. The absolute value of the autocorrelation presents a measure of informational efficiency that measures both the under- and over-reaction of returns to information entering the market. We choose a 10-second frequency as we assume the UK markets, in combination with our sample period, to be very liquid. Following Lo and MacKinlay (1988) we compute the variance-ratio for each security i on day d on each venue as $VarRatio_{i,d} = \left| \sigma_{kl}^2 / k\sigma_l^2 - 1 \right|$, with σ_{kl}^2 and $k\sigma_l^2$ as the variance of l-second and kl-second mid-point returns. Stock prices that follow a random walk would have a variance of returns as a linear function of the return measurement frequency, hence $\sigma_{k,l}^2$ is k times larger than σ_{1-l}^2. Higher values indicate greater inefficiency. In our study we us an $l, and\ k, l$ combination of 1 second, 10 seconds. Further, we measure the intraday mid-point standard deviations by computing returns of 10-second horizons. $HFTVol_{i,d}$ is a proxy for noise and temporary deviation of prices from their true value.

3.5.2 Instrumental variable regression

We are able to exploit a natural experiment to provide causal evidence about the impact of SI trading on market quality. In doing so, we overcome a potential endogeneity issue. We decide on a three-month trading horizon before and after the introduction of the regulatory changes by MiFIR/MiFID II. The regulatory changes on 3rd January 2018 did not explicitly target trading via SI. However, trading volume jumped by 14.5 percentile points overnight. This is mainly due to the fact that SI were exempted from certain tick size regulation on a temporary basis, which provided them with the advantage to be able to quote at different and better prices. Using the regulation as our main source of exogenous variation in SI trading, we analyse the causal impact of SI trading on liquidity and informational efficiency. The empirical design overcomes endogeneity and data issues that have prevented research up until now.

One of the main challenges in empirically studying the impact of SI trading on market quality is the likely endogeneity of SI trading to market conditions. Due to the absence of prior research, we assume that SI trading is similar to dark trading regarding its relationship to market quality parameters. Dark trading tends to increase when spreads are constrained to the minimum tick size because dark trades are allowed to occur within the spread at sub-penny price increments (see Kwan et al. (2015)). Buti et al. (2011) show that dark pool activity is higher when limit-order depth is high, spreads are narrow and tick sizes are large. The conditional nature of the decision to execute in the dark results in an endogeneity issue between market quality and dark trading.

To overcome any potential endogeneity issues, we use the regulatory changes on 3rd January 2018 as an instrumental variable for SI trading in a 2SLS framework.

The first stage is a regression of the level of SI trading $SI\_V_{i,d}$ on the instrumental variables and a set of control variables. $SI\_V_{i,d}$ is the share of SI trading volume for a security i on day d. The main instrumental variable is a dummy variable M_d^{Post} which equals to 1 after the 3rd January 2018 and 0 otherwise. This instrument alone is sufficient for identification. We follow the approach of Foley and Putniņš (2016) and include in addition the lagged level of SI trading $SI\_V_{i,d-1}$:

$$SI\_V_{i,d} = \alpha_i + \beta_1 M_d^{Post} + \beta_2 SI\_V_{i,d-1} + \sum_{j=1}^{3} \gamma_j control_{j,i,d} + \varepsilon_{i,d} \tag{6}$$

With $SI\_V_{i,d}$ as the daily market share of trading via SI, M_d^{Post} as a dummy variable, equal to 1 post 3rd January 2018 and 0 prior. $SI\_V_{i,d-1}$ is the lagged level of SI trading. We include a set of three control variables: $time_d$, which takes the value 0 on the first day of the sample and increments by one every subsequent day. This variable removes general time-series trends in trading. Further, we include $vol_{i,d}$, referring to the intraday volatility of i on day d. To account for differences in firm size across the sample we include the daily market cap $market\ cap_{i,d}$. The second-stage regression is run as

$$y_{i,d} = \alpha_i + \beta_1 \widehat{SI\_V}_{i,d} + \sum_{j=1}^{3} \gamma_j control_{j,i,d} + \varepsilon_{i,d} \tag{7}$$

The dependent variable $y_{i,d}$ refers to measures of market liquidity and informational efficiency as described in Chapter 3.5.1. After the first-stage regression we estimate the fitted values $\widehat{SI\_V}_{i,d}$ of the SI trade volume share, which is included in the second-stage regression. α_i is a set of stock-fixed effects. $control_{j,i,d}$ includes the same control variables as in the first-stage regression. As a robustness test, we run the second-stage regression with altered first-stage regressions, by adapting regression (1) and exclude $SI\_V_{i,d-1}$, as well as for different data subsets regarding time and market capitalisation.

We deepen our analysis by distinguishing between systematic internaliser trading executed at the mid-point and as a limit-order. Foley and Putniņš (2016) demonstrate consistent evidence that dark limit-orders significantly impact market quality. We distinguish SI trading executed at the prevailing NBBO, which would be classified as a SI mid-point trade, and trade execution at a price other than the prevailing mid-point, which we would classify as a SI limit-order trading. We calibrate the respective daily market shares $SI\_V\_mid_{i,d}$ and $SI\_V\_limit_{i,d}$. We run a first-stage regression for each type of trading and estimate the respective fitted values:

$$SI\_V\_mid_{i,d} = \alpha_i + \beta_1 M_d^{Post} + \beta_2 SI\_V\_mid_{i,d-1} + \sum_{j=1}^{3} \gamma_j control_{j,i,d} + \varepsilon_{i,d} \quad (8)$$

And

$$SI\_V\_limit_{i,d} = \alpha_i + \beta_1 M_d^{Post} + \beta_2 SI\_V\_limit_{i,d-1} + \sum_{j=1}^{3} \gamma_j control_{j,i,d} + \varepsilon_{i,d} \quad (9)$$

The control variables are the same as described above. We evaluate the impact of SI mid-point and limit-order trading in a joint regression:

$$y_{i,d} = \alpha_i + \beta_1 \widehat{SI\_V\_mid}_{i,d} + \beta_2 \widehat{SI\_V\_limit}_{i,d} + \sum_{j=1}^{3} \gamma_j control_{j,i,d} + \varepsilon_{i,d} \quad (10)$$

where $y_{i,d}$ is a market quality parameter and $\widehat{SI\_V\_mid}_{i,d}$ and $\widehat{SI\_V\_limit}_{i,d}$ the respective fitted values from the first stage regressions (8) and (9). To assure the robustness of our findings we run additional first-stage regression variations and assess the impact of the fitted values separately in different settings. The specific parameters are described in the relevant Chapter 3.6.2. The second stage regressions with fitted values deriving from different first-stage regressions are run as follows

$$y_{i,d} = \alpha_i + \beta_1 \widehat{SI\_V\_mid}_{i,d} + \sum_{j=1}^{3} \gamma_j Control_{j,i,d} + \varepsilon_{i,d} \quad (11)$$

And

$$y_{i,d} = \alpha_i + \beta_1 \widehat{SI\_V\_limit}_{i,d} + \sum_{j=1}^{3} \gamma_j Control_{j,i,d} + \varepsilon_{i,d} \quad (12)$$

3.6 EMPIRICAL ANALYSIS

Our study uses the comprehensive restructuration of the European market regulation in the form of MiFIR/MiFID II as a natural experiment. It acts as a source of exogenous variation to identify the causal effects of trading via SI. As the literature presents heterogeneous results on the relationship between dark trading and market quality, we show that those findings are due to the type of trading on the relevant dark trading facility. Our analyses distinguish between mid-point and limit-order trading via SI, showing that limit-order dark trading does impact the associated lit trading venues. Chapter 3.6.1 provides a comprehensive overview concerning the developments of liquidity and market quality parameters across UK trading venues. Chapters 3.6.2 and 3.6.3 focus on the actual causal impact of SI trading on market quality parameters.

3.6.1 Descriptive Statistics

Table 14 in Chapter 3.1 showed that MiFIR/MiFID II led to a significant shift among the market shares of different types of trading. Trading via SI jumps by 14.5 percentile points in our sample, while trading via Continuous Lit trading venues increased by 4.8 percentile point. Especially trading via SI limit-orders, which experienced a significant increase of 13.9 percentile points.

Our main analysis begins with descriptive statistics regarding the impact of the regulatory changes on market liquidity and market quality parameters across different venues in general. We test the mean difference pre and post three months to 3rd January 2018 with a t-test and the change in distribution with a Wilcoxon Rank-sum test. Table 16 shows the average daily trading volume across our sample per trade type and the relevant trading venues. This provides an overview of which venues dominate for each type of trading and what venues experienced a change in trading activity by MiFIR/MiFID II.

Table 16: Average daily trading activity per order book prior to and post the introduction of MiFIR/MiFID II

The table reports the descriptive statistics on the nation- and venue-wide average daily trading volume during the three months preceding MiFIR/MiFID II (1st October 2017 - 2nd January 2018) and the three months after (3rd January 2018 - 31st March 2018). The trading volume is calculated daily, as the sum across all securities. The mean, median and standard deviation are calculated from the daily observations. For display purposes. those parameters are divided by 1,000. The last two columns report the significance of the difference in means (%) in the form of a t-test as well as the significance in difference of the variance with the Wilcoxon Rank-sum test. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

Venue	Pre-regulation			Post-regulation			T-Test	Wilcoxon Rank-sum
	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median		
Panel A: Continuous lit trading								
All Venues	900,439.88	209,830.09	884,699.36	1,111,457.10	211,620.92	1,097,918.48	23.43%***	29.00***
Aquis	14,326.75	3,361.72	13,614.28	24,147.38	5,021.70	23,781.67	68.55%***	7.00***
CBOE BXE	64,450.12	12,840.51	62,895.58	92,022.68	18,292.13	93,614.02	42.78%***	85.00***
CBOE CXE	196,246.97	40,716.72	194,159.32	233,344.97	51,801.44	229,596.58	18.90%***	36.00***
LSE	522,036.92	117,815.16	516,169.29	617,706.96	119,117.45	604,314.88	18.33%***	37.00***
Turquoise	121,545.11	25,316.83	118,424.61	144,235.09	30,693.58	143,791.20	18.67%***	48.00***
Panel B: Dark pool trading								
All Venues	73,686.27	18,802.81	73,282.01	64,894.94	18,688.92	69,999.01	-11.93%***	145.00***
CBOE BXE	27.82	22.35	21.64	34.40	39.18	18.54	23.65%	982.00
CBOE CXE	56.83	47.58	48.05	56.11	57.04	43.68	-1.27%	107.00
Instinet BlockMatch	4,718.69	1,509.05	4,644.47	2,643.96	1,517.83	2,883.67	-43.97%***	180.00***
ITG Posit	23,532.38	6,486.19	23,099.93	20,767.78	8,021.00	19,997.10	-11.75%*	0.00***
Liquidnet	18,371.81	7,917.04	16,933.20	20,332.27	7,120.03	19,260.59	10.67%	751.00
Turquoise	106.67	139.71	67.40	95.20	109.10	60.65	-10.75%	105.00
UBS Dark	28,715.06	6,771.40	28,978.44	20,965.18	11,115.83	24,151.45	-26.99%***	159.00
Panel C: Periodic auction trading								
All Venues	49.33	635.14	814.97	21,923.66	16,173.48	16,150.22	44,343.19%***	178.00***
CBOE BXE	40.33	629.80	811.91	21,583.81	15,594.44	16,150.21	53,418.04%***	0.00***
LSE	8.80	18.71	0.00	6.40	23.55	0.03	-27.53%	230.00
SIGMA X	0.00	0.00	0.03	144.21	435.11	0.00	-***	0.00***
Turquoise	0.21	0.02	0.03	189.18	327.32	0.31	89,986.54%***	0.00***
Panel D: Systematic internaliser trading								
All Venues	42,487.44	20,146.51	40,060.94	578,603.14	140,188.18	585,768.61	1,261.82%***	0.00***
CBOE APA	43,074.13	19,419.01	40,790.81	487,802.39	119,660.30	480,098.26	1,032.47%***	0.00***
LSE TRADEcho	370.76	703.27	0.03	90,800.74	33,861.22	93,973.43	24,390.44%***	0.00***

Panel A focuses on continuous-lit trading, the most prominent type of trading. We observe a significant increase in the trade volume across all lit trading venues of 23.4%. The most significant increase is observed for Aquis, which shows a relative jump of over 68% in the average daily trading volume, followed by CBOE Bats with an increase of 42%. Overall, volatility seems to increase when MiFIR/MiFID II came into effect. Panel B presents a general drop in the average daily trading volume in dark pool order books by 12%. This trend would be in line with the aim of MiFID II. The decrease is mainly driven by UBS Dark (-27%) and Instinet BlockMatch (-44%).[57] Panel B also demonstrates that classic dark pools dominate and the average trade volume of dark order books on multilateral trading facilities with various trading types is far behind those. As shown in Panel C, periodic auction trading presents a significant increase in the average daily trading volume. While our data presents a jump around the introduction of MiFIR/MiFID II, we need to be cautious. The introduction of the DVCM led to a significant shift of trading in dark pools to periodic auctions for capped securities at each suspension start date; the first is the 12th March 2018. The increase in trading via periodic auctions is not solely attributed to the introduction of MiFIR/MiFID II in January but also the introduction of the DVCM. The periodic auction book of CBOE BXE is the most dominant venue before and after the event and experiences a jump of 44,343%. Panel D focuses on the two APAs in our sample. CBOE APA dominates pre and post the introduction of MiFIR/MiFID II. Similar to periodic auctions, we need to keep in mind that TRADEcho was introduced on the 21st November 2017, and therefore CBOE APA was the only APA within our sample up to that date. We consider the introduction of the DVCM and TRADEcho in our multivariate analyses presented in Chapter 3.6.2. Combined, the average daily trading volume jumps by 1,261%.

Table 17 focuses on the average daily trade volume per security within the FTSE 100 index and FTSE 250 index to account for different impacts depending on the market capitalisation. Panel A shows that across all venues and both indices, the average trade volume per security is increased post the introduction of MiFIR/MiFID II. We provide in addition in Appendix A.2 a corresponding overview of the impact on trade size. Naturally, the average daily trading volume of securities within the FTSE 100 index is superior to securities' respective trading volume within the FTSE 250 index. However, across all venues besides Turquoise, securities of the FTSE 250 index experience a higher increase in trading activity. The difference varies between 20-30% more for FTSE 250 index constituents traded on Aquis, CBOE BXE and CXE. Panel B focuses on dark pool trading. FTSE 250 index securities are only traded on 'classic' dark pools not on the dark order books of multilateral trading facilities. In accordance with Table 16, only classic dark pools experience a significant drop in the average trade volume, with Instinet BlockMatch experiencing an over 42% drop.

Table 17: Average daily trading activity on security base prior to and post the introduction of MiFIR/MiFID II

The table below shows the descriptive statistics on the venue-wide average daily trading volume per security during the three months preceding the introduction of MiFIR/MiFID II (1st October 2017 - 2nd

[57] Both MTF itself offer a classic mid-point matching order book, see UBS (2020) and Instinet (2020).

January 2018) and the three months after (3rd January 2018 - 31st March 2018). The trading volume per security is calculated on a daily basis, as the sum across all trading activity per day within the relevant trade type and venue. We present the daily mean and median as well as the average standard deviation. For display purposes, those parameters are divided by 100. We distinguish between securities within the FTSE 100 index and FTSE 250 index. The mean, median and standard deviation are computed from the daily observations. The last two columns report the significance of the difference in means in from of a t-test as well as the significance in difference of the variance with the Wilcoxon Rank-sum test. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

Venue	Index	Pre-regulation			Post-regulation			T-Test	Wilcoxon Rank-sum
		Mean	Std. Dev.	Median	Mean	Std. Dev.	Median		
Panel A: Continuous lit trading									
Aquis	FTSE 100	1,138.81	2,090.36	376.91	1,738.00	4,240.57	544.21	24.97***	505.61***
	FTSE 250	202.39	542.80	41.11	309.65	738.63	38.91	11.30***	4,014.50***
CBOE BXE	FTSE 100	4,630.28	11,218.90	1,705.37	6,489.48	15,109.87	2,314.41	8.01***	1,903.80***
	FTSE 250	573.80	1,304.56	185.17	916.71	2,007.89	296.82	18.25***	11,582.00***
CBOE CXE	FTSE 100	13,930.99	35,939.97	4,790.85	16,626.26	40,826.05	6,268.24	4.02***	1,954.60***
	FTSE 250	1,804.49	3,805.46	551.02	2,256.59	4,538.44	632.37	9.74***	12,638.00***
LSE	FTSE 100	34,552.05	83,055.37	12,823.96	41,303.38	92,914.13	16,061.46	4.44***	2,060.50***
	FTSE 250	529,745.7	10,477.05	1,928.71	6,456.35	11,706.77	2,436.29	9.62***	13,366.00***
Turquoise	FTSE 100	8,349.15	22,619.60	2,916.86	10,258.97	27,000.38	3,539.87	4.40***	2,016.90***
	FTSE 250	1,226.65	2,951.70	383.38	1,388.46	2,887.32	423.57	5.09***	12,968.00***
Panel B: Dark pool trading									
CBOE BXE	FTSE 100	2.61	34.26	0.00	3.27	5.55	0.10	0.87	2,184.00
	FTSE 250	0.00	0.00	0.00	0.00	0.00	0.03	-	-
CBOE CXE	FTSE 100	5.34	71.13	0.00	5.34	77.59	0.01	0.00	2,184.00
	FTSE 250	0.00	0.00	0.00	0.00	0.00	0.01	-	-
Instinet	FTSE 100	303.50	1,071.62	45.97	171.75	769.26	5.25	-8.17***	2,982.30***
Blockmatch	FTSE 250	53.01	285.77	0.00	31.52	162.26	0.00	-8.41***	15,550.00***
ITG Posit	FTSE 100	1,374.52	5,191.41	182.01	1,230.54	5,940.83	73.31	-1.49	2,702.20***
	FTSE 250	317.37	1,755.12	5.21	292.42	1,845.56	0.03	-1.26	15,867.00***
Liquidnet	FTSE 100	836.92	5,316.04	0.00	1,004.34	5,436.99	0.24	1.79*	2,051.90***
	FTSE 250	354.42	312,001.5	0.00	371.89	2,463.97	0.00	0.56	13,353.00
Turquoise	FTSE 100	9.88	167.72	0.00	9.06	140.38	0.04	-0.36	2,189.40
	FTSE 250	0.00	0.00	0.00	0.00	0.00	0.00	-	-
UBS Dark	FTSE 100	1,894.08	4,871.29	599.78	1,410.49	4,703.37	262.83	-5.83***	2,823.00***
	FTSE 250	301.89	807.35	61.94	226.54	669.22	16.05	-9.28***	16,599.00***
Panel C: Periodic auction trading									
CBOE BXE	FTSE 100	72.90	569.23	1.67	1,393.05	4,839.85	273.15	21.86***	457.64***
	FTSE 250	6.52	55.33	0.00	266.92	1,075.64	21.91	30.73***	5,628.10***
ITG Posit	FTSE 100	0.00	0.00	0.00	0.01	0.12	0.02	11.38***	2,089.80***
	FTSE 250	0.00	0.00	0.00	0.01	0.14	0.00	6.71***	13,415.00***
LSE	FTSE 100	0.00	0.00	0.00	266.92	1,075.64	21.91	-	-
	FTSE 250	0.37	13.13	0.00	0.23	14.67	0.00	-0.46**	7,563.00***
SIGMA X	FTSE 100	0.00	0.00	0.00	11.89	128.64	0.02	-0.85***	14,555.00***
	FTSE 250	0.00	0.00	0.00	5.81	73.25	0.00	6.56***	1,411.70***
Turquoise	FTSE 100	0.00	0.12	0.00	15.50	129.56	0.01	9.65***	1,790.80***
	FTSE 250	0.00	0.00	0.00	1.00	16.58	0.01	7.72***	12861.00***
Panel D: Systematic internaliser trading									
CBOE APA	FTSE 100	3,266.23	12,190.46	649.44	34,556.86	100,839.98	10,064.60	24.97***	50.56***
	FTSE 250	745.09	3,423.26	152.90	4,752.03	12,412.13	120.92	37.78***	3,394.90***
LSE	FTSE 100	21.57	242.33	0.00	5,839.69	23.083.42	530.93	20.52***	1,073.70***
TRADEcho	FTSE 250	5.19	52.49	0.00	1,039.64	6,988.03	3.93	19.23***	7,675.90***

Trading via periodic auctions increased overall, as shown in Panel C. ITG Posit and Sigma X, itself known for their dark order books, implemented periodic auction books after the introduction of MiFIR/MiFID II. Similar Turquoise, which launched their Plato Lit Auction platform in late 2017. Therefore, the most dominant periodic auction book pre MiFIR/MiFID II is on CBOE BXE. The average daily trading volume on CBOE BXE jumped by roughly 1,980%. Post MiFIR/MiFID II, the book remains the most active, followed by LSE and Turquoise. Panel D presents the development for trading via SI. As described above, LSE, or more specifically, TRADEcho and CBOE APA, act as a reporting, not an execution venue. The inferior trading volume on TRADEcho prior to MiFIR/MiFID II is partly due to the later introduction of TRADEcho in November 2017. Both reporting venues show a significant jump. The average trading volume of FTSE 100 index securities reported via CBOE APA increases from $0.33 million to $3.4 million, a jump of over 9,300%. While the average trade volume of FTSE 250 index securities is only around 15% of the size of FTSE 100 index securities, it increases by over 6,400%. LSE TRADEcho experiences a similar jump.

Table 18 reports the descriptive statistics on daily market quality metrics and selected control variables.[58] We focus first on liquidity and informational inefficiency parameters for securities within the FTSE 100 and 250 indices, respectively, to point out the magnitude in variation of those parameters depended on market capitalisation. Before the regulatory changes, quoted spreads for securities within the FTSE 100 index had a mean of 5.8bps and an effective spread of 6.5bps. Realised spreads are small at -0.5bps and price impact accordingly at 8.0bps. FTSE 100 index constituents have an average daily quoted depth of $28,837USD. Securities within the FTSE 250 index have an average quoted spread of 9.1bps and an effective spread of 18.5bps. Securities within the FTSE 250 index have a significantly higher realised spread than FTSE 100 index securities. Our sample shows a realised spread of 2.6bps and presents a price impact of 9.2bps. Securities within the FTSE 250 index only have a depth of 36% of the size FTSE 100 index securities. We apply a t-test to evaluate the significance in chance over the introduction of MiFIR/MiFID II.

Table 18: Descriptive statistics on liquidity, informational efficiency, and control variables by market capitalisation

The table below shows the descriptive statistics on index-wide average daily liquidity, informational efficiency and control parameters per security during the three months preceding the implementation of the MiFID II regulation (1st October 2017 - 2nd January 2018) and the three months after (3rd January 2018 - 31st March 2018). We distinguish between securities within the FTSE 100 index and FTSE 250 index. Quoted spreads are time-weighted based on the lit best bid and offer. Realised and effective spreads are time-weighted for all trades during continuous lit trading. Realised spreads are computed as the mid-point 1 second after the trade. Quoted, effective and realised spread measures are calculated relative to the mid-point in bps. $Price\ Impact_{i,d}$ refers to daily, security-specific difference of effective and realised spread. $Lit\ Quoted\ Depth_{i,d}$ is the time-weighted quoted \$-Depth at the NBBO on a security-day basis. $Autocorrelation_{i,d}$ is based on 10-second mid-point return. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Variance\ Ratio_{i,d}$ measures the variance-ratio of the standard deviation on 1-second and 10-second mid-point returns. $Lit\ \$Volume_{i,d}$ refers to the traded \$-Volume on a security-day basis on the continuous lit venue. $MarketCap_{i,d}$ is the securities' historical daily market capitalisation. $Off.Closing\ Price_{i,d}$ refers to the daily official closing price of the relevant security. The last two columns report the difference in means of the relevant parameter before and after the regulation came into effect, using a two-tailed t-test and the

[58] Table 16 provides an overview of the same market quality parameters across the lit trading venues.

significance in difference of the variance with a Wilcoxon Rank-sum test. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

Measure	Index	Pre-regulation			Post-regulation			T-Test	Wilcoxon Rank-sum
		Mean	Std. Dev.	Median	Mean	Std. Dev.	Median		
Panel A: Liquidity parameters									
$Quoted$	FTSE 100	5.80	4.95	4.55	5.57	4.93	4.02	-3.97%***	204.20***
$Spread_{i,d}$	FTSE 250	9.12	7.04	8.05	9.97	7.36	9.23	9.32%***	898.24***
$Effective$	FTSE 100	6.51	3.37	6.26	5.50	3.02	4.88	-15.51%***	236.68***
$Spread_{i,d}$	FTSE 250	18.47	16.57	12.89	19.24	15.53	14.50	4.17%***	903.79***
$Realised$	FTSE 100	-0.53	2.94	-0.68	-0.46	3.04	-0.62	-13.21%***	191.35***
$Spread_{i,d}$	FTSE 250	2.62	26.51	-0.36	3.85	23.90	-	46.95%***	905.25***
$Price$	FTSE 100	8.02	6.16	8.70	9.11	9.21	9.07	13.59%***	176.93***
$Impact_{i,d}$	FTSE 250	9.24	7.66	10.02	10.33	5.51	9.63	11.80%***	858.62***
$Lit\ Quoted$	FTSE 100	25,252.06	17,221.47	20,655.76	28,837.46	22,580.72	24,351.65	14.20%***	535.25***
$Depth_{i,d}$	FTSE 250	12,594.56	13,440.68	8,346.48	10,501.40	11,439.59	7,419.72	-16.62%***	2,734.30***
Panel B: Informational inefficiency parameters									
$Autocor-$	FTSE 100	-0.06	0.07	-0.05	-0.05	0.08	-0.03	16.67%***	164.86***
$relation_{i,d}$	FTSE 250	-0.08	0.10	-0.54	-0.07	0.10	-0.04	12.50%***	891.92***
$Variance$	FTSE 100	1.21	0.20	1.16	1.10	0.13	1.06	-9.09%***	274.39***
$Ratio_{i,d}$	FTSE 250	1.27	0.24	1.21	1.16	0.17	1.10	-8.66%***	12,278.00**
$HFVol_{i,d}$	FTSE 100	38.12	66.12	15.36	50.19	82.74	17.56	31.66%***	173.49***
	FTSE 250	33.36	56.01	14.81	45.05	79.77	17.96	35.04%***	868.15***
Panel C: Control parameters									
$LitVolume_{i,d}$	FTSE 100	4,903.6	12,628.2	445.3	7,688.6	18,658.5	1,013.8	56.79%***	535.25***
$*\ ('000)$	FTSE 250	489.6	1,659.2	4.4	723.5	2,330.2	8.9	47.76%***	2,734.30***
$Market$	FTSE 100	35,045.52	54,671.49	12,416.92	35,961.25	56,094.02	12,613.34	2.61%***	529.49***
$Cap_{i,d}$	FTSE 250	2,716.47	3,769.11	2,034.24	2,696.24	3,635.57	2,005.96	-0.74%*	2,780.80***
$Off.$	FTSE 100	21.48	23.23	12.50	24.65	23.78	17.17	14.76%***	170.11***
$Closing\ Price_{i,d}$	FTSE 250	9.93	27.84	5.07	11.66	30.24	6.44	17.42%***	849.08***
$Volatility_{i,d}$	FTSE 100	109.16	56.53	95.54	120.33	49.60	107.84	10.23%***	155.05***
	FTSE 250	176.71	117.89	145.42	177.42	89.83	158.72	0.40%***	888.78***

3.6.2 Instrumental variables regressions for SI trading

The endogeneity of dark trading with respect to market conditions is one of the main challenges when studying the empirical relation of any form of opaque trading on market quality in general. Kwan et al. (2015) show that spreads constrained the minimum tick size led to enhanced dark trading as dark trading venues allow trading at sub-penny increments. Buti et al. (2011) find a positive relation between dark pool liquidity and lit market depth, small spreads, and larger tick sizes. To overcome the endogeneity issue, we rely on the unexpected shift of non-price forming OTC trading to SI as an instrumental variable for systematic internaliser trading in a 2SLS model. The first-stage of the 2SLS model is a regression of the level of systematic internaliser trading, measured as the daily market share in trade value of the relevant instrument. A comprehensive overview is provided in Chapter 3.5.2. Our multivariate analyses cover a horizon from 5th October 2017 to 28th March 2018. We include, therefore, events with potential bias as the introduction of TRADEcho on 21st November 2017 and when the DVCM came into effect on 12th March 2018. Our additional tests show that our results are robust independent of the chosen horizon.

We estimate the first-stage regression without and with stock-fixed effects to assure robust results as shown in Table 19 in specification (1) and (2).

Table 19: First-stage regression of the impact of SI trading on market quality

The table presents the estimates from the first-stage instrumental variables regressions in which the endogenous variable for which we instrument is the share of SI total dollar volume $SI\_V_{i,d}$ of a security i on day d :

$$SI\_V_{i,d} = \alpha_i + \beta_1 M_d^{Post} + \beta_2 SI\_V_{i,d-1} + \sum\nolimits_{j=1}^{3} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The instrumental variables are M_d^{Post}, which equals 1 after the 3rd January 2018 and 0 prior, and $SI\_V_{i,d-1}$ the lagged share of SI trading. We add 3 control variables. $trend_{i,d}$ is a variable starting at 0 at the beginning of our sample and increments by 1 till the last day within our sample. $Volatility_{i,d}$ refers to the mean daily interday volatility of a relevant security. We include the market capitalisation of a relevant security to account for differences in the size of an instrument. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index from 5th October 2017 till 28th March 2018, which is equivalent to 60 full trading days before and after the event. Standard errors are clustered by security and date. Specification (2) is the same as specification (1) with additional stock-fixed effects. T-statistics are reported in parentheses. ***, **, * indicated the statistical significance at a 1%, 5% and 10% level respectively. The F-statistic tests the null hypothesis that all instruments do not affect the level of SI trading.

	(1)	(2)
$Intercept_{i,d}$	0.07***	0.05***
	(12.61)	(15.08)
$Post_{i,d}$	0.24***	0.26***
	(131.40)	(143.55)
$SI\ trading_{i,d-1}$	0.37***	0.19***
	(157.87)	(90.76)
$Trend_{i,d}$	0.00***	0.00***
	(35.75)	(39.40)
$Volatility_{i,d}$	-0.01***	-0.02***
	(-20.04)	(-14.69)
$Market\ cap_{i,d}$	0.00***	0.00***
	(29.95)	(4.78)
Obs.	207,263	207,263
Adj. R^2	0.51	0.54
F-Test	44,380	44,120
Fixed Effects	None	Stock

We estimate our second-stage regression based on the fitted estimates of specification (2). The findings indicate that when MiFIR/MiFID II came into effect, the market share of systematic internaliser trading increased by 14.5 percentile points, see specification (2) when all other parameters are held constant. Those results align with our descriptive results shown in Table 14.[59]

Table 19 shows, the lagged SI trade volume share increases by 19.5%, when all parameters are held constant at a 1% significance level. The F-statistics reject the null hypothesis of weak instrumental variables.[60] The respective security's market capitalisation, as well as the time trend, do not seem to drive the SI market share also, the parameters are significant. Our results show a highly significant negative relation between interday volatility and SI market share. Table 18

[59] Our study will specify the study on the impact of SI trading on market quality by distinguishing between limit and mid-point orders. We will run first-stage regressions with SI trade volume share via limit and mid-point orders separately and estimate their fitted values accordingly to study the respective impact.

[60] Critical values are specified in tables presented in Stock and Yogo (2005).

showed that MiFIR/MiFID II's introduction led to a significant jump in interday volatility overall. Securities within the FTSE 250 index present a much higher interday volatility prior to and post the regulatory changes and have a significantly lower mean daily SI trade volume than securities within the FTSE 100 index. The relationship presented in Table 20 is therefore expected. The second-stage regressions estimate the quantitative impact of systematic internaliser trading on parameters of liquidity and informational efficiency. Based on specification (2), we estimated the respective market quality parameter with the estimated fitted values for the SI trade value share-based on specification (1) and the findings in Table 19. We include the same control variables as described for the first-stage regression.

Table 20 reports our second-stage estimates, evaluating the impact of SI trading overall, without consideration of the trade type, on liquidity and informational efficiency parameters. We present three parameters for transaction costs, which present inconsistent results. SI trading tightens effective spread by 5.1bps at a 10% significance level. Quoted spread decreases by approximately 1.7bps when the SI trade value share increases by 1% at a 10% significance level. Realised spread however, increases by approximately 0.04bps, but the coefficient is insignificant. We find a falling price impact of 5.5bps at a 5% significance level. SI trading presents a positive relationship to quoted depth on the lit venues, however, only at a 10% significance level. The opposite direction and difference in magnitude of impact for two liquidity parameters and otherwise insignificant findings suggest that evaluating the relation is not definite, supporting the hypothesis. The last three columns present the results for the relation between SI trading and parameters for informational efficiency.

Table 20: Second-stage regression of the impact of SI trading on market quality

The table reports the estimates from the second-stage instrument variables regressions:

$$y_{i,d} = \alpha_i + \beta_1 \widehat{SI\_V}_{i,d} + \sum_{j=1}^{3} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The dependent variables $y_{i,d}$ are estimates of transaction costs, liquidity and informational efficiency. Quoted spreads are time-weighted based on the lit best bid and offer on the relevant venue. Realised and effective spreads are time-weighted for all trades during continuous lit trading. Realised spreads are computed as the mid-point 1 second after the trade. Quoted, effective and realised spread measures are calculated relative to the mid-point in basis points. $Price\ Impact_{i,d}$ refers to the difference of effective and realised spread, computed on a security-day basis. $(Lit)\ Quoted\ Depth_{i,d}$ is the time-weighted quoted \$-Depth at the NBBO on a security-day basis. $Autocorrelation_{i,d}$ is based on 10-second mid-point returns, whereas $HFVol_{i,d}$ is added as a 10-second mid-point return standard deviations during continuous lit trading hours. $Variance\ Ratio_{i,d}$ measures the variance-ratio of the standard deviations on 1-second and 10-second mid-point returns.

We include 3 control variables. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $MarketCap_{i,d}$ is the security's market capitalisation on a daily basis. $Trend_d$ controlling for changes in the dependent variable over our study horizon. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index during the period of 5th October 2017 till 28th March 2018, which is equivalent to 60 full trading days before and after the event.

Standard errors are clustered by security and day. Adj. R^2 s do not report the variance explained by the fixed effects. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	$Effective\ Spread_{i,d}$	$Quoted\ Spread_{i,d}$	$Realised\ Spread_{i,d}$	$Price\ Impact_{i,d}$	$\log\left(\frac{Quoted}{Depth}\right)_{i,d}$	$Autocor\text{-}relation_{i,d}$	$Variance\ Ratio_{i,d}$	$HFVol_{i,d}$
$Intercept_{i,d}$	10.13***	7.24***	2.06***	10.69***	9.33***	-0.06***	27.47***	12.13***
	(58.53)	(68.19)	(8.44)	(9.78)	(29.96)	(-23.17)	(12.26)	(58.57)
$SI\ \widehat{trading}_{i,d}$	-5.08*	-1.65*	4.26	-5.47**	0.61*	-0.17***	-32.68***	-2.04
	(-1.42)	(-1.85)	(3.21)	(-1.48)	(1.37)	(-7.24)	(-3.39)	(-1.47)
$Market\ cap_{i,d}$	-0.00***	-0.00***	-0.00	-0.00***	0.00	0.00	0.00	-0.00***
	(-3.22)	(-4.57)	(-1.27)	(-3.59)	(0.32)	(1.09)	(0.34)	(-3.22)
$Trend_{i,d}$	-0.01	0.01***	-0.04	-0.01	-0.01***	-0.00***	0.29***	-0.01
	(-0.28)	(4.59)	(-1.09)	(1.04)	(-3.75)	(-6.56)	(7.96)	(-0.28)
$Volatility_{i,d}$	0.04***	-0.03***	0.02	-0.00***	-0.00	-0.00	0.01	0.04***
	(20.95)	(-4.16)	(1.26)	(-3.79)	(-0.13)	(-1.08)	(0.23)	(20.98)
Obs.	207,261	207,261	207,261	78,468	203,406	207,263	207,263	207,261
Adj. R^2	0.51	0.61	0.21	0.49	0.75	-0.01	0.07	0.59
F-Test	114.70	18.63	16.43	7.41	4.77	316.40	37.10	31.10
Fixed Effects	Stock	Stock	Stock	Stock	Stock	Stock	Stock	Stock

The findings suggest that SI trading is beneficial to informational efficiency. Autocorrelation, variance-ratio as well as high-frequency volatility. In contrast to liquidity measures, the magnitude of the impact is better evaluated in terms of standard deviations. A one standard deviation increase in SI trade value share would decrease autocorrelation by 0.065 standard deviations and variance-ratio by 5.943 standard deviations when controlling for other market parameters and security-fixed effects. The relation between liquidity and informational efficiency is consistent with our findings of a positive relation between SI trading and informational efficiency.[61]

The positive relation of aggregate SI trading and informational efficiency is most likely driven by limit-order SI trading. As Boulatov and George (2008) show, the ability to submit SI limit-orders increases the liquidity provision of informed traders and trade aggressiveness, enhancing informational efficiency. Time trend coefficients are not indicating a consistent development of spreads over our sample period. Quoted spreads seem to widen our sample period, while effective spread and realised spread do not follow a statistically significant trend. Quoted depth on the lit trading venues significantly falls over our sample period, which is driven by securities traded on the two largest venues in our sample and likely securities with smaller market capitalisation.[62] Higher volatility is associated with a wider effective spread and a drop in quoted spreads. The adjusted R^2 of our regressions ranges between 21% and 75% for liquidity parameters and 0% to 59% for informational efficiency parameters. This suggests especially for the regressions including informational efficiency parameters that other factors than the variables

[61] See Chordia et al. (2008).

[62] Please see the descriptive statistics in Table 18. A drop in quoted depth on the lit trading venues cannot be interpreted as a solely negative impact, as we are not able to observe market depth in total. The drop can indeed indicate a drop in market depth overall, however likely not the full magnitude. We display the shift at the best bid and ask; therefore, the finding could represent a shift within the order book but can also show a shift of market depth to venues, where we are not able to observe the order book.

included drive those parameters.

We vary equation (2) to test the robustness of our findings in Table 20. Table 21 reports the SI trading coefficients only for the relevant liquidity and informational efficiency parameters.

The findings act as robustness tests and extended analyses and are overall consistent with our baseline speciation presented in column (1). Our results are robust when we extend the sample horizon, including major regulatory events which impact the UK trading environment, see specification (3). The significance in impact on transaction costs is lowered, however market efficiency parameters increase in significance. Minor variations to the first-stage regression ((2) and (4)) do not lead to contrary findings in the second-stage regression. We find that mostly spreads of securities with an inferior trade value share in SI trading are narrowing if the SI trade value share increases, see specifications (8) and (9). Securities with an already dominant share in SI trading are less sensitive to changes in the market of SI trading. Specification (6) shows that predominantly securities with a larger market capitalisation improve in liquidity, especially transaction costs parameters. However, specifications (6) and (7) also provide further insight into the statistically insignificant coefficient of quoted depth in the baseline specification (1).

A higher SI trade value share leads to a drop in quoted depth for securities within the FTSE 100 index at a 5% significance level but increases the same parameter at a slightly higher rate for securities within the FTSE 250 index at a 1% significance level. Table 18 showed that securities within the FTSE 100 index present a much higher quoted depth than securities within the FTSE 250 index and improve post MiFIR/MiFID II came into effect while the same measure drops significantly for securities within the FTSE 250 index. Informational efficiency coefficients are largely consistent with the baseline specification.

Table 21: Second-stage regression of the impact of SI trading on market quality: Robustness analyses
The table reports the coefficients of the independent variables in the second-stage regressions for eight different specifications. The independent variable to which the coefficient estimates $\widehat{SI\_V}_{i,d}$ correspond is the fitted estimate of the security's trade value market share in systematic internaliser. The rows correspond to different dependent variables and the columns correspond to a variation of equation (2) which we refer to as our baseline specification. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index during the period of 5th October 2017 till 28th March 2018, which is equivalent to 60 full trading days before and after the event.
Specification (1) matches our baseline regression and estimates as shown in Table 20 and acts as an easy comparison to our additional specifications. Specification (2) is identical to the baseline specification except the first-stage regression is based on a pooled regression. Specification (3) matches the baseline specification but limits the sample horizon to exclude major events. The sample covers a period of 22nd November 2017 till 9th February 2018, which is equivalent to 28 full trading days before and after the event therefore excluding the introduction of TRADEcho prior to the new market regulation and the start of the DVCM after the introduction of MiFIR/MiFID II. Specification (4) is identical to (1) but uses only the dummy variable defining the pre- and post- period in regard to the introduction of MiFIR/MiFID II as an instrumental variable. Specification (5) matches the baseline specification but excludes 5 full trading days prior to and post MiFIR/MiFID II came into effect to account for market volatility due to the regulatory changes. Specification (6) limits our sample to securities within the FTSE 100 index over our sample period

and matches otherwise the baseline specification. Accordingly limits specification (7) our sample to securities of the FTSE 250 index and matches otherwise our baseline specification. Specification (8) is identical to our baseline specification but limits the sample to securities with a SI trade value market share larger than >50% whereas specification (9) limits the security sample to securities with a SI trade value market share below 50%. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Effective\ Spread_{i,d}$	-5.08**	-2.13	-2.43**	-1.75	-5.76*	-7.27***	0.92	-14.89	-7.23***
$Quoted\ Spread_{i,d}$	-1.65*	-5.27***	-1.84*	-5.89***	-2.89	-5.86***	-4.66*	-14.72*	-7.89***
$Realized\ Spread_{i,d}$	4.26***	-7.32	5.45*	9.70**	0.05	-0.72	-8.02	84.99	1.81
$Price\ Impact_{i,d}$	-5.35**	-2.60*	-2.03	-1.88**	-5.80*	-7.05	-1.36**	-8.86	-5.72**
$l\ (Quoted\ Depth)_{i,d}$	0.61	0.59*	0.61*	0.43	0.34	-0.56**	0.67***	-0.71	-0.45
$Autocorrelation_{i,d}$	-0.17***	-0.05*	-0.15***	-0.07**	-0.21***	-0.05	-0.08*	-0.11	-0.08**
$Variance\ Ratio_{i,d}$	-32.68***	-0.16*	-0.37***	-0.16	-0.14	-0.26**	-0.15	-2.37*	-0.12
$HFVol_{i,d}$	-2.04	-28.79**	-34.09***	-37.41**	-45.94*	-26.66	-43.69**	-885.23**	-23.59
Obs.	207,261	207,261	398,124	207,261	172,679	122,076	85,184	8,967	198,294
First-stage	Stock	Pooled	Stock	Stock	Stock	Stock	Stock	Stock	Stock
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS

3.6.3 Instrumental variables regressions for mid-point and limit-order SI trading

Our study aims to provide a deeper insight into contradictory findings on the relation between dark trading and market quality. In Chapter 3.6.2, we were able to show that SI trading as a form of dark trading presents a similar relation to market quality as literature finds. In this chapter, we aim to determine whether different trade types are driving the findings. We disaggregate SI trading into trading via limit-orders and mid-point orders. SI mid-point trades are defined as trades executed at the prevailing mid-point of the best bid and ask for the relevant security, often referred to as the EBBO. Consequently, trades executed at another price than the mid-point of the prevailing EBBO are classified as limit-order trades. We compute the respective trade value share of those two types of SI trading versus the relevant security's total daily trade value.[63] We run first-stage regressions following equations (8) and (9) as described in Chapter 3.5.2 separately and estimate the respective fitted values $\widehat{SI-mid}_{i,d}$ and $\widehat{SI-limit}_{i,d}$.[64]

We follow the same methodology as used in Chapter 3.6.2, including two instrumental variables for the respective mid-point and limit-order SI trade value share, an event dummy equal to zero prior to the event and equal to one after MiFIR/MiFID II came into effect. In addition, we add the lagged value share of the respective type of trading.

Table 22 presents the second-stage regression estimates, showing that SI trades executed

[63] Please note that we are relying on the NBBO in our study, as we cannot observe quotes across all European lit trading venues. The NBBO observed on the five biggest lit trading venues in the UK (and Europe) should be a close proxy or equivalent to the EBBO for securities listed within the FTSE 100 index and FTSE 250 index.

[64] The respective F-statistic of each first-stage regression (F-statistic equals 363.81 for limit-order SI trading and 289.12 for mid-point SI trading, respectively) is greater than the critical values specified by Stock and Yogo (2005), showing that the joint hypothesis that the instruments are insignificant is false.

at the prevailing mid-point have either no impact on market quality or a negative.

The finding is consistent with our hypotheses 2 and 3. Limit-order SI trading is associated with lower transaction costs and higher liquidity on the lit venues. Furthermore, limit-order SI trading is beneficial to informational efficiency. If the SI trade value share of trading executed at the mid-point of the prevailing NBBO increases by 1%, the quoted depth on the lit venues by 441% if all other parameters are held constant. The coefficients for spreads are not statistically significant. That is not surprising as, by definition, mid-point SI trading has a zero spread. Parameters for informational efficiency in the form of variance-ratio and high-frequency volatility do not show a significant relation to mid-point SI trading. Autocorrelation, however, increases by 0.042 standard deviations at a 1% significance level if mid-point SI trade value share increases by one standard deviation.[65] Our results suggest SI trading executed via limit-orders is strongly beneficial to market quality. Our coefficients for informational efficiency, autocorrelation and variance-ratio show a highly significant positive relation to limit-order SI trading, high-frequency volatility improves at a 5% significance level.

In terms of magnitude, a one standard deviation increase in limit-order SI trade value share improves autocorrelation by 0.005 standard deviations, variance-ratio by 0.006 standard deviations and high-frequency volatility by 0.002 standard deviations.[66] Liquidity parameters are consistently improving with an increasing market share of limit-order SI trade value. Effective spread and realised spread are narrowing by 3.63bps and 9.07 respectively at a 5% significance level if the limit-order SI trade value share increases by 1%. Accordingly, quoted spreads narrow by 3.67bps at a 1% significance level. Quoted depth improves at a 1% significance level about 6% when the SI trade value share via limit-orders increases by 1%. Our results show further that effective spread narrows by 3.14bps at a 10% significance level when mid-point trading via SI increases.

Table 22: Second-stage regression of the impact of mid-point and limit-order SI trading on market quality

The table reports the estimates from the second-stage instrument variables regressions including both the fitted values of both forms of SI trading:

$$y_{i,d} = \alpha_i + \beta_1 \widehat{SI\_mid}_{i,d} + \beta_2 \widehat{SI\_limit}_{i,d} + \sum_{j=1}^{3} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The dependent variables $y_{i,d}$ are estimates of transaction costs, liquidity and informational efficiency. Quoted spreads are time-weighted based on the lit best bid and offer on the relevant venue. Realised and effective spreads are time-weighted for all trades during continuous lit trading. Realised spreads are

[65] One standard deviation mid-point SI trade value share is equivalent to 0.48%; autocorrelation has a standard deviation of 0.085. The magnitude is equivalent to 0.0048*(0.75/0.085).

[66] One standard deviation limit-order SI trade value share is equivalent to 2.98%, autocorrelation has a standard deviation of 0.085, variance-ratio 0.185 and high-frequency volatility 70.5. The magnitude is equivalent to 0.0298*(-0.14/0.085), 0.0298*(-0.37/0.185) and 0.0298*(-3.63/70.5).

computed as the mid-point 1 second after the trade. Quoted, effective and realised spread measures are calculated relative to the mid-point in bps. $Price\ Impact_{i,d}$ refers to the difference of effective and realised spread, computed on a security-day basis. $Lit\ Quoted\ Depth_{i,d}$ is the time-weighted quoted \$-Depth at the NBBO on a security-day basis. $Autocorrelation_{i,d}$ is based on 10-second mid-point returns, whereas $HFVol_{i,d}$ is added as a 10-second mid-point return standard deviations during continuous lit trading hours. $Variance\ Ratio_{i,d}$ measures the variance-ratio of the standard deviations on 1-second and 10-second mid-point returns.
We include 3 control variables. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $MarketCap_{i,d}$ is the security's market capitalisation on a daily basis. $Trend_d$ controlling for changes in the dependent variable over our study horizon. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index during the period of 5th October 2017 till 28th March 2018, which is equivalent to 60 full trading days before and after the event.
Standard errors are clustered by security and day. Adj. R^2 s do not report the variance explained by the fixed effects. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	$Effective\ Spread_{i,d}$	$Quoted\ Spread_{i,d}$	$Realised\ Spread_{i,d}$	$Price\ Impact_{i,d}$	$l(Quoted\ Depth)_{i,d}$	$Autocorrelation_{i,d}$	$Variance\ Ratio_{i,d}$	$HFVol_{i,d}$
$Intercept_{i,d}$	10.88***	7.56***	5.87***	9.12***	9.62***	-0.06***	1.23***	11.81***
	(40.63)	(20.98)	(3.04)	(12.36)	(18.93)	(-20.4)	(106.01)	(40.63)
$\widehat{SI-mid}_{i,d}$	3.14*	-8.44	14.82	4.63	-4.41***	0.75*	-0.19**	39.14
	(1.16)	(-0.80)	(0.25)	(0.78)	(-5.01)	(2.78)	(0.18)	(1.16)
$\widehat{SI-limit}_{i,d}$	-3.63**	-3.67***	-9.07**	-6.16***	0.06***	-0.14***	-0.37***	-3.62**
	(-2.36)	(-3.33)	(-2.18)	(-3.57)	(2.97)	(-6.59)	(-3.73)	(-2.36)
$Market\ cap_{i,d}$	-0.00***	-0.00***	0.00	-0.00	0.00***	0.00	0.00***	0.00
	(-2.69)	(-3.86)	(0.14)	(-0.41)	(2.76)	(1.16)	(2.86)	(0.04)
$Trend_{i,d}$	-0.02	-0.29***	-0.03	0.00***	0.00***	-0.00***	-0.00	-1.78***
	(-0.45)	(-7.57)	(-1.12)	(3.89)	(6.44)	(-6.77)	(-1.43)	(-3.83)
$Volatility_{i,d}$	0.05***	-0.04***	-0.04*	0.00***	-0.00***	-0.00	0.00*	0.02
	(19.89)	(-5.86)	(-1.90)	(25.91)	(-17.15)	(-0.42)	(1.81)	(0.46)
Obs.	207,261	207,261	207,261	78,468	203,406	207,263	207,263	207,261
Adj. R^2	0.52	0.61	0.21	0.49	0.75	-0.01	0.07	0.59
F-Test	114.75	18.63	16.43	7.41	4.71	316.40	37.10	31.10
Fixed Effects	Stock	Stock	Stock	Stock	Stock	Stock	Stock	Stock

Our findings support our hypothesis that the relation between SI trading and market quality depends on the order type. Limit-order SI trading is clearly beneficial to market quality. In contrast, our findings for SI trading via mid-points are insignificant but not strictly negative.

To support our results, we run similar robustness tests as for our analyses about the impact of aggregate SI trading on market quality. We report those robustness tests in Table 23 for SI trading following the same methodology as applied in Table 22. In Table 24, regressions are split in trading via limit-orders SI trading executed at the mid-point of the prevailing NBBO respectively to evaluate the impact when the respective other types of trading is not controlled for.

With the exception of quoted depth on lit trading venues, the coefficients in Panel A do not interfere with our conclusions that limit-order SI trading overall tends to be beneficial to market quality. Panel A reports twice a weak negative relation between quoted depth on lit trading venues and an increase in limit-order SI trade share. Once in specification (7), therefore for securities within the FTSE 250 index as well as for securities with a lower SI trade value market share, see specification (9). We are not able to observe the total depth available on the market. We are unable to observe depth on any dark trading venue, systematic internaliser, as well as on dark pools. Therefore, a drop (or consequently an increase) in lit market quoted depth does not imply an overall market drop or jump in depth.[67] There is variation in our dependent variables regarding the magnitude and significance across our specifications. We find that the significance of our results relates on the stock-fixed effects used in the first-stage regression. Specification (2) shows less significant coefficients in terms of the relation of limit-order SI trading and market liquidity, and only variance-ratio as a parameter for informational efficiency presents a positive relation at a 10% significance level, whereas other coefficients are insignificant. Specification (3) shows that our findings are highly significant over a shorter horizon of 3 months pre, and post MiFIR/MiFID II came into effect. Specification (4), similar to (2), alters the first-stage regression. The second stage findings become mostly insignificant but do not contradict our findings in (1). Specification (5) indicates that the initial jump in market quality parameters is more driven by limit-order trading than the remaining sample period. When we concentrate our sample on securities within the FTSE 100 index seem to drive our findings. Specification (6) has highly significant coefficients for effective and quoted spread are highly significant with a higher magnitude than in the baseline specification.

Table 23: Second-stage regression of the impact of limit-order and mid-point SI trading on market quality: Robustness test

The table reports the coefficients of the independent variables in the second-stage regressions for eight additional specifications. The independent variable to which the coefficient estimates $\widehat{SI\_limit}_{i,d}$ correspond is the fitted estimate of the security's limit-order trade value market share in systematic internaliser. Accordingly, $\widehat{SI\_mid}_{i,d}$ refers to the fitted estimate of the security's mid-point trade value market share in SI. The rows correspond to different dependent variables and the columns correspond to a variation of the following equation which we refer to as our baseline specification

$$y_{i,d} = \alpha_i + \beta_1 \widehat{SI\_limit}_{i,d} + \beta_2 \widehat{SI\_mid}_{i,d} + \sum_{j=1}^{3} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

Panel A shows the coefficients for $\widehat{SI\_limit}_{i,d}$, Panel B reports the coefficients for $\widehat{SI\_mid}_{i,d}$. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index during the period of 5th October 2017 till 28th March 2018, which is equivalent to 60 full trading days before and after the event.

Specification (1) matches our baseline specification and acts as an easy comparison to our additional specifications. Specification (2) is identical to the baseline specification expect the first-stage regression is based on a pooled regression. Specification (3) matches the baseline specification but limits the sample horizon. The sample covers a period from 22nd November 2017 to 9th February 2018, which is equivalent to 28 days post and prior to implementation, therefore excluding the introduction of TRADEcho prior to the new market regulation and the start of the DVCM after the introduction of MiFIR/MiFID II. Specification (4) is identical to (1) but uses only the dummy variable defining the pre- and post- period in regard to the introduction of MiFIR/MiFID II as an instrumental variable. Specification (5) matches the baseline specification but excludes 5 full trading days prior to and post MiFIR/MiFID II came into effect to account for market volatility due to the regulatory changes. Specification (6) limits our sample to

[67] Foley and Putniņš (2016) find that dark trading on an aggregate level is not significantly related to relative lit market depth, computed as the ratio of lit dollar depth to lit traded dollar volume.

securities within the FTSE 100 index over our sample period and matches otherwise the baseline specification. Accordingly limits specification (7) our sample to securities of the FTSE 250 index and matches otherwise our baseline specification. Specification (8) is identical to our baseline specification but limits the sample to securities with a SI trade value market share larger than >50% whereas specification (9) limits the security sample to securities with a SI trade value market share below 50%. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Second-stage regression of the impact of limit-order SI trading on market quality									
$Effective\ Spread_{i,d}$	-3.63**	-2.29	-3.78**	56.69***	-5.83*	-6.68***	-0.90	-29.63	-7.43***
$Quoted\ Spread_{i,d}$	-3.67***	-3.67***	-1.93**	-10.51***	-2.92	-5.77***	-3.95**	-19.77**	-7.93***
$Realized\ Spread_{i,d}$	-9.07**	-4.15	-9.21**	-4.33	1.25	-0.65	-8.07*	73.80	1.71
$Price\ Impact_{i,d}$	-5.16***	-4.32*	5.01	4.64	-2.45*	-2.07**	-2.50	-4.27	-2.57**
$l(Quoted\ Depth)_{i,d}$	0.06***	-0.32	-0.56	0.12	-0.14	-0.45	-0.08*	0.45	-0.22*
$Autocorrelation_{i,d}$	-0.14***	0.03	0.13***	-0.02	0.13***	0.06	0.04	-0.28	0.07**
$Variance\ Ratio_{i,d}$	-0.37***	-0.12*	-0.36***	-0.23	-0.16	-0.27**	-0.12	0.62	-0.11
$HFVol_{i,d}$	-3.62**	-14.02	-34.08***	-42.11*	-25.98	-34.04**	-14.67	3.08	-24.70
Panel B: Second-stage regression of the impact of mid-point SI trading on market quality									
$Effective\ Spread_{i,d}$	3.14	39.63	-223.05*	31.77	88.89**	51.86	-92.03**	91.72	23.78
$Quoted\ Spread_{i,d}$	-8.44	2.78	176.38**	12.78	14.08	-20.31	-31.50**	31.59	-8.44
$Realized\ Spread_{i,d}$	14.82	15.68	536.20*	108.90	12.45	42.94	-69.97	41.80	25.84
$Price\ Impact_{i,d}$	3.63	-3.70	-8.01*	4.73	-4.64	-3.33*	-4.28	4.78	-22.68
$l\ (Quoted\ Depth)_{i,d}$	-4.41***	2.34	-0.92	1.22*	2.14***	-2.31***	3.21	1.92	1.62**
$Autocorrelation_{i,d}$	0.75*	0.99***	3.86**	0.86**	1.39**	0.67	0.32	0.08	0.45**
$Variance\ Ratio_{i,d}$	-0.19**	-0.38	2.59	-0.86	-1.89	0.84	-0.98	-2.75	-0.64
$HFVol_{i,d}$	39.14	1.47	179.45	-274.71	5.34	-386.47*	343.93**	9.83	-241.74**
Obs.	207,261	207,261	86,242	209,486	190,683	63,557	143,704	5,070	162,984
First-stage	Stock	Pooled	Stock	Stock	Stock	Stock	Stock	Stock	Stock
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS

Those findings are in accordance with Buti et al. (2011b), their model suggests that market orders for larger and likely more liquid securities are rather executed on dark pools, which in turn tightens spreads on the lit venues. Illiquid securities tend to be executed via limit-orders on dark trading venues which widens spreads. Specification (9) shows that in accordance with the findings in Table 22, effective spread is mainly driven by securities with limit-order SI trading below 50% of the average trade value.

Panel B reports the main coefficients for SI trading via mid-points across our specifications. Those results are overall less significant and for effective spread and quoted depth not in line with the baseline scenario. We find that if we shorten the sample horizon, effective spread is in fact improving at a 10% significance level. Securities within the FTSE 250 index show a drop in effective spread at a 5% significance level. Similar, we observe heterogeneous results for quoted depth on the lit trading venues, quoted spread and high-frequency volatility. Those findings might be in line with literature where no definitive relation can be determined. As mid-point trading by definition should not contribute to either price discovery or spreads, those findings might be driven by statistical outliers.

We extend our robustness test by running the second-stage regression for both types of SI trading separately, allowing us to evaluate the impact of both types of trading on an individual base. We estimate the first-stage equations separately as previously, however run the second-stage regressions for each limit-order and mid-point SI trading on an individual base. Table 24, Panel A shows our findings for limit-order SI trading.

The results are in general conforming with Table 22. The coefficients are less significant than the original results in Table 22 but present a superior significance level to the robustness tests shown in Panel A in Table 23. Transaction cost parameters effective and quoted spread are mostly significant. The findings show that transaction costs of securities within the FTSE 100 index are driven by limit-order SI trading, whereas securities with a lower market cap seem to unimpacted. We can conclude that transaction costs in form of effective spread and quoted spread drop at a significant level, if securities are within the FTSE 100 index and are not already traded via limit-order SI trading at a superior level, hence, their respective limit-order SI trade value share is below 50%. The coefficient for realised spread is indicating a 6.41bps wider spread for our baseline scenario at a 10% significance level. However, the remaining specifications are either indicating a positive relation between an increase in limit-order SI trading and transaction costs or none.

Especially when shortening the sample horizon (specification (3)), realised spreads are significantly tighter. While we find that the coefficients variance-ratio and high-frequency indicate that a higher share of limit-order SI trading enhances informational efficiency, which is in accordance with the results shown in Table 23, the coefficients for autocorrelation for specification (2) and (9) indicate a negative relation at a 10% significance level.

Table 24: Second-stage regression of the impact of limit-order SI trading on market quality: Robustness test

The table presents the coefficients of the independent variables in the second-stage regressions for nine additional specifications. The independent variable to which the coefficient estimates $\widehat{SI_{limit}}_{i,d}$ correspond is the fitted estimate of the security's trade value market share in limit-order systematic internaliser trading. Accordingly, $\widehat{SI_{mid}}_{i,d}$ corresponds to the he fitted estimate of the security's trade value market share in mid-point systematic internaliser trading. The rows correspond to different dependent variables and the columns correspond to a variation of the following equation which we refer to as our baseline specification for Panel A:

$$y_{i,d} = \alpha_i + \beta_1 \widehat{SI_{limit}}_{i,d} + \sum\nolimits_{j=1}^{3} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The baseline specification or specification (1) for Panel B is estimation as:

$$y_{i,d} = \alpha_i + \beta_1 \widehat{SI_{mid}}_{i,d} + \sum\nolimits_{j=1}^{3} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

Our sample compromises all securities within the FTSE 100 index and FTSE 250 index during the period of 5th October 2017 till 28th March 2018, which is equivalent to 60 full trading days before and after the event.

Specification (1) matches our baseline specification and acts as an easy comparison to our additional specifications. Specification (2) is identical to the baseline specification expect the first-stage regression is based on a pooled regression. Specification (3) matches the baseline specification but shortens the sample horizon. The sample covers a period from 22nd November 2017 to 9th February 2018, which is equivalent to 28 days post and prior to implementation, therefore excluding the introduction of TRADEcho prior to the new market regulation and the start of the DVCM after the introduction of MiFIR/MiFID II. Specification (4) is identical to (1) but uses only the dummy variable defining the pre- and post- period in regard to the introduction of MiFIR/MiFID II as an instrumental variable. Specification (5) matches the baseline specification but excludes 5 full trading days prior to and post MiFIR/MiFID II came into effect to account for market volatility due to the regulatory changes. Specification (6) limits our sample to securities within the FTSE 100 index over our sample period and matches otherwise the baseline specification. Accordingly limits specification (7) our sample to securities of the FTSE 250 index and matches otherwise our baseline specification. Specification (8) is identical to our baseline specification but limits the sample to securities with a SI trade value market share larger than >50% whereas specification (9) limits the security sample to securities with a SI trade value market share below 50%. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Second-stage regression of the impact of limit-order SI trading on market quality									
$Effective\ Spread_{i,d}$	-2.14**	-1.77**	-2.55***	-1.75	-3.38***	-7.27***	0.92	-4.89	-7.20***
$Quoted\ Spread_{i,d}$	-5.27***	-3.86***	-1.84*	-5.90***	-1.81*	-5.86***	-4.67*	-14.72*	-7.85***
$Realized\ Spread_{i,d}$	6.41*	3.70	-4.85***	-9.71**	1.48	-1.02	-1.82**	85.00	1.81
$Price\ Impact_{i,d}$	-4.60*	-5.38*	-5.04	-2.88**	-2.80*	-2.06*	-1.36**	-2.06	-4.57**
$l(Quoted\ Depth)_{i,d}$	0.12	-0.16	0.22	0.01	-0.03	0.23	-0.32**	0.22*	-0.20
$Autocorrelation_{i,d}$	-0.05*	0.04*	-0.16***	-0.08**	-0.13***	0.06	0.06*	-0.11	0.05*
$Variance\ Ratio_{i,d}$	-0.17*	-0.14*	-0.37***	-0.16	-0.16	-0.26**	-0.89	0.76	-0.12
$HFVol_{i,d}$	-28.75**	-9.31*	-4.08***	-3.41**	-6.55	-3.04**	-4.69**	-5.97	-4.70
Panel B: Second-stage regression of the impact of mid-point SI trading on market quality									
$Effective\ Spread_{i,d}$	-2.95**	-9.88**	-2.95***	-6.99***	-8.11**	11.62*	-4.06**	-8.18*	14.20
$Quoted\ Spread_{i,d}$	-2.58***	-3.70**	-2.68**	5.15***	-4.14**	8.53***	-7.09**	-25.59	-51.12
$Realized\ Spread_{i,d}$	12.12***	7.24*	12.12***	3.75**	11.75	2.21	24.48**	-9.02	59.63
$Price\ Impact_{i,d}$	-4.47	-4.65	-3.47	-3.61**	-10.38*	5.53*	-4.66**	-0.40	-11.16
$l(Quoted\ Depth)_{i,d}$	2.11*	1.23**	0.83**	0.76*	0.78*	0.93**	0.96**	0.00	0.78**
$Autocorrelation_{i,d}$	1.35**	0.61**	3.03***	2.91**	1.05**	-7.78	1.20**	0.10	0.82
$Variance\ Ratio_{i,d}$	-2.99*	-1.35*	-6.27**	-6.13	-1.10	1.40	-1.95	-1.16	-3.89
$HFVol_{i,d}$	1.07***	-3.74*	-8.69*	-1.80*	-1.03	-7.3**	-9.98*	3.01*	-9.55*
First-stage	Stock	Pooled	Stock	Stock	Stock	Stock	Stock	Stock	Stock
Estimation method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS

Specification (2) utilises a pooled regression, whereas specification (9) relates to securities which a lower share of limit-order SI trading. Since other informational efficiency parameters in specification (9) are insignificant, it is possible that those indeed experience a potential negative impact on informational efficiency. In contrast to our findings reported in Table 23 but similar to our results in Panel A in Table 24, the coefficients for quoted depth on the lit venues are inconsistent and not as clear as Table 23 suggests. We cannot observe the complete quoted depth, neither on all UK trading venues nor international. An increase in limit-order SI trading may lead to a shift from lit trading venues to others or to an overall decline or increase. Therefore any interpretation should be made with caution.

We repeat the methodology applied for mid-point SI trading, as shown in Panel B. The coefficients are more significant than our comparable results in Panel B in Table 24. Most surprisingly, quoted depth on lit venues is throughout improving at a weak significance level. When evaluating the relationship of mid-point SI trading and transaction costs alone, we find overall no difference to limit-order SI trading, in fact, often the magnitude is even higher. An interesting difference to our findings for limit-order trading is the coefficients shown in specifications (6) and (7). While transaction costs for securities within the FTSE 100 index improve with increasing limit-order SI trading, spreads widen under increased mid-point trading. However, SI trading at the mid-point is significantly lowering transaction costs for securities with a lower market capitalisation, see specification (7). Coefficients for autocorrelation are increasing or are insignificant. In contrast, high-frequency volatility and variance-ratio are improving over the majority of our specifications.

3.7 CONCLUSIONS

This study is the first to show that limit-order SI trading is beneficial to the overall market quality, improving informational efficiency and transaction costs on lit trading venues significantly: Effective and quoted spread drop by a minimum of 3.6bps each if the market share of limit-order SI trading increases by 1%. We find that realised spread drops by 9.07bps and price impact by 6.16bps. Autocorrelation and variance-ratio drop at a highly significant level. SI trading at the mid-point, similar to dark pool trading executed at the mid-point, presents insignificant or weak significant coefficients for transaction costs and contradictive findings for informational efficiency. On an aggregate level, we find that SI trading is highly beneficial for informational efficiency and indicates tighter spreads at a low significance level.

When MiFIR/MiFID II came into effect on 3rd January 2018, the trade volume market share of internalised trading in the UK jumped by 14.5%. MiFIR/MiFID II determines a SI as a firm that deals on its own account by executing client orders outside of regulated trading venues. Regulated venues such as MTFs differ from SI as these offer multilateral trading, whereas SI support bilateral trading and act as a counterparty, not a trading venue. SI replaced BCNs and were exempted from the introduced tick size reforms. This study provides first insights and causal evidence on the impact of internalised trading on market quality overall. We demonstrate that by distinguishing between limit-order and mid-point SI trading, one can clearly determine how lit trading venue's transaction costs and informational efficiency are impacted. We can overcome issues regarding data availability on SI trading and endogeneity issues in the methodology by exploiting the jump in January 2018 and applying a 2SLS model.

SI trading received negative press due to ESMA excluding SI trading from the tick size regime introduced in January 2018, which allowed a certain advantage in price improvements and competition to regulated trading venues. As of June 2020, SI need to comply with the tick size regime to level the contribution of regulated trading venues and SI to an efficient price discovery mechanism. Since there is neither academic nor public practitioner quantitative research, which could provide a 'neutral' foundation for discussion around the relationship of SI trading and market quality, any regulatory decisions seem driven by the interest of stakeholders, in this case potentially competing exchanges. This study provides first insights, attempting to close the gap. We find that SI trading, driven by limit-order SI trading, simply increases market fragmentation, which in general improves market quality. Proprietary data sets of ELP and banks could help to understand the shift from non-price forming trading from OTC to SI and provide further insights in price discovery, order routing and market behaviour.

CHAPTER 4: PRICE DISCOVERY VIA PERIODIC AUCTION AND SYSTEMATIC INTERNALISER TRADING

4.1 INTRODUCTION

The European markets offer various trading opportunities, serving the different needs of market participants. Overall market fragmentation across venues with different levels of transparency, individual execution speed and venue-specific trading systems drive market quality and price discovery on an aggregate level. Due to concerns of ESMA that the growing share of trade execution outside of central limit-order books could harm the overall market quality, investor trust and the price discovery process, ESMA introduced the Markets in Financial Regulation and the Markets in Financial Instruments Directive and Markets on 3rd January 2018. MiFIR/MiFID II is a comprehensive regulatory system that promotes transparency and a robust price formation process. The new regulation shifted the focus to two forms of order flow: systematic internaliser and periodic auctions.

While literature and practitioners agree that the respective CLOBs lead the discovery process, there is no empirical foundation as to whether and how periodic auction and SI trading contribute.

A SI is defined as a firm that deals on its own account by executing client orders outside of regulated trading venues. In contrast to regulated trading venues, which match client orders, a SI is a counterparty in the form of an (investment) bank or electronic liquidity provider (henceforth ELP) offering bilateral trading, not a trading venue. Periodic auctions, alternatively referred to as Frequent Batch Auctions (henceforth FBAs), are lit order books that execute continuously very short auctions throughout the day. The matching process is comparable to conventional open and closing auctions; however, the call period varies between 25 and 150 milliseconds only. Our data set indicates a periodic auction trade every 0.8 seconds.

Both forms of trading gained market share and attention due to unrelated regulatory changes, forcing traders to move trade execution from fully opaque to alternative venues. Trading via broker-crossing networks needed to be reclassified and moved as BCNs were closed under MIFIR/MiFID II, resulting in a significant increase in the market share of SI. ESMA introduced the Double Volume Cap Mechanism to mitigate the extensive use of pre-trade transparency waivers, explicitly stating those waivers could harm price discovery.[68] The DVCM sets a threshold on the use of the reference price and negotiated price waiver, which triggers a six-month suspension for trading under those waivers for the individual security is reached. When a suspension is triggered, data shows that trading shifts from dark pools to CLOBs and periodic auctions.[69]

This study is the first to focus on the contribution of periodic auction and SI trading to price discovery by determining the quantitative level of informed trading in the respective order flow. Both forms of trading offer traits different to a CLOB, serving potentially different clientele. In contrast to a CLOB, SI do not need to disclose real-time pre-transparency information for above-market sized orders. The scenario might attract market participants who would like to ensure execution at a certain price and/or might not want to immediately disclose their potentially superior information for large orders. For participants making such a conscious decision, we expect a high likelihood to be informed.

In comparison to dark pools, SI are not affected by any pre-trade transparency waiver suspensions. Similar to SI, periodic auctions could attract informed participants. The order books only display the potential auction price in real-time, not the complete quote information as the CLOB. However, the actual auction mechanism could be favoured by less informed and potentially slower market participants, as they receive a competitive price without the need to compete for speed or the fear of being exploited.

How market segmentation across different forms of order flow affects price discovery and how order flow incorporates prices in a timely and informative manner is highly relevant not only for market participant's pricing and hedging purposes but also for regulatory authorities' supervisory activities. The study contributes to closing a literature gap, as existing empirical and theoretical studies focus on the relationship between dark and CLOB trading and their respective contribution to price discovery. Our methodology cannot directly rely on theoretical literature, and we are guided by literature on the relationship of dark trading and price discovery and periodic auctions and market quality in general. While specific traits of periodic auctions and SI order books define them as semi-transparent compared to CLOBs, we are aware of the limitations when relying on theoretical literature on completely opaque venues and market efficiency. Our study quantifies the level of informed trading in each order flow and the respective contribution to price discovery in the CLOB with a three-step approach:

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[68] See Art. 5 MiFIR, ESMA (2019).

[69] CBOE considers periodic auctions in Europe as such a success that it requested approval to introduce periodic auction books for US equities, see FinanceFeeds (2020).

First, we study how different measures of transaction costs are affected by an increasing market share of those forms of trading. Transaction costs are driven by adverse selection costs, which are a sign of informed trading in the CLOB.

We find that a 1% increase in the market share of periodic auction trading for a combined sample of the FTSE 100 index and FTSE 250 index constituents widens effective spread by at least 21 basis points. Wider spreads indicate enhanced adverse selection and, therefore, a higher level of informed trading. Informed participants prefer trading in the CLOB instead of periodic auction trading at a disproportional level. For the same sample, SI limit-order trading lowers effective spreads by at a minimum of 4bps and price impact by 2bps depending on our model specification. The results indicated that SI limit-order trading is attractive for informed participants, however, at a lower level than trading in the CLOB. Our study points out significant differences between liquid (constituents of the FTSE 100 index) and illiquid (constituents of the FTSE 250 index) securities in the level of informativeness in the order flow via periodic auction and SI trading. Our study shows that for constituents of the FTSE 100 index, trade execution via periodic auctions is the most informative form of trading after trade execution in the CLOB. When increasing the market share of liquid securities of periodic auctions by 1%, our results show a drop in effective spread of at least 4bps via an ordinary-least squares regression model and up to 178bps via a 2-stage least square regression model. The findings show that higher levels of periodic auction trading in illiquid securities increase the CLOB's adverse selection risk, requiring informed market participants to quote wider spreads and vice versa for liquid securities. We observe the same findings for SI trading at the mid-point, where illiquid securities indicate wider spreads and price impact, and constituents of the FTSE 100 index led to significantly lower effective spreads. We assume that SI mid-point trading might attract informed participants executing above-average market sized orders who take advantage of pre-trade transparency waivers.

Second, we rely on a vector-autoregression model with a subsequent impulse response function to study the price impact as a proxy of private information 60 seconds after a shock of £10,000GBP for a sample of the FTSE 100 index constituents.

Our results support the previous findings, showing that periodic auction trading is the second most informative order flow after CLOB trading. SI limit-order trading is the least informative order flow, with a metric significantly smaller than any other form of order flow, even dark trading. In contrast, SI mid-point trading is partially highly informative for constituents of the FTSE 100 index, but in general, less informative than periodic auctions.

Last, we study multi-market price discovery, allowing us to quantify the informativeness of the CLOB versus periodic auction and SI trading when liquidity shifts, respectively.

We find that a 1% shift in market share in liquid securities from the CLOB to periodic auctions leads to a drop between 0.4bps and 1.5bps in the informativeness of the CLOB, dependent on our model specification. That shows that periodic auction trading is informative, however, at a significantly lower level than trading via the CLOB. Similarly, the execution of liquid securities via SI mid-point trading decreases the informativeness in the CLOB between 0.4bps and 15bps. However, SI limit-order trading in liquid securities increases the informativeness in the CLOB between 0.2bps and 1.2bps. The results align with our findings on the impact on the effective spread. SI limit-order trading in FTSE 100 index constituents seems to attract relatively uninformed participants. For our combined sample, limit-order SI trading lowers the informativeness, showing that trading of illiquid securities is much more informative than in liquid securities.

The remainder of the study is organised as follows. Chapter 4.2. provides an overview of literature related to price discovery and market fragmentation, dark trading and periodic auctions. Chapter 4.3 describes our study's institutional setting, followed by the data in Chapter 4.4. We present the methodology of specific metrics and the regression models in Chapter 4.5. Chapter 4.6 shows our findings on the impact of periodic auction and SI trading on transaction costs and information leadership share and their respective permanent price impact. Chapter 4.7 summarises our study.

4.2 LITERATURE AND RESEARCH OBJECTIVES

The study studies how less-prominent forms of trading contribute to the overall price discovery process on the CLOB. The process is affected by market fragmentation and the structure of the individual order book. The structure is characterised by pre-and post-trade transparency, execution mechanism, which lead to segmentation of informed and uninformed trading. Asymmetric speed among market participants may increase adverse selection cost, see Glosten and Milgrom (1985), and affect market quality in general. Literature has addressed price discovery in relation to fragmentation in lit markets and lately to dark trading. Periodic auctions were a dominant form of trading until the 2000s in Europe and regained ground due to the DVCM.

Market fragmentation

Literature on fragmentation often indicates lower transaction costs and increased execution speed (see O'Hara and Ye (2011)). Stoll (2003) shows that enhanced fragmentation across transparent trading venues is usually related to increased competition, narrowing spreads.[70] Research by

[70] See also Ngygen et al. (2007).

Foucault and Menkveld (2008) signals a larger market depth when new venues enter the market. Growing fragmentation may also lead to larger research costs for traders, which increases adverse selections costs. Bennett and Wei (2006) find that, for the New York stock exchange, for securities moving from a fragmented market dominated by dealers to a consolidated market, spreads narrow. Degryse et al. (2015) show for the Dutch market that the increased fragmentation after MiFID I improved market depth at a consolidated level; however, the market depth of the Amsterdam Exchange dropped. Those studies omit alternative trading forms, such as dark pools, OTC trading, SI trading, or continuous auction markets. When with growing fragmentation, the number of liquidity providers increases, those can bypass time priority, which ultimately leads to superior pricing and a drop in transaction costs (see Biais et al. (2000), Biais et al. (2010), Foucault and Menkveld (2008)). Buti et al. (2011) show that increased dark pool activity is related to enhanced liquidity on lit venues. Gresse (2017)'s approach incorporates lit and opaque market fragmentation and finds that neither actually harms overall market liquidity. The study shows that enhanced lit market fragmentation narrows spreads and improves depth at the aggregate level. Gajewski and Gresse (2007) find that off-book trading in a hybrid market tends to increase spreads. Their study signals that opaque venues operating crossing engines might skim off the uninformed order flow. Enhanced speed in the CLOB promotes inter-HFT trading, which will widen spreads by increasing adverse selection costs (Menkfeld and Zoican (2017)).

Periodic call auction trading

Continuous call auctions have been a prominent trading method worldwide until the 1990s/2000s when exchanges switched to electronic CLOB. While there have been significant publications on the relationship between auctions and market quality, we argue that findings should be treated carefully, as they might no longer relate to the current trading environment, which is dominated by speed and fragmentation.[71] Madhavan (1992) states that periodic auction markets improve price discovery as they collect information from different traders over time. Literature studied the switch from auction-based trading to a continuous system (Kehr et al. (2001), Muscarella and Piwowar (2001)), usually finding superior liquidity, which in turn improved market quality. In some cases, exchanges kept a continuous call auction book for less liquid securities (Hofmann and van Bommel (2009).

Many empirical publications study call auction trading on the Taiwan Stock Exchange, which increased the frequency of call auctions throughout the day continuously over the past years. Twu and Wang (2018) show that reducing periodic auction call intervals leads to improvements in

[71] In Brennan and Cao's (1996) theoretical model, informed investors follow a contrarian trading strategy whereas uninformed follow the trend. See Kalay et al. (2002) and Amihud et al. (1997).

market quality. They find the highest level of market efficiency at a call interval of 25 seconds and superior liquidity at intervals of five seconds. They show that investors are trading less aggressively when auction intervals become more frequent. Their research indicates that a shorter auction interval might improve market quality even further. Haas et al. (2020) present a model where enhanced trading speed is beneficial in high-frequency batch auction markets as it limits the probability that a single informed trader participates in the auction. Trading speed improves the competition between arbitrageurs and therefore enhances liquidity. Menkfeld and Zoican (2017) argue that extreme speed could harm market liquidity in the CLOB as it leads to zero-sum trading. Wah and Wellman (2015) present a model where periodic auctions benefit welfare overall, as they match supply and demand more efficiently, and HFTs will follow slower traders for arbitrage purposes.

Our dataset indicates that a single stock of the FTSE 100 index has at least one periodic auction per second, where the call auction period lasts a maximum of 0.1 seconds. Periodic auctions disclose, in contrast to CLOBs and SI, the auction price only in real-time. Informed participants could expect to be able to disguise intentions, prevent front-running and receive a fair price. Slower market participants could benefit because periodic auctions level the playing field, taking away the advantage of fast traders.

Based on Twu and Wang (2018) and Madhavan (1992), we suggest that periodic auction trading is informative, however not as informative as CLOB trading. We would expect that price discovery is not harmed by periodic auction trading. We need to consider that any other form of order flow than lit order flow will not contribute to price discovery at the same level, which in turn means that price discovery on an aggregate level will always be harmed if markets are fragmented into different forms of order flow. These are important, as they serve the needs of different market participants. Regulators, however, need to consider to what degree they accept market fragmentation, order flow segmentation, loss of transparency and their aggregate impact on market quality. Concerning MiFIR/MiFID II, which aims to improve price discovery by shifting trading from dark pools to other venues, such that regulators expect any other venue type to be more informative than dark trading. Comerton-Forde and Putniņš (2015) show that low to moderate dark trading levels do not harm informational efficiency but even support it. Our research provides further empirical insights.

SI trading

A SI is a counterparty, whereas a trading venue is a multilateral facility. SI have the same requirements to pre-trade transparency as a CLOB up to average-sized orders. Quotes for large-in-scale orders do not need to be disclosed up-front, making trading via SI relatively opaque, similar to dark pools. Since SI provides a certain level of pre-trade transparency, market participants could infer from quotes for up to average market size orders an estimation about the execution probability and timing, which is impossible in dark pools.

Literature on price discovery for trading across lit and dark venues presents various theories and findings. Zhu (2014) argues that informed traders, facing inferior execution probability on dark trading venues, move their trading to lit trading venues. As a result, uninformed traders would dominate dark trading venues, leading to lower informativeness for dark trading. A departure of uninformed traders from CLOB makes it harder for the informed to hide in the order flow. Ye (2012), on the other hand, describes a situation where trade aggressiveness declines on lit trading venues if an alternative opaque trading option exists. A monopolistic informed participant is interested in executing in the dark, as larger spreads in the lit order books make dark trading for uninformed participant more attractive, which in turn provides opportunities for the monopolist. The situation would mean that dark pools trades should present a certain level of informativeness. Critics of SI focused on the possibility that internalisation might reduce market quality as the lower degree of price transparency might negatively impact price discovery, similar to dark pools. Nimalendran and Rai (2014) show that quoted spread and price impact increases significantly after large dark pool trading. Weaver (2011) finds for a sample of US securities that dark trades harm market quality. Informed traders usually trade on the same side of the order book leading ultimately to lower execution probabilities on opaque venues. Therefore, uninformed traders dominate dark pools or other forms of opaque trading, and lit markets experience relatively more informed trading (see Zhu (2014)). Foley and Putniņš (2016) study the impact of dark trading on the Australian and Canadian stock exchanges on general market quality metrics. The study distinguishes one-sided dark trading, usually executed at the mid-point, from two-sided dark trading, which is more commonly known as limit-order trading. The authors show that dark limit-orders are overall beneficial to market quality, lower quoted, effective, and realised spread, reduce price impact and metrics of illiquidity, and improve informational efficiency. Boulatov and George (2013) show that dark pools on a limit-order basis motivate informed traders to supply liquidity. The study finds increased aggressive informed trading, which in turn improves informational efficiency. Those findings, together with Foley and Putniņš (2016), suggest that strong competition in dark limit-order venues has certain spill-over effects on the lit market since spreads need to narrow to compete with the dark trading venues. Zhu (2014) finds that informed participants are less likely to use mid-point matching dark venues due to a low execution probability since informed traders often cluster on one side. Adverse selection risk on competing lit order books increases which might harm liquidity overall, although price discovery induced by informed trading is beneficial. It seems important to consider the specific type of dark trading venue to explain the different findings the literature presents. Ready (2014) shows in a study on Liquidnet and ITG Posit that securities with a higher dark trade volume share present less adverse selection risk. Buti et al. (2015) show that non-mid-point trading venues contribute to superior market quality. The authors analyse how dark trading can be used for jumping the queue ahead of transparent lit trading venues. In an opaque limit-order market, informed traders are less concerned about revealing any trade intentions and provide liquidity more actively (Boulatov and George (2013)). Doing so, they can undercut the spread in the lit venue, which in turn might support price discovery in general, which is supported by the results of Foley and Putniņš (2016).

We distinguish between SI trading at the mid-point and via limit-orders for two reasons. First, literature on dark pool trading suggests significant differences in the respective form of trading and their relation to market quality. Second, we assume that mid-point trading might be the closest alternative to dark pool trading, especially for large-in-scale orders, which do not require any disclosure of quotes before execution. Hence, we expect limit-order and mid-point trading to have a different impact on price discovery. Based on the previous literature, we suggest that mid-point trading decreases transaction costs, whereas limit-order trading leads to wider spreads. We further follow the theory of Zhu (2014), Comerton-Forde and Putniņš (2015) and Foley and Putniņš (2016), where an increase in transaction costs relates to an increase in adverse selection costs as a sign of a superior level of informed participants in the lit market. We assume that market participants submitting large/above average market-size orders are more likely deciding based on superior information. To avoid front-running and increased order implementation costs, those market participants might prefer to execute in an opaque venue. SI do not need to publish pre-trade information for large-in-scale orders (above average market-size), similar to dark pools. We expect that mid-point trading is used more strategically by informed market participants and, therefore, is more informative than SI limit-order trading. Market participants in the CLOB observe those large trade executions only post-trade. If those participants are aware that informed large orders are predominantly executed outside the CLOB and the CLOB price is not immediately impacted and the adverse selection risk is lowered, liquidity might be willing to provide better quotes. We expect that SI mid-point trading is not harming price discovery.

4.3 MIFIR/MIFID II, PERIODIC AUCTIONS, SI AND OTHER TRADING FORMS

MiFIR/MiFID II resulted from a comprehensive revision of MiFID I by the EU in 2014 and became effective on 3rd January 2018.[72] MiFID I created a competitive environment for equity trading, introducing new trading venues known as MTFs and SI. While the LSE is, until today,

[72] MiFID I is a legislative framework instituted by the EU to regulate financial markets and improve investor protection which came into effect on 1st November 2007. It introduced rules to create a more harmonized competitive and transparent trading environment across the EU.

the dominant venue in the UK, the market share of MTFs nowadays is significant. The continuous lit order books of CBOE Europe, combining CBOE BXE and CBOE CXE, have a total market share of 22.6% across Europe and 23.7% London listed securities. MTFs provide diversified trading opportunities, offering to trade in dark pools and periodic auction books, competing against classic dark pools such as UBS Dark. Table 25 provides an overview of the trade types offered by each venue.

Table 25: Trade types across the trading venues

The table below provides an overview of the different order books included in this study. Please note that SI trading is only reported via an APA but executed by an ELP acting as a SI or a bank via their own SI.

Venue	Continuous lit trading	Dark trading	Periodic auction trading	Systematic internaliser trading
LSE (TradEcho)	x	-	x	x
CBOE BXE	x	x	x	-
CBOE CXE	x	x	-	-
Turquoise	x	x	x	-
Aquis	x	-	-	-
Instinet BlockMatch	-	x	-	-
ITG Posit	-	x	x	-
Liquidnet	-	x	-	-
UBS Dark	-	x	-	-
Sigma X	-	-	x	-
CBOE APA	-	-	-	x

Continuous lit trading refers to trading in the CLOB on the primary trading market or MTFs during continuous trading hours with real-time pre-trade transparency for at least the first five price levels. Trading within the opening or closing auction is excluded.

Dark (pool) trading stands in contrast to lit trading. Dark order books do not disclose any pre-trade information. Opaque markets allow participants to execute trades without revealing their intentions. Most dark order books match orders at the mid-point; participants might receive a better price than in more transparent markets, especially for large orders. However, the uncertainty of existing liquidity in a dark pool leads to subsequent risk of non or delayed execution. Before January 2018, dark order books benefited from the unlimited use of pre-trade transparency waivers under four scenarios. Visible large orders can face the risk of front-running and are likely executed at higher costs. Large-in-scale waivers can be used for large orders exceeding a certain size threshold following the specific product’s average daily trading volume. Dark pools usually rely on reference price waivers, which can be applied if the price within a dark pool is determined according to a reference price, originating from another system and public (Petrescu and Wedow (2017)). The negotiated price waiver is used if a regulated venue executes a privately negotiated trade between participants. Order management facility waivers can be utilised for orders held in an order management facility operated by a regulated venue or MTF. Under MiFIR/MiFID II, the usage of those waivers is limited by the DVCM, which aims to shift trading to transparent venues. As of 12th March 2018, the negotiated trade and reference price waiver usage for a security is tracked venue- and Europe-wide. If the trade volume under one of those waivers exceeds 4% of the total trading volume on all European venues in the previous 12 months, trade execution under those waivers will be suspended for six months.

Further, if the trade volume under these waivers exceeds 8% of the total trading volume on all European venues in the previous 12 months in general, trading under those waivers for the relevant security will be suspended for six months. Trade volume statistics are recalibrated on a monthly and suspension organised by ESMA. The DVCM applies to dark order books only; trading of capped products continues on other venues.

MiFID II extends the scope of MiFID I's regulatory requirements to equity products such as shares, depositary receipts, exchange-traded funds, certificates and more. The regulation aims to enhance efficiency, resilience, and integrity by introducing greater transparency to prevent market abuse, increase reporting obligations, and standardise practices across the EU.

The transparency regime addresses pre-trade transparency, designed to provide market participants with a near real-time broadcast of basic trade data around firm quotes. Additionally, a post-trade transparency regime was introduced to provide market participants with near-real-time reporting of basic trade data around executed trades. According to the Regulatory Technical Standards (RTS), the regulation requires a timebound publication of executed trades to an Arranged Publication Arrangement to promote price transparency. MiFIR/MiFID II established a new tick-size regime so that every trading venue must price certain financial instrument in the same increments.[73] RTS 11 specifies the minimum tick-size regime in accordance with the instrument's liquidity and price level. Instruments can switch between liquidity bands and price levels over time. The tick-size regime refers to equity and equity-like instruments only and must be adopted by regulated markets, hence trading venues such as LSE or CBOE BXE. SI are not subject to the requirement, which builds the foundation for our experiment.

4.3.1 Systematic internaliser

SI were introduced under MiFID I in 2007 and are commonly defined as 'investment firms which, on an organised, frequent, systematic and substantial basis, deal on own account when executing client orders outside a regulated market, a MTF or an OTF without operating a multilateral system' under MiFID II.[74] The main differences between SI and classic trading venues are that trading venues deal with the client's capital, while SI deal on their account and is thus also termed

[73] Please see Art. 9 MiFID II and the Commission Delegated Regulation 2017/588 of 14th July 2016.

[74] AMFE (2011) estimated between 2008 and 2010, the turnover share of OTC trading, including SI and BCNs, was around 12%. SI trading experienced a peak after introduction in 2007 but experienced a rapid drop, from 14% to 2% market share. See The Trade (2020).

a principal trader. Based on that definition, a SI is a counterparty, whereas a trading venue is a facility. A SI is a single dealer who cannot engage in matched principal trading, whereas a trading venue is a multilateral dealer platform that can engage in matched principal trading if it is registered as an OTF. The SI regime introduced under MiFIR/MiFID II extended the scope of SI eligible instruments from equity to equity-like instruments as depositary receipts, ETFs, certificates, and non-equity instruments. Art. 4 (1) (1) MiFID II defines an investment firm as a legal person whose business occupation is the provision of investment services or performance of investment activities. Most major international banks or electronic liquidity providers qualified for SI. The purpose of expanding the SI scope under MiFID II was to capture previously opaque OTC trading and ensure that order flow internalisation would not affect price efficiency overall. For equity and equity-like instruments, ‘frequent’ and ‘systematic’ are defined as an investment firm executing at least 0.4% of the total number of transactions in a liquid financial instrument across any venue or OTC in the EU over the past six months via the firm’s account while executing client orders while dealing daily on own account. ESMA defines ‘substantiality’ if either the investment firm’s OTC trade volume share in an instrument versus its total trading volume is larger than 15% or if it is 0.4% of the European Union’s total trading in the relevant instrument. A SI will not combine third-party buying and selling interests functionally the same way as a trading venue.[75] To determine whether an investment firm is “executing client orders” when dealing on its own account outside of trading venues, investment firms assess which of the two parties to the transactions acts in the capacity of executing client orders. This can be determined on a transaction-by-transaction basis or by type of transactions or type of counterparties. A SI operates a bilateral system, which prevents the investment firm from matching buying and selling orders in the way trading venues do. If a SI does so, it would no longer be considered a SI but would require authorisation to operate an MTF or OTF. A multi-dealer platform with multiple dealers interacting for the same financial instrument should not be considered a SI.[76] SI are competing with trading venues over customers’ order flow. To provide

[75] The investment firm shall assess whether it meets the conditions mentioned quarterly based on data from the last six months for equity-like instruments. Newly issues instruments shall only be considered when historical data covers at least three months. If those conditions are met, the investment firm shall comply within two months with all requirements set in Art. 13, 14, 15, and 16 of MiFIR. Please see also Deutsche Boerse (2018).

[76] It has been underlined in Recital 19 of the said Commission Delegated Regulation (EU) 2017/565 of 25 April 2016: "According to Directive 2014/65/EU, a SI should not be allowed to bring together third-party buying and selling interests in functionally the same way as a trading venue. A SI should not consist of an internal matching system that executes client orders on a multilateral basis, an activity that requires authorization as a multilateral trading facility. In this context, an internal matching system is a system for matching client orders that results in the investment firm undertaking matched principal transactions on a

a level playing field, ESMA underlined that trading venues and SI using similar technology and systems should process transactions for post-trade publication at the same speed.[77] Consequently, ESMA expects that trading venues and investment firms, particularly SI, that use expedient systems publish transactions as close to real-time as technically possible. SI must provide public real-time pre-trade quotes either by choice or on request either through a trading venue, an APA or the SI's web for orders up to standard market size. Accordingly, post-trade information needs to be reported to an APA of choice. SI have the same right to offer pre-or/and post-trade transparency waiver for eligible trades as trading venues have.

4.3.2 Periodic auctions

Since MiFID II came into effect, the share of periodic auction trading is rising. Periodic auctions collect bid and ask prices and determine a single auction price that maximises the execution volume. While the methodology can vary, in general, quotes are collected throughout the day. A 'call period' of usually less than a 0.1 seconds is triggered each time orders can be matched. The indicative price and volume are published, and participants submit orders. That is a significant difference from CLOB, which publish active quotes in real-time. The period auction only publishes the potential auction price, not the initial orders at the beginning of the auction. That provides an opportunity for traders to avoid real-time pre-trade transparency obligations. Periodic auction books accept various order types, such as limit, market and mid-EBBO pegged orders, which can be matched against each other. The call auction phase ends randomly within the defined maximum duration.

A periodic auction differs significantly from trading in central limit-order books as trades are only executed at the end of a call period, while a CLOB executes trades continuously throughout the day. Our data show for the FTSE 100 index around 6.5 thousand auctions per hour, with an increasing trend. We record approximately 137 thousand lit trades per hour.[78] Periodic auctions offer slower market participants a way to receive a competitive price (see FCA (2018)). Within a CLOB, trade and latency are critical to receiving the best execution. In a periodic auction book, the reduced speed provides advantages for less sophisticated traders and with superior price protection.

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regular and not occasional basis." Besides, if an investment qualifies as an MTF or OTF, it would automatically need to comply with the tick-size regime.

[77] Real time post-trade transparency requirements, as expressed in Art. 6 and 10 of MiFIR and specified in Art. 14 of RTS 1.

[78] In comparison, SI trading presents around 14 thousand trades per hour, dark trading 9.8 thousand trades. Those are average values across the sample horizon, which fluctuate due to common daily events and market events.

4.4 DATA AND DESCRIPTIVE STATISTICS

Our study aims to quantify the relationship of trading via systematic internaliser and periodic auctions in the UK and price discovery measures. Our sample data covers the constituents of the FTSE 100 index and FTSE 250 index between 1st October 2017 and 30th September 2018, which compromised approximately 355 of the most actively traded securities in the UK in the relevant horizon.

Our data is sourced predominantly from Thomson Reuters DataScope tick data. The study includes TR DataScope data from streams reporting trading via continuous lit trading order books and periodic auction order books from LSE, CBOE BXE, CBOE CXE and Aquis. The London Stock Exchange, LSE, is the only venue acting as a listing venue, whereas the others, except CBOE BXE for unrelated products, are MTFs solely. Further, we include the stream for trade reporting of SI trading via CBOE APA and dark pool order books of BLINK MTF, CBOE BXE, CBOE CXE, Instinet Blockmatch, ITG Posit, Liquidnet, SIGMA X, Turquoise, and UBS Dark. TR DataScope reports trades executed on the dark pools and SI trading reported via CBOE APA via a consolidated stream. Extensive research and data manipulation allowed us to allocate those trades to five dark pools and CBOE APA. We verified the data with market data reported publicly on CBOE Europe and Fidessa. TR DataScope reports for dark pools and SI trades data only, sufficient to compute metrics for price discovery across trade types. OTC, periodic auction, out-of-trading hours trading, off-market-on-book trading is reported via the respective lit-order book stream, where the trade is executed. All lit order books report continuous quote updates of the best bid and ask. Metrics were calibrated as detailed in Chapter 4.4 on a stock-day basis. For analyses shown in Chapter 4.5, we winsorise our metrics at 1%.

Our data considers a horizon from 22nd November 2017 to 7th September 2018. We create three subsets within that time frame; each is the foundation of a different analysis. We chose a horizon from 22nd November 2017 to 9th February 2018 around the introduction of the MiFIR/MiFID II regulation on 3rd January 2018, which corresponds to 21 trading days prior to and post the event to study the relationship between SI trading and price discovery. The event itself acts as an instrumental variable in the 2SLS regression. The 21 day period is chosen to avoid any bias due to relevant market events: First, the go-live of TRADEcho on 21st November 2017 and second, the go-live of the DVCM on 12th March 2018.[79] TRADEcho is operated by LSE and provides on-exchange off-book reporting and is approved as an Arranged Publication Arrangement (APA), which provides OTC and SI trade reporting in all MiFID II securities, regardless of their asset

[79] Please see TRADEcho (2020) for an overview.

class.[80] The purpose of APAs is to increase transparency by publishing the pre-trade quote and post-trade trade information. An APA reports on behalf of investment firms their trade reports per Art. (4)(1)(52) MiFID II. SI trading is reported via APAs only. The dominant data source for SI trading in TR DataScope is CBOE APA, which drives our SI data from the 21st November 2017 onwards. Firms can choose their preferred APA individually. We do not observe a significant shift from CBOE APA to TRADEcho APA.[81] The go-live of the DVCM on 12th March 2018 marks the first cut-off date. The DVCM (Art. 5 of MiFIR) aims to limit the trading under the reference price waiver (Art. 4 (1)(a) of MiFIR) and the negotiated transaction waiver for liquid instruments (Art. 4 (1)(b)(i) of MiFIR) in equity instruments if a certain usage threshold in the 12 months prior is exceeded. Implementing such a mechanism is likely to significantly change the trading environment and might lead to bias.

Table 26 presents the summary statistics over all variables included in our regression models to study the relationship between SI trading and price discovery.

Panel A shows the daily average market share for securities within the FTSE 100 and FTSE 250 indices for different trading forms. Additionally, we show our measures for transaction costs. Trading on lit trading venues, the continuous central limit-order books on LSE and the MTFs, has for securities within the FTSE 100 index and the FTSE 250 index the highest market share of over 50% and over 60%, respectively. The market share drops slightly by 2.2% and 4.3% when MiFIR/MiFID II came into effect. Trading on dark pool order books shows the second-highest market share and falls after 3rd January 2018. The drop is significantly higher for securities within the FTSE 250 index, for which the market share declines by 4.2%. Periodic auction trading and trading via SI present overall a much lower market share than trading via central limit-order books or dark order books. The market share of periodic auction trading increases significantly from 0.2% for securities within the FTSE 100 index to 1.2%, while the market share for securities within the FTSE 250 index from 0.1% on average to 1.9%. The market share of SI trading increases by 20.7% for securities within the FTSE 100 index and 17.1% for securities within the

[80] This affected the tick data provided by TR DataScope. First, TR DataScope introduced new Reuters Identification Codes (RICs) specifically for off-market trades executed on-exchange in addition to the existing corresponding RICs for any security traded on LSE to translate the implementation of on-exchange off-market reporting into their tick data. Prior, on-exchange off-market trading was reported via the existing RIC for securities traded on LSE, those were discontinued for that kind of trading. However, these were reintroduced on 18th April 2018, leading to a certain double reporting of on-exchange off-market trading, which required extensive data cleaning. The reasons for the reintroduction were not disclosed by TR DataScope.

[81] We assume those trades are prior undisclosed SI trades executed via LSE, whereas CBOE APA is predominantly reporting any SI trading executed on the MTFs, which in contrast to LSE operate dark pools and focus on opaque trading.

FTSE 250 index. SI trades executed away from the best mid-point dominate. Overall, securities within the FTSE 250 index indicate a larger shift in market share across different forms of trading when MiFID/MiFIR II is introduced.

Table 26: Descriptive statistics around the introduction of MiFIR/MiFID II

The table below presents the descriptive statistics on the index-wide average trade share and informational efficiency parameters on a security base. Our sample period covers 28 trading days prior to and post MiFID II on 3rd January 2018 came into effect. Panel A shows the mean and median daily trade value share as well as the standard deviation per security while distinguishing by the FTSE 100 index and FTSE 250 index. We compute the daily trade value share for each security as the total daily trade value for the specific form of trading divided by the total trade value across all types of trading. In addition, we show basic measures of transaction costs. Effective spreads are time-weighted for all trades during continuous lit trading. Quoted and effective spread measures are calculated relative to the mid-point in basis points. Quoted spreads are time-weighted based on the lit best bid and offer. Panel B presents the descriptive statistics for informational efficiency parameters. $Autocorrelation_{i,d}$ is based on a 10-second mid-point return. $Variance\ Ratio_{i,d}$ measures the variance-ratio of the standard deviation on 1-second and 10-second mid-point returns. $ILS_{LIT,i,d}$ measures the information leadership share of trading on the lit market relative to other forms of trading. For completeness, the control parameters integrated in the 2SLS regression in Chapter 4.5. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to the mean daily interday volatility of a relevant security. The last two columns report the difference in means of the relevant parameter before and after the regulation came into effect, using a two-tailed t-test and the significance in difference of the variance with a Wilcoxon Rank-sum test. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	Index	Pre-regulation			Post-regulation			Rel. Difference (%)	Wilcoxon Rank-sum
		Mean	Std. Dev.	Median	Mean	Std. Dev.	Median		
Panel A: Liquidity parameters									
$Lit\ trading_{i,d}$	FTSE100	55.40%	49.50%	98.50%	54.40%	48.60%	89.20%	-1.81%**	34.23***
	FTSE250	62.70%	48.00%	99.80%	60.80%	47.60%	99.10%	-3.03%***	23.67***
$Dark\ pool\ trading_{i,d}$	FTSE100	33.10%	47.10%	0.00%	33.00%	47.00%	0.00%	-0.30%***	63.43**
	FTSE250	28.80%	45.00%	0.00%	24.60%	42.70%	0.00%	-14.58%***	95.34***
$Per. Auction\ trading_{i,d}$	FTSE100	0.20%	1.40%	0.00%	1.20%	4.30%	0.00%	500.00%***	17.66***
	FTSE250	0.10%	1.20%	0.00%	1.90%	5.30%	0.00%	18,00.00%***	19.58***
$SI\ trading_{i,d}$	FTSE100	4.80%	31.30%	0.00%	25.50%	31.60%	0.00%	431.25%***	21.24***
	FTSE250	3.20%	27.30%	0.00%	20.30%	34.00%	0.00%	534.38%***	51.02**
$SI\text{–}\ mid_{i,d}$	FTSE100	1.00%	1.40%	0.60%	1.10%	1.80%	0.60%	10.00%**	21.54***
	FTSE250	0.60%	0.60%	0.60%	1.30%	4.10%	0.30%	116.67%***	13.34***
$SI\text{–}\ limit_{i,d}$	FTSE100	3.80%	5.50%	2.20%	24.40%	10.90%	22.50%	542.11%**	23.84***
	FTSE250	2.60%	5.00%	1.00%	19.00%	14.10%	16.70%	630.77%***	41.10***
$Effective\ Spread_{i,d}$	FTSE100	6.47	3.34	6.27	5.44	2.95	4.84	-15.92%***	25.55***
	FTSE250	18.10	15.97	12.82	18.81	15.44	14.18	3.92%**	26.21***
$Price\ Impact_{i,d}$	FTSE100	4.68	2.55	4.44	4.11	2.41	5.41	-12.18%***	22.17***
	FTSE250	9.30	5.82	9.53	9.79	6.222	10.09	5.27%**	33.64**
Panel B: Informational efficiency									
$Autocorrelation_{i,d}$	FTSE100	-0.063	0.074	-0.0	-0.04	0.0	-0.03	-36.51%**	44.18***
	FTSE250	-0.095	0.11	-0.065	-0.07	0.09	-0.04	-26.32%**	21.67***
$Variance\ Ratio_{i,d}$	FTSE100	1.24	0.21	1.19	1.14	0.16	1.09	-7.77%*	87.30***
	FTSE250	1.31	0.24	1.27	1.22	2.20	1.15	-6.37%**	56.70*
$ILS_{LIT,i,d}$	FTSE100	7.91%	22.45%	0.23%	8.34%	14.62%	4.54%	1.27%**	14.53***
	FTSE250	51.32%	45.27%	53.82%	44.54%	46.65%	15.92%	-14.06%***	22.76**
Panel C: Control parameters									
$HFTVol_{i,d}$	FTSE100	45.151	81.217	16.613	46.55	76.66	16.73	3.10%**	11.86***
	FTSE250	40.43	69.94	16.92	44.36	82.69	16.11	9.72%***	34.55***
$Volatility_{i,d}$	FTSE100	97.02	63.06	94.41	115.86	49.07	102.85	19.42%***	12.43**
	FTSE250	149.24	113.18	139.74	-323.73	1,443.23	-1,017.10	-316.92%**	55.12*
$Market\ cap_{i,d}$	FTSE100	35,234.39	55,326.46	12,604.08	36,935.11	58,549.67	12,732.80	4.83%*	45.11***
	FTSE250	2,693.17	3,705.43	2,026.64	2,735.16	3,669.14	2,049.89	1.56%*	77.43***

In addition, we show measures of transaction costs. For securities within the FTSE 100 index transaction costs, proxied by effective and quoted spread, seems to drop at a highly significant level, while securities within the FTSE 250 index present an increase in transaction costs at a 10% significance level.

Measures of informational efficiency present overall a drop post 3rd January 2018. Our measure for informational leadership share of lit trading for the securities within the FTSE 100 index presents an increase of 0.4% at a 5% significance level. Securities within the FTSE 250 index, on the other hand, show a decline of 6.78% at a 1% significance level. Panel C shows the control variables included in our regression models. HFT-volatility increases for securities of the FTSE 100 index and FTSE 250 index by 3.10% (5% significance level) and 9.72% (1% significance level), respectively. Interday volatility drops significantly for securities within the FTSE 250 index increases for securities of the FTSE 100 index.

We select a horizon from 4th January 2018 to 9th March 2018 to analyse trading's informativeness via continuous lit trading, SI, dark pool and periodic auction order books. The sample horizon is limited. Before MiFIR/MiFID II came into effect on 3rd January 2018, the market share of SI and periodic auction trading was negligible. Also, other regulatory changes as the new tick size regime might bias the results. For the same reason as for the previous sample horizon, we select the 9th March 2018 as a cut-off date. The introduction of the DVCM would potentially bias the findings.

To study the relationship between periodic auction trading and price discovery, the third sample horizon starts on 12th February and ends on 7th September 2018. The sample was chosen to cover six cycles of DVCM suspensions with an event horizon of 20 trading days prior to and post each suspension start date.[82] The specific dates mark the start date of a six-month suspension for securities exceeding the thresholds for trading under the reference price waiver (Art. 4 (1)(a) of MiFIR) and the negotiated transaction waiver for liquid instruments (Art. 4 (1)(b)(i) of MiFIR) in equity instruments under the DVCM (Art. 5 of MiFIR). Those are the 12th March 2018, 13th April 2018, 14th May 2018, 12th June 2018, 11th July 2018 and 10th August 2018. We overlay those six datasets to one dataset. The structure of our model requires us to include only securities which were suspended under the DVCM.[83] Only for those, the suspension start date in the form

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[82] A horizon of 20 trading days avoids the problem that the earliest day within a single cycle dataset is before the previous month's suspension date. A longer horizon would lead to bias.

[83] Please see ESMA (2021). We only consider International Securities Identification Numbers (henceforth ISINs) included in the FTSE 100 index and FTSE 250 index during our sample horizon. We select suspension level 'EU Level', disregarding suspensions on specific venues only. We focus on suspensions start dates between March 2018 and September 2018. In theory, each suspended ISIN should only appear once in this sample. However, it is possible that due to data irregularities, a securities' suspension status

of a dummy variable with a subsequent significant increase in periodic auction trading is a suitable instrumental variable for the 2SLS model. In total, 286 securities of our sample were suspended at some point during our six suspension cycles.

Table 27 presents the descriptive statistics for our sample data set. We study the average, standard deviation and median over the 20 days before starting a new suspension cycle and 20 days after. Overall, all securities experience significant changes in market quality parameters and market efficiency, independent of whether the DVCM regulation impacted them. A potential reason could be that portfolios, in general, need to be restructured when the trading strategy for certain securities must shift. Panel A shows that market shares of unimpacted securities shift in the same direction as suspended securities at a significant level. The idea behind the DVCM is to limit the use of transparency waivers to a certain threshold to maintain markets with sufficient price discovery and efficiency. Trading should shift towards more transparent venues which drive price discovery. Our sample finds that the trade share via dark pools, where the main order books transparency waivers are used, experiences a relative drop of over 49% for suspended securities, and around 2.5% for non-suspended securities. In absolute terms, before a suspension start date, then suspended securities have on average a higher market share (4.8%) than non-suspended securities (3.1%). In total, the market share of dark order books drops by 2.4%. Trading via continuous lit order books drops at the same time 1.1%.

In our sample, trading does not shift directly to the CLOB book, with the potentially best price discovery. The market share of trading via periodic auctions increases by 2.7%, 2.5% for securities for which the use of transparency waivers is partially suspended. In relative terms, the latter corresponds to an increase of over 210.8%. The market share of SI trading drops overall. SI are like dark pools, likely users of transparency waivers. We observe a drop of 3.9% for non-capped securities and a drop of over 8.6% for suspended securities. In relative terms, non-suspended securities experience a larger drop of over 56.9%, whereas the market share of suspended securities drops by 36.8% only. All reported shifts of market share are significant at a minimum of a 5% significance level. Effective spread, one of our measures of transactions costs, presents an insignificant increase for suspended and non-suspended securities. However, for

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is updated. First, there are three possible updates: An upgraded suspension from a venue-wide suspension to an EU-level suspension if a security breaches the EU-wide threshold for using transparency waivers after it already breached it on a single venue. We do not observe this case in our sample. Second, a security can be re-suspended if, due to data issues, a suspension was temporarily revoked. Last, a suspension is revoked after a security had been suspended. The latter happens due to delayed updates in the data provided to ESMA or false calibrations. We manually work through our sample to account for those developments.

quoted spread, non-suspended securities experience an increase of 0.15bps at a 1% significance level, whereas we observe a drop of 0.06bps at a 5% significance level for suspended securities.

Table 27: Descriptive statistics before and after the suspension start dates of the Double-Volume-Cap Mechanism

The table below presents the descriptive statistics on the trade share and informational efficiency parameters on security-day-base during the 20 trading days prior to and post each monthly suspension start date of the DVCM between March till September 2018. We overlap all sample horizons and distinguish between securities for which trading under certain transparency waivers was suspended and securities without any restrictions. Panel A shows the mean and median daily trade value share as well as the standard deviation per security, while distinguishing by the FTSE 100 index and FTSE 250 index. We compute the daily trade value share for each security as the total daily trade value for the specific form of trading divided by the total trade value across all types of trading. In addition, we show basic measures of transaction costs. Effective spreads are time-weighted for all trades during continuous lit trading. Quoted and effective spread measures are calculated relative to the mid-point in basis points. Quoted spreads are time-weighted based on the lit best bid and offer. Panel B presents the descriptive statistics for informational efficiency parameters. $Autocorrelation_{i,d}$ is based on a 10-second mid-point return. $Variance\ Ratio_{i,d}$ measures the variance-ratio of the standard deviation on 1-second and 10-second mid-point returns. $ILS_{LIT,i,d}$ measures the information leadership share of trading on the lit market relative to other forms of trading. For completeness, the control parameters integrated in the 2SLS regression in Chapter 4.5. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to the mean daily interday volatility of a relevant security. The last two columns report the difference in means of the relevant parameter before and after the regulation came into effect, using a two-tailed t-test and the significance in difference of the variance with a Wilcoxon Rank-sum test. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

Parameter	Capped	Pre suspension date			Post suspension date			Rel. Difference	Wilcoxon
		Mean	Std. Dev.	Median	Mean	Std. Dev.	Median	(%)	Rank-sum
Panel A: Liquidity parameters									
$Lit\ trading_{i,d}$	No	80.32%	17.52%	83.68%	79.6%	17.84%	82.53%	-1.44%**	34.23***
	Yes	67.63%	13.73%	69.85%	67.21%	13.89%	69.16%	-0.62%**	23.67***
$Dark\ pool\ trading_{i,d}$	No	3.11%	8.89%	0.34%	3.03%	8.76%	0.31%	-2.57%***	63.43**
	Yes	4.82%	2.35%	2.14%	2.46%	7.83%	0.00%	-49.17%***	95.34***
$Per.\ auction\ trading_{i,d}$	No	0.72%	2.00%	0.00%	0.92%	2.17%	0.00%	27.78%***	17.66***
	Yes	1.19%	1.75%	0.64%	3.69%	4.15%	2.48%	210.86%***	19.58***
$SI\ trading_{i,d}$	No	6.90%	15.19%	12.18%	2.96%	15.81%	13.41%	-56.98%***	21.24***
	Yes	24.28%	12.78%	24.27%	15.46%	12.99%	24.98%	-36.85%***	51.02***
$SI\text{-}mid_{i,d}$	No	0.45%	2.78%	0.00%	0.18%	1.56%	0.00%	-60.00%***	21.54***
	Yes	1.21%	2.99%	0.47%	0.08%	2.36%	0.11%	-30.58%***	13.34***
$SI\text{-}limit_{i,d}$	No	6.43%	11.82%	0.00%	2.75%	8.37%	0.00%	-56.77%***	23.84***
	Yes	23.27%	13.51%	22.21%	14.62%	15.84%	12.10%	-37.17%**	41.10***
$Effective\ Spread_{i,d}$	No	11.35	5.12	9.02	11.50	3.44	8.76	1.34%	25.55***
	Yes	13.44	6.84	9.91	13.51	7.65	9.85	0.41%	26.21***
$Price\ Impact_{i,d}$	No	9.03	7.96	8.19	9.27	8.15	8.4	2.62%***	22.17***
	Yes	8.82	5.95	7.73	8.76	6.04	8.34	-0.71%**	33.64***
Panel B: Informational efficiency									
$Autocorrelation_{i,d}$	No	-0.05	0.09	-0.02	-0.05	0.09	-0.02	-0.73%	44.18***
	Yes	-0.06	0.09	-0.04	-0.06	0.09	-0.04	-2.81%***	21.67***
$Variance\ Ratio_{i,d}$	No	1.07	0.07	1.04	1.07	0.07	1.04	-0.28%***	87.30***
	Yes	1.09	0.08	1.07	1.09	0.08	1.06	-0.17%**	56.70***
$ILS_{LIT,i,d}$	No	54.34%	46.28%	74.34%	51.86%	46.22%	46.23%	-6.91%***	14.53***
	Yes	34.21%	42.43%	9.12%	35.33%	42.11%	12.43%	4.89%***	22.76***
Panel C: Control parameters									
$HFTVol_{i,d}$	No	40.07	69.21	18.18	38.09	63.21	17.16	-5.76%***	11.86***
	Yes	45.67	82.15	16.51	48.94	87.71	18.35	7.15%**	34.55***
$Volatility_{i,d}$	No	51.36	96.71	136.37	-47.82	97.04	136.54	-193.12%***	12.43***
	Yes	74.18	67.6	142.63	-132.81	72.29	137.82	-278.84%***	55.12***
$Market\ cap_{i,d}$	No	11,708.28	43,261.03	2,024.29	11,568.99	43,398.22	1,945.07	-0.15%**	45.11***
	Yes	13,358.26	32,599.27	3,887.81	13,223.46	32,108.37	3,978.32	-0.30%***	77.43***

Panel B presents an overview of the trend for measures of informational efficiency. We observe a highly significant but minimal drop for our autocorrelation measure for suspended securities. Similarly, both suspended and non-suspended securities present a statistically significant but small drop in the variance-ratio. The measure for information leader share of lit trade prices drops by 2.4% for non-suspended securities and increases 1.1% for suspended securities. This trend could indicate that even though the market share of lit trading drops, the informativeness increases, which would support the success of the DVCM.

Our control parameters for the OLS and 2SLS regressions in Chapter 4.5 show a highly significant and large drop in interday volatility for both suspended and non-suspended securities. High-Frequency trading picks up suspended securities at a 5% significance level and drops for non-suspended by over 5.7% at a 1% significance level.

4.5 METHODOLOGY

This study studies the relationship of trading via SI and periodic auction trading and price discovery. Following, we provide an overview of the methodology and measures used.

4.5.1 Liquidity and informational efficiency metrics

All metrics are calibrated based on data sourced from DataScope as described in Chapter 4.3. We consider continuous trading hours or equivalent only and computed all metrics on a security-day-venue basis.

We compute the daily trade volume of continuous lit trading, systematic internaliser trading, dark trading and periodic auction trading as the sum of the individual trade volumes throughout trading hours. We can identify and distinguish those types of trading from other types by the intraday tick data's qualifiers. The enhanced reporting requirements introduced by MiFID II/MiFIR led to the introduction of more detailed qualifiers even before regulatory changes came into effect. The enhanced information to each trade or quote information allows us to determine the type, delayed reporting, corrections, and others. Unlike other studies, we do not exclude a certain time frame at the beginning and end of each trading day to account for the opening and closing auction. The data structure allows us to identify the auction trades and therefore filter for the relevant trade type. The approach is also used for liquidity measures such as spreads; hence only lit trades executed during continuous trading hours are considered. Based on the total daily trade volume per trade type, we compute for each stock-day the respective shares for each type of trading. That information is the basis for the OLS and 2SLS regression detailed in Chapter 4.5.2 and Chapter 4.5.3.

Proxies of transaction costs

In our study, we use effective spread and price impact, two widely used metrics as proxies for transaction costs. The effective spread metric takes the possibility into account that trades might be executed within the best bid and ask quotes. The effective spread for a security i on day d on each venue is defined as the difference between the trade price $p_{i,t}$ at any time t and the prevailing mid-point $m_{i,t}$, immediately prior to the trade (Foley and Putniņš (2016), Fong, Holden and Trzcinka (2017)). The direction of the trade is indicated by d, where d equals to 1 if the trade is buyer-initiated and -1 if the trade is seller-initiated. The trade direction is determined in accordance with the Lee and Ready (1991) algorithm. The value-weighted daily relative effective spread is computed as $Effective\ Spread_{i,d} = 2d((p_{i,t} - m_{i,t})/m_{i,t})$. In Chapter 4.5, we estimate the impact of SI trading and trading via periodic auctions on transactions costs using an OLS as well as a 2SLS regression. The empirical approach is stated in Chapter 4.4.3 and Chapter 4.4.4.

To measure the presences of informed trading in the order flow we rely on the price impact. The metric measures how liquidity providers adjust their quotes to new information in the order flow, e.g., it measures the share of informed versus liquidity traders and the level of superior information in the market. We compute the metric as $Price\ Impact_{i,d} = Effective\ Spread_{i,d} - Realized\ Spread_{i,d}$ for each security i on day d on each venue as the sum of the time-weighted effective and realised spread (Bessembinder and Venkaraman (2010)).

Measures of informational efficiency

As a first step to evaluate the relationship between SI trading as well as trading via periodic auctions and price discovery, we quantify the impact of those two types of trading on widely used measures of informational efficiency. The findings of an OLS and 2SLS regression are shown in Chapter 4.5. The informational efficiency of prices is evaluated by autocorrelations and variance-ratios.

Informational efficiency metrics measure how prices deviate from a random walk and might be predictable on prior prices. In an informationally efficient market, prices only deviate from the fundamental value when new information arrives. Prices should not be predictable.

Autocorrelations moving away from 0 indicate that quoted spreads deviate from stochastic random walk and exhibit short-term return predictability. The predictability is mainly driven by partial price adjustment to certain information as over- and under-reaction (Anderson et al. (2013)), that indicates an informationally inefficient market. The measure is computed as the absolute value of first-order autocorrelations for each security on a daily basis at a 10-second frequency in accordance with Hendershott and Jones (2005) $AutoCorr_{i,d} = |Corr(r_{k,\tau}, r_{k,\tau-1})|$, where $r_{k,\tau}$ is the τ^{th} mid-point return for a time period k over a day d. The absolute value of the autocorrelation presents a measure of informational efficiency that measures both the under- and over-reaction of returns to information entering the market. We choose a 10-second frequency as we assume the UK markets in combination with our sample period to be very liquid.

Following Lo and MacKinlay (1988) we compute the variance-ratio for each security i on day d on each venue as $VarRatio_{i,d} = \left| \sigma^2_{k,l} / k\sigma^2_l - 1 \right|$. With $\sigma^2_{k,l}$ and $k\sigma^2_l$ as the variance of l-second and k, l-second mid-point returns. Stock prices that follow a random walk would have a variance of returns as a linear function of the return measurement frequency, hence $\sigma^2_{k,l}$ is k times larger than σ^2_{1-l}. Higher values indicate greater inefficiency. In our study we us an $l\ and\ k, l$ combination of 1 second, 10 seconds.

Permanent Price Impact

Our approach follows closely Comerton-Forde and Putniņš (2015), who transform the VAR framework developed by Hasbrouck (1991) to measure the informativeness of dark and block trading. Hasbrouck (1991) assumes that in markets with asymmetric information, trades convey information that lead to a permanent price impact. The magnitude of the price impact is a positive function of the proportion of informed traders overall, and the probability to face an informed market participant. In a market where a single market-maker faces potentially informed traders, spreads and the level of asymmetry are positively correlated. Similar, the level of asymmetry relates positively to the price impact. Therefore, tick size regimes interact directly with the level of asymmetric information as they drive spreads.[84] Studies of the relationship of price impact and information asymmetry assumed a long-time serial independence of trades, no delays of the price impact and in general a linear price impact. Hasbrouck (1991) developed a model of auto- and cross-correlations, where the informational impact of a trade is the permanent price impact as a result of an unexpected trade component.[85] Hasbrouck (1988) suggests that the information inferred from trading based on asymmetric information is driving the permanent price impact. A permanent price impact metric is preferred to the immediate as it is not biased by liquidity effects. By focussing on price innovation and its impact on price discovery, the predictable relationship between trade and price impact is excluded, which would not contain any information. Comerton-Forde and Putniņš (2015) refocus Hasbrouck's (1991) model on different types of trading, which allows the authors to analyse the permanent price impact of dark and block trading specifically. In our study, we aim to analyse how a shock of £10,000GBP in a respective type of trading impacts the price in the form of $r_t^{midpoint}$ 60 seconds after based on an impulse

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[84] This is one of the reasons we only start our sample horizon on 3rd January 2018, when a new tick size regime came into effect. We avoid bias from changing regimes.

[85] Hasbrouck (1991) refers to it as the "persistent price impact of the trade innovation".

response function (IRF). A VAR is in general, a model to predict multiple time series variables with a single model. Lagged values of all-time series are integrated as independent variables. We regress the vector of a time series on lagged vectors of those variables.

For our study, we compute the total value of lit (Lit), dark (DA), SI limit-order (lSI), SI mid-point (mSI), and periodic auction (PA), trading every one second during continuous trading hours. We include dark trading, to compare it to the results of Comerton-Forde and Putniņš (2015), and to evaluate how SI trading, as the next most opaque form of trading, compares to it. In addition, we calibrate the one-second mid-point return of the best quotes across all lit trading venues. In accordance with Comerton-Forde and Putniņš (2015) we run a vector-auto regression model followed by a cumulative impulse function for each stock-day in the form of:[86]

$$\begin{aligned}
x_t^{lSI} &= \mu^{lSI} + \textstyle\sum_{i=1}^{60} \theta_i^{r}\, r_{t-i} + \sum_{i=1}^{60} \theta_i^{lSI}\, x_{t-i}^{lSI} + \sum_{i=1}^{60} \theta_i^{mSI}\, x_{t-i}^{mSI} + \sum_{i=1}^{60} \theta_i^{Lit}\, x_{t-i}^{Lit} + \sum_{i=1}^{60} \theta_i^{DA}\, x_{t-i}^{DA} + \\
&\quad \textstyle\sum_{i=1}^{60} \theta_i^{PA}\, x_{t-i}^{PA} + \varepsilon_t^{lSI} \\
x_t^{mSI} &= \mu^{mSI} + \textstyle\sum_{i=1}^{60} \lambda_i^{r}\, r_{t-i} + \sum_{i=1}^{60} \lambda_i^{mSI}\, x_{t-i}^{SI-mSI} + \sum_{i=1}^{60} \lambda_i^{lSI}\, x_{t-i}^{lSI} + \sum_{i=1}^{60} \lambda_i^{Lit}\, x_{t-i}^{Lit} + \sum_{i=1}^{60} \lambda_i^{DA}\, x_{t-i}^{DA} + \\
&\quad \textstyle\sum_{i=1}^{60} \lambda_i^{PA}\, x_{t-i}^{PA} + \varepsilon_t^{mSI} \\
x_t^{Lit} &= \mu^{Lit} + \textstyle\sum_{i=1}^{60} \upsilon_i^{r}\, r_{t-i} + \sum_{i=1}^{60} \upsilon_i^{mSI}\, x_{t-i}^{SI-mSI} + \sum_{i=1}^{60} \upsilon_i^{lSI}\, x_{t-i}^{lSI} + \sum_{i=1}^{60} \nu_i^{Lit}\, x_{t-i}^{Lit} + \sum_{i=1}^{60} \upsilon_i^{DA}\, x_{t-i}^{DA} + \\
&\quad \textstyle\sum_{i=1}^{60} \upsilon_i^{PA}\, x_{t-i}^{PA} + \varepsilon_t^{Lit} \\
x_t^{DA} &= \mu^{DA} + \textstyle\sum_{i=1}^{60} \pi_i^{r}\, r_{t-i} + \sum_{i=1}^{60} \pi_i^{mSI}\, x_{t-i}^{SI-mSI} + \sum_{i=1}^{60} \pi_i^{lSI}\, x_{t-i}^{lSI} + \sum_{i=1}^{60} \pi_i^{Lit}\, x_{t-i}^{Lit} + \sum_{i=1}^{60} \pi_i^{DA}\, x_{t-i}^{DA} + \\
&\quad \textstyle\sum_{i=1}^{60} \pi_i^{PA}\, x_{t-i}^{PA} + \varepsilon_t^{DA} \qquad (14) \\
x_t^{PA} &= \mu^{PA} + \textstyle\sum_{i=1}^{60} \varphi_i^{r}\, r_{t-i} + \sum_{i=1}^{60} \varphi_i^{mSI}\, x_{t-i}^{SI-mSI} + \sum_{i=1}^{60} \varphi_i^{lSI}\, x_{t-i}^{lSI} + \sum_{i=1}^{60} \varphi_i^{Lit}\, x_{t-i}^{Lit} + \sum_{i=1}^{60} \varphi_i^{Dark}\, x_{t-i}^{Dark} + \\
&\quad \textstyle\sum_{i=1}^{60} \varphi_i^{PA}\, x_{t-i}^{PA} + \varepsilon_t^{PA}
\end{aligned}$$

and ultimately

$$\begin{aligned}
r_t^{midpoint} &= \mu^{r} + \textstyle\sum_{i=1}^{60} \tau_i^{r}\, r_{t-i} + \sum_{i=1}^{60} \tau_i^{lSI}\, x_{t-i}^{lSI} + \sum_{i=1}^{60} \tau_i^{mSI}\, x_{t-i}^{mSI} + \sum_{i=1}^{60} \tau_i^{DA}\, x_{t-i}^{DA} + \sum_{i=1}^{60} \tau_i^{Lit}\, x_{t-i}^{Lit} + \\
&\quad \textstyle\sum_{i=1}^{60} \tau_i^{PA}\, x_{t-i}^{PA} + \varepsilon_t^{r}.
\end{aligned}$$

Information leadership share

A vast number of literature studies how new information is incorporated in prices-price discovery. Several factors as market fragmentation, overall efficiency spreads drive the speed and noisiness of prices move following new information on the underlying. Today, three measures dominate the literature.

Hasbrouck's (1995) developed a measure to quantify the contribution of various types of order flow to price discovery called information share (IS). The measure distinguishes price innovations in a permanent, reflecting the contribution of an efficient price, and temporary impact, which presents the deviation from the efficient price. Gonzalo and Granger (1995) developed a similar measure called common factor share (CS). Both metrics are structural models with a cointegrated price series, based on a join random-walk efficient price. The two metrics quantify

[86] Any time and security related subscripts are omitted, for a better overview.

a combination of timeliness in impounding new information and avoidance of transitory shocks, which are different forms of market efficiency (Putniņš (2013)).

Hasbrouck's IS measure is more suitable to identify the leader in impounding new information but is also influenced by the relative amount of choice in the price channels, as shown in Putniņš (2013). Putniņš (2013) extends Yan and Zivot's (2010) work, which isolates the relative speed at which information is impounded by a price series from its relative level of noise. The author combines the IS and CS metric and defines the information leadership share (ILS). Putniņš (2013) shows that ILS is robust to different noise levels and therefore correctly attributes price discovery in a wider range of settings.[87] The metric is able to identify the price series that is the first to impound new information. The model allows two price series to differ in the amount of noise as well as the speed of incorporating new information. Following Putniņš (2013), we estimate the following vector error correction model (VECM) for each stock-day using one-second intervals t:

$$\begin{aligned}\Delta p_{1,t} &= \alpha_1(p_{1,t-1} - p_{2,t-1}) + \sum_{i=1}^{60} \gamma_i \Delta p_{1,t-1} + \sum_{i=1}^{60} \delta_j \Delta p_{2,t-j} + \varepsilon_{1,t} \\ \Delta p_{2,t} &= \alpha_2(p_{1,t-1} - p_{2,t-1}) + \sum_{k=1}^{60} \phi_i \Delta p_{1,t-k} + \sum_{m=1}^{60} \rho_m \Delta p_{2,t-m} + \varepsilon_{2,t}\end{aligned} \tag{15}$$

Where $p_{1,t}$ and $p_{2,t}$ are the last available log prices of 1 and 2, respectively.

Following Baillie et al. (2002) and Putniņš (2013), we calibrate IS_1, IS_2 as well as CS_1, CS_2:

$$\begin{aligned}CS_1 &= \gamma_1 = {}^{\alpha_2}\!/_{(\alpha_2 - \alpha_1)} \\ CS_2 &= \gamma_2 = {}^{\alpha_1}\!/_{(\alpha_1 - \alpha_2)}\end{aligned} \tag{16}$$

where the compound shares are obtained from the normalised orthogonal to the vector of error correction coefficients $\alpha_{\perp}$=$(\gamma_1, \gamma_2)'$. The IS are calibrated based on the covariance matric of the reduces form VECM error terms:

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix} \tag{17}$$

With a Cholesky factorisation $\Omega = MM'$, where

$$\mathrm{M} = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2(1-\rho^2)^{1/2} \end{pmatrix} \tag{18}$$

This leads to:

$$IS_1 = {}^{(\gamma_1 m_{11} + \gamma_2 m_{12})^2}\!\Big/_{(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}, \tag{19}$$

[87] Please see Narayan and Smyth (2015). The authors provide an extensive discussion on existing measures of price discovery.

$$IS_2 = {(\gamma_2 m_{22})^2} \Big/ {(\gamma_1 m_{11} + \gamma_2 m_{12})^2 + (\gamma_2 m_{22})^2}$$

In accordance with Putniņš (2013), due that the IS is driven by the order of the price series in the VECM, the IS is calculated as the mean of the two possible orders.[88] The final information leadership share facilitates the interpretation of the Yan-Zivot's information leadership metric as[89]:

$$ILS_1 = \left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right| \Big/ \left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right| + \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right|$$
$$ILS_2 = \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right| \Big/ \left|\frac{IS_1}{IS_2}\frac{CS_2}{CS_1}\right| + \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right| \tag{20}$$

The metrics ranges from 0 to 100%. Values larger 50% indicate the price series impounds new information faster, than the other price series which is acts as comparison. Yan and Zivot (2010) define the information leadership metric as:

$$IL_1 = \left|\frac{IS_1}{IS_2}\frac{CS_1}{CS_2}\right|,$$
$$IL_2 = \left|\frac{IS_2}{IS_1}\frac{CS_1}{CS_2}\right| \tag{21}$$

This allows determining which price series leads when incorporating new information about the underlying value. The authors combine CS and IS, which cancels out the relative noise level and results in a metric of relative information leadership share. In their model, the structural cointegration model CS quantifies noise level in one price series relative to the other. The IS metric, on the other hand, measures a combination of relative noise and leadership when incorporating information in the underlying value. The metric is not shared as CS and IS. Putniņš (2013) simplifies the interpretation by introducing ILS.

The ILS is commonly used to study the information leadership share of cross-listed stocks. In this study, we study how trading on lit order books contributes to price discovery compared to (i) limit-order/mid-point SI trading and (ii) periodic auction trading.

Therefore, we use our detailed differentiation of various trading forms and compare not the price series of a stock on two different venues but via two different forms of trading. The findings are shown in Chapter 4.6.3.

[88] Putniņš (2013) follows the approach by Baillie et al. (2002), Booth et al. (2002), Cao et al. (2009), Chen and Gau (2010) and Korczak and Phylaktis (2010), therefore the proceeding is well established.

[89] Yan and Zivot (2010).

4.5.2 Ordinary Least squares and Instrumental variable regression

In this study, we exploit two natural experiments that quantify the impact of (i) SI trading on price discovery and (ii) periodic auction trading on price discovery.

We run different forms of OLS regression models for studying the relationship of both forms of trading with transaction costs, followed by the relationship to parameters of informational efficiency and last, the impact on information leadership share. The OLS regressions models are followed by different 2SLS regression models, which overcome potential endogeneity issues when analysing the impact of those two trading types on the parameters above. We rely on two major regulatory innovations, which act as an instrumental variable and allow us to overcome a potential endogeneity issue. First, we study the relationship of SI trading and parameters of transaction costs, informational efficiency, and information leadership share by introducing MiFIR/MiFID II as an instrumental variable. Second, we analyse the impact of periodic auction trading on price discovery. We limit our sample to suspended securities within the first six cycles of the DVCM and use the suspension start date as an instrumental variable. All our first- and second-stage instrumental variable regression models include a set of four control variables. $FTSE100_{i,d}$ is a dummy variable equivalent to 1 if the security is a constituent of the FTSE 100 index and 0 otherwise. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $Trend_d$ is controlling for changes in the dependent variable over our study horizon.

SI trading

We use a 21-trading day horizon before and after introducing the regulatory changes on 3rd January 2018. None of the regulations explicitly target trading via SI, but trading volume jumped by 20% overnight. SIs are exempted from certain tick size regulation, which provided them with the advantage to quote at different and better prices. Using the regulation as our main source of exogenous variation in SI trading, we analyse the causal impact of SI trading on liquidity and informational efficiency. The empirical design overcomes endogeneity and data issues that have prevented research up until now.

One of the main challenges in empirically studying the impact of SI trading on market quality is the likely endogeneity of SI trading to market conditions. Due to the absence of prior research, we assume that SI trading is similar to dark trading regarding its relationship to market quality parameters. Dark trading tends to increase when spreads are constrained to the minimum tick size because dark trades are allowed to occur within the spread at sub-penny price increments (see Kwan et al. (2015)). Buti and Werner (2011) show that dark pool activity is higher when limit-order depth is high, spreads are narrow, and tick sizes are large. The conditional nature of the decision to execute in the dark results in an endogeneity issue between market quality and dark trading. To overcome any potential endogeneity issues, we use the regulatory changes on 3rd January 2018 as an instrumental variable for SI trading in a two-stage least squares framework.

In our study, we distinguish between systematic internaliser trading executed at the mid-point and as a limit-order, similar to Foley and Putniņš (2016), showing that dark limit-orders and market quality differ significantly from the relationship of dark trading executed at the mid-point and market quality. SI trades executed at the prevailing NBBO are classified as a SI mid-point trade. Trades executed at another price than the prevailing mid-point are classified as a SI limit-order trades.

Our OLS regression models will be run in the form of:

$$y_{i,d} = \alpha_i + \beta_1 SI\_V\_mid_{i,d} + \beta_2 SI\_V\_mid_{i,d} * FTSE\ 100_{i,d} + \beta_3 SI\_V\_limit_{i,d} + \beta_4 SI\_V\_limit_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,id} + \varepsilon_{i,d} \tag{22}$$

where $SI\_V\_mid_{i,d}$ and $SI\_V\_limit_{i,d}$ are equivalent to the daily share of the respective form of SI trading for security i. We include the four control variables as described above. y_{id} is one of our dependent variables used in Chapter 4.6. We study the impact of SI trading on parameters of transaction costs, $Effective\ Spread_{id}$ and $Price\ Impact_{id}$, informational efficiency, $Autocorrelation_{id}$ and $Variance\ Ratio_{id}$, as well as information leadership share, ILS_{id}, see Chapter 4.6.1 and Chapter 4.6.2. We run OLS regression models with no, stock- and date-fixed effects.

For the 2SLS regression model, we run the first-stage regression for each form of trading and estimate the respective fitted values:

$$SI\_V\_mid_{i,d} = \alpha_i + \beta_1 M_d^{Post} + \beta_2 SI\_V\_mid_{i,d-1} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d} \tag{23}$$

And

$$SI\_V\_limit_{i,d} = \alpha_i + \beta_1 M_d^{Post} + \beta_2 SI\_V\_limit_{i,d-1} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d} \tag{24}$$

$SI\_V\_mid_{i,d}$ is equivalent to the daily share of SI trading executed at the mid-point for a security i. The main instrumental variable is a dummy variable M_d^{Post} which equals to 1 post the 3rd January 2018 and 0 otherwise. We follow the approach of Foley and Putniņš (2016) and include in addition the lagged level of SI trading $SI\_V\_mid_{i,d-1}$. We include two instrumental variables in our first-stage regression and refer in Chapter 4.6 to those as set 1. Both instrumental variables are proven to be valid, the F-statistic is tested in accordance with critical values specified by Stock and Yogo (2005). As a control, we run the first-stage regression with just the dummy variable M_d^{Post}, which we refer to as set 2 in Chapter 4.6:

$$SI\_V\_mid_{i,d} = \alpha_i + \beta_1 M_d^{Post} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d} \tag{25}$$

and

$$SI\_V\_limit_{i,d} = \alpha_i + \beta_1 M_d^{Post} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d} \tag{26}$$

The control variables are the same as described above. We predict the fitted values $\widehat{SI\_V\_mid}_{i,d}$ and $\widehat{SI\_V\_limit}_{i,d}$ for any form of first-stage regression. And run the second-stage regression for all first-stage regression includes the respective fitted values and is modelled in form:

$$\begin{aligned} y_{i,d} = \alpha_i &+ \beta_1 \widehat{SI\_V\_mid}_{i,d} + \beta_2 \widehat{SI\_V\_mid}_{i,d} * FTSE\ 100_{i,d} + \beta_3 \widehat{SI\_V\_limit}_{i,d} + \beta_4 \widehat{SI\_V\_limit}_{i,d} \\ &* FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d} \end{aligned} \tag{27}$$

where y_{id} is the respective dependent variable that we aim to analyse in Chapter 4.6. $Control_{j,i,d}$ includes the same control variables as in the first-stage regression. In Chapter 4.6 we present our analysis with and without stock-fixed effects.

Periodic Auction trading

We describe in Chapter 4.4 how we overlay six datasets with each 20 trading days prior to and post the start of a suspension start date within the DVCM.[90] For our OLS regression, we do not consider the suspension start date however, limit for comparison with the 2SLS regression

[90] Please see ESMA (2021) for an overview on the suspended securities within our sample.

model our sample to securities for which trading with a certain transparency waiver was suspended. We model several OLS regression models as follows:

$$y_{i,d} = \alpha_i + \beta_1 PA\_V_{i,d} + \beta_2 PA\_V_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d} \tag{28}$$

where $PA\_V_{i,d}$ is equivalent to the daily share of the trading via periodic auctions for security i. The four control variables are the same as for our analysis described in Chapter 4.5.2. y_{id} presents the of our parameters of interest, e.g., a proxy of transaction costs, informational efficiency or information leadership share. We run OLS regression models with no, stock- and date-fixed effects.

We continue with the 2SLS regression model: The suspension start date acts for suspended securities as an instrumental variable for periodic auction trading, similar to the introduction of MiFIR/MiFID II for SI trading. By suspending the use of certain transparency waivers, trading moved to different forms of trading. As shown in Chapter 4.4, trading on lit trading venues did, on average does not increase following a securities' suspension, we observe however, a significant increase in periodic auction trading. We verify the suitability of the suspension start date in the form of an event dummy as an instrumental variable. We follow the procedure as described in Chapter 4.5 when studying SI trading. We run the first-stage regression as follows:

$$PA\_V_{i,d} = \alpha_i + \beta_1 M_d^{Post} + \beta_2 PA\_V_{i,d-1} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d} \tag{29}$$

$PA\_V_{i,d}$ is equivalent to the daily share of PA trading for security i. The dummy variable M_d^{Post}, which equals 1 post the suspension start date and 0 before, is the main instrumental variable. In addition, we include the lagged level of PA trading $PA\_V_{i,d-1}$. Those two instrumental variables form instrumental variable set 1. We verify the eligibility of those two instrumental variables. For robustness, we run the same first-stage regression with just the dummy variable M_d^{Post}. In Chapter 4.6, the latter refers to instrumental variables set 2:

$$PA\_V_{i,d} = \alpha_i + \beta_1 M_d^{Post} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d} \tag{30}$$

In both cases. we include four control variables as described previously. We estimate the fitted values for periodic auction trading $\widehat{PA\_V}_{i,d}$ for both first-stage regressions and run the second stage regression:

$$y_{i,d} = \alpha_i + \beta_1 \widehat{PA\_V}_{i,d} + \beta_2 \widehat{PA\_V}_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d} \tag{31}$$

where y_{id} is a parameter of transactions costs, price discovery or informational efficiency as shown in Chapter 4.6. $Control_{j,i,d}$ includes the same control variables as in the first-stage regression. We study the relationship with no, date-fixed as well as stock-fixed effects.

4.6 EMPIRICAL ANALYSIS

The remaining parts of the chapter present our findings on the relationship between price discovery and both SI and periodic auction trading. Since liquidity and price discovery are closely connected, we focus in Chapter 4.6.1 first on the general impact of SI and periodic auction trading on transaction costs and informational efficiency. We turn then to the permanent price impact measure by Hasbrouck (1991), which provides insights on the informativeness of different trading forms. Last, in Chapter 4.6.3, we present our findings on the impact of SI and periodic auction trading on the lit market's information leadership share.

4.6.1 Transaction costs and Informativeness of SI and periodic auction trading

In a market with only two order books, an increase in market share of SI would mean that the lit market loses in market share, which impacts the informational content of the primary market since either informed traders or less informed participants move to the second venue. In our case, the second venue would be a market where especially large orders could be executed in a more price-efficient way since SI are not required to disclose quotes for large-in scale orders. Large-in-scale orders are likely submitted by overall superior participants, who might decide against a dark pool since they face uncertainty around immediate execution.[91] Via a SI, quotes for non-large-in-scale orders are public, which likely supports an estimation on execution probability. Therefore, in a two-market scenario, informed traders aiming to submit a large order have reasons to prefer SI trading.[92] We first assess the impact of SI trading on transaction costs and general measures of informational efficiency in Tables 28 and 29. In Appendix A.3 and A.5 we present alternative OLS and 2SLS model specification for further robustness. The first four columns in Table 28 show the coefficients for different specified OLS regression models. We run an OLS regression with the daily security-specific effective spread measure and the price impact as the dependent variables to assess how a 1 percentage point increase in the market share of SI trading at the mid-point or limit-orders impacts the transaction costs metric.

The effective spread measure can be seen as the liquidity provider's gross revenue, or the cost paid by the trader. To estimate the informational content of trades, we include the price impact measure. Order flow imbalances are a good indicator for the presence of informed participants, which in turn are used by market makers to adjust their quotes. The level of adjustment can be considered a measure of the extent of superior information in the market. We

[91] Or the respective security was suspended under the DVCM.

[92] We are not attempting to study the order size of individual orders. The individual 'average-market-size' is recalibrated on a daily basis and accordingly data would need to be adjusted. It would be an interesting area for future research.

run OLS and 2SLS regressions to evaluate whether the price impact increases when the market share of SI limit-order or, respectively, mid-point trading increases.

We find that limit-order SI trading for the combined sample of FTSE 100 index and FTSE 250 index constituents lowers the effective spread by over 7.8bps or higher across all model specifications at a 1% significance level. An increase in the market share of SI limit-order trading of FTSE 100 index securities widens the transaction costs for OLS regressions by 1.7bps to 2.0bps.

The 2SLS regressions coefficients are less conclusive but do not contradict those findings. The 2SLS regression model with date-fixed effects presents a 2.4bps increase in effect spread at a 5% significance level. A general decrease in transaction costs can be related to lower adverse selection costs and less informed market participants in the CLOB. That would mean SI limit-order trading, in general, is attractive to informed market participants, however, at a smaller level than CLOB trading.[93] If, however, constituents of the FTSE 100 index are traded, SI limit-order trading seems to increase transaction costs in the CLOB. That would mean that at a disproportional level, less informed traders move to SI limit-order trading. SI trading at the mid-point does not impact transaction costs in general at a significant level. SI mid-point trading of FTSE 100 index constituents narrows effective spread between 1.7 and 2.0bps via OLS regressions and lowers effective spread significantly between 78.0bps and 178.6bps based on a 2SLS regressions model. Given the potential endogeneity of our data, we rely rather on the 2SLS regression results. In that case, it would mean that SI trading at the mid-point is very attractive to informed market participants in the CLOB. The control variables are throughout highly significant. Constituents of the FTSE 100 index present significantly lower transaction costs than securities within the FTSE 250 index.

Table 28: Impact of mid-point and limit-order SI trading on transaction costs

The table reports the estimates of an OLS regression and the second-stage instrument variables regression on the impact of SI limit-order and mid-point market share on transaction costs. The first four columns present two different OLS regression models for $Effective\ Spread_{i,d}$ and $Price\ Impact_{i,d}$ each.

$$y_{i,d} = \alpha_i + \beta_1 SI\_V\_mid_{i,d} + \beta_2 SI\_V\_mid_{i,d} * FTSE\ 100_{i,d} + \beta_3 SI\_V\_limit_{i,d} + \beta_4 SI\_V\_limit_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,id} + \varepsilon_{i,d}$$

The 2SLS regression modes in the last four columns for the same measures include both the fitted values of both forms of SI trading. The first-stage regression results are not reported but the F-statistics all reject

[93] We analyse a 1% shift in market share from CLOB trading to the respective form of SI trading. Following an exaggerated example of a mechanical interpretation of our results: If 100% of the market share would consist of 100% informed trading, and effective spread would be a direct measure of adverse selection costs which would indicate informed trading, a coefficient should be around -100bps, see Zhu (2014). A coefficient of 0bps would mean 100% of the shift in market share would be uninformed trading. We are aware that this is not the case in reality, however adverse selection costs are a main driver of effective spread. Further we evaluate the findings in conjunction with other analyses.

the null hypotheses that the instrumental variables are weak (Stock and Yogo (2005)). The models are run as follows with two different sets of instrumental variables:

$$y_{i,d} = \alpha_i + SI\_\widehat{V\_mid}_{i,d} + \beta_2 SI\_\widehat{V\_mid}_{i,d} * FTSE\ 100_{i,d} + \beta_3 SI\_\widehat{V\_limit}_{i,d} + \beta_4 SI\_\widehat{V\_limit}_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}\, \beta_1$$

The first instrumental variable set (Set 1) is a combination of a dummy variable equivalent to 0 prior to the introduction of MiFIR/MiFID II regulation and 1 after, and the lagged observation of the respective type of SI trade share. The second set (Set 2) is limited to the dummy variable. The dependent variables $y_{i,d}$ of the second-stage regressions are estimates of transaction costs. The metric $Price\ Impact_{i,d}$ is time-weighted and computed as the difference of effective and realised spread on the lit venue. $Effective\ Spread_{i,d}$ is a time-weighted daily for all trades during continuous lit trading. Both spread measures are calculated relative to the mid-point in basis points. Each regression model incorporates four control variables in addition to the main independent variables. $FTSE100_{i,d}$ is a dummy variable equivalent to 1 if the security is a constituent of the FTSE 100 index and 0 otherwise. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $Trend_d$ controlling for changes in the dependent variable over our study horizon. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index during the period of 22nd November 2017 till 9th February 2018, which is equivalent to 28 full trading days before and after the event. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	$Effective\ Spread_{i,d}$	$Effective\ Spread_{i,d}$	$Price\ Impact_{i,d}$	$Price\ Impact_{i,d}$	$Effective\ Spread_{i,d}$	$Effective\ Spread_{i,d}$	$Price\ Impact_{i,d}$	$Price\ Impact_{i,d}$
$Intercept_{i,d}$	17.66***	12.83***	12.80***	10.45***	20.35***	11.73***	13.90***	10.11***
	(45.02)	(114.17)	(32.90)	(104.11)	(42.43)	(66.18)	(29.83)	(62.62)
$SI\_V\_mid_{i,d}$	-2.21	-0.98	1.00	1.36				
	(-1.23)	(-0.55)	(0.67)	(0.87)				
$SI\_V\_mid_{i,d} * FTSE\ 100_{i,d}$	-6.00**	-4.51***	7.79***	7.46***				
	(-2.01)	(-6.96)	(3.80)	(3.71)				
$SI\_V\_limit_{i,d}$	-9.76***	-7.89***	-2.74***	-2.31***				
	(-18.78)	(-16.23)	(-6.35)	(-5.66)				
$SI\_V\_limit_{i,d} * FTSE\ 100_{i,d}$	1.71***	2.01***	-0.62	-0.66*				
	(3.85)	(4.58)	(-1.58)	(-1.69)				
$SI\_\widehat{V\_mid}_{i,d}$					14.88	124.40***	10.78	37.83**
					(0.73)	(6.60)	(0.58)	(2.17)
$SI\_\widehat{V\_mid}_{i,d} * FTSE\ 100_{i,d}$					-178.56***	-78.04***	24.80	54.83**
					(-6.94)	(-3.53)	(1.04)	(2.40)
$SI\_\widehat{V\_limit}_{i,d}$					-32.19***	-11.45***	-9.61***	-4.09***
					(-20.01)	(-10.79)	(-7.18)	(-4.36)
$SI\_\widehat{V\_limit}_{i,d} * FTSE\ 100_{i,d}$					2.36**	-1.22	-3.76***	-5.08***
					(2.29)	(-1.32)	(-4.04)	(-5.60)
$FTSE\ 100_{i,d}$	-9.73***	-10.10***	-6.87***	-7.04***	-6.88***	-8.56***	-6.33***	-6.85***
	(-116.86)	(-122.86)	(-89.52)	(-92.22)	(-34.72)	(-50.46)	(-33.82)	(-39.37)
$HFTVol_{i,d}$	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***	-0.00***	-0.01***	-0.01***
	(-13.6)	(-8.64)	(-25.05)	(-23.12)	(-14.80)	(-7.06)	(-24.44)	(-21.59)
$Trend_{i,d}$	-0.15***	0.01***	-0.12***	-0.03***	-0.16***	0.02***	-0.16***	-0.02***
	(-11.22)	(4.76)	(-8.88)	(-10.81)	(-11.12)	(3.94)	(-9.32)	(-5.95)
$Volatility_{i,d}$	0.03***	0.03***	0.04***	0.04***	0.03***	0.03***	0.04***	0.04***
	(58.39)	(57.96)	(81.32)	(81.93)	(53.43)	(55.64)	(75.96)	(76.99)
Obs.	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842
Method	OLS	OLS	OLS	OLS	SLS	SLS	SLS	SLS
Adj. R^2	0.26	0.25	0.27	0.27	0.25	0.26	0.27	0.27
F-Test	5,574.0	5,660.0	45,56.0	4,608.0	5,725.0	6,023.0	4,802.0	4,938.0
Fixed Effects	Date	None	Date	None	Date	None	Date	None
Instrumental Variables	-	-	-	-	Set 1	Set 1	Set 1	Set 1

We observe a similar pattern running the OLS and 2SLS regression models with and without fixed effects for price impact. On average, a 1% increase in the market share of limit-order SI trading leads to a drop of at least 2.3bps in price impact via both models. The 2SLS regression coefficients are even larger, suggesting that SI limit-order trading attracts informed market participants at a much lower level than the CLOB. We find that SI mi-point trading widens price impact in the CLOB only for constituents of the FTSE 100 index using an OLS regression model and indicated the same using a 2SLS regression model. Those findings contrast with our 2SLS regression coefficients but would be in line with the OLS regression results.

When compared, SI limit-order trading should be more attractive to informed participants than SI trading at the mid-point at an aggregate level. Based on our findings for constituents of the FTSE 100 index, the results indicate that informed market participants strongly prefer to trade more liquid securities, constituents of the FTSE 100 index, in the CLOB rather than via SI limit-order trading. The results indicate that trading of FTSE 100 index constituents via SI mid-point might be highly informed; however, the results are not conclusive.

Table 29 presents the findings across our sample when studying the relationship between periodic auction trading and transaction costs. We first analyse the relationship with an OLS regression model (first four columns) and deepen our understanding with a 2SLS regression.

We find that effective spread increases over 21.7bps at a 1% significance level independent of the fixed-effect specifications with an OLS regression. The 2SLS regression coefficients indicate an even higher increase in effective spread between 34.5bps and 207.8bps. The coefficients for price impact present complement our findings: A 1% increase in periodic auction market share leads to a highly significant increase of 12.4bps and 13.1bps, respectively, via an OLS regression model. Similar, periodic auction trading leads to an increase of 157.4bps and 24.6bps, respectively, using a 2SLS model. On an aggregate level, that indicates that periodic auction trading is disproportionally less informed than CLOB trading. In Appendix A.5, we provide further robustness tests.

Table 29: Impact of periodic auction trading on transaction costs

The table reports the estimates of an OLS regression and the second-stage instrument variables regression on the impact of trade execution via periodic auctions on transaction costs. The first four columns present two different OLS regression models for $Effective\ Spread_{i,d}$ and $Price\ Impact_{i,d}$ each.

$$y_{i,d} = \alpha_i + \beta_1 PeriodicAuction_{i,d} + \beta_2 PeriodicAuction_{i,d} * FTSE100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,id} + \varepsilon_{i,d}$$

The last four columns report the estimates when running a 2SLS model. The first-stage regression results are not reported. The null hypotheses that the instrumental variables are weak was rejected (Stock and Yogo (2005)). The models are run as follows with two different sets of instrumental variables. We present the findings based on instrumental variable set 1 only.

$$y_{i,d} = \alpha_i + \beta_1 \widehat{PeriodicAuction}_{i,d} + \beta_2 \widehat{PeriodicAuction}_{i,d} * FTSE100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,id} + \varepsilon_{i,d}$$

The first instrumental variable set (Set 1) is a combination of a dummy variable equivalent to 0 prior to a suspension cut-off date within the DVCM and 1 after, and the lagged observation of the respective type of periodic auction trade share. The second set (Set 2) is limited to the dummy variable. The dependent variables $y_{i,d}$ of the second-stage regressions are estimates of transaction costs. The metric $Price\ Impact_{i,d}$

is time-weighted and computed as the difference of effective and realised spread on the lit venue. $Effective\,Spread_{i,d}$ is a time-weighted daily for all trades during continuous lit trading. Both spread measures are calculated relative to the mid-point in basis points. Each model includes four control variables. $FTSE100_{i,d}$ is a dummy variable equivalent to 1 if the security is a constituent of the FTSE 100 index and 0 otherwise. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $Trend_d$ controlling for changes in the dependent variable over our study horizon. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index, which were suspended using transparency waivers anytime between March 2018 and August 2018 in terms of the thresholds of the DVCM. Before and after each monthly cut-off date, we include 20 trading days before and after the event. This results in six datasets that we overlay to one data set. Date* fixed-effects refer not to actual dates, but numbers between -21 and 21 indicating the days prior to and after the suspension's start date. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	$Effective\ Spread_{i,d}$	$Effective\ Spread_{i,d}$	$Price\ Impact_{i,d}$	$Price\ Impact_{i,d}$	$Effective\ Spread_{i,d}$	$Effective\ Spread_{i,d}$	$Price\ Impact_{i,d}$	$Price\ Impact_{i,d}$
$Intercept_{i,d}$	7.20***	7.53***	5.91***	6.26***	2.45***	7.18***	2.19***	5.89***
	(56.52)	(60.29)	(46.47)	(49.78)	(5.70)	(47.33)	(5.19)	(37.39)
$Periodic\ Auction_{i,d}$	22.36***	21.68***	12.40***	13.07***				
	(14.12)	(14.49)	(7.77)	(8.69)				
$Periodic\ Auction_{i,d} * FTSE\ 100_{i,d}$	-7.42***	-8.42***	-6.85***	-4.14**				
	(-3.92)	(-4.62)	(-3.27)	(-2.04)				
$\widehat{Periodic}\ Auction_{i,d}$					207.82***	34.47***	157.45***	24.60***
					(12.95)	(9.63)	(9.97)	(6.73)
$\widehat{Periodic}\ Auction_{i,d} * FTSE\ 100_{i,d}$					-15.37***	-25.26***	-17.54***	-8.87**
					(-4.00)	(-6.51)	(-4.36)	(-2.15)
$FTSE\ 100_{i,d}$	-8.36***	-8.43***	-7.14***	-7.29***	-6.89***	-8.02***	-5.91***	-7.09***
	(-119.73)	(-121.79)	(-97.47)	(-99.94)	(-45.76)	(-71.43)	(-38.83)	(-58.72)
$HFTVol_{i,d}$	0.01***	0.01***	-0.00***	-0.00***	0.01***	0.01***	-0.00***	-0.00***
	(12.45)	(12.32)	(-5.47)	(-5.55)	(14.33)	(12.46)	(-3.61)	(-5.34)
$Trend_{i,d}$	0.00	0.00	0.01***	0.01***	0.01***	0.00	0.01***	0.01***
	(1.01)	(1.11)	(3.17)	(3.13)	(3.03)	(1.21)	(4.67)	(3.23)
$Volatility_{i,d}$	0.05***	0.05***	0.06***	0.06***	0.05***	0.05***	0.06***	0.06***
	(79.12)	(78.79)	(93.16)	(91.96)	(73.39)	(78.78)	(88.16)	(92.45)
Obs.	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842
Method	OLS	OLS	OLS	OLS	SLS	SLS	SLS	SLS
Adj. R^2	0.41	0.41	0.39	0.39	0.40	0.40	0.39	0.39
F-Test	4,966.1	4,966.1	2,414.8	554.9	241.4	4,754.4	66.4	2,833.0
Fixed Effects	Date*	None	Date*	None	Date*	None	Date*	None
Instrumental Variables	-	-	-	-	Set 1	Set 1	Set 1	Set 1

Effective spread drops by 7.4bps and 8.4bps via an OLS regression and 15.4bps and 25.3bps via a 2SLS regression model. Price impact drops by 4.1bps and 6.9bps in our OLS model specifications, and 8.9bps and 17.5bps with a 2SLS regression.

Those results would show that adverse selection in the CLOB drops significantly (see Zhu (2014) and Glosten and Milgrom (1985)). The level of decrease indicates that periodic auction trading presents a certain level of information at a lower level than the CLOB. The majority of order flow moving from the CLOB towards periodic auctions is not informative.

The results for liquid securities are in line with Madhavan (1992), who finds that periodic auction markets support price discovery as they collect information from different traders over a time interval. Our data present for the FTSE 100 index around 6.5 thousand trades per hour, with an increase over our sample horizon. We record approximately 137 thousand lit trades per hour.[94] Periodic auctions might attract traders with superior information. Those might avoid front running since periodic auctions only disclose the auction price – not real-time quote updates.

The increase in transaction costs for less liquid securities could be a result of reduced liquidity. A less informed/slower participant might prefer periodic auctions, as they offer a way to bypass the need for speed and still receive a competitive price. The changes in transaction costs combined with an increased price impact are in line with Zhu (2014), who argues that informed traders prefer transparency, which increases adverse selection costs and will result in wider spreads. That would mean periodic auctions might be preferred by less informed participants for less liquid securities. Trading in periodic auctions with liquid securities, however, attracts both informed and uninformed traders.[95]

Table 30 focuses on measures of informational efficiency relating to SI limit-order and mid-point trading. The results rely on the same methodology used as in Tables 28 and 29. In Appendix A.4, we provide further robustness tests.

Table 30: Impact of mid-point and limit-order SI trading on informational efficiency

The table reports the estimates of different OLS regression and second-stage instrument variables regression models on the impact of SI limit-order and mid-point trading on measures of informational efficiency. The first four columns present different OLS regressions for $Autocorrelation_{i,d}$ and $Variance\ Ratio_{i,d}$ each.

$$y_{i,d} = \alpha_i + \beta_1 SI\_V\_mid_{i,d} + \beta_2 SI\_V\_mid_{i,d} * FTSE\ 100_{i,d} + \beta_3 SI\_V\_limit_{i,d} + \beta_4 SI\_V\_limit_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,id} + \varepsilon_{i,d}$$

The 2SLS regressions in the last four columns for the same parameters include both the fitted values of both forms of SI trading:

$$y_{i,d} = \alpha_i + \beta_1 SI\_\widehat{V\_mid}_{i,d} + \beta_2 SI\_\widehat{V\_mid}_{i,d} * FTSE\ 100_{i,d} + \beta_3 SI\_\widehat{V\_limit}_{i,d} + \beta_4 SI\_\widehat{V\_limit}_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The first-stage regression results show highly significant F-statistics, rejecting the null hypotheses that the instrumental variables are weak (see Stock and Yogo (2005)). The first instrumental variable set (Set 1) is a combination of a dummy variable equivalent to 0 prior to the introduction of MiFIR/MiFID II regulation and 1 after, and the lagged observation of the respective type of SI trade share. The second set (Set 2) is limited to the dummy variable. The dependent variables $y_{i,d}$ are estimates of informational efficiency. $Autocorrelation_{i,d}$ is based on 10-second mid-point returns, whereas $HFVol_{i,d}$ is added as 10-second mid-

[94] In comparison, SI trading presents around 14 thousand trades per hour, dark trading 9.8 thousand trades. Those are average values across the sample horizon, which fluctuate due to common daily events and market events.

[95] We need to consider that our sample considers capped securities under the DVCM only. Those are securities which tend to trade in dark pools under pre-trade transparency waivers. That might lead to a certain bias due to the sample, and results should be evaluated with caution. Further research in non-capped securities via an OLS regression should be conducted and other potential instrumental variables considered.

point return standard deviations during continuous lit trading hours. $Variance\ Ratio_{i,d}$ measures the variance-ratio of the standard deviations on 1-second and 10-second mid-point returns. We add four control variables to each model. $FTSE100_{i,d}$ is a dummy variable equivalent to 1 if the security is a constituent of the FTSE 100 index and 0 otherwise. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $Trend_d$ controlling for changes in the dependent variable over our study horizon. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index during the period of 22nd November 2017 till 9th February 2018, which is equivalent to 28 full trading days before and after the event. Adjusted R^2 s do not report the variance explained by the fixed effects. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	$Autocorrelation_{i,d}$	$Autocorrelation_{i,d}$	$Variance\ Ratio_{i,d}$	$Variance\ Ratio_{i,d}$	$Autocorrelation_{i,d}$	$Autocorrelation_{i,d}$	$Variance\ Ratio_{i,d}$	$Variance\ Ratio_{i,d}$
$Intercept_{i,d}$	-0.05***	-0.07***	1.18***	1.27***	-0.06***	-0.07***	1.09***	1.11***
	(-20.75)	(-81.76)	(212.62)	(635.71)	(-20.11)	(-59.45)	(13.62)	(632.22
$SI\_V\_mid_{i,d}$	0.02**	0.03***	-0.01	0.00				
	(2.25)	(2.74)	(-0.45)	(0.07)				
$SI\_V\_mid_{i,d}$	-0.06**	-0.06**	0.15**	0.12				
$* FTSE\ 100_{i,d}$	(-2.39)	(-2.51)	(2.08)	(1.61)				
$SI\_V\_limit_{i,d}$	0.01***	0.02***	0.03***	0.04***				
	(4.10)	(6.72)	(4.68)	(5.82)				
$SI\_V\_limit_{i,d}$	-0.02***	-0.02***	-0.05***	-0.04***				
$* FTSE\ 100_{i,d}$	(-5.79)	(-5.72)	(-5.79)	(-4.51)				
$\widehat{SI\_V\_mid}_{i,d}$					0.23**	0.34***	-0.62**	-0.54**
					(2.00)	(2.99)	(-2.49)	(-2.17)
$\widehat{SI\_V\_mid}_{i,d}$					-2.02***	-1.80***	3.93***	4.49***
$* FTSE\ 100_{i,d}$					(-7.78)	(-6.99)	(6.39)	(7.28)
$\widehat{SI\_V\_limit}_{i,d}$					0.04***	0.05***	0.10***	0.12***
					(4.47)	(8.01)	(4.81)	(7.71)
$\widehat{SI\_V\_limit}_{i,d}$					0.02*	0.01	-0.18***	-0.18***
$* FTSE\ 100_{i,d}$					(1.89)	(1.08)	(-7.73)	(-7.85)
$FTSE\ 100_{i,d}$	0.02***	0.02***	-0.04***	-0.04***	0.03***	0.03***	-0.06***	-0.07***
	(22.57)	(21.47)	(-18.16)	(-18.80)	(16.57)	(16.09)	(-13.37)	(-14.94)
$HFTVol_{i,d}$	-0.00***	-0.00***	0.00***	0.00***	0.03***	0.03***	-0.06***	-0.07***
	(-19.22)	(-18.05)	(23.52)	(18.85)	(16.57)	(16.09)	(-13.37)	(-14.94)
$Trend_{i,d}$	0.00***	0.00***	-0.00***	-0.00***	-0.00***	-0.00***	0.00***	0.00***
	(4.24)	(36.93)	(-5.73)	(-76.27)	(-18.87)	(-18.82)	(22.93)	(18.95)
$Volatility_{i,d}$	-0.00***	-0.00***	0.00***	0.00***	0.00***	0.00***	-0.00***	-0.00***
	(-53.84)	(-56.06)	(61.20)	(55.49)	(5.32)	(19.45)	(-7.64)	(-55.07)
Obs.	83,454	83,454	83,454	83,454	83,454	83,454	83,454	83,454
Method	OLS	OLS	OLS	OLS	SLS	SLS	SLS	SLS
Adj. R^2	0.10	0.09	0.17	0.13	0.10	0.09	0.17	0.13
F-Test	696.2	861.2	987.2	1,725.0	695.0	879.0	996.7	1,783.0
Fixed Effects	Date	None	Date	None	Date	None	Date	None
Instrumental Variables	-	-	-	-	Set 1	Set 1	Set 1	Set 1

Our sample presents negative autocorrelations, which are the result of bid-ask bounce, see Roll (1984). Our findings are highly consistent when varying the fixed effects. The OLS regression coefficients show that a one standard deviation increase in the market share of SI limit-order trading relates to a decrease in autocorrelation of 0.00024 standard deviations.[96] Our

[96] The market share of mid-point SI trading presents an average standard deviation of 1.2%, the market share of limit-order SI trading 5.2% respectively. Our sample shows a standard deviation of -0.04 for the autocorrelation metric and 1.15 for the variance-ratio metric. The impact of a one standard deviation

coefficients for autocorrelation are significant at a 1% level across the OLS and 2SLS regression specifications, showing that SI trading via limit-orders has a detrimental effect on CLOB's informational efficiency.

The corresponding coefficients for variance-ratio are positive, confirming our findings for autocorrelation. However, our coefficients for trading in liquid securities are negative when studying the relationship with an OLS regression, indicating a beneficial effect on informational efficiency in the CLOB. The corresponding 2SLS regressions, however, are not consistent for autocorrelation. The coefficients for variance-ratio present a highly significant positive effect of SI limit-order trading in liquid securities.

Our findings for SI mid-point trading are less conclusive. We find that the coefficients evaluating the impact on autocorrelation present a negative impact. The respective coefficients for variance-ratio, however, present a positive relationship. Similar, the findings for liquid securities are inconclusive. Our results show that an increase in SI mid-point trading in liquid securities improves informational efficiency when measured by autocorrelation. We find a detrimental impact on informational efficiency in the CLOB when measured by variance-ratio. The inconsistent pattern has been discussed in Lin et al. (2021) and Chordia et al. (2008).

In Table 31, we are studying the relationship between a growing market share of periodic auction trading and informational efficiency. Our findings find a non-detrimental effect of periodic auction trading for liquid and illiquid securities on the CLOB's informational efficiency consistently. We find highly significant negative coefficients for constituents of the FTSE 100 index when studying the relationship to variance-ratio. The corresponding coefficient for autocorrelation is insignificant. In Appendix A.6we provide further robustness tests.

We conclude that our results show that periodic auction trading, in general, has a non-detrimental to a positive impact on the informational efficiency in the CLOB. SI limit-order trading in liquid security indicates a positive relationship, whereas the remaining results are inconclusive.

increases in the SI limit-order trade volume market share based on our OLS regression model. would be calibrated as 0.012*(0.02/(-0.04)).

Table 31: Impact of periodic auction trading on informational efficiency

The table reports the estimates of different OLS regression and second-stage instrument variables regression models on the impact of periodic auction trading on measures of informational efficiency. The first four columns present two different OLS regressions for $Autocorrelation_{i,d}$ and $Variance\ Ratio_{i,d}$ each.

$$y_{i,d} = \alpha_i + \beta_1 PeriodicAuction_{i,d} + \beta_2 PeriodicAuction_{i,d} * FTSE100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,id} + \varepsilon_{i,d}$$

The 2SLS regressions in the last six columns for the same parameters include both the fitted values of both forms of SI trading:

$$y_{i,d} = \alpha_i + \beta_1 \widehat{PeriodicAuction}_{i,d} + \beta_2 \widehat{PeriodicAuction}_{i,d} * FTSE100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,id} + \varepsilon_{i,d}$$

The first-stage regression results show highly significant F-statistics, rejecting the null hypotheses that the instrumental variables are weak (see Stock and Yogo (2005)). The first instrumental variable set (Set 1) is a combination of a prior to a suspension cut-off date within the DVCM and 1 after and the lagged observation of the periodic auction trade share. The second set (Set 2) is limited to the dummy variable. The dependent variables $y_{i,d}$ are estimates of informational efficiency. $Autocorrelation_{i,d}$ is based on 10-second mid-point returns, whereas $HFVol_{i,d}$ is added as 10-second mid-point return standard deviations during continuous lit trading hours. $Variance\ Ratio_{i,d}$ measures the variance-ratio of the standard deviations on 1-second and 10-second mid-point returns. Each model includes four control variables. $FTSE100_{i,d}$ is a dummy variable equivalent to 1 if the security is a constituent of the FTSE 100 index and 0 otherwise. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $Trend_d$ controlling for changes in the dependent variable over our study horizon. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index, which were suspended using transparency waivers anytime between March 2018 and August 2018 in terms of the thresholds of the DVCM. Before and after each monthly cut-off date, we include 20 trading days before and after the event. This results in six datasets, that we overlay to one data set. Date* fixed-effects refer not to actual dates, but numbers between -21 and 21 indicating the days prior to and after the suspension's start date. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	$Autocorrelation_{i,d}$	$Autocorrelation_{i,d}$	$Variance\ Ratio_{i,d}$	$Variance\ Ratio_{i,d}$	$Autocorrelation_{i,d}$	$Autocorrelation_{i,d}$	$Variance\ Ratio_{i,d}$	$Variance\ Ratio_{i,d}$
$Intercept_{i,d}$	-0.05***	-0.05***	1.08***	1.08***	-0.04***	-0.05***	1.08***	1.08***
	(-42.29)	(-43.58)	(991.65)	(1,002.41)	(-12.63)	(-36.50)	(391.78)	(800.35)
$Periodic\ Auction_{i,d}$	-0.04***	-0.03**	0.01	-0.00				
	(-3.84)	(-2.53)	(0.70)	(-0.37)				
$Periodic\ Auction_{i,d} * FTSE\ 100_{i,d}$	-0.02	0.01	-0.08***	-0.10***				
	(-0.53)	(0.53)	(-3.14)	(-4.14)				
$\widehat{Periodic}\ \widehat{Auction}_{i,d}$					-0.43***	0.02	0.02	0.01
					(-3.80)	(0.79)	(0.16)	(0.22)
$\widehat{Periodic}\ \widehat{Auction}_{i,d} * FTSE\ 100_{i,d}$					0.06	0.09*	-0.29***	-0.29***
					(1.34)	(1.89)	(-6.43)	(-6.29)
$FTSE\ 100_{i,d}$	0.02***	0.02***	0.01	-0.00	0.02***	0.02***	-0.03***	-0.03***
	(27.41)	(27.41)	(0.70)	(-0.37)	(13.84)	(17.92)	(-23.34)	(-25.19)
$HFTVol_{i,d}$	-0.00***	-0.00***	0.00***	0.00***	-0.00***	-0.00***	0.00***	0.00***
	(-19.12)	(-19.21)	(25.56)	(25.57)	(-19.37)	(-19.18)	(25.08)	(25.11)
$Trend_{i,d}$	-0.00	-0.00	0.00	0.00	-0.00	-0.00	0.00	0.00
	(-0.40)	(-0.51)	(0.67)	(0.78)	(-0.80)	(-0.32)	(0.53)	(0.61)
$Volatility_{i,d}$	-0.00***	-0.00***	0.00***	0.00***	-0.00***	-0.00***	0.00***	0.00***
	(-13.81)	(-13.37)	(12.40)	(12.06)	(-12.59)	(-13.32)	(12.09)	(11.93)
Obs.	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842
Method	OLS	OLS	OLS	OLS	SLS	SLS	SLS	SLS
Adj. R^2	0.06	0.06	0.10	0.10	0.06	0.06	0.10	0.10
F-Test	446.6	443.1	914.7	917.4	447.5	447.5	912.3	914.9
Fixed Effects	Date*	None	Date*	None	Date*	None	Date*	None
Instrumental Variables	-	-	-	-	Set 1	Set 1	Set 1	Set 1

4.6.2 Permanent price impact of different forms of trading

To deepen our understanding, we study how much private information the respective forms of order flow contain by applying a permanent price impact measure. We base our analysis on Hasbrouck's (1991) vector-auto-regression model, which originally studies how asymmetric information drives the response of security prices to sudden trading activity. He shows that the informational trade content can be measured by the persistent price impact of the trade's unexpected component (innovation). That means the trade's true impact on the price is not instant but appears with a protracted lag. The function of the impact of "innovation on the quote is non-linear, positive, and increasing but concave" (see Hasbrouck (1991). We describe the methodology in Chapter 4.5.1. We estimate a vector-autoregression model with a subsequent cumulative impulse function. Table 32 shows how a shock of £10,000GBP in a specific order flow impacts the respective mid-point return for constituents of the FTSE 100 index 60 seconds after.[97]

Table 32: Informativeness of trading via lit orderbooks, periodic auctions, systematic internaliser and dark pools

The table below presents the mean, standard deviation and median of the observed trade informativeness of trading via lit, periodic auction, systematic internaliser (distinguished by trade execution at or away from the mid-point), and dark pool order books. Our sample comprises stocks of the FTSE 100 index from 4th January 2018 till 9th March 2018. The permanent price impact in basis points presents the permanent market-wide price move in the stock after a £10,000GBP shock in the respective order book, as shown below. Hasbrouck (1991) describes this measure of order flow as a signal of private information in the respective order flow. The parameter is based on an adapted vector auto-regression model by Hasbrouck (1991), where mid-point returns, the lit, periodic auction, systematic internaliser value are calibrated at a 60-second interval for each stock per day. The informativeness is calibrated as the cumulative impulse function of mid-point returns in basis points for a shock in the respective type of trading of £10,000GBP.

Type	Permanent price impact	Std. dev.	Median	Min	Max
Panel A: Equal-weighted					
$Lit_{i,d}$	0.876	1.859	0.001	-0.099	56.370
$Periodic\ Auction_{i,d}$	0.741	3.620	0.000	-38.734	39.56
$SI\text{–}\ mid_{i,d}$	0.279	5.305	0.000	-18.787	120.705
$SI\text{–}\ Limit_{i,d}$	0.020	0.299	0.000	-1.428	6.645
$Dark\ pool_{i,d}$	0.119	2.123	0.000	-14.919	54.665
Panel B: Value-weighted					
$Lit_{i,d}$	0.001	0.002	0.000	-0.000	0.624
$Periodic\ Auction_{i,d}$	0.001	0.016	0.000	-0.049	0.613
$SI\text{–}\ mid_{i,d}$	0.000	0.003	0.000	-0.024	0126
$SI\text{–}\ Limit_{i,d}$	0.000	0.000	0.000	-0.002	0.005
$Dark\ pool_{i,d}$	0.000	0.002	0.000	-0.016	0.084

[97] For reasons of computational capacity, we limit the sample to constituents of the FTSE 100 index. Further research could extend the sample to deepen the understanding how market segmentation in trading of illiquid securities impacts price discovery.

For the FTSE 100 index, we find that the permanent price impact of lit trades is the largest compared to other forms of trading. The average equal-weighted price impact of lit trading is around 0.87bps per £10,000GBP and 0.001bps per £10,000GBP when we apply a value-weighted average. Using a paired t-test, we find a highly significant statistically difference between all forms of trading but SI mid-point trading and periodic auction trading, where the means are only statistical different at a 10% significance level. We find the second most informative trading form is periodic auctions (0.74bps per GBP10.000), followed by trading via SI at the mid-point with 0.28bps per £10,000GBP. Our sample presents an average permanent price impact of 0.12bps for dark trades. Trading via SI limit-orders stands out with a permanent price impact of only 0.02bps.

We find especially with SI mid-point trading a high standard deviation in comparison to their mean. In combination with the extreme results for minimum and maximum permanent price impact, we suspect that SI mid-point trading is indeed used to execute large-in-scale orders. Similar to execution in dark pools, execution at the SI mid-point avoids front-running, reduced market impact on the CLOB and information leakage. In contrast to dark pools, participants observe the quotes in real-time for orders up to average size. That provides a certain advantage to estimate the probability of order execution time. Due to our sample horizon’s selection, our findings are not biased by the DVCM, where traders, who would usually execute under some pre-trade transparency waiver in a dark pool, must decide on an alternative execution venue. The findings align with the results in Table 28, where SI mid-point trading of the constituents of the FTSE 100 index lowers the effective spread significantly. We do not argue that SI mid-point trading is potentially as informative as trading in the CLOB; the results in Table 32 do not support the idea, some of those trades are highly informative. Liquidity providers in the CLOB could, post-trade execution, quote narrower spreads, as they observe that in a different order book, information and therefore adverse selections risk was incorporated, which reduces their adverse selection risk in turn. They will adapt their spreads accordingly.

In our sample, we observe periodic auction trading with a similar mean permanent price impact as for trading in the CLOB. The standard deviation indicates a higher variance in the level of informational content in periodic auctions. Madhavan (1992) argues that periodic auction markets improve price discovery as they collect information from different traders over time. For the EU markets, periodic auctions only disclose the auction quote information, but not actual quotes make them attractive to informed traders who want to avoid front-running. We observe for periodic auction trading similar findings to SI mid-point trading in Table 29. Spreads and price impact on the lit trading venue drop when the market share of periodic auction trading increases. That shows a lower level of adverse selection risk in the CLOB as a significant share of informed trading moves towards periodic auctions, see Zhu (2014).

We need to keep in mind that the general market share of periodic auction trading and SI mid-point trading is rather small compared to CLOB trading.

SI limit-order trading presents the least permanent price impact in our sample, with the lowest variance. The result corresponds to our findings in Table 28, where we find that a 1% increase in SI limit-order trading seems to increase adverse selection costs in the form of a wider effective spread. That means that with an increase in SI-limit-order trading, a disproportionally large share of uninformed trading moves from the CLOB, increasing the level of informed trading in the CLOB.

We include dark trading as an additional form of order flow to better understand how these semi-transparent and market share gaining forms of trading compare to fully opaque trading. Further, it allows us to compare our findings to Comerton-Forde and Putniņš (2015), who study the relationship of dark and block trading with price discovery. In comparison to their sample covering constituents of the Australian All Ordinaries index between 2008 and 2011, we find that lit trading is overall less informative. The authors find for CLOB and dark trading a permanent price impact over 3.3bps for a shock of $10.000USD (~£7,250GBP in early 2018). The price impact is significant to a relatively small price shock of $10.000USD (~$9,700AUD in 2012). There are potential drivers such as overall liquidity, transaction costs and speed, which could lead to a higher price impact, especially compared to a much larger stock exchange as LSE and significant developments in executions speed since 2008. We cannot find that dark trading and CLOB trading have a similar permanent price impact in our sample. The permanent price impact of dark trading is over 7-times smaller than the permanent price impact of lit trading. The findings can be driven by sample composition, sample horizon, but it is also reasonable to assume that the UK markets present a different trading environment in 2018 than the Australian market between 2008 and 2011.

Any regulation moving trading from opaque dark pools might improve price discovery if trading moves to periodic auctions and SI mid-point trading. In relation to MiFIR/MiFID II, that would be the DVCM. While we cannot observe an increase in SI mid-point trading, we observe a significant increase in periodic auction trading, indicating an overall positive impact of the DVCM. On an aggregate level, we observe that spreads widen, driven by the overall changes in portfolios and trading behaviour in case of suspensions.

The findings support, in general, the theoretical work of Zhu (2014). Zhu (2014) argues that uninformed are more likely to trade in more opaque venues, making trades of those forms of trading less informative by definition.

4.6.3 Impact of trading via SI and periodic auctions on information leadership share

This chapter studies whether and to which magnitude a certain order flow incorporates new information about a security first. We run different specifications of OLS and ILS regression models, analysing how an increase in the market share of limit-order SI, mid-point SI trading and periodic auction trading affects the information leadership share (ILS) of lit trading (see Putniņš (2013)). We show in Chapter 4.5.1 how the measure is derived based on Hasbrouck's (1991) information measure and Gonzalo and Granger's (1995) common factor share. All those metrics measure the avoidance of transitory shocks and the timeliness in incorporating new information. For this study, we focus on the latter. The ILS measure ranges from zero to one, indicating how one price series impounds information compared to another price series.

In Table 33, we estimate a vector error correction model, first to study to relative contribution to price discovery of lit trading compared to SI limit-order and SI mid-point trading and second to study the relative contribution of lit trades compared to periodic auction trading.

Since we compare two forms of trading in an OLS/2SLS regression, we assume that if the independent variable's market share increases by 1%, the market share via lit trading venues would decrease by 1%. If the 1% shift in market share contains 100% informed trading, we should observe a coefficient of -1. If we observe a coefficient x between 0 and -1, we observe an order flow with x% informed trading shifting from lit trading. That would indicate that the respective form of trading contains on average less information than continuous lit trading, see Zhu (2014) and Comerton-Forde and Putniņš (2015). If the coefficient were smaller than -1, we would observe a disproportionally shift from informed trading from the lit trading venues, which would indicate that the other form of trading would be more informative than trades on the lit trading venue. The opposite would be a positive coefficient. Not only would that indicate that the shift in order flow would be 100% uninformed, but we would observe a superior concentration of informed trading on the lit trading venue.

Table 33 presents the coefficients from the OLS and 2SLS regression models studying the impact of an increase of 1% SI trading at the mid-point and via limit-orders, respectively, on the lit trading venues' information leadership.

Table 33: Impact of mid-point and limit-order SI trading on information leadership share

The table reports OLS regression estimates and the second-stage instrument variables regression models on the impact of SI limit-order and mid-point trading on a measure of price discovery share in the lit market. The first three columns present three different OLS regression models with $ILS_{i,d}$ as the dependent variable:

$$ILS_{i,d} = \alpha_i + \beta_1 SI\_V\_mid_{i,d} + \beta_2 SI\_V\_mid_{i,d} * FTSE\ 100_{i,d} + \beta_3 SI\_V\_limit_{i,d} + \beta_4 SI\_V\_limit_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,id} + \varepsilon_{i,d}$$

The 2SLS regression models in the last six columns include both the fitted values of both forms of SI trading. The corresponding first-stage regression results are not reported but show highly significant F-statistics, rejecting the null hypotheses that the instrumental variables are weak (see Stock and Yogo (2005)). We apply two different sets of instrumental variables and run the models with and without fixed effects. The first instrumental variable set (Set 1) is a combination of a dummy variable equivalent to 0 prior to the introduction of MiFIR/MiFID II regulation, and 1 after, and the lagged observation of the respective type of SI trade share. The second set (Set 2) is limited to the dummy variable. The models are run as follows:

$$ILS_{i,d} = \alpha_i + \beta_1 \widehat{SI\_V\_mid}_{i,d} + \beta_2 \widehat{SI\_V\_mid}_{i,d} * FTSE\ 100_{i,d} + \beta_3 \widehat{SI\_V\_limit}_{i,d} + \beta_4 \widehat{SI\_V\_limit}_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,id} + \varepsilon_{i,d}$$

The dependent variable Information leadership share, $ILS_{i,d}$, presents a measure of the informational content of trades executed in the CLOB relative to other forms of trading. A comprehensive overview of the measure is provided in Chapter 4.4.1. We add four control variables to each model. $FTSE100_{i,d}$ is a dummy variable equivalent to 1 if the security is a constituent of the FTSE 100 index and 0 otherwise. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $Trend_d$ controlling for changes in the dependent variable over our study horizon. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index during the period of 22nd November 2017 till 9th February 2018, which is equivalent to 28 full trading days before and after the event. Adjusted R^2 s do not report the variance explained by the fixed effects. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$
$Intercept_{i,d}$	0.38***	0.87***	0.52***	0.41***	0.91***	0.46***	0.21***	1.42***	0.64***
	(105.68)	(102.36)	(118.83)	(63.22)	(66.51)	(57.58)	(27.28)	(79.75)	(68.52)
$SI\_V\_mid_{i,d}$	0.16***	0.16**	0.15**						
	(6.15)	(2.53)	(2.43)						
$SI\_V\_mid_{i,d}$	-0.04	-0.44***	-0.43***						
$* FTSE\ 100_{i,d}$	(-0.83)	(-4.48)	(-4.27)						
$SI\_V\_limit_{i,d}$	-0.23***	-0.45***	-0.46***						
	(-17.19)	(-24.50)	(-25.23)						
$SI\_V\_limit_{i,d}$	0.18***	0.46***	0.47***						
$* FTSE\ 100_{i,d}$	(12.43)	(26.79)	(26.59)						
$\widehat{SI\_V\_mid}_{i,d}$				-3.91***	2.26***	4.44***	23.15***	13.41***	-14.13***
				(-5.92)	(2.78)	(5.62)	(15.50)	(9.07)	(-10.37)
$\widehat{SI\_V\_mid}_{i,d}$				-5.14***	-9.18***	-3.61***	-14.69***	-15.95***	-4.50**
$* FTSE\ 100_{i,d}$				(-4.26)	(-8.02)	(-3.19)	(-6.36)	(-7.87)	(-2.26)
$\widehat{SI\_V\_limit}_{i,d}$				-0.95***	-1.42***	-0.87***	-2.21***	-9.10***	0.24***
				(-27.74)	(-23.59)	(-21.20)	(-35.18)	(-46.60)	(3.86)
$\widehat{SI\_V\_limit}_{i,d}$				0.55***	0.90***	0.68***	0.93***	1.15***	0.35***
$* FTSE\ 100_{i,d}$				(13.41)	(21.33)	(16.27)	(11.51)	(15.77)	(4.91)
$FTSE\ 100_{i,d}$		-0.41***	-0.45***		-0.35***	-0.42***		-0.06***	-0.50***
		(-110.76)	(-121.01)		(-40.28)	(-49.72)		(-3.73)	(-40.45)
$HFTVol_{i,d}$	0.00***	-0.00***	0.00**	0.00***	-0.00***	0.00***	0.00***	-0.00***	-0.00**
	(7.07)	(-11.87)	(1.96)	(4.75)	(-11.72)	(3.26)	(9.19)	(-11.38)	(-2.55)
$Trend_{i,d}$	0.00***	-0.01***	-0.00***	0.01***	-0.01***	0.00***	0.01***		-0.00***
	(5.82)	(-45.81)	(-4.19)	(27.74)	(-29.85)	(5.96)	(34.73)		(-6.95)
$Volatility_{i,d}$	-0.00***	0.00***	0.00***	-0.00***	0.00***	0.00***			
	(-8.54)	(11.06)	(10.13)	(-15.43)	(7.21)	(9.16)			
Obs.	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842
Method	OLS	OLS	OLS	SLS	SLS	SLS	SLS	SLS	SLS
Adj. R^2	0.49	0.26	0.21	0.48	0.25	0.20	0.50	0.26	0.20
F-Test	68.1	4,642.0	4,357.0	193.2	4,017.0	3,780.0	340.9	6,045.0	4,680.0
Fixed Effects	Stock	Date	None	Stock	Date	None	Stock	Date	None
Instrumental Variables	-	-	-	Set 1	Set 1	Set 1	Set 2	Set 2	Set 2

We find that for SI limit-order trading in general, a highly significant coefficient ranging from -0.2bps (OLS regressions) to -9.1bps (2SLS regressions). The coefficients via the 2SLS vary from an increase of 0.2 to a decrease of -9.1bps. In conjunction with the OLS regression, the results indicate that proportionally SI limit-order trading's contribution to price discovery increases at a slower rate than their market share, which shows that CLOB trading is much more informative. When refining the regression by controlling for the constituents of the FTSE 100 index, we find the opposite. SI limit-order trading in liquid securities increases the informational level in CLOB, hence having an adverse effect. That indicates a disproportional uninformative trading environment.

That finding aligns with the results in Table 32, where SI limit-order trading presents the least permanent price impact. The results in Table 28 are not fully conclusive but show a significant drop in permanent price impact overall.

In contrast, the coefficients for mid-point SI trading present the opposite picture. On an aggregate level, all the OLS and 2SLS regression models' specifications are mostly positive and highly significant. The findings show that SI mid-point trading increases the informational leadership share in the lit market when relying on an OLS regression. The findings via a 2SLS regression model vary from -14.1bps to 13.3bps, with no obvious pattern. When focussing on FTSE 100 index constituents, we find conclusively that with a 1% increase in SI mid-point trading, the information leadership share on the lit trading venue decreases between 0.04bps and 15.9bps. That shows that the price discovery for SI mid-point trading increases at a slower rate than the respective market share. Those findings align with Table 32, where results for FTSE 100 index constituents indicate a much higher permanent price impact for SI mid-point trading and, therefore, a higher level of informed trading.

Table 34 shows the regression coefficients when studying the contribution of periodic auction trading and information leadership share in the lit market. Independent of whether we rely on an OLS model or a 2SLS model, we find significant coefficients between -0.3bps and 8.4bps. When controlling for stock-fixed effects, the results indicate that periodic auctions are rather informative also at a much lower level than CLOB. If we do not control for fixed effects or date-fixed effects, the results indicate that periodic auction trading is disproportional less informative than CLOB.

The findings for liquid securities present negative coefficients, which overall shows that periodic auction trading for that market segment is informative, also not at the level of the CLOB.

If we observed the same level of information in trading as in the CLOB, we would find a coefficient of -100bps.

Compared to SI mid-point trading, which also presents a certain level of information in Table 33 for FTSE 100 index constituents, the results indicate that SI mid-point trading is more informative than periodic auction trading. We find the opposite in Table 34.

Table 34: Impact of periodic auction trading on information leadership share

The table reports the estimates of OLS regression and the second-stage instrument variables regression models on the impact of periodic auction trading on a measure of price discovery share in the lit market. The first three columns present three different OLS regression models with $ILS_{i,d}$ as the dependent variable:

$$y_{i,d} = \alpha_i + \beta_1 PeriodicAuction_{i,d} + \beta_2 PeriodicAuction_{i,d} * FTSE100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The 2SLS regression models in the last six columns include both the fitted values periodic auction trading. The corresponding first-stage regression results are not reported but show highly significant F-statistics, rejecting the null hypotheses that the instrumental variables are weak (see Stock and Yogo (2005)). We apply two different sets of instrumental variables and run the models with and without fixed effects. The first instrumental variable set (Set 1) is a combination of a dummy variable equivalent to 0 prior to a suspension cut-off date within the DVCM and 1 after, and the lagged observation of the respective type of SI trade share. The second set (Set 2) is limited to the dummy variable. The models are run as follows:

$$y_{i,d} = \alpha_i + \beta_1 \widehat{PeriodicAuction}_{i,d} + \beta_2 \widehat{PeriodicAuction}_{i,d} * FTSE100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The dependent variable information leadership share, $ILS_{i,d}$ presents a measure of the informational content of trades executed in the central limit-orderbook relative to other forms of trading. A comprehensive overview over the measure is provided in Chapter 4.4.1. Each model includes four control variables. $FTSE100_{i,d}$ is a dummy variable equivalent to 1 if the security is a constituent of the FTSE 100 index and 0 otherwise. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $Trend_d$ controlling for changes in the dependent variable over our study horizon. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index, which were suspended using transparency waivers anytime between March 2018 and August 2018 in terms with the thresholds of the DVCM. Before and after each monthly cut-off date we include 20 trading days before and after the event. This results in six datasets which we overlay to one data set. Date* fixed-effects refer not to actual dates, but numbers between -21 and 21 indication the days prior to and after the suspension's start date. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$	$ILS_{LIT,i,d}$
$Intercept_{i,d}$	0.81***	0.81***	0.81***	0.79***	0.79***	0.79***	0.80***	0.80***	0.80***
	(21.88)	(31.37)	(73.34)	(61.57)	(61.57)	(20.08)	(20.54)	(20.54)	(61.54)
$Periodic\ Auction_{i,d}$	-0.26***	0.80***	0.83***						
	(-6.46)	(14.57)	(15.58)						
$Periodic\ Auction_{i,d} * FTSE\ 100_{i,d}$	-0.42***	-0.53***	-0.49***						
	(-5.49)	(-5.71)	(-6.05)						
$\widehat{Periodic}\ Auction_{i,d}$				-0.01	8.38***	1.52***	0.03	7.12***	0.40**
				(-0.04)	(12.33)	(7.28)	(0.26)	(11.94)	(2.19)
$\widehat{Periodic}\ Auction_{i,d} * FTSE\ 100_{i,d}$				-1.46*	-1.38***	-0.79***	-1.41***	-1.21***	-1.36***
				(-9.55)	(-6.86)	(-3.65)	(-8.97)	(-6.21)	(-6.76)
$FTSE100_{i,d}$	-	-0.32***	-0.32***	-0.31***	-0.31***	-0.31***	-0.31***	-0.32***	-0.31***
		(-35.48)	(-81.63)	(-78.95)	(-78.72)	(-27.55)	(-27.61)	(-12.61)	(-79.04)
$HFTVol_{i,d}$	0.00**	0.00***	0.00***	0.00**	0.00***	0.00***	0.00**	0.00***	0.00***
	(2.00)	(4.37)	(4.24)	(2.02)	(12.53)	(4.38)	(2.10)	(11.88)	(4.43)
$Trend_{i,d}$	0.00	-0.00	-0.00	0.00*	0.01***	-0.00	0.00*	0.01***	-0.00
	(1.45)	(-0.92)	(-0.82)	(1.85)	(11.95)	(-0.63)	(1.82)	(10.17)	(-0.79)
$Volatility_{i,d}$	-0.00***	0.00***	0.00***	-0.00***	-	0.00***	-0.00***	-	0.00***
	(-20.24)	(11.88)	(9.73)	(-19.62)		(9.69)	(-19.42)		(10.23)
Obs.	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842
Method	OLS	OLS	OLS	SLS	SLS	SLS	SLS	SLS	SLS
Adj. R^2	0.53	0.17	0.16	0.53	0.16	0.16	0.53	0.16	0.15
F-Test	154.7	252.1	1,546.5	1,543.1	1,543.1	154.8	158.4	158.4	1,543.2
Fixed Effects	Stock	Date*	None	Stock	Date*	None	Stock	Date*	None
Instrumental Variables	-	-	-	Set 1	Set 1	Set 1	Set 2	Set 2	Set 2

4.7 CONCLUSIONS

Our findings in chapter 4 show that for constituents of the FTSE 100 index, trade execution via periodic auctions is the most informative form of trading after trade executions in the CLOB. When increasing the market share of periodic auctions by 1%, our results show a drop in effective spread of at least 4bps via an OLS regression model and up to 178bps via a 2SLS regression model. The information leadership share of the CLOB drops between 0.4bps and 1.5bps, dependent on our model specification. The permanent price impact measure (see Hasbrouck (1991)) supports those findings. The findings show that higher levels of periodic auction trading increase the CLOB's adverse selection risk, which in turn requires informed market participants to quote wider spreads, due to a higher risk of an informed counterparty. We study further the relationship of SI trading executed at the mid-point and via limit-orders. While, as expected, both trading forms are less informative than CLOB trading, we find significant differences. Trades executed via a SI limit-order seem to be the least informative. Our results show that a market share increase in SI limit-order trading leads to larger spreads and higher information leadership share, which indicates that CLOB trading becomes disproportionally more informative because uninformed trade executions dominate SI limit-order trading. Hasbrouck's (1991) permanent price impact measure is much lower for SI limit-order trading than any other form of order flow, even dark trading. In contrast, SI mid-point trading is partially highly informative for constituents of the FTSE 100 index, but in general, less informative than periodic auctions.

Periodic auction trading and SI trading became a prominent form of order flow in Europe after MiFIR/MiFID II came into effect in January 2018 due to the closure of BCNs and the introduction of the DVCM. While both forms of order flow were not new, SI trading has not been covered by literature. Research on periodic auctions focuses on auctions with a much lower frequency, based on data from the Taiwanese stock exchange or European stock exchanges before 2000. SI and periodic auction trading within the European regulations have not been covered. We contribute to the literature by providing the first empirical results on the relationship of those forms of order flow with price discovery by studying how an increase in the respective order flow affects spreads, price impact, permanent price impact and information leadership share. The interpretation of those findings is driven by literature on dark trading. While dark trading is a fully opaque form of trading, SI and periodic auctions are not as transparent as a CLOB. Periodic auctions only display the auction price in real-time before execution. SI do not need to publish quotes for large-in-scale orders. Both provide potential opportunities for informed participants who do not want to disguise their intentions to avoid front running and higher execution costs. Uninformed traders might prefer periodic auctions as they reduce the advantage of superior/fast market participants. Uninformed participants receive a fair price without the need to compete for speed. A comprehensive understanding of how those forms of order flow affect price discovery is essential since regulators worldwide discuss the potential harm of dark trading to overall price discovery. MiFIR/MiFID II successfully introduced measures to reduce dark trading. This study is the first to provide quantitative insights into how the ‘alternative’ forms of order flow impact price discovery.

CHAPTER 5: CONCLUSIONS

This dissertation examines the impact of regulatory changes in Finland and the United Kingdom on market liquidity, efficiency, transaction costs, and price discovery. The actual, quantitative, causal consequences of market design on market quality are often a complex matter to demonstrate due to data availability, theory and methodology, and literature focusing on prominent trading forms.

First, we study how increasing informational asymmetry due to declining broker ID disclosure affects market liquidity for individual and institutional investors and their trading behaviour, respectively.

Unlike virtually all market microstructure research that is, of necessity, restricted to actual trades, we analyse the underlying orders before their disguise in the form of trades to examine trading cost implications for institutional investors and households separately. We examine three unique policy changes which came into effect at the Nasdaq OMX Helsinki. On 13th March 2006, Nasdaq OMX Helsinki switched from pre-trade broker ID disclosure to post-trade broker ID disclosure. On 2nd June 2008, the exchange introduced complete opacity. On 14th April 2009, for all security, except for the top 5 traded stocks, broker ID disclosure was reintroduced post-trade.

We study the impact of the first two regulatory decisions on market quality with an event study. The last event allows us to conduct a DiD analysis, where the top traded five stocks act as the control group. We rely on two different data sets and introduce a different methodology than the previous literature: With intraday tick data, we analyse all policy changes based on daily measures of transaction costs, market resilience and liquidity. We analyse the impact on these parameters using the Euroclear data set, which provides us with additional information regarding both trade sides, as the account numbers and the investor type.

Most importantly, we connect sequences of trades in the same direction of the same investors to simulate the underlying order of an investor. With this approach, we can analyse the impact not only on overall market liquidity but specifically on issued orders.

We contribute to the literature, as the study is the first to analyse the impact of different stages of broker ID disclosure on the base of orders and in such an extensive way: With the underlying order, we demonstrate the impact of these policy changes on various determinants of market liquidity separately for buyer- and seller-initiated orders and distinguish between the type of investor, individual as well as institutional investors. Our results show that the commonly used daily measures often do not match the impact on single orders and differ across investor types.

In addition, we can show how the market participants adapt their trading behaviour.

Our results present a consistently positive effect of broker ID disclosure on transaction costs. We find that the impact differs significantly between institutional and individual investors and depends on the order direction. The overall positive effect of broker ID disclosure for all market participants stands in contrast to previous literature and common assumptions, where only household investors benefit from transparency. With enhanced disclosure, institutional investors submit smaller orders; however, they submit more frequently when the market becomes more transparent. Their informational advantage is significantly reduced, which leads to an increase in adverse selection costs and means they cannot implement orders as cheaply into the market as in an opaque market. To ensure that a certain level of informational advantage can still be exploited, these might need to trade more aggressive, leading to a decrease in transaction costs. Households do no longer rely solely on the order flow for information. The decreased informational asymmetry encourages individual traders to trade more frequently and contributes to the overall liquidity increase. The transaction costs decrease as the informational content of the order flow decreases overall. This study shows that the decision in 2009 to reverse the implementation of total opacity was correct and allows NASDAQ OMX Helsinki a superior position in a competitive market environment.

Specifically, the findings indicate that individual household investors are not just 'noise traders' but respond to changing levels of information disclosure and are more responsive on the buy-side of the market. The number of daily submitted orders increases significantly in 2009. In 2006, institutional traders increased their sell-order size with an increasing level of anonymity. However, they lower the level of splitting up buyer-initiated orders for illiquid securities, hence are less careful about disguising their intentions. In 2009 across all investor types and securities, the number of daily order submissions jumps significantly compared to the control group. The trading volume of institutional investors does not increase with a declining level of transparency. The last regulatory change in 2009 shows that institutional investors submit significantly larger orders for less liquid securities with the reintroduction of broker ID transparency.

Second, we explore the question, how trading via systematic internaliser, relates to overall market quality.

The already fragmented UK market shifted when trading via SI jumped by over 14% in January 2018, when MiFIR/MiFID II's ambitious regulatory changes to increase transparency and efficiency came into effect. SI are investment firms dealing on their own account outside a regulated market and are a counterparty, not a trading venue. The concept of semi-opaque counterparty trading was not new; however, it captured as of January 2018 the previously opaque BCN trading. SI received a lot of negative press from competitors. We provide first insights and causal evidence on the impact of internalised trading on market quality overall, showing that on an aggregate level, SI trading, driven by limit-order SI trading, seems to improve market quality by enhancing competition in the limit order book. Effective and quoted spread drop by a minimum of 3.6bps each if the market share of limit-order SI trading increases by 1%. We find that realised spread drops by 9.1bps and price impact by 6.2bps. Autocorrelation and variance-ratio drop at a highly significant level. SI trading at the mid-point, similar to dark pool trading executed at the mid-point, presents insignificant or weak significant coefficients for transaction costs and contradictive findings for informational efficiency. On an aggregate level, we find that SI trading is highly beneficial for informational efficiency and indicates tighter spreads at a low significance level.

Our findings are essential to evaluate SI trading on a quantitative basis, allowing regulators to evaluate decisions and provide a foundation for future discussions on internalised trading.

As of today, there is neither academic nor public practitioner quantitative research, which could provide a 'neutral' foundation for discussion around the relationship of SI trading and market quality. Any regulatory decisions seem driven by the interest of stakeholders, in this case potentially competing exchanges. This study provides first insights, attempting to close the gap. We can overcome issues regarding data availability on SI trading and endogeneity issues in the methodology by exploiting the jump in January 2018 and applying a 2SLS model. We find that SI trading, driven by limit-order SI trading, simply increases fragmentation, which in general improves market quality.

Last, we examine the level of informed trading in systematic internaliser and periodic call auction trading and how it drives price discovery on the lit trading venues.

As have other regulators worldwide, ESMA expressed for a decade or more concerns on the potential harm done by opaque trading for price discovery. Recent literature indicates that these concerns might not be valid. In Europe, MiFIR/MiFID II addressed those concerns, introducing comprehensive regulation to shift OTC and dark trading to less opaque venues. New forms of trading gained market share: trading via systematic internaliser and periodic auctions.

Periodic auctions only display the auction price in real-time before execution. SI do not need to publish quotes for large-in-scale orders. Both provide potential opportunities for informed participants who do not want to disguise their intentions to avoid front running and higher execution costs. Uninformed traders might prefer periodic auctions as they reduce the advantage of superior/fast market participants. Uninformed participants receive a fair price without the need to compete for speed.

A comprehensive understanding of how those forms of order flow affect price discovery is essential since regulators worldwide discuss the potential harm of dark trading to overall price discovery. MiFIR/MiFID II successfully introduced measures to reduce dark trading. However, neither regulatory nor academic literature has yet quantified how those forms of trading contribute to price discovery. Driven by different levels of transparency and market structure, the respective impact on informed and uninformed traders' segmentation drives price discovery at an aggregate level.

We show that for constituents of the FTSE 100 index, trade execution via periodic auctions is the most informative form of trading after trade executions in the CLOB. When increasing the market share of periodic auctions by 1%, our results show a drop in effective spread of at least 4bps via an OLS regression model and up to 178bps via a 2SLS regression model. The information leadership share of the CLOB drops between 0.4bps and 1.5bps, dependent on our model specification. The permanent price impact measure (Hasbrouck (1991)) supports those findings. The results indicate that higher levels of periodic auction trading increase the CLOB's adverse selection risk, which in turn requires informed market participants to quote wider spreads due to a higher risk of an informed counterparty. We study further the relationship of SI trading executed at the mid-point and via limit-orders. While, as expected, both trading forms are less informative than CLOB trading, we find significant differences. Trades executed via a SI limit-order seem to be the least informative. Our results show that a market share increase in SI limit-order trading leads to larger spreads and higher information leadership share, which indicates that CLOB trading becomes disproportionally more informative because uninformed trade executions dominate SI limit-order trading. Hasbrouck's (1991) permanent price impact measure is much lower for SI limit-order trading than any other form of order flow, even dark trading. In contrast, SI mid-point trading is partially highly informative for constituents of the FTSE 100 index, but in general, less informative than periodic auctions.

While both forms of order flow were not new, SI trading has not been covered by literature. Research on periodic auctions focuses on auctions with a much lower frequency, based on data from the Taiwanese stock exchange or European stock exchanges before 2000. SI and frequent periodic call auction trading within the European regulations have not been covered.

The study fills a significant gap in the literature and provides a foundation for regulators to evaluate introduced regulations and discuss future market design changes. We contribute by providing the first empirical results on the relationship of those forms of order flow with price discovery by studying how an increase in the respective order flow affects spreads, price impact, permanent price impact and information leadership share. This study is the first to provide quantitative insights into how the 'alternative' forms of order flow impact price discovery.

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APPENDICES

A.1 Tick size regime under MiFIR/MiFID II

Tick size is a key instrument to drive markets and increasingly important in fragmented markets. Literature finds that the ideal tick size should be small enough to minimise transaction costs (Werner et al. (2019)) but must be non-zero to incentivise liquidity supply by market participants (Harris (1991), Harris (1996), Foucault et al. (2005)). Research provides inconsistent findings. Bourghelle and Declerck (2004) provide a negative relation of tick size and spreads for unconstrained securities based on Euronext's research. Rindi and Werner (2019) show that larger tick sizes encourage liquidity provision overall and improve market depth for unconstrained securities in the U. S Pilot Tick size program 2016. Art. 49 MiFID II provides a table presenting tick sizes in relation to price ranges and various average daily ranges of transactions. Broadly, tick sizes increase with a higher instrument price or a lower average number of transactions. Tick sizes range from 0.0001 to 500. In general, illiquid securities with a meagre price have a very small tick size. The higher the price, the larger the tick size. Securities can move along the table with changing prices, liquidity, and tick-sized venues independent and individual for each security. An overall, distinct impact is difficult to determine, however, Laruelle et al. (2018) show that the regime improved market quality while improving transaction costs for securities with inadequate tick sizes (i.e., too low) before MiFID II.

The decision to exclude SI from the tick size regime under MiFID II led to extensive discussions among competitors around the impact of enhanced SI trading on the market and supposed "unfair" advantage. The majority of the trading is executed by SI operated by banks, which reclassified internal OTC trading, which is usually non-price forming (Euronext (2019)). It is not clear why banks chose to redirect non-price-forming trades to SI. Amfe et al. (2018) urged ESMA in a joint paper with CBOE and LSE to include price-forming trades across all venues in the tick size regime to achieve a levelled market environment

A.2 Development in trade size over the implementation of the MiFIR/MiFID II regime

Table 35: Trade size across venues

The table below shows the descriptive statistics on venue-wide average daily trading volume per security during the three months preceding the MiFID II (1st October 2017 – 2nd January 2018) and the three months after (3rd January 2018-31st March 2018). The trade size per security is calculated on a daily basis, as the ratio between the daily trade volume and the daily number of trades within the relevant trade type and venue. We distinguish between securities within the FTSE 100 index and FTSE 250 index. The mean, median and standard deviation are computed from the daily observations. The last two columns report significance of the difference in means in from of a t-test as well as the significance in difference of the variance with the Wilcoxon Rank-sum test.

Venue	Index	Pre-regulation			Post-regulation			T-Test	Wilcoxon Rank-sum
		Mean	Std. Dev.	Median	Mean	Std. Dev.	Median		
Panel A: Continuous lit trading									
Aquis	FTSE 100	417.6	495.6	256.8	475.4	575.4	280.7	57.86***	2017.50***
	FTSE 250	250.4	287.5	155.0	357.0	486.7	210.0	106.65***	3,606.60***
CBOE BXE	FTSE 100	408.0	481.0	265.6	407.7	520.9	240.3	-0.33	2,211.20
	FTSE 250	409.0	705.4	242.8	463.1	744.2	276.2	54.15***	12,463.00***
CBOE CXE	FTSE 100	483.2	588.3	302.9	466.9	601.7	274.2	-16.33	2,249.20
	FTSE 250	430.3	831.1	266.7	436.1	741.1	274.0	5.81	13,105.00**
LSE	FTSE 100	570.9	701.2	368.0	558.6	727.4	327.5	-12.36	2,321.50
	FTSE 250	592.4	893.6	347.9	611.2	850.0	372.3	18.83**	14,018.00***
Turquoise	FTSE 100	528.9	676.2	321.4	501.7	694.8	280.7	-27.22**	2,282.80***
	FTSE 250	504.6	1,292.9	279.9	548.6	1,443.1	287.7	44.04***	13,111.00***
Panel B: Dark pool trading									
CBOE BXE	FTSE 100	5.9	87.0	0.0	5.4	77.1	0.0	-0.51	2,184.00
	FTSE 250	0.0	0.0	0.0	0.0	0.0	0.0	-	-
CBOE CXE	FTSE 100	5.2	57.9	0.0	4.7	59.9	0.0	-0.52	2,174.00
	FTSE 250	0.0	0.0	0.0	0.0	0.0	0.0	-	-
Instinet	FTSE 100	1,223.0	2,613.2	503.9	1,370.5	5,037.9	195.4	147.51**	2,734.70***
Blockmatch	FTSE 250	737.0	2,468.0	0.0	677.7	2,641.5	0.0	-59.32**	15,348.00
ITG Posit	FTSE 100	4,885.8	20,881.9	897.0	12,703.8	83,167.7	627.7	7,818.06***	2,501.80***
	FTSE 250	5,360.0	37,848.3	220.8	8,616.7	58,624.5	0.0	3,256.76***	5,489.00***
Liquidnet	FTSE 100	36,788.6	206,823.0	0.0	43,531.0	233,050.4	0.0	6,742.48*	2,055.30***
	FTSE 250	16,358.6	104,817.8	0.0	17,722.8	95,219.8	0.0	1,364.22	13,355.00
Turquoise	FTSE 100	6.8	87.4	0.0	9.8	262.7	0.0	3.02	2,189.40
	FTSE 250	0.0	0.0	0.0	0.0	0.0	0.0	-	-
UBS Dark	FTSE 100	825.1	1,303.1	436.9	1,314.0	9,590.1	309.9	488.96***	2,617.30***
	FTSE 250	682.8	1,667.9	335.5	914.9	4,617.2	220.0	232.17***	15,391.00***
Panel C: Periodic auction trading									
CBOE BXE	FTSE 100	702.1	1,497.6	96.3	743.8	1,376.6	336.7	41.73*	1,513.40***
	FTSE 250	163.6	1,143.6	0.0	887.3	2,649.2	227.6	723.75***	6,163.30***
ITG Posit	FTSE 100	0.0	0.0	0.0	0.1	0.2	0.0	0.14***	2,089.80***
	FTSE 250	0.0	0.0	0.0	0.0	0.1	0.0	-	13,415.00***
LSE	FTSE 100	0.0	0.0	0.0	0.0	0.0	0.0	-	-
	FTSE 250	13.2	472.2	0.0	8.2	518.4	0.0	-5.01	14,555.00***
SIGMA X	FTSE 100	0.0	0.0	0.0	136.1	1,782.1	0.0	136.11***	1,411.70***
	FTSE 250	0.0	0.0	0.0	112.5	1,852.6	0.0	112.53***	2,206.90***
Turquoise	FTSE 100	0.0	1.5	0.0	94.9	614.8	0.0	94.92***	1,790.80***
	FTSE 250	0.0	0.0	0.0	28.0	1,125.2	0.0	28.03***	12,861.00***
Panel D: Systematic internaliser trading									
CBOE APA	FTSE 100	1,645.1	8,269.0	376.5	6,393.4	13,063.7	2,511.3	4,748.32***	700.43***
	FTSE 250	2,380.0	31,399.0	397.8	5,794.2	22,583.6	1,948.8	3,414.22***	3,098.50***
LSE APA	FTSE 100	213.4	1,864.2	0.0	9,083.5	27,532.1	1,429.7	8,870.11***	1,104.50***
	FTSE 250	86.6	2,029.3	0.0	4,871.9	21,705.7	127.8	4,785.38***	7,692.10***

A.3 Impact of mid-point and limit-order SI trading on transaction costs-Robustness specifications

In addition to the results shown in Table 28, we defined further OLS and 2SLS regression, as a robustness check.

Table 36: Impact of mid-point and limit-order SI trading on transaction costs-Robustness specifications

The table reports the estimates of an OLS regression and from the second-stage instrument variables regression on the impact of SI limit-order and mid-point trading on transaction costs. The first four columns present two different OLS regression models for $Effective\ Spread_{i,d}$ and $Price\ Impact_{i,d}$ each.

$$y_{i,d} = \alpha_i + \beta_1 SI\_V\_mid_{i,d} + \beta_2 SI\_V\_mid_{i,d} * FTSE\ 100_{i,d} + \beta_3 SI\_V\_limit_{i,d} + \beta_4 SI\_V\_limit_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The 2SLS regression modes in the last four columns for the same measures include both the fitted values of both forms of SI trading. The first-stage regression results are not reported but the F-statistics all reject the null hypotheses that the instrumental variables are weak (Stock and Yogo (2005)). The models are run as follows with two different sets of instrumental variables:

$$y_{i,d} = \alpha_i + \beta_1 \widehat{SI\_V\_mid}_{i,d} + \beta_2 \widehat{SI\_V\_mid}_{i,d} * FTSE\ 100_{i,d} + \beta_3 \widehat{SI\_V\_limit}_{i,d} + \beta_4 \widehat{SI\_V\_limit}_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The first instrumental variable set (Set 1) is a combination of a dummy variable equivalent to 0 prior to the introduction of MiFIR/MiFID II regulation, and 1 after, and the lagged observation of the respective type of SI trade share. The second set (Set 2) is limited to the dummy variable. The dependent variables $y_{i,d}$ of the second-stage regressions are estimates of transaction costs. The metric $Price\ Impact_{i,d}$ is time-weighted and computed as the difference of effective and realised spread on the lit venue. $Effective\ Spread_{i,d}$ is a time-weighted daily for all trades during continuous lit trading. Both spread measures are calculated relative to the mid-point in basis points. Each regression model incorporates four control variables in addition to the main independent variables. $FTSE100_{i,d}$ is a dummy variable equivalent to 1 if the security is a constituent of the FTSE 100 index and 0 otherwise. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $Trend_d$ controlling for changes in the dependent variable over our study horizon. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index during the period of 22nd November 2017 till 9th February 2018, which is equivalent to 28 full trading days before and after the event. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	$Effective\ Spread_{i,d}$	$Price\ Impact_{i,d}$	$Effective\ Spread_{i,d}$	$Price\ Impact_{i,d}$	$Effective\ Spread_{i,d}$	$Effective\ Spread_{i,d}$	$Effective\ Spread_{i,d}$	$Price\ Impact_{i,d}$	$Price\ Impact_{i,d}$	$Price\ Impact_{i,d}$
$Intercept_{i,d}$	11.84*** (122.24)	10.03*** (104.28)	11.95*** (88.87)	10.16*** (73.93)	24.14*** (74.53)	47.34*** (42.30)	35.78*** (96.15)	27.19*** (82.03)	49.67*** (44.63)	40.87*** (115.24)
$SI\_V\_mid_{i,d}$	-0.93 (-0.71)	-1.12 (-0.76)								
$SI\_V\_mid_{i,d} * FTSE\ 100_{i,d}$	3.83* (2.62)	1.46 (0.81)								
$SI\_V\_limit_{i,d}$	0.39 (1.04)	-0.72* (-1.88)								
$SI\_V\_limit_{i,d} * FTSE\ 100_{i,d}$	-4.75*** (-14.78)	-2.57*** (-7.43)								
$SI\_\widehat{V\_mid}_{i,d}$			11.16 (0.72)	-28.18* (-1.72)	-1,82.09*** (-28.00)	-2,74.72*** (-43.11)	-3,17.12*** (-54.52)	-266.97*** (-40.31)	-383.55*** (-63.04)	-418.82*** (-76.28)
$SI\_\widehat{V\_mid}_{i,d} * FTSE\ 100_{i,d}$			-42.59** (-2.45)	49.53* (2.16)	-43.94*** (-4.75)	-61.06 (-0.88)	47.19 (0.65)	-35.21*** (-9.07)	-29.17*** (-3.15)	-31.15*** (-4.66)
$SI\_\widehat{V\_limit}_{i,d}$			-1.16 (-1.36)	-3.68*** (-4.20)	69.04*** (25.51)	-16.88 (-1.42)	128.55*** (51.88)	93.36*** (34.61)	48.37*** (4.06)	159.45*** (68.38)
$SI\_\widehat{V\_limit}_{i,d} * FTSE\ 100_{i,d}$			-7.10*** (-9.99)	-6.26*** (-7.94)	-22.75*** (-8.45)	-7.78*** (-2.80)	-12.41*** (-4.57)	-32.74*** (-10.91)	-14.37*** (-4.83)	-18.93*** (-6.49)
$FTSE\ 100_{i,d}$						-6.36*** (-9.86)	-12.38*** (-30.43)		-8.09*** (-12.24)	-12.86*** (-29.67)
$HFTVol_{i,d}$	-0.02*** (-17.90)	-0.01*** (-10.01)	-0.02*** (-18.37)	-0.01*** (-10.51)	-0.03*** (-26.99)	-0.02*** (-35.13)	-0.02*** (-35.70)	-0.02*** (-24.21)	-0.03*** (-54.57)	-0.03*** (-54.70)
$Trend_{i,d}$	0.01** (2.07)	-0.02*** (-5.77)	0.02*** (3.89)	0.01 (1.50)	0.02*** (3.16)		-0.06*** (-9.63)	0.02*** (2.86)		-0.06*** (-9.89)
$Volatility_{i,d}$	0.02*** (31.36)	0.02*** (44.73)	0.02*** (29.49)	0.02*** (41.68)	-0.02*** (-26.99)	-0.02*** (-35.13)	-0.02*** (-35.70)	-0.02*** (-24.21)	-0.03*** (-54.57)	-0.03*** (-54.70)
Obs.	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842
Method	OLS	OLS	SLS	SLS	SLS	SLS	SLS	SLS	SLS	SLS
Adj. R^2	0.57	0.45	0.57	0.45	0.57	0.25	0.25	0.45	0.27	0.27
F-Test	363.0	399.0	463.0	569.0	636.5	8,125.0	7,235.0	620.0	6,854.0	6,082.0
Fixed Effects	Stock	Stock	Stock	Stock	Stock	Date	None	Stock	Date	None
Instrumental Variables	-	-	Set 1	Set 1	Set 2	Set 2	Set 2	Set 2	Set 2	Set 2

A.4 Impact of mid-point and limit-order SI trading on informational efficiency-Robustness specifications

In addition to the results shown in Table 30, we defined further OLS and 2SLS regression, as a robustness check.

Table 37: Impact of mid-point and limit-order SI trading on informational efficiency-Robustness specifications

The table reports the estimates of different OLS regression and of second-stage instrument variables regression models on the impact of SI limit-order and mid-point trading on measures of informational efficiency. The first four columns present different OLS regressions for $Autocorrelation_{i,d}$ and $Variance\ Ratio_{i,d}$ each.

$$y_{i,d} = \alpha_i + \beta_1 SI\_V\_mid_{i,d} + \beta_2 SI\_V\_mid_{i,d} * FTSE\ 100_{i,d} + \beta_3 SI\_V\_limit_{i,d} + \beta_4 SI\_V\_limit_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,id} + \varepsilon_{i,d}$$

The 2SLS regressions in the last four columns for the same parameters include both the fitted values of both forms of SI trading:

$$y_{i,d} = \alpha_i + \beta_1 \widehat{SI\_V\_mid}_{i,d} + \beta_2 \widehat{SI\_V\_mid}_{i,d} * FTSE\ 100_{i,d} + \beta_3 \widehat{SI\_V\_limit}_{i,d} + \beta_4 \widehat{SI\_V\_limit}_{i,d} * FTSE\ 100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,id} + \varepsilon_{i,d}$$

The first-stage regression results show highly significant F-statistics, rejecting the null hypotheses that the instrumental variables are weak (see Stock and Yogo (2005)). The first instrumental variable set (Set 1) is a combination of a dummy variable equivalent to 0 prior to the introduction of MiFIR/MiFID II regulation, and 1 after, and the lagged observation of the respective type of SI trade share. The second set (Set 2) is limited to the dummy variable. The dependent variables $y_{i,d}$ are estimates of informational efficiency. $Autocorrelation_{i,d}$ is based on 10-second mid-point returns, whereas $HFVol_{i,d}$ is added as 10-second mid-point return standard deviations during continuous lit trading hours. $Variance\ Ratio_{i,d}$ measures the variance-ratio of the standard deviations on 1-second and 10-second mid-point returns. We add four control variables to each model. $FTSE100_{i,d}$ is a dummy variable equivalent to 1 if the security is a constituent of the FTSE 100 index and 0 otherwise. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $Trend_d$ controlling for changes in the dependent variable over our study horizon. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index during the period of 22nd November 2017 till 9th February 2018, which is equivalent to 28 full trading days before and after the event. Adjusted R^2 s do not report the variance explained by the fixed effects. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	$Autocorrelation_{i,d}$	$Variance\ Ratio_{i,d}$	$Autocorrelation_{i,d}$	$Variance\ Ratio_{i,d}$	$Autocorrelation_{i,d}$	$Autocorrelation_{i,d}$	$Autocorrelation_{i,d}$	$Variance\ Ratio_{i,d}$	$Variance\ Ratio_{i,d}$	$Variance\ Ratio_{i,d}$
$Intercept_{i,d}$	-0.08***	1.31***	-0.08***	1.31***	-0.10***	-0.20***	-0.21***	1.30***	1.59***	1.61***
	(-101.66)	(712.53)	(-76.02)	(526.69)	(-36.94)	(-27.96)	(-89.52)	(221.02)	(99.15)	(308.04)
$SI\_V\_mid_{i,d}$	0.04***	-0.01								
	(4.11)	(-0.32)								
$SI\_V\_mid_{i,d} * FTSE\ 100_{i,d}$	-0.03	0.16**								
	(-1.33)	(2.16)								
$SI\_V\_limit_{i,d}$	0.01***	-0.00								
	(3.26)	(-0.18)								
$SI\_V\_limit_{i,d} * FTSE\ 100_{i,d}$	-0.01***	-0.01								
	(-3.33)	(-0.97)								
$SI\_\widehat{V\_mid}_{i,d}$			0.43***	0.12	4.82***	19.03***	19.61***	-3.21***	-47.85***	-46.42***
			(4.19)	(0.55)	(10.80)	(49.32)	(56.35)	(-3.22)	(-55.17)	(-57.58)
$SI\_\widehat{V\_mid}_{i,d} * FTSE\ 100_{i,d}$			-0.21	1.45**	-9.28***	-14.35***	-14.01***	18.91***	22.76***	26.55***
			(-0.81)	(2.45)	(-10.38)	(-20.24)	(-19.89)	(8.95)	(12.63)	(14.79)
$SI\_\widehat{V\_limit}_{i,d}$			0.05***	0.06***	-0.08***	-0.50***	-0.67***	0.24***	1.06***	1.87***
			(7.83)	(4.21)	(-4.07)	(-6.53)	(-41.78)	(5.44)	(6.33)	(48.98)
$SI\_\widehat{V\_limit}_{i,d} * FTSE\ 100_{i,d}$			-0.03***	-0.08***	0.31***	0.49***	0.48***	-0.74***	-0.89***	-1.01***
			(-2.93)	(-3.45)	(9.13)	(18.22)	(17.82)	(-9.37)	(-13.06)	(-14.79)
$FTSE\ 100_{i,d}$						0.11***	0.11***		-0.18***	-0.23***
						(21.07)	(28.97)		(-14.64)	(-24.08)
$HFTVol_{i,d}$	-0.00***	0.00***	-0.00***	0.00***	-0.00***	-0.00	0.00	0.00***	0.00	-0.00***
	(-15.39)	(13.93)	(-14.15)	(13.75)	(-11.57)	(-1.35)	(0.73)	(13.60)	(0.83)	(-3.36)
$Trend_{i,d}$	0.00***	-0.00***	0.00***	-0.00***	0.00***		0.00***	-0.00***		-0.00***
	(33.02)	(-69.07)	(14.12)	(-48.54)	(6.47)		(13.19)	(-41.30)		(-43.29)
$Volatility_{i,d}$	-0.00***	-0.00	-0.00***	-0.00						
	(-10.43)	(-0.74)	(-8.20)	(-0.13)						
Obs.	83,702	83,702	83,702	83,702	83,702	83,702	83,702	83,702	83,702	83,702
Method	OLS	OLS	SLS	SLS	SLS	SLS	SLS	SLS	SLS	SLS
Adj. R^2	0.26	0.34	0.26	0.34	0.26	0.10	0.09	0.34	0.17	0.13
F-Test	696.2	124,1.0	336.5	1,282.0	404.2	924.6	999.4	1,517.0	1,337.0	2,019.0
Fixed Effects	Stock	Stock	Stock	Stock	Stock	Date	None	Stock	Date	None
Instrument-al Variables	-	-	Set 1	Set 1	Set 2	Set 2	Set 2	Set 2	Set 2	Set 2

A.5 Impact of periodic auction trading on transaction costs - Robustness specifications

In addition to the results shown in Table 29, we defined further OLS and 2SLS regression, as a robustness check.

Table 38: Impact of periodic auction trading on transaction costs-Robustness specifications

The table reports the estimates of an OLS regression and from the second-stage instrument variables regression on the impact of trade execution via periodic auctions on transaction costs. The first six columns present three different OLS regression models for $Effective\ Spread_{i,d}$ and $Quoted\ Spread_{i,d}$ each.

$$y_{i,d} = \alpha_i + \beta_1 PeriodicAuction_{i,d} + \beta_2 PeriodicAuction_{i,d} * FTSE100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The last four columns report the estimates when running a 2SLS model. The first-stage regression results are not reported. The null hypotheses that the instrumental variables are weak was rejected (Stock and Yogo (2005)). The models are run as follows with two different sets of instrumental variables.

$$y_{i,d} = \alpha_i + \beta_1 \widehat{PeriodicAuction}_{i,d} + \beta_2 \widehat{PeriodicAuction}_{i,d} * FTSE100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The first instrumental variable set (Set 1) is a combination of a dummy variable equivalent to 0 prior to a suspension cut-off date within the DVCM and 1 after, and the lagged observation of the respective type of periodic auction trade share. The second set (Set 2) is limited to the dummy variable. The dependent variables $y_{i,d}$ of the second-stage regressions are estimates of transaction costs. The metric $Price\ Impact_{i,d}$ is time-weighted and computed as the difference of effective and realised spread on the lit venue. $Effective\ Spread_{i,d}$ is a time-weighted daily for all trades during continuous lit trading. Both spread measures are calculated relative to the mid-point in basis points. Each model includes four control variables. $FTSE100_{i,d}$ is a dummy variable equivalent to 1 if the security is a constituent of the FTSE 100 index and 0 otherwise. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $Trend_d$ controlling for changes in the dependent variable over our study horizon. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index, which were suspended using transparency waivers anytime between March 2018 and August 2018 in terms with the thresholds of the DVCM. Before and after each monthly cut-off date we include 20 trading days before and after the event. This results in six datasets which we overlay to one data set. Date* fixed-effects refer not to actual dates, but numbers between -21 and 21 indication the days prior to and after the suspensions start-date. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	$Effective\ Spread_{i,d}$	$Price\ Impact_{i,d}$	$Effective\ Spread_{i,d}$	$Price\ Impact_{i,d}$	$Effective\ Spread_{i,d}$	$Effective\ Spread_{i,d}$	$Effective\ Spread_{i,d}$	$Price\ Impact_{i,d}$	$Price\ Impact_{i,d}$	$Price\ Impact_{i,d}$
$Intercept_{i,d}$	10.61***	8.79***	10.42***	8.43***	10.39***	-1.59***	7.53***	8.40***	-2.31***	5.89***
	(60.15)	(49.68)	(58.50)	(46.41)	(57.87)	(-78.79)	(47.94)	(45.83)	(-92.77)	(37.39)
$Periodic\ Auction_{i,d}$	2.17*	-0.49								
	(1.95)	(-0.37)								
$Periodic\ Auction_{i,d} * FTSE\ 100$	-1.54	-3.75**								
	(-1.21)	(-2.10)								
$\widehat{Periodic\ Auction}_{i,d}$			11.40***	15.61***	12.17***	71.51***	20.13***	15.81***	85.23***	24.60***
			(4.92)	(5.45)	(5.25)	(79.41)	(5.53)	(5.44)	(93.37)	(6.73)
$\widehat{Periodic\ Auction}_{i,d} * FTSE\ 100$			-9.76***	-14.62***	-10.73***	-8.80**	-8.98**	-14.97***	-13.48***	-8.87**
			(-3.80)	(-4.45)	(-4.01)	(-2.23)	(-2.27)	(-4.43)	(-3.27)	(-2.15)
$FTSE\ 100_{i,d}$						53.70***	-8.42***		65.38***	-7.09***
						(77.97)	(-71.72)		(92.09)	(-58.72)
$HFTVol_{i,d}$	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	0.73***	0.01***	-0.02***	0.86***	-0.00***
	(-6.40)	(-6.14)	(-6.39)	(-6.14)	(-6.39)	(80.18)	(12.48)	(-6.13)	(92.91)	(-5.34)
$Trend_{i,d}$	0.00	0.00**	0.00*	0.01**	0.00*	1.34***	0.00	0.00**	1.60***	0.01***
	(1.62)	(2.21)	(1.84)	(2.51)	(1.80)	(78.75)	(0.95)	(2.46)	(93.09)	(3.23)
$Volatility_{i,d}$	0.02***	0.03***	0.02***	0.03***	0.02***		0.05***	0.03***		0.06***
	(38.99)	(47.60)	(39.11)	(47.88)	(39.13)		(78.98)	(47.90)		(92.45)
Obs.	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842
Method	OLS	OLS	SLS	SLS	SLS	SLS	SLS	SLS	SLS	SLS
Adj. R^2	0.76	0.62	0.76	0.62	0.76	0.4	0.39	0.62	0.39	0.39
F-Test	322.3	478.7	336.8	454.9	348.4	10213	8458	489.5	8861	7324
Fixed Effects	Stock	Stock	Stock	Stock	Stock	Date*	None	Stock	Date*	None
Instrument-al Variables	-	-	Set 1	Set 1	Set 2	Set 2	Set 2	Set 2	Set 2	Set 2

A.6 Impact of periodic auction trading on informational efficiency - Robustness specifications

In addition to the results shown in Table 31, we defined further OLS and 2SLS regression, as a robustness check.

Table 39: Impact of periodic auction trading on informational efficiency-Robustness specifications
The table reports the estimates of different OLS regression and of second-stage instrument variables regression models on the impact of periodic auction trading on measures of informational efficiency. The first four columns present two different OLS regressions for $Autocorrelation_{i,d}$ and $Variance\ Ratio_{i,d}$ each.

$$y_{i,d} = \alpha_i + \beta_1 PeriodicAuction_{i,d} + \beta_2 PeriodicAuction_{i,d} * FTSE100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The 2SLS regressions in the last six columns for the same parameters include both the fitted values of both forms of SI trading:

$$y_{i,d} = \alpha_i + \beta_1 \widehat{PeriodicAuction}_{i,d} + \beta_2 \widehat{PeriodicAuction}_{i,d} * FTSE100_{i,d} + \sum_{j=1}^{4} \gamma_j Control_{j,i,d} + \varepsilon_{i,d}$$

The first-stage regression results show highly significant F-statistics, rejecting the null hypotheses that the instrumental variables are weak (see Stock and Yogo (2005)). The first instrumental variable set (Set 1) is a combination of a prior to a suspension cut-off date within the DVCM and 1 after and the lagged observation of the periodic auction trade share. The second set (Set 2) is limited to the dummy variable. The dependent variables $y_{i,d}$ are estimates of informational efficiency. $Autocorrelation_{i,d}$ is based on 10-second mid-point returns, whereas $HFVol_{i,d}$ is added as 10-second mid-point return standard deviations during continuous lit trading hours. $Variance\ Ratio_{i,d}$ measures the variance-ratio of the standard deviations on 1-second and 10-second mid-point returns. Each model includes four control variables. $FTSE100_{i,d}$ is a dummy variable equivalent to 1 if the security is a constituent of the FTSE 100 index and 0 otherwise. $HFTVol_{i,d}$ is added as a proxy for high-frequency trading as the total number of daily quotes over trades during continuous lit trading hours. $Volatility_{i,d}$ refers to interday volatility of the relevant security on the continuous lit venue. $Trend_d$ controlling for changes in the dependent variable over our study horizon. Our sample compromises all securities within the FTSE 100 index and FTSE 250 index, which were suspended using transparency waivers anytime between March 2018 and August 2018 in terms with the thresholds of the DVCM. Before and after each monthly cut-off date we include 20 trading days before and after the event. This results in six datasets which we overlay to one data set. Date* fixed-effects refer not to actual dates, but numbers between -21 and 21 indication the days prior to and after the suspensions start-date. ***, ** and * indicate the statistical significance of 1%, 5% and 10% respectively.

	$Autocorrelation_{i,d}$	$Variance\ Ratio_{i,d}$	$Autocorrelation_{i,d}$	$Variance\ Ratio_{i,d}$	$Autocorrelation_{i,d}$	$Autocorrelation_{i,d}$	$Autocorrelation_{i,d}$	$Variance\ Ratio_{i,d}$	$Variance\ Ratio_{i,d}$	$Variance\ Ratio_{i,d}$
$Intercept_{i,d}$	-0.07***	1.09***	-0.07***	1.09***	-0.07***	2.70***	-0.05***	1.09***	-1.18***	1.08***
	(-51.80)	(996.30)	(-49.38)	(916.28)	(-48.81)	(13.59)	(-36.01)	(898.68)	(-6.46)	(800.35)
$Periodic\ Auction_{i,d}$	0.00	-0.00								
	(0.22)	(-0.30)								
$Periodic\ Auction_{i,d} * FTSE\ 100_{i,d}$	0.01	-0.15***								
	(0.28)	(-6.35)								
$\widehat{Periodic\ Auction}_{i,d}$			0.06**	0.02	0.08***	-99.34***	0.07**	0.02	81.87***	0.01
			(2.26)	(0.68)	(2.71)	(-13.90)	(2.29)	(0.73)	(12.43)	(0.22)
$\widehat{Periodic\ Auction}_{i,d} * FTSE\ 100_{i,d}$			0.10**	-0.35***	0.10**	0.01	0.01	-0.36***	-0.27***	-0.29***
			(2.45)	(-8.64)	(2.22)	(0.30)	(0.30)	(-8.76)	(-5.91)	(-6.29)
$FTSE\ 100_{i,d}$						-0.76***	0.02***		0.62***	-0.03***
						(-13.41)	(18.68)		(11.77)	(-25.19)
$HFTVol_{i,d}$	-0.00***	0.00***	-0.00***	0.00***	-0.00***	-0.00***	-0.00***	0.00***	0.00***	0.00***
	(-3.58)	(9.66)	(-3.55)	(9.49)	(-3.50)	(-16.09)	(-19.15)	(9.31)	(14.83)	(25.11)
$Trend_{i,d}$	0.00	-0.00	0.00	-0.00	0.00	-0.00***	-0.00	-0.00	0.00***	0.00
	(0.16)	(-0.46)	(0.41)	(-0.71)	(0.40)	(-13.73)	(-0.30)	(-0.68)	(12.31)	(0.61)
$Volatility_{i,d}$	0.00***	-0.00*	0.00***	-0.00**	0.00***		-0.00***	-0.00**		0.00***
	(6.82)	(-1.85)	(7.07)	(-2.04)	(7.21)		(-13.15)	(-2.14)		(11.93)
Obs.	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842	59,842
Method	OLS	OLS	SLS	SLS	SLS	SLS	SLS	SLS	SLS	SLS
Adj. R^2	0.24	0.31	0.24	0.31	0.24	0.06	0.06	0.31	0.10	0.10
F-Test	12.8	28.5	17.6	39.64	18.3	534.1	446.4	40.07	1,090.0	914.9
Fixed Effects	Stock	Stock	Stock	Stock	Stock	Date*	None	Stock	Date*	None
Instrumental Variables	-	-	Set 1	Set 1	Set 2	Set 2	Set 2	Set 2	Set 2	Set 2