Essays in Empirical Market Microstructure

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Introduction

"Markets are fascinating" Larry Harris (2003)

With these words Larry Harris, former Chief Economist of the U.S. Securities and Exchange Commission, begins his standard text book on "Trading & Exchanges" .[1] Since the publication of his book in 2003, the total world-wide equity trading volume has increased from 28.5 trillion USD to 77.6 trillion USD in 2017.[2] During the same period, the regulatory and technological setting, the types of participants in financial markets and the range of market designs have changed radically. This dissertation emerged in this period of fundamental market evolution characterized by a rise in high frequency trading and an increase in market fragmentation. It examines the trading process and its consequences for market outcomes against the background of these changes. It is devoted to the fact that modern markets are (more than ever) fascinating and an important object of study.

The branch of financial economics that is particularly concerned with "trading, the people who trade [...], the marketplaces where they trade, and the rules that govern trading"[3] is called market microstructure.[4] In other words, market microstructure is "the study of the process and outcomes of exchanging assets under explicit trading rules".[5] It provides an alternative framework to the frictionless Walrasian market model in which supply and demand determine equilibrium prices in a not exactly specified market clearing process. By illuminating all aspects of the trading process, market microstructure tries to open the black box of the price formation process and to answer the question of how asset markets should be organized (i) to produce informative prices and (ii) to allow traders to trade assets easily and at low cost. The first part of the question refers to the informational efficiency, the second to the liquidity of markets. In three self-contained chapters, this dissertation provides a contribution to the answering of this question. The first part of this introduction places the different chapters of this dissertation in the greater context of market microstructure research. A more detailed summary of the different chapters is provided at the end of this introduction.

By aggregating information from public information releases and privately informed traders, informationally efficient markets produce prices that reflect the fundamental value of the traded assets.[6] Efficient prices allow for an efficient allocation of resources in an economy and thus have

[1] Harris (2003)
[2] Based on data from the World Federation of Exchanges database aggregated by https://data.worldbank.org.
[3] Harris (2003, p.3)
[4] The term 'market microstructure' was first used by Garman (1976).
[5] O'Hara (1995)
[6] Fama (1970)

a first order effect on social welfare. While not the main focus of this dissertation, we touch on informational efficiency in Chapters 2 and 3 of this thesis. Chapter 2 analyzes the effect of investor attention on asset prices and potential inefficiencies induced by attention-based trading. Chapter 3 investigates the impact of a regulatory change to the market structure on short-term price efficiency.

Reasons for deviations of transaction prices from the long-term fundamental value lie in market frictions related to the costs of trading. Liquidity reflects the degree of these frictions in the market. As trading is affected by various frictions, liquidity must be a multi-dimensional concept and thus is difficult to define. Brunnermeier and Pedersen (2009) refer to it as "the ease with which [an asset] is traded". This thesis defines it as the possibility to trade a certain amount of an asset at a given point in time without a large price impact. In the spirit of Black (1971), Harris (1990) and O'Hara (1995), this definition points to the multiple dimensions of liquidity: A price (width), a quantity (depth) and a time dimension (immediacy & resiliency). *Width* refers to the bid-ask spread for a given number of shares. The bid-ask spread measures the difference between the best quoted ask (the price at which a liquidity consumer can buy the asset) and best quoted bid (the price at which a liquidity consumer can sell the asset) in the market. *Depth* refers to the volume that can be traded within a given price range. *Immediacy* describes how quick trades of a given size can be realized at a given cost and *resiliency* measures how fast prices recover after they changed due to an uninformed trade that was large enough to have a price impact. All those liquidity dimensions are intertwined. A large trade will have an impact on spreads (width) and affect the volumes available for trade (depth). It will require some time to execute if the trader wants to limit costs (immediacy) and markets will potentially need some time to recover from such a liquidity shock (resiliency). No single measure will be able to jointly capture all these aspects.

While considering all dimensions of liquidity, this dissertation will concentrate on the width of the market, i.e. the bid-ask spread. As suggested by Huang and Stoll (1997), it can be decomposed into three components, all related to a specific trading friction. The order processing cost component refers to costs of infrastructure and the opportunity costs of trading that are unrelated to the specific security traded.[7] The inventory holding cost component arises from the fact that risk averse traders want to be compensated for the risks connected to holding large inventories.[8]The adverse selection component of the spread refers to the fact that uninformed traders demand a compensation for facing the risk of trading with informed counterparties.[9] Due to the potential informational content of trades, prices tend to increase [decrease] after a liquidity demander buys [sells]. We refer to this change in price as the *price impact* of a trade.[10]

All chapters of this dissertation contribute to the understanding of stock market liquidity. Chapter 1 of this dissertation provides an overview of existing low-frequency liquidity estimators

[7]Roll (1984)

[8]Garman (1976), Stoll (1978), Ho and Stoll (1981)

[9]Bagehot (1971), Kyle (1985), Glosten and Milgrom (1985)

[10]This short summary of the dimensions of liquidity and the three spread components is meant to place this dissertation in the continuum of research on liquidity. A thorough analysis of liquidity, its dimensions and their interaction is beyond the scope of this dissertation. See O'Hara (1995), Biais et al. (2005) and Madhavan (2000) for a more detailed insight into this topic.

and evaluates to what extent these measures capture the spread and the price impact of trades. Chapter 2 analyzes the effect of investor attention on trading volumes, spreads and price impacts and specifically addresses the dynamic relationship between informed and uninformed (attention) traders. Chapter 3 investigates the impact of a regulatory change to the market structure on market fragmentation and liquidity.

To better understand the central role of liquidity for financial markets, it is necessary to explicitly asess the costs and benefits of increased liquidity. O'Hara (2004) summarizes the "dark" and the "bright" side of liquidity. The traditional "dark" view on liquidity, brought forward by Keynes (1935), Tobin (1978) and Summers and Summers (1989), argues that too much liquidity will by construction promote a short-term orientation of traders. As a consequence, traders pay less attention to firm fundamentals and markets will be destabilized. Coffee (1991) argues that high liquidity will result in more diversified stock ownership and thus lower shareholder activism, which might result in corporate governance problems. In contrast to this negative view on liquidity, most of the more recent market microstructure literature has a "brighter" opinion on liquidity. A more liquid market will increase the willingness of potential traders to participate in the market and thus have a stabilizing effect. Utilitarian investors, i.e. traders with "good" economic reasons to trade (e.g. hedging or risk sharing), will be more prone to enter the market. If it is cheaper to trade, more information will be impounded into prices which increases the informational efficiency of the market.

In addition, liquidity is important for market outcomes.[11] It affects asset prices[12] and is related to corporate financing decisions.[13] This dissertation contributes to these research areas in Chapter 2 by relating attention-based trading to stock returns and in Chapter 3 by quantifying the impact of a regulatory change on stock prices.

The above explanations survey the fundamental concepts of market microstructure research and relate them to the studies conducted in this dissertation. Against this background, the following paragraphs shall depict the major technological changes that shaped trading in recent years and that are directly related to the chapters of this dissertation.

First, the internet has fundamentally transformed the information landscape of today's markets. It affects the amount of information available and the speed at which this information can be incorporated into prices. It is the foundation for today's electronic trading platforms that have largely replaced the traditional floor trading. Consequences are an improved accessibility of markets, faster trade executions and lower costs. All studies in this dissertation rely on large datasets crawled from the internet that would not have been accessible and manageable some years ago. Chapter 2 is particularly dependent on modern information sources as it exploits aggregate internet search behavior to make inferences about variations in investor attention.

[11] See Holden et al. (2014) for a survey on the empirical evidence.

[12] See e.g. Amihud and Mendelson (1986a), Amihud et al. (1997), Datar et al. (1998), Pástor and Stambaugh (2003), Amihud (2002), Acharya and Pedersen (2005a), Bekaert et al. (2007), Fang et al. (2009), Amihud et al. (2015b), and Amihud et al. (2015a)

[13] Recent examples include research on corporate governance (Chung et al. (2010) and Brogaard et al. (2017)), shareholder activism (Norli et al. (2015)), share offerings (Hanselaar et al. (2018)), corporate investment (Field et al. (2018)), payout policy (see Brockman et al. (2008) and Hillert et al. (2016) for share repurchases and Amihud and Li (2006), and Michaely and Qian (2017) for dividend policy). See Amihud and Mendelson (2008) for an overview on the relation between liquidity and corporate finance.

Second, technology has permitted the advent of Algorithmic Trading, a term that refers to order placement decisions made by machines according to specific rules.[14] One specific form of algorithmic trading, high-frequency trading, relies on strategies that depend on the speed (or low latency) of the algorithm's trades. High-frequency trading subsumes various trading strategies, and has grown substantially over the past decade.[15] The literature on the effects of high-frequency trading on market quality is divided. While the theoretical literature predominantly claims that high-frequency trading is detrimental to market quality due to negative externalities connected to their speed advantage,[16] the empirical literature provides rather mixed evidence.[17] We add to this literature in Chapter 2 by discussing the dynamics of trading between (attention-constrained) retail traders and high-freqency traders. In addition, Chapter 3 analyzes how a change in the market structure affects equilibrium order routing strategies of all market participants, specifically including those of high frequency traders.

Third, over the last decades, regulators, responding to the progress in technology, have implemented substantial changes to the structure of markets. Chapter 1 and especially Chapter 3 exploit such regulatory changes for identification purposes to understand the endogenous and bi-directional relationship between liquidity and market outcomes. Most importantly, regulators have opened the market for competition among various market places.[18] Those might for example differ in the market mechanism applied, the information on prices and order flow provided to traders (transparency) and the clientele admitted to the market. Some theoretical literature suggests that the resulting fragmentation of order flow might induce negative network externalities as liquidity is not concentrated any more on a single order book.[19] Opposed to this, Harris (1993) expects positive effects of fragmentation as it allows heterogeneous traders to select themselves into trading venues that suit their specific needs.[20] Chapter 3 specifically addresses the role of fragmentation in a market with various degrees of transparency.

In summary, the above paragraphs suggest that liquidity and price efficiency have a positive effect on social welfare and are thus a desirable objective of a market. Moreover, it has been established that the complexity of the trading landscape has increased and influences the way we think about liquidity. But how do traders react to liquidity shocks in such a complex setting? How do exchanges compete for liquidity? And how should regulators design a market to foster liquidity and market efficiency? This dissertation examines the determinants of market quality in modern equity markets and contributes to the decision making process of regulators, platform providers and traders. It is thus relevant beyond the academic discussion in the field of market microstructure. Chapter 3 highlights a need for caution in designing and implementing regulatory changes in todays complex and fragmented markets as they will affect equilibrium strategies of both traders and plattform providers. Chapter 2 contributes to the decision making

[14]See Goldstein et al. (2014) and Biais et al. (2014) for surveys on algorithmic trading.

[15]These strategies include market making , arbitrage strategies, order anticipation and many more. See Miller and Shorter (2016) for an overview on these strategies.

[16]See Menkveld (2016) and Biais et al. (2015a).

[17]See Boehmer et al. (2015), Jones (2013), and Chakrabarty et al. (2014)

[18]In 2007, Regulation National Market System (Reg NMS) in the US and the Markets in Financial Instruments Directive (MiFiD) in Europe have established rules to facilitate competition among amrket places.

[19]See Pagano (1989) and Mendelson (1987)

[20]For a survey on the literature on market fragmentation see Gomber et al. (2017).

process of retail investors facing attention constraints. At the same time, it emphasizes the interdependence of the trading strategies of different market participants. Chapter 1 guides researchers in their search for appropriate liquidity measures and thus supports future insights in the field of economics.

All chapters of this thesis provide perspectives on market efficiency and especially liquidity in modern equity markets. The conducted studies are empirical in nature and rely on unique, large and non-standard datasets. Despite these commonalities, they differ substantially with respect to the specific research question, the markets, the sample period and the regulatory setting under regard. Finally, various empirical methodologies are applied. Table 1 summarizes these differences.

Table 1: Dissertation Overview
This table provides an overview of the three chapters (*Chap.*) of this dissertation along various dimensions. *Research question (broad)* summarizes the research question addressed in one sentence. *Market / Sample period* defines the stock universe / sample period covered. *Databases* names the primary databases used in the study and *Methodologies* lists the most central econometrical techniques used to analyze the data.

Chap.	Research question (broad)	Market	Sample period	Databases	Methodologies
1	What is the "best" low-frequency liquidity measure?	US	1993 - 2012	CRSP TAQ	Correlation Analysis Principle Component Analysis Difference-in-Differences (DiD)
2	How are a stock's liquidity, turnover, volatility and returns driven by short-term fluctuations in investor attention?	Germany	2004 - 2011	Google Trends Microstructure Database Xetra	Panel Regression Maximum Likelihood Estimation Fama-Macbeth Regression IV Regression
3	What is the effect of dark trading on liquidity and price efficiency?	Europe	2018	ESMA DVC Reports Thompson Reuters Tick History Fidessa Fragulator	Semiparametric DiD Regression Discontinuity Design Event Study Methodology

Chapter 1.[21] Above, we established liquidity as a multidimensional concept and bid-ask spreads as the most widely used measure of liquidity. Direct estimation of the spread requires intraday data on bid and ask prices. This data is often unavailable or at least difficult to analyze due to the strong increase in trading volume over recent years. Thus, researchers have developed various methods to estimate the spread from low-frequency (usually daily) data.

In this Chapter we conduct the most comprehensive comparative analysis of these low-frequency liquidity measures so far. We review a large number of estimators and use a broad range of procedures to evaluate them. We use the effective spread and the price impact calculated from high-frequency data as benchmark measures and evaluate the low-frequency estimators against these by analyzing their cross-sectional and time-series correlations as well as the mean absolute and root mean squared error. Our main objective is to provide researchers with clear guidelines for the selection of the best liquidity estimator in a specific research application. To do so, we employ different weighting schemes (equal-weighted, value-weighted and observation-weighted), analyze correlations in levels and first differences, apply the liquidity proxies to individual stocks as well as to portfolios, compare stocks of different liquidity, market capitalization and from different markets (NYSE, Nasdaq and Amex).

We find that the performance of the estimators is highly dependent on the particular ap-

[21] This Chapter is based on the working paper "The Best in Town: A Comparative Analysis of Low-Frequency Liquidity Estimators" (Johann and Theissen (2018)).

plication, and that no single best estimator exists. The low-frequency estimators are generally better able to track the (cross-sectional and time-series) variation in the effective spread than variation in the price impact. They are further better at tracking levels than first differences. The performance of some of the low-frequency estimators is extremely sensitive to minor changes in methodology. Some estimators perform well in general while others display good performance only in specific settings or fail completely.

We further find that linear combinations of various estimators do not improve upon the performance of the best individual estimators and that regulatory changes may affect the performance of the low-frequency estimators. We show that the time-series correlation of the low-frequency estimators with the effective spread benchmark depends, in predictable ways, on the cross-sectional level of liquidity, market capitalization, turnover, age and the listing location of a stock. Moreover, the thus identified best performing estimator may not always be accessible as estimators differ with respect to their data requirements. Data availability as a limiting factor must be taken into account when choosing the estimator for a specific research project.

All these findings support researchers from the fields of market microstructure, corporate finance and asset pricing in their choice of appropriate liquidity measures.

Chapter 2.[22] We identified the internet as the most fundamental recent change to our professional and personal life. It provides access to an unprecedented amount of information. However, attention is a scarce resource[23] and retail investors especially must filter the available information. This Chapter analyzes how a stock's liquidity, turnover, volatility and returns are driven by short term fluctuations in investor attention. It shows that attention, as measured by daily Google Search Volume, increases both volatility and turnover in the German stock market but has only weak or no influence on daily stock returns and liquidity. The increase in turnover and volatility is consistent with increased trading by both uninformed and informed traders on high attention days. As increases in uninformed trading are largely offset by dynamic increases in informed trading, adverse selection costs and consequently liquidity are unaffected. The relation between attention and trading dynamics is stronger for large stocks, stocks with a generally lower level of cross-sectional attention, and stocks with a higher proportion of retail trading. These findings are robust to a large variety of regression specifications (panel and Fama and MacBeth (1973) regressions), subsample sorts, and endogeneity tests.

The results of the study have implications for many market participants. Most importantly, it contributes to the understanding of retail investors' decision making process under attention constraints and its effects on multiple market microstructure dimensions, most importantly turnover and volatility.

From a researcher's perspective this paper establishes a refined and more precise measure of daily investor attention, namely *daily* Google Search Volume. It can be used in various future research settings as a daily active attention measure. Furthermore, we use intraday data for German equities so as not to rely on low-frequency measures of market quality as done in

[22]This Chapter is based on the working paper "May I Have Your Attention Please: The Market Microstructure of Investor Attention" (Fink and Johann (2018)).

[23]Kahneman (1973)

previous research. This data is made available to other researchers, aggregated to a daily level.[24]

Chapter 3.[25] Modern equity markets are characterized by competition among various trading mechanisms for order flow. One dimension along which venues can differentiate is the pre-trade transparency, which refers to the information available to market participants before they submit their orders. In this Chapter, we show that "quasi-dark" trading venues, i.e. markets with varying degree of opacity, are important parts of modern equity market structure alongside lit markets (offering real-time information on current orders and quotes) and dark pools (offering no pre-trade information). In 2018, European MiFiD II regulation imposed a complete ban on small trades in dark pools for stocks that historically traded more than 8% of their volume in such venues. Using this regulation as a quasi-natural experiment, we find that dark pool bans lead to (i) volume spill-overs into quasi-dark trading mechanisms; (ii) little volume returning to transparent public markets; and consequently, (iii) a negligible impact on market liquidity and short-term price efficiency. Additionally, positive announcement returns of banned stocks indicate that investors appreciate the suspension of dark pools. Consistent with the ban's largely insignificant effect on market quality this announcement return is reversed with the actual implementation of the ban.

These results are established employing a difference-in-differences methodology, a regression discontinuity design and a placebo test using a subset of stocks that were incorrectly not banned. Altogether, these techniques allow us to dissolve the endogeneous relation between market fragmentation and liquidity.

The results show that quasi-dark markets serve as close substitutes for dark pools and consequently mitigate the effectiveness of dark pool regulation. Our findings highlight the need for a cautious approach to transparency regulation in modern markets that takes into consideration the peculiarities of today's fragmented markets and the equilibrium strategies of investors and profit-maximizing venue operators.

[24]See Market Microstructure Database Xetra (https://www.ifk-cfs.de/research/databases/market-microstructure-database-xetra.html). This database was build during this dissertation and is extensively analyzed and documented in Johann et al. (2018a) and Johann et al. (2018b).

[25]This Chapter is based on the working paper "Quasi-dark trading: The effects of banning dark pools in a world of many alternatives" (Johann et al. (2019)).

Chapter 1

The Best in Town: A Comparative Analysis of Low-Frequency Liquidity Estimators

1.1 Introduction

The availability of accurate measures of liquidity is of utmost importance for empirical research in finance. This is obviously true for research in market microstructure where liquidity is recognized to be one of the most important, if not the most important measure of market quality. The empirical asset pricing literature has accumulated convincing evidence that the liquidity of an asset affects its expected rate of return and, in turn, the cost of capital of the issuer (see e.g. Amihud and Mendelson (1986a), Pástor and Stambaugh (2003), Acharya and Pedersen (2005a)). More recently, research in corporate finance has uncovered several channels through which liquidity and corporate financing decisions are interrelated.[1]

The most widely used measures of liquidity are quoted and effective bid-ask spreads. Direct estimation of the spread requires intraday data on bid and ask prices and (for the effective spread) transaction prices. This data is often unavailable. Even if the data is available direct estimation of the spread may be burdensome because of the tremendous increase in trading and quotation activity we have witnessed in the last two decades. Therefore, researchers have developed and applied various methods to estimate the spread from low-frequency (usually daily) data.[2] This immediately raises the questions (1) of the general accuracy of these low-frequency measures and (2) of their relative performance.

In the present chapter we address both questions. We use the effective spread and the price impact calculated from high-frequency data as benchmark measures and then evaluate

[1] Recent examples include research on share repurchases (Hillert et al. (2016)), on corporate governance (Chung et al. (2010)) and on shareholder activism (Norli et al. (2015)). See also the survey by Amihud and Mendelson (2008).

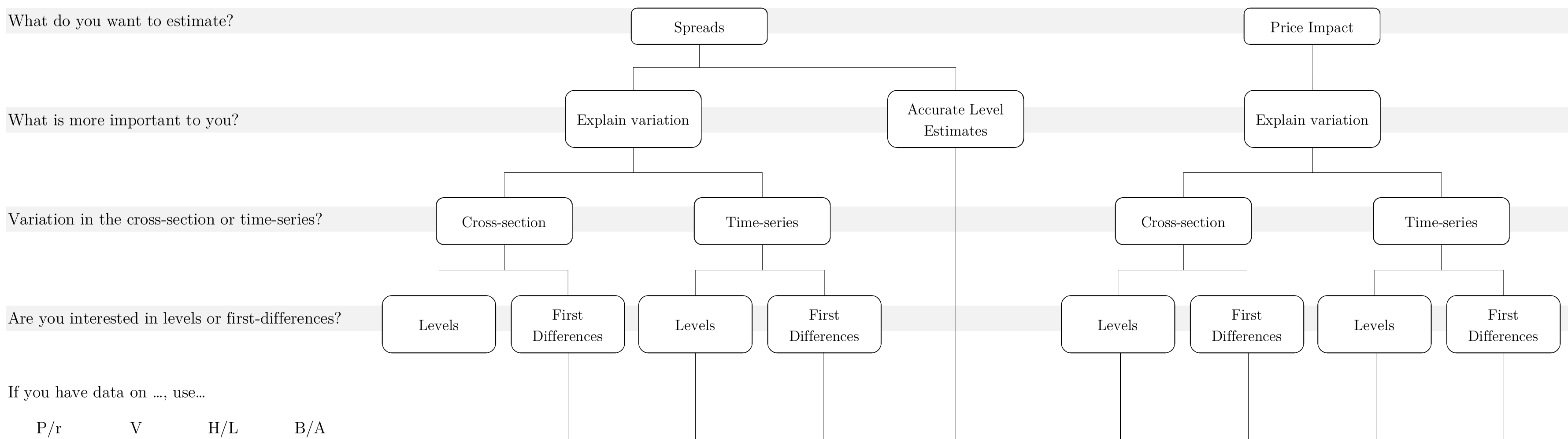
[2] Examples of papers that apply low-frequency liquidity estimators include Amihud et al. (1997), Berkman and Eleswarapu (1998), Domowitz et al. (1998), Acharya and Pedersen (2005a), Lesmond (2005), Liu (2006), Bekaert et al. (2007), Fernandes and Ferreira (2009), Lipson and Mortal (2009), Asparouhova et al. (2010), Baele et al. (2010), Lee (2011), Næs et al. (2011), Gopalan et al. (2012), Edmans et al. (2013), Balakrishnan et al. (2014), Amihud et al. (2015a), and Koch et al. (2016).

the low-frequency estimators against these high-frequency benchmarks. The main metrics to assess the performance of the low-frequency estimators are their cross-sectional and time-series correlations with the high-frequency benchmarks and the mean absolute and root mean squared error (RMSE).

We are not the first to evaluate the relative performance of alternative liquidity proxies. Several papers that propose a new low frequency estimator compare its performance to that of existing measures in order to demonstrate the superiority of the measure that is advocated in the paper. These horse races yield ambiguous results (see Goyenko et al. (2009), Hasbrouck (2009), Holden (2009b), Fong et al. (2017), Corwin and Schultz (2012), Abdi and Ranaldo (2017), Fong et al. (2017)). Some papers have extended the evaluation approach to asset classes other than equities. Marshall et al. (2012) evaluate liquidity proxies in commodities markets and conclude that the Amihud (2002) illiquidity ratio, the Amivest measure and the effective tick measure (Holden (2009b), Goyenko et al. (2009)) perform well. In contrast, Karnaukh et al. (2015) find that the Corwin and Schultz (2012) high-low estimator performs well in FX markets. This result is confirmed for bond markets by Schestag et al. (2016). These authors conclude that the Roll (1984) serial covariance estimator and the Hasbrouck (2009) Gibbs sampling approach also perform well in bond markets.

The contribution of our work to the literature is threefold. First, ours is the most comprehensive study so far. We evaluate a large number of low-frequency estimators. We estimate both cross-sectional and time-series correlations as well as mean absolute errors and root mean squared errors, we employ different weighting schemes (equal-weighted, value-weighted and observation-weighted), apply the liquidity proxies to individual stocks as well as to portfolios, and use data from different markets (NYSE, Nasdaq and Amex). Further, we use both the effective spread and the price impact as high-frequency benchmarks. This is potentially important because some of the low-frequency estimators we evaluate (most notably the Amihud (2002) illiquidity ratio) do not try to estimate the bid-ask spread but are rather measures of the price impact. We also follow Chung and Zhang (2014) and include the daily closing bid-ask spreads contained in the CRSP data base in our evaluation. Second, inspired by Baker and Wurgler (2006) we construct two composite liquidity measures. The first is based on the first principal component of a set of low frequency estimators while the second is based on an approach that maximizes the correlation between a linear combination of low-frequency estimators and the effective bid-ask spread. We then perform out-of-sample tests to assess the extent to which these composite measures improve upon the performance of the best individual low-frequency estimators. Third, we shed light on the variables that determine the performance of the estimators. In this context we show that the time-series correlation of the low-frequency estimators with the effective spread benchmark depends, in predictable ways, on the liquidity, market capitalization, turnover, age and listing location of a stock. It is further conceivable that the performance of some or all of the estimators we analyze depends on the regulatory regime. We therefore analyze how the accuracy of the liquidity proxies is affected by changes in the minimum tick size and other regulatory changes on the NYSE (NYSE Open Book and NYSE Hybrid) and Nasdaq (Nasdaq Order Handling Rules).

Figure 1.1: Summary of Results
This flowcharts summarizes the main findings of this chapter described in Section 1.4. Every column of the table at the end of the flowchart refers to one specific analysis conducted in this chapter. The abbreviations in the lower left of the chart are:
P/r for daily Closing Price/return; V for daily dollar trading volume; H/L for daily high/low prices; and B/A for daily clsoing bid/ask prices.
We decided to recommend *none* estimator if the correlation of all eligible estimators with the respective variable of interest (effective spread or 5-minute price impact) was below 10%.



P/r	V	H/L	B/A									
✓	✓	✓	✓	VoV High-Low	Closing Spread	Closing Spread	Closing Spread	Abdi 2-day	VoV Daily	none	VoV daily	VoV daily
✓	×	✓	✓	Closing Spread	Closing Spread	Closing Spread	Closing Spread	Abdi 2-day	Closing Spread	none	Closing Spread	Closing Spread
✓	✓	×	✓	Closing Spread	Closing Spread	Closing Spread	Closing Spread	Effective Tick	Closing Spread	none	VoV Sigma	VoV Sigma
✓	✓	✓	×	VoV High-Low	VoV daily	VoV daily	VoV daily	Abdi 2-day	VoV Daily	none	VoV daily	VoV daily
✓	×	×	×	Roll (0) ret	Roll (0) ret	Roll (0) ret	Roll (0) ret	Effective Tick	Lesmond	none	Roll (0) ret	none

Our results can be summarized as follows. The low-frequency estimators are generally better able to track the (cross-sectional and time-series) variation in the effective spread than variation in the price impact. They are further better at tracking levels than first differences. The performance of some of the low-frequency estimators is extremely sensitive to minor changes in methodology. Some estimators (e.g. the CRSP closing spread and the measures recently proposed by Tobek (2016)) generally perform well while other estimators display good performance only in specific settings or fail completely. Composite estimators do not improve upon the performance of the best individual estimators. The introduction of the Nasdaq order handling rules in 1997 tended to increase the accuracy of the low-frequency estimators while the reduction of the tick size on the NYSE from sixteenths to decimals in 2001 had the opposite effect. Other regime changes (most notably the introduction of NYSE Open Book and NYSE hybrid) did not have a first-order effect on the performance of the low-frequency proxies. The estimators we evaluate differ with respect to their data requirements. While some only require daily prices or returns, others also require data on trading volume and/or daily high and low prices. Data availability is thus also a decisive factor in the choice of the best estimator. Our results, summarized in Figure 1.1, allow researchers to choose the best low-frequency estimator in a specific research setting.

The chapter is structured as follows. Section 2 introduces the liquidity measures that we analyze. Section 3 describes our data and the methodology. The results of our empirical analysis are presented in section 4. Section 5 concludes.

1.2 Liquidity Measures

In this section we describe the liquidity measures analyzed in this chapter. We start by briefly introducing the high-frequency benchmark measures (based on intraday data), the effective bid-ask spread and the price impact. We then introduce the low-frequency measures (based on daily data). We sort these into two categories, low-frequency spread estimators and low-frequency price impact estimators.

1.2.1 Benchmark Measures and CRSP Closing Spread

The low frequency measures we evaluate are based on transaction prices. Therefore the appropriate benchmark measure is the effective spread because (1) it accounts for possible price improvement, and (2) it implicitly accounts for the fact that transactions tend to occur when the quoted bid-ask spread is low. The effective spread and the relative effective spread are calculated as

$$s_t^e = 2|p_t - m_t| \quad ; \quad s_t^{e,rel} = \frac{2|p_t - m_t|}{m_t} \tag{1.1}$$

where p_t denotes the transaction price and m_t the quote midpoint in effect immediately prior to the transaction.

In the presence of informed traders order flow is informative. Consequently, transactions will have a (permanent) impact on prices. This price impact can be measured by the change in the quote midpoint in an interval of length Δt after a trade,

$$s_t^{pi} = Q_t \left(m_{t+\Delta t} - m_t\right) \quad ; \quad s_t^{pi,rel} = Q_t \frac{\left(m_{t+\Delta t} - m_t\right)}{m_t} \tag{1.2}$$

where the trade indicator Q_t is 1 when the trade is buyer-initiated and (-1) when it is seller-initiated. Trade classification is based on the Lee and Ready (1991) algorithm. A common choice for Δt is 5 minutes. We follow this convention.[3]

The CRSP database provides data on closing bid and ask prices for our entire sample period.[4] Obviously, this data can be used to construct an estimate of the quoted bid-ask spread. Chung and Zhang (2014) provide evidence that the CRSP spread estimate is highly correlated with the spread estimated from intraday (TAQ) data in cross-section. The time-series correlation is high only for Nasdaq stocks. Against the backdrop of this favorable evidence we include the CRSP closing spread among the low-frequency estimators we evaluate in our empirical analysis.

1.2.2 Low-Frequency Estimators of the Bid-Ask Spread

The Roll measure

Roll (1984) has proposed a simple procedure to estimate the spread from transaction prices. Under a set of assumptions that effectively assumes away traders with private information he shows that the effective bid-ask spread is related to the serial covariance of successive price changes. Similarly, the relative effective bid-ask spread is related to the serial covariance of successive returns:

$$s^{Roll,level} = 2\sqrt{-Cov\left(\Delta p_t, \Delta p_{t-1}\right)} \quad ; \quad s^{Roll,ret.} = 2\sqrt{-Cov\left(\Delta r_t, \Delta r_{t-1}\right)} \tag{1.3}$$

The logic of the Roll (1984) spread estimator applies to price changes at any frequency. Therefore, the Roll estimator can be applied to intradaily prices as well as to daily prices.[5]

Empirically it is often the case that the serial covariance of successive price changes is positive.[6] This is particularly true for stocks with low spreads. In these cases the Roll measure is not defined. Three procedures that are commonly applied in these cases are (1) to set the spread estimate to zero in these cases or (2) to drop the corresponding observations or (3) to calculate the Roll estimator as $s^{Roll} = -2\sqrt{Cov\left(\Delta p_t, \Delta p_{t-1}\right)}$ in those cases (which will result in negative spread estimates). We implemented all of those procedures. However, we only present results for the first version (i.e. we set the spread to zero if the covariance is positive) because this specification resulted in the most accurate estimates. In the following we refer to the version

[3] A five-minute interval to estimate the price impact is excessively long in the presence of high-frequency trading. However, given that (1) our sample period starts in 1993, long before high-frequency traders appeared in the markets, and (2) our sample is dominated by small firms for which the amount of high frequency trading is likely to be low, we decided to use five-minute intervals in our analysis. We also note that the choice of the interval length does not have a first-order effect on the results. This has been shown at the "short end" (1 to 20 seconds) by Conrad et al. (2015) and at the "long end" (5 to 30 minutes) by Huang and Stoll (1996).

[4] For a detailed account of the availability of closing bid and ask price data see Chung and Zhang (2014).

[5] Roll (1984) applied his estimator to daily and weekly prices.

[6] In our sample this is the case for 33% of the stock-month observations. See also Fama (1970), Ohlson and Penman (1985) and Fama and French (1988). For a detailed discussion of the statistical properties of the Roll estimator see Harris (1990). He puts special emphasis on the small sample properties of the estimator.

of the measure based on price changes as *Roll 0* and to the version based on returns as *Roll 0 (ret)*.

Hasbrouck (2009) builds on the Roll (1984) measure and proposes a Bayesian estimation approach. The spread estimates are constructed using a Gibbs sampling procedure. The programs to calculate this measure are available on Joel Hasbrouck's homepage.[7] We also include Hasbrouck's Gibbs measure (denozed as *Gibbs*) in our analysis.

Zero-return based estimators

Lesmond et al. (1999) develop an estimator of total transaction costs denoted LOT. Total transaction costs include brokerage commissions and exchange fees besides the spread. Consequently, the LOT estimator should be larger than direct estimates of the effective bid-ask spread. The LOT estimator is based on a simple intuition. Absent transaction costs a trader with private information on the value of a security will trade on her information up to the point where the marginal price is equal to her estimate of the asset value. The price will thus eventually reflect her private information. If, however, the total transaction cost exceeds the expected gain from trading the trader will refrain from trading. Her information will then not be impounded into prices. If transaction costs even for the trader with the highest expected gain from trading exceed those expected gains, a zero return will be recorded. By this argument a zero return observation is indicative of high transaction costs. Therefore, the fraction of zero return observations in a period can be used as a very simple proxy for transaction costs.

$$Zero = \frac{\#\ of\ zero\ return\ days\ in\ period}{\#\ of\ trading\ days\ in\ period} \tag{1.4}$$

We calculate two versions of the Zero estimator. In the first we use all trading days and in the second we only include days with positive trading volume. The results of both approaches are very similar. Therefore, we only report the results for the first version.

Lesmond et al. (1999) then develop an extended model that also uses the information provided by non-zero returns. Assume that the unobservable "true" returns are generated by a market model

$$r^*_{i,t} = \beta_i r_{m,t} + \epsilon_{i,t} \tag{1.5}$$

If transaction costs were zero, observable returns would also be generated by that market model. With positive transaction costs, however, observed returns will be

$$r_{i,t} = \begin{cases} r^*_{i,t} - \alpha_{1,i} & \text{if } r^*_{i,t} \leq \alpha_{1,i} \\ 0 & \text{if } \alpha_{1,i} < r^*_{i,t} \leq \alpha_{2,i} \\ r^*_{i,t} - \alpha_{2,i} & \text{if } r^*_{i,t} > \alpha_{2,i} \end{cases} \tag{1.6}$$

where $\alpha_{1,i} < 0; \alpha_{2,i} > 0$ denote the transaction costs for a sale and a purchase, respectively. The intuition is similar to the one presented above. The marginal trader (the trader with

[7] http://people.stern.nyu.edu/jhasbrou/Research/GibbsCurrent/gibbsCurrentIndex.html.

the highest expected benefit from trading) will only trade if the true expected return exceeds the transaction costs. Otherwise, a zero return is observed. The model allows for different transaction costs for buying and selling as the marginal seller might be a short seller, and short sales may cause higher transaction costs than regular trades. Lesmond et al. (1999) derive the likelihood function which can be used to obtain maximum likelihood estimates of the parameters $\alpha_{1,i}$ and $\alpha_{2,i}$. The measure of the proportional roundtrip transaction costs is then

$$LOT = \alpha_{2,i} - \alpha_{1,i} \tag{1.7}$$

To estimate their model Lesmond et al. (1999) categorize the trading days in their sample into three groups, namely days with zero return of the stock under consideration, days with non-zero stock returns and negative market returns, and days with non-zero stock returns and positive market returns. Goyenko et al. (2009) propose an alternative categorization. They sort by the stock return only and thus categorize the observations into zero return days, positive return days and negative return days. They denote the resulting modified estimator LOT Y-split.

Fong et al. (2017) simplify the LOT measure. They assume that transaction costs for buying and selling are symmetrical ($-\alpha_{1,i} = \alpha_{2,i}$). Additionally, they replace the market model assumption by the assumption that true returns are normally distributed. Thus, they obtain the estimator

$$FHT = 2\sigma\Phi^{-1}\left(\frac{1+Zero}{2}\right) \tag{1.8}$$

where Φ denotes the cumulative density of the standard normal distribution, σ is the standard deviation of daily returns, and $Zero$ is the proportion of zero return days as defined above.

Tobek (2016) proposes a modification of the LOT and FHT estimators. He does not differentiate between zero return and non-zero return days but rather between zero volume and positive volume days.

In our empirical analysis we include five of the estimators discussed in this section, namely, the number of zero returns (denoted *Zero*), the original LOT estimator (LOT), the LOT Y-split estimator (LOT *y-split*), the FHT estimator (FHT) and the modification of the FHT estimators proposed by Tobek (2016) (*Tobek* FHT).

The effective tick estimator

The minimum tick size set by the exchange determines the set of admissible prices. If the minimum tick size is one cent, all prices ending on full cents are admissible while prices ending on a fraction of a cent (sub-penny prices) are not. However, observed prices are not uniformly distributed over the full set of admissible prices. Rather, traders have a preference for particular (e.g. round) numbers. This phenomenon is referred to as price clustering (see Harris (1991)). The observed price clustering can be used to draw inferences on the spread (Holden (2009b), Goyenko et al. (2009)). Assume the minimum tick size is one cent and the spread is five cent. It is assumed that a five cent spread is implemented on a five cent price grid. That is, even so the minimum tick size is one cent, traders behave as if it was five cents. By that assumption, we will not observe bid and ask prices of 40.41 and 40.46, respectively. Rather, we would observe 40.40 and 40.45.

Now assume a transaction price of 40.41 is observed. This price will only be observed when the spread (and thus the price grid that traders use) is one cent. Thus, we can attach a 100% probability to a one cent price grid to the observation. Assume next we observe a price of 40.45. This price can result from a one cent grid or from a five cent grid. The probability of observing a price ending on x5 cent when a one cent grid is used is 10% (10 prices out of a total of 100). The probability of observing a price ending on x5 cents when a five cent grid is used is 50% (10 prices out of a total of 20 because it is assumed that a 5 cent spread is implemented on a price grid that only comprises prices ending on x0 and x5). Thus, the price of 40.45 comes from a one cent grid with probability 0.167 ($=\frac{0.1}{0.6}$) and from a five cent grid with probability 0.833 ($=\frac{0.5}{0.6}$). Combining these numbers results in an expected spread equal to 4.33 cent ($= 0.167 * 0.01 + 0.833 * 0.05$). By this logic each price implies an expected distribution of price grids from which it is drawn. We can then calculate the expected spread that is implied by the observed price. Averaging this over a sample of closing prices yields an estimate of the effective bid-ask spread(Holden (2009b)[8], Goyenko et al. (2009)).

The resulting estimator, known as the effective tick estimator, can be calculated with or without observations from zero-volume days. If these observations are included, the quote midpoint is used to infer the bid-ask spread. We have implemented both versions. Because the results were almost identical we only report those for the version that excludes zero-volume days. We denote the estimator *Effective Tick*.

Obviously the effective tick estimator has to be adjusted to the prevailing minimum tick size.[9] Our sample period covers three minimum tick size regimes, eighths, sixteenths, and decimals. We derive an appropriate version of the effective tick estimator for each of these regimes and apply it to our data during the period in which the respective regime was in effect.[10]

High-low spread estimators

Corwin and Schultz (2012) propose an estimator that is based on the following intuition: The highest [lowest] price observed on a trading day will typically result from a transaction at the ask [bid] price. The difference between the daily high and low price thus contains one component which is related to the spread and one component which is related to the volatility of asset returns. The problem is to disentangle these components. Corwin and Schultz (2012) assume that (a) true asset prices follow a diffusion process and (b) the bid-ask spread is constant over time. Consequently, the variance of changes in the true asset value increases proportionally with time while the contribution of the spread to the high-low difference does not. Under these assumptions the difference between the daily high and low price contains once the component related to the variance of price changes and once the component related to the spread. The

[8] Holden (2009b) also constructs combined estimators which are a linear combination of the effective tick and the Roll estimators.

[9] See appendix A in Holden (2009b).

[10] A more detailed derivation of the effective tick estimator for the decimal price grid can be found in Appendix A to this chapter.

difference between the highest and the lowest price measured over a two-day interval contains twice the component related to the variance of price changes but still only once the component related to the spread.[11] We thus essentially have two equations and two unknowns and can solve for the spread estimator

$$CS = \frac{2\left(e^{\alpha}-1\right)}{1+e^{\alpha}} \tag{1.9}$$

with $\alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}}$, where β and γ are the sample estimates of $E\left\{\sum_{j=0}^{1}\left[ln\left(\frac{H_{t+j}}{L_{t+j}}\right)\right]^2\right\}$ and $E\left\{\left[ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2\right\}$, respectively. H and L denote the observed high and low prices. The parameter β contains the sum of the high-low price ratio for two individual days t and (t+1) while the parameter γ contains the high-low price ratio calculated from the high and low prices observed over the two-day interval from day t to day (t+1). One advantage of the CS estimator is that it does not require a long time series. Observations from any two trading days are sufficient to derive a spread estimate. The CS estimator can become negative. As with the Roll estimator, this is more likely to happen when the spread is small.

The derivation of the CS estimator as presented above is based on a simplifying assumption that essentially treats Jensen's inequality as an equality. We also implement a version of the CS estimator that does not require this assumption. The modified estimator has the drawback that it can only be obtained numerically. The results were similar to (but slightly worse than) those obtained when using the simple CS estimator. We therefore only include the simple CS estimator in our analysis.

Tobek (2016) proposes a modified version of the CS estimator. The main difference is that Tobek (2016) uses the arithmetic mean of the log price range over a two-day interval, $\frac{1}{2}\left[ln\frac{H_t}{L_t} + ln\frac{H_{t+1}}{L_{t+1}}\right]$, while Corwin and Schultz (2012) use the square root of the sum of squared price ranges, $\left\{\left[ln\frac{H_t}{L_t}\right]^2 + \left[ln\frac{H_{t+1}}{L_{t+1}}\right]^2\right\}^{0.5}$. Tobek (2016) argues that the arithmetic mean is more robust and that, therefore, his estimator will be less affected by variations in volatility.

We implement two versions of the CS estimator, the original version (denoted *Corwin 0*) and the modified version developed by Tobek (2016) (denoted *Tobek Corwin 0*). In both cases negative spread estimates are set to zero.[12]

Abdi and Ranaldo (2017) propose an alternative estimator based on daily high and low prices. They argue that the average of the mid-range between the daily high and low prices on day t and the midrange on day $(t+1)$ is a natural proxy for the quote midpoint (or, for that matter, the efficient price) at the close of day t. The squared difference between the actual closing price and this estimator of the efficient price can then be interpreted as an estimate of

[11] This idea is reminiscent of the market efficiency coefficient (MEC) proposed by Hasbrouck and Schwartz (1988). The MEC is simply the ratio of a stock's return variance measured over a long interval divided by T times the return variance over a short interval. T is the length of the long interval divided by the length of the short interval. The MEC is expected to be smaller than one, and to decrease in the illiquidity of a stock.

[12] We also implemented versions of both estimators which include negative values in the calculation of the monthly or yearly averages. We found, however, that the performance of the estimators improves when negative values are set to zero. Therefore, only results for this latter version are reported in this chapter.

the sum of the squared effective half-spread and a term that captures the transitory volatility of the efficient price. The squared differences between the midrange of the daily high and low prices on day $(t+1)$ and the midrange on day t delivers an estimate of the transitory volatility. Combining both expressions yields a spread estimator of the form

$$s^2_{Abdi} = 4E\left[\left(c_t - \frac{\eta_t + \eta_{t+1}}{2}\right)^2\right] - E\left[(\eta_{t+1} - \eta_t)^2\right] \tag{1.10}$$

with c_t being the log closing price on day t and $\eta_t = \frac{ln(H_t)}{ln(L_t)}$. Obviously, the expectations have to be replaced by appropriate estimates. Abdi and Ranaldo (2017) propose two approaches. In the first approach (which we denote *Abdi monthly*) expectations are replaced by monthly averages to obtain a monthly spread estimator. If the resulting estimator of the squared spread is negative it is replaced by zero. In the second approach an estimator of the squared spread is obtained for consecutive two-day periods. Negative estimates are again replaced by zero. The square roots of these estimates are then averaged over the days of the month to obtain a monthly spread estimate. We refer to this version as *Abdi 2-day*. We include both versions of the Abdi and Ranaldo (2017) estimator in our empirical analysis.

The Volatility-over-Volume measure

As mentioned above, Tobek (2016) develops modified versions of several low frequency estimators. However, the main contribution of his paper is to show empirically that the bid-ask spread is closely related to a function of volume and volatility.[13] Specifically, Tobek finds that the ratio

$$VoV_i = 2.5\frac{\sigma_i^{0.6}}{V_i^{0.25}} \tag{1.11}$$

has very high cross-sectional correlation with the bid-ask spread. σ is estimated either by the sum of squared daily returns or by the Parkinson (1980) high-low volatility estimator, and V_i is the average of the daily trading volume. The factor 2.5 is simply a scaling factor that aligns the mean of the volatility-to-volume ratio with the average spread in the US during Tobek's sample period 1926-2015. We include the Tobek estimator in our horse race and denote it VoV (for "volatility over volume").[14] We follow the recommendation by Tobek (2016) and estimate the standard deviation using the high-low variance estimator proposed by Parkinson (1980). However, since there may be occasions where data on high and low prices is unavailable we also include the version of the estimator that uses the sum of squared daily returns to estimate sigma. The two estimators are denoted *VoV High-Low* and *VoV Sigma*, respectively.

[13] Kyle and Obizhaeva (2014) develop, on theoretical grounds, a liquidity measure which is closely related to this measure. It is defined as the dollar trading volume to the power of $\frac{1}{3}$ divided by the standard deviation of returns to the power of $\frac{2}{3}$.

[14] A new version of this paper exists as Fong et al. (2017). However, as Fong et al. (2017) do not include the modified versions of other low frequency estimators, we use the older variant of the VoV estimator as defined in Tobek (2016).

1.2.3 Low-Frequency Estimators of the Price Impact

The Amihud illiquidity ratio

In a liquid market the price change in response to a given trading volume will be small; in an illiquid market it will be large. This intuition suggests relating price changes to trading activity. The first measure we are aware of that builds on this intuition is the Amivest ratio.[15] It is defined as the sum of daily volume divided by the sum of absolute daily returns.

$$Amivest_{it} = \frac{\sum V_{i,t}}{\sum |r_{it}|}, \tag{1.12}$$

Amihud (2002) has proposed the illiquidity ratio

$$Illiq_i = \frac{1}{D_i} \sum_{t=1}^{D_i} \frac{|r_{it}|}{V_{it}}, \tag{1.13}$$

$r_{i,t}$ and $V_{i,t}$ are the return and the dollar trading volume of stock i on day t, respectively, and D_i is the number of days in the evaluation period (often a month or a year). Only days with non-zero volume are included. The illiquidity ratio has several advantages. It has low data requirements, it is easy to calculate, and it has a theoretical foundation based on Kyle (1985). Therefore it has become very popular and is widely used. However, the measure also has its drawbacks.[16] Most importantly, it is unable to differentiate between price changes that are related to new information and those that are not. Every event that causes a large price change (such as a merger announcement) is taken as evidence of illiquidity.

The Amihud illiquidity ratio measures by how much one dollar of trading volume moves the price of an asset. An alternative question is 'how much volume does it take to move the price of an asset by one dollar?'. This is the question the LIX measure, proposed by Danyliv et al. (2014), tries to answer. The measure is defined as

$$LIX_{it} = log_{10} \left(\frac{V_{i,t} P_{close}}{H_{i,t} - L_{i,t}} \right) \tag{1.14}$$

The authors propose the log specification in order to restrict the range of values their measure can assume. They argue that a log with the base 10 would result in values between 5 and 10.

We include in our empirical analysis all three measures, the Amivest ratio (denoted *Amivest*), the Amihud (2002) illiquidity ratio (*Amihud*) and the LIX measure (*LIX*). Note that the Amivest ratio and the LIX measure are measures of liquidity because larger numerical values indicate higher levels of liquidity. We therefore multiply both measures by (-1) before including them in our horse race.

[15] The Amivest ratio has been applied in academic research by Cooper et al. (1985).

[16] Grossman and Miller (1988) discuss the suitability of the Amivest ratio. Their arguments also apply to the illiquidity ratio. Acharya and Pedersen (2005a) contend that the illiquidity ratio is not stationary. Its unit of measurement is percent return per dollar of trading volume. Thus, the measure ignores inflation. This is an important issue in asset pricing studies which typically cover very long sample periods. Acharya and Pedersen (2005a, p. 386) propose to solve this problem by scaling the illiquidity ratio. Brennan et al. (2013) analyze the asset pricing implications of the illiquidity ratio in detail. They find that it is reliably priced, but that the pricing is caused by those components of the illiquidity ratio that are related to negative return days.

Tobek (2016) also proposed a modified version of the Amihud (2002) illiquidity ratio based on the volatility-to-volume ratio. The daily version is defined as

$$VoV_{daily} = \frac{log\left[\frac{H_t}{L_t}\right]^{0.6}}{V_{i,t}^{0.25}} \tag{1.15}$$

Monthly and yearly estimates are obtained by averaging over the daily values. We include the modified illiquidity ratio in our horse race and denote it *VoV daily*.

The Pastor/Stambaugh measure

Pástor and Stambaugh (2003) propose to run the following regression

$$\left(r_{i,(t+1)} - r_{m,(t+1)}\right) = \alpha_i + \phi_i r_{i,t} + \gamma_i * \left(sign\left(r_{i,t} - r_{m,t}\right) * V_{i,t}\right) + \epsilon_{i,t}, \tag{1.16}$$

where $r_{i,t}$ is the return of stock i on day t, $r_{m,t}$ is the return on a stock index on day t and $V_{i,t}$ is the dollar trading volume of stock i on day t. The coefficient γ_i measures the sensitivity of a stock's excess return over the index with respect to lagged signed volume.

The intuition is as follows: Volume moves prices. However, some of the price change is transitory and will be reversed on the next trading day.[17] The coefficient γ_i measures this reversal and is thus expected to be negative. The less liquid a stock, the higher the temporary price change and the reversal should be. Thus, less liquid stocks should have higher absolute (i.e. more negative) γ_i. We multiply γ_i by (-1) in order to obtain larger values for less liquid stocks.

Estimation of γ_i requires a market proxy $r_{m,t}$. We use the CRSP value weighted index, the CRSP equally weighted index and the S&P500. The results are very similar. We therefore only report the results for the CRSP value weighted index. The resulting estimator is denoted *Gamma*.

1.2.4 Summary of Estimators

Table 1.1 lists all estimators that we include in our empirical analysis and the data that is necessary to apply them. While some of the estimators only require data on closing prices or daily returns, others also require volume data or a time series of daily high and low prices. Three estimators (the two versions of LOT and the Pástor and Stambaugh (2003) γ) require a time series of market returns. Consequently, there may be situations in which only a subset of the low-frequency estimators can be applied because of unavailability of data. The results of our empirical analysis may inform researchers about which of the feasible estimators (i.e. those for which the required data is available) is expected to perform best in a specific application.

[17] Pástor and Stambaugh (2003) implicitly assume that aggregate order flow has a transitory price impact which shows up in daily returns and is reversed on the next day. In contrast, other price impact measures (e.g. the 5-minute price impact introduced earlier or the trade indicator models proposed by Glosten and Harris (1988), Huang and Stoll (1997) and Madhavan et al. (1997)) implicitly assume that the transitory price impact is very short-lived.

Table 1.1: Overview of Spread Measures and Variable requirements
This table provides an overview over the different Spread Measures analyzed in this chapter and required input variables. Columns are set equal to 1 if the respective input variable is needed to calculate the estimator. We document all our results for estimators in **bold**. Results for all other estimators are available upon request.

Estimator	**Required Input**					
	Close	**Return**	**Volume**	**High/Low**	**Bid/Ask**	**Market Return**
Roll	1					
Roll 0	1					
Roll Inverted	1					
Roll (ret)		1				
Roll 0 (ret)		1				
Roll Inverted (ret)		1				
LOT		1				1
LOT y-split		1				1
Zero		1				
Zero 2		1	1			
Corwin				1		
Corwin 0				1		
Corwin numeric				1		
Corwin numeric 0				1		
Effective Tick	1		1			
Effective Tick 2	1		1			
Amihud		1	1			
Amivest		1	1			
Closing Spread					1	
Gibbs	1					
LIX	1		1	1		
FHT		1				
Gamma		1	1			1
Holden	1		1			
Abdi Monthly	1			1		
Abdi 2-day	1			1		
Tobek Corwin				1		
Tobek Corwin 0				1		
Tobek FHT			1	1		
VoV High-Low			1			
VoV Sigma		1	1			
VoV daily			1	1		

1.3 Data

In order to calculate the different estimators daily information on the entire US equity market is collected from CRSP. Due to differing data requirements, the number of stock-month observations might differ across estimators.[18] Most estimators are easy to compute, however, some estimators (e.g. the LOT and the Gibbs estimators) are computation-intensive.

To assess the quality of the different estimators, we use (as described in section 2) effective spreads and price impacts calculated from the TAQ data base as benchmark measures. We

[18] As an untabulated robustness check we repeat our entire analysis on a subsample for which all estimators are available in each month. The results are qualitatively similar to those presented in this chapter.

obtained daily averages of these variables from the Market Microstructure Database maintained by the Vanderbilt University.[19] These daily averages are later aggregated to stock-month and stock-year averages in order to compare them to the Low-frequency estimators which we also calculate at the stock-month and stock-year level.

1.3.1 Sample Selection

We include all (common) stocks (sharecode 10 and 11) that were listed on one of the three exchanges Nyse, Amex, Nasdaq during the period from January 1^{st} 1993 until December 31^{st} 2012. We then eliminate months with stock splits, exchange, ticker or cusip changes and months with special trading or security status. We thus end up with a sample of about 27 million firm-day observations. This includes both firms that were delisted as well as firms that were newly listed during our sample period. In contrast to previous literature, we use the whole universe of stocks listed on one of the three exchanges and not just a random subsample.

Table 1.2: Filtering Procedure
This table shows the filtering procedure applied to our dataset. "Common stock" refers to CRSP share codes 10 and 11. Stock splits are identified by changes in the "cfacpr"-item. "Unusual status" refers to unexpected trading or security status of a stock; we call a trading status unusual if it is "halted", "suspended" or "unknown"; we call a security status unusual if it is "When Issued", "Ex-Distributed" or "Bankruptcy".
Rows NYSE, AMEX, NASDAQ show the distribution across the different exchanges after the last filtering step applied to the CRSP daily stock sample.
The last three lines show the sample after it is aggregated to the stock-month level, i.e. after low-frequency estimators have been calculated. They are merged to the monthy average spreads derived from the TAQ data. Finally, the "12 days/month"-filter assures that every estimator is estimated from at least 12 days of non-missing observations.

	Observations	**Firms**
CRSP Raw Data	38,198,992	19,449
Common Stock	28,324,608	14,157
Exchange NYSE, AMEX, or NASDAQ	27,873,362	14,157
Eliminate months with stock splits	27,545,856	14,127
Eliminate months with listing changes	27,515,228	14,127
Eliminate months with ticker changes	27,442,650	14,127
Eliminate months with cusip changes	27,348,380	14,126
Eliminate months with unusual status	27,338,272	14,126
NYSE	8,646,671	3,400
AMEX	3,501,152	1,707
NASDAQ	19,356,468	10,410
After estimator calculation (from daily to monthly frequency)	1,307,133	14,122
After joining with liquidity data	1,083,680	13,599
12 days/month filter applied	1,079,509	13,578

[19] We thank the Vanderbilt University for providing the data. The daily averages for NYSE [Amex] stocks are based on NYSE [Amex] quotes only. Daily averages for Nasdaq stocks are based on the NBBO. We checked the quality of the data by directly calculating effective spreads from TAQ data for one year. The daily average spreads were identical for 99% of the sample.

Based on this sample we calculate the different estimators for each firm-month and each firm-year. We implement both versions because in some applications (e.g. in asset pricing) researchers typically use monthly data while in other application yearly data is preferred.

Table 1.2 shows that we end up with about 1.3 million firm-month observations after calculating all estimators. We match this data set with the intraday data (aggregated to the monthly/yearly level) based on 8-digit CUSIPs. The matched data set contains 1,083,680 observations. In some cases the stock-month liquidity estimates are based on a small number of daily observations. To reduce estimation error we therefore include only stock-month observations that are based on at least 12 daily observations. The final data set contains 1,079,509 stock-month observations.

Table 1.3 shows the number of firms in our sample, both in total and in each year of the sample period. The number of stocks peaks in the late 1990s while it reaches its minimum towards the end of our sample period after the financial crisis. Market shares of the three different exchanges in terms of listed firms are actually very stable over time. 60% and 30% of all firms are listed on NASDAQ and NYSE, respectively.

Table 1.3: Sample Overview
This table shows the number of distinct firms per year and exchange in our sample. Firms are identified by CRSP permno. The last line shows the total number of distinct firms in our sample.

Year	NYSE	AMEX	NASDAQ
1993	2041	731	3979
1994	2102	744	4387
1995	2152	758	4701
1996	2233	789	5259
1997	2255	801	5338
1998	2198	795	5098
1999	2102	735	4955
2000	1948	730	4957
2001	1759	555	3859
2002	1650	515	3381
2003	1605	517	3302
2004	1627	546	3446
2005	1636	571	3317
2006	1615	583	3289
2007	1604	613	3226
2008	1497	537	2828
2009	1400	435	2422
2010	1443	428	2530
2011	1425	404	2455
2012	1393	331	2296
Total	**3364**	**1617**	**10038**

1.3.2 Summary Statistics

Table 1.4 provides descriptive statistics for our sample. We only include observations for which our benchmark measure, the effective spread, is available. The market capitalization, averaged over more than 1 million stock-month observations, is \$ 1,840 million. The median value is only \$ 248 million, implying that the size distribution is heavily skewed. The same applies to the distributions of the daily turnover ratio (defined as the ratio of dollar trading volume and market capitalization) and the number of trades. The average percentage quoted and effective spreads amount to 1.88% and 1.47%, respectively. The average CRSP closing spread is larger, at 2.16%.

Table 1.4: Descriptive Statistics
The table provides monthly Mean (equally-weighted and value-weighted), Median, Standard Deviation, 5% and 95% percentile of several variables for our sample of US stocks. The unit of measurement is usually provided in brackets.
The first 3 lines provide statistics for variables derived from the CRSP daily file:*Market Value* is the respective firm's market value at the end of each month in mio \$. *Daily Turnover* is measured as the daily dollar-volume traded divided by the firm's market capitalization.
Lines 4-9 are based on the TAQ dataset and starting from line 10 the different low-frequency spread estimators are depicted. For a derivation of those estimators see Section 1.2.

	N	**Mean**	**Median**	**Sd**	**5%**	**95%**
Market Value (in mio)	1083665	1839.685	248.136	5269.770	18.043	8969.699
Daily Return (in %)	1083276	0.081	0.057	0.697	-1.003	1.217
Daily Turnover (in %)	1083681	0.660	0.380	0.811	0.036	2.283
Daily Trades	1083684	1396.319	84.727	4162.555	3.267	7238.143
Relative Effective Spread (in %)	1083684	1.471	0.798	1.753	0.069	5.092
Dollar Effective Spread	1083684	0.178	0.118	0.200	0.017	0.557
Relative Quoted Spread (in %)	1083684	1.875	1.000	2.278	0.068	6.644
Dollar Quoted Spread	1083684	0.230	0.156	0.265	0.017	0.729
5min Price Impact (in %)	820695	0.002	0.001	0.004	0.000	0.008
Closing Spread CRSP (in %)	1078424	2.164	1.236	2.766	0.059	7.332
Roll 0 (in cents)	1070594	29.610	16.811	41.103	0.000	109.849
Roll 0 (ret) (in %)	1082508	6.509	5.232	4.828	1.588	15.693
Gibbs (in cents)	1082909	35.497	27.856	26.329	9.400	89.620
Zero (in %)	1083276	10.554	5.000	12.736	0.000	36.842
LOT (in %)	1083150	3.226	2.372	3.594	0.000	9.442
LOT y-split (in %)	1083111	1.549	0.805	2.390	0.000	5.376
FHT (in %)	1082823	0.823	0.351	1.263	0.000	3.271
Tobek FHT (in %)	1081005	1.707	0.997	2.250	0.350	5.796
Effective Tick (in %)	1083632	0.913	0.441	1.286	0.031	3.241
Corwin 0 (in %)	1058265	1.200	0.909	1.041	0.210	3.151
Tobek Corwin 0 (in %)	1058265	0.971	0.706	0.935	0.109	2.696
Abdi 2-day (in %)	1083573	1.701	1.254	1.500	0.384	4.489
Abdi monthly (in %)	1083573	1.607	1.048	1.984	0.000	5.383
VoV High-Low (in %)	1081005	2.042	1.692	1.409	0.560	4.732
VoV daily (in %)	1081005	2.533	2.192	1.558	0.725	5.509
VoV Sigma (in %)	1082858	2.154	1.763	1.523	0.577	5.106
Amihud (in 10^6)	1083252	8.334	0.407	25.550	0.007	44.203
(-) Amivest (in mio)	1083175	71.917	6.107	210.563	0.085	372.739
(-) LIX	1081005	6.258	6.205	0.930	4.861	7.887
(-) Gamma 1 (in 10^9)	1082881	-42.978	0.042	1547.062	-1131.191	1177.963

The summary statistics shown in Table 1.4 mask the significant changes that occurred during the sample period. Figure 1.2 reveals that the daily dollar trading volume increased almost tenfold between 1993 and 2013 while the effective spread decreased from slightly below 2% to approximately 0.5% (with a temporary increase during the financial crisis).

Figure 1.2: Dollar-Volume / Effective Spreads over Time
This table shows the equal-weighted average daily dollar-volume (in millions) (solid line) and effective spread per stock (dashed line) in our sample. Both variables are winsorized at the 1% level.

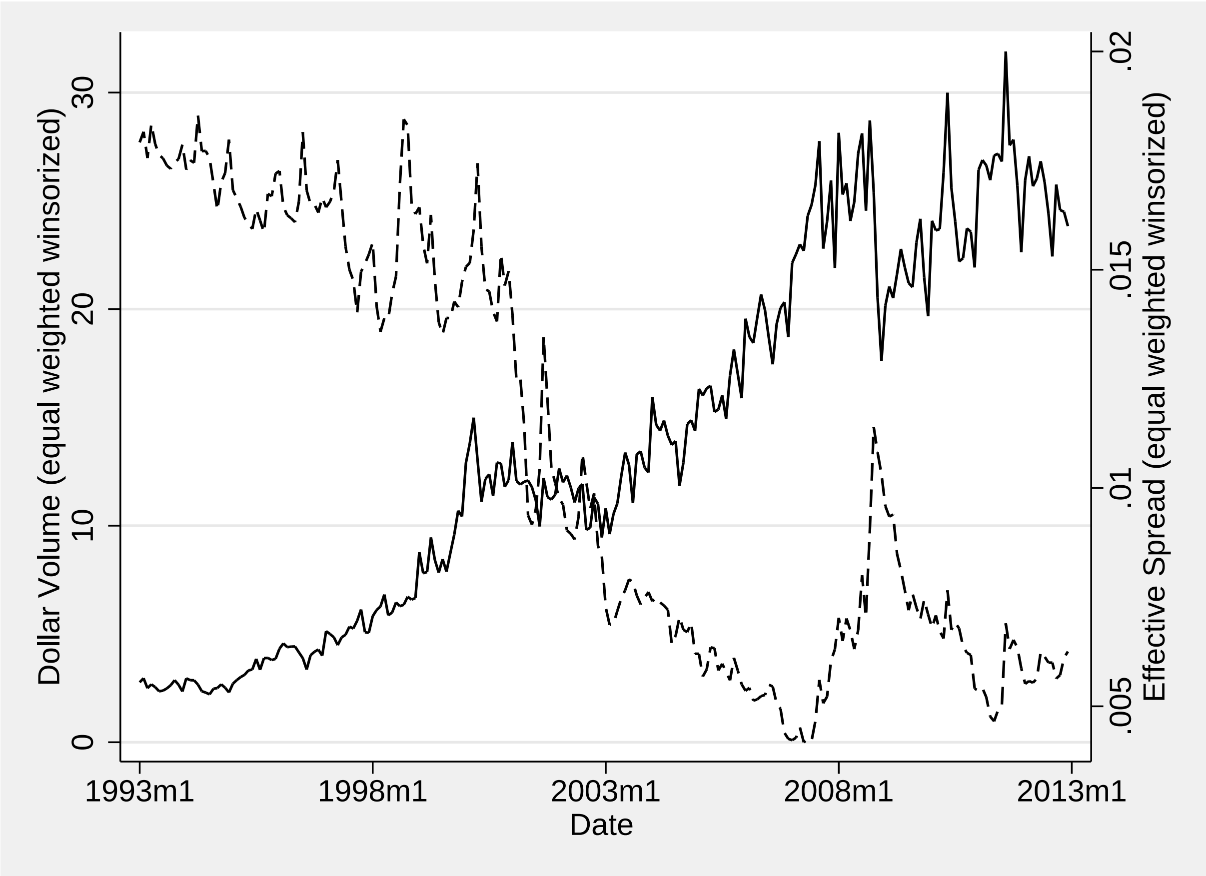
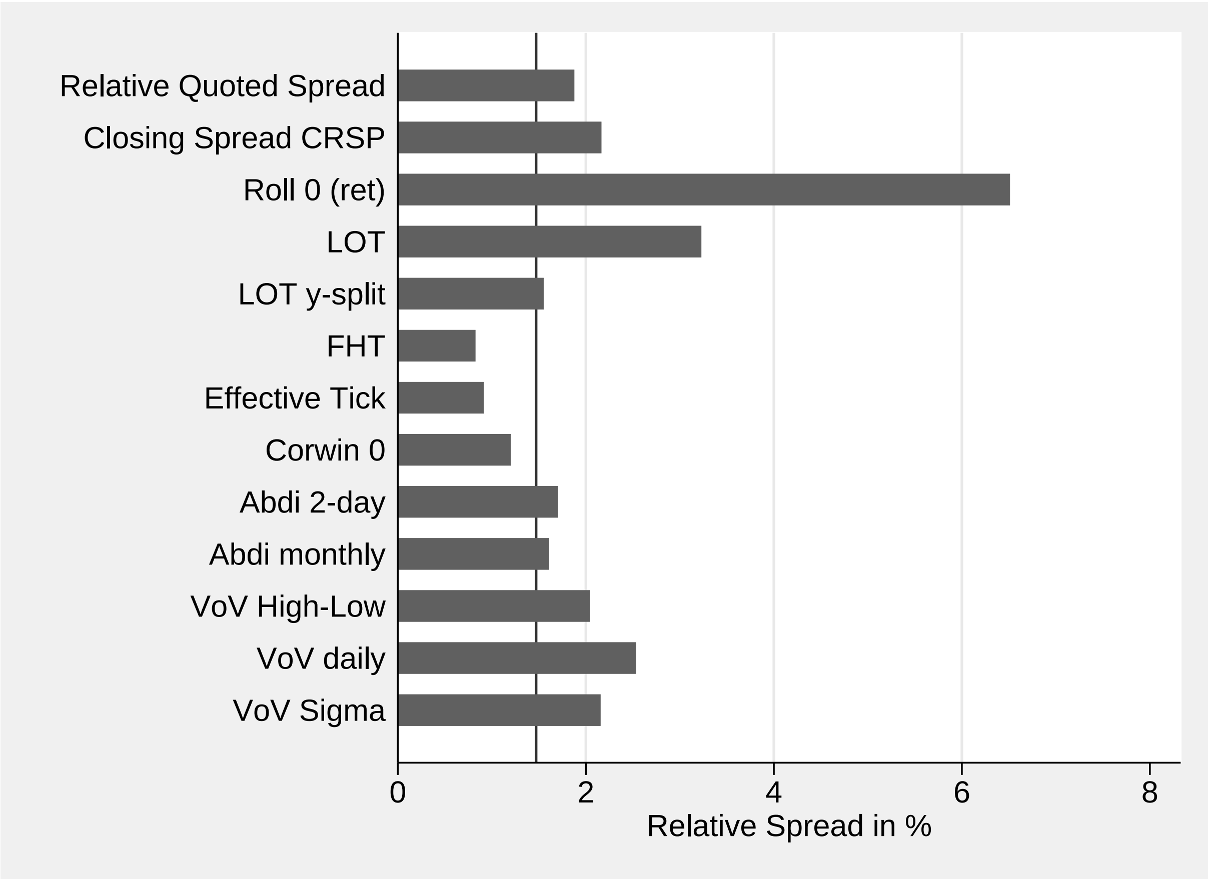


Table 1.4 also shows summary statistics for all the spread estimators that we include in our analysis. When comparing the mean values to the average quoted and effective spreads it should be kept in mind that not all estimators attempt to estimate the spread level. This holds for the Amivest ratio, the Amihud illiquidity ratio and the LIX measure, for the percentage of zero returns, and for the Pástor and Stambaugh (2003) gamma. The LOT and FHT measures estimate the total transaction costs and should therefore be larger than the effective spread. The Roll 0 estimator and the Hasbrouck (2009) Gibbs sampler estimate the dollar spread while the remaining estimators estimate the percentage spread. Figure 1.3 visualizes the mean values. Only the LOT y-split estimator yields a mean value that is within 10% of the mean effective spread. An additional two low-frequency estimators (Abdi 2-day and Corwin 0) yield a mean within a 20% range around the mean effective spread. Of course a mean value close to the benchmark value does not guarantee that a low-frequency estimator is an accurate liquidity

proxy. In the main analysis of this chapter we will therefore analyze the cross-sectional and time series correlation between the proxies and the benchmark, and we will evaluate the mean absolute errors and the root mean squared errors of the low-frequency estimators.

Figure 1.3: Mean Spread Levels with non-missing spreads
This figure shows the equal-weighted mean relative spread level across those estimators that actually aim to predict the relative spread level. In addition to the estimators, the actual effective spread calculated from TAQ data is depicted as a vertical line in the graph.



1.3.3 Methodology

Our main analysis proceeds as follows: As described above, we first calculate the benchmark measures and all low-frequency estimators (including the CRSP closing spread) for each stock and each month. Based on this data we then estimate correlations between each of our low-frequency estimators and (a) the percentage effective spread and (b) the 5-minute price impact. We repeat the procedure using stock-year observations instead of stock-month observations.

The correlations are estimated in three different ways. First, we calculate cross-sectional correlations (both in levels and in first differences) for each month of the sample period, resulting in a time-series of 240 (239 for the first-differenced data) monthly correlations. Second, we calculate time-series correlations at the portfolio level. To this end, we first calculate the (equally-weighted and value-weighted) average liquidity for all sample stocks in a given months. This procedure is implemented both for the benchmark measures and the low-frequency estimators. We thus obtain one time series of portfolio-level liquidity for each measure. Based on these time series we then calculate time-series correlations in levels and first differences. We refer to this procedure as "time-series portfolio". Third, we calculate time-series correlations between the benchmark measures and the low-frequency estimators at the individual stock level, again both in levels and in first differences. We then calculate (equally-weighted, value-weighted and observation-weighted[20]) cross-sectional averages of these time-series correlations. We refer to this procedure as "time-series stock-by-stock". Finally we calculate mean absolute errors (MAE) and root mean squared errors (RMSE) for those low-frequency estimators that attempt to estimate the percentage effective spread.

To put our approach into perspective, Table 1.5 lists which previous papers have used what methodology to evaluate which low-frequency spread estimators. The table reveals that our work is the most comprehensive study so far. Ours is the only analysis besides Goyenko et al. (2009) that uses both monthly and yearly liquidity estimates as the basic unit of investigation. It further is the only work that implements both a stock-by-stock and a portfolio approach to evaluate the time-series correlation, and it is the only one that implements several weighting schemes for the correlation analysis (equal-/value- and observation-weighting).

[20] Observation-weighting puts more weight on a correlation coefficient that is based on more monthly/yearly observations.

Table 1.5: Overview of Existing Papers and Applied Procedures

This table provides an overview over the samples, procedures and estimators used by the different papers that aim to compare different liquidity proxies.
Crosssection, Pooled, Timeseries, RMSE equal one if the respective analysis is conducted in the paper. *TS: e-/v-/o-weighted* equals "e"/"v"/"o" if assets were equally-/value-/observation-weighted in the timeseries analysis of the respective paper. *TS: stock/portfolio* equals "s"/"p" if the timeseries analysis was done on a stock-by-stock/portfolio basis.
Measures equal 1 if they are analyzed in the respective paper. Asterix indicate that the regarded estimator was newly developed in the respective paper.

	Paper	Roll	Lesmond	Amivest	Amihud	Pástor/Stambaugh	Hasbrouck	Holden	Goyenko et al.	Corwin/Schultz	Fong et al.	Chung/Zhang	Danyliv et al.	Abdi/Ranaldo	Tobek	This paper
	Year	1984	1999	2002	2002	2003	2009	2009	2009	2011	2011	2014	2014	2016	2016	2016
Sample	**Market**	US	US (NYSE/AMEX)		US (NYSE)	US (NYSE/AMEX)	US	US	US	US	International	US		US	US	US
	Period	1963 - 1982	1963 - 1990		1963 - 1997	1963 - 1999	1993 - 2005	1993 - 2005	1993 - 2005	1993 - 2006	1996 - 2007	1993 - 2009		2003 - 2014	1993 - 2015	1993 - 2012
	Frequency	Yearly	Yearly		Monthly	Monthly	Yearly	Monthly	Monthly / Yearly	Monthly	Monthy	Monthly / Yearly		Monthly	Monthly	Monthly / Yearly
Analyses	**Crosssection**	1	0		1	0	0	1	1	1	1	1		1	1	1
	Pooled	0	0		0	0	1	0	0	0	0	0		0	0	0
	Timeseries	0	0		0	0	0	1	1	1	1	1		1	0	1
	TS: e-/v-/o-weighted							e	e	e	e	e		e		e/v/o
	TS: stock/portfolio							p	p	s	p	p		s		s/p
	RMSE	0	0		0	0	0	1	1	0	1			1	1	1
Measures	**Roll**	**1***	1	0	0	0	1	1	1	1	1	1	0	1	1	1
	Zero	0	**1***	0	0	0	1	1	1	0	1	1	0	0	1	1
	LOT	0	**1***	0	0	0	0	1	1	1	1	1	0	0	1	1
	Amivest	0	0	**1***	0	0	0	0	1	0	1	0	0	0	0	1
	Amihud	0	0	0	**1***	0	1	0	1	0	1	1	0	0	1	1
	Gamma	0	0	0	0	**1***	0	1	1	0	1	1	0	0	0	1
	Effective Tick	0	0	0	0	0	0	**1***	1	1	1	1	0	1	1	1
	Gibbs	0	0	0	0	0	**1***	1	1	0	0	1	0	1	1	1
	LOT y-split	0	0	0	0	0	0	**1***	**1***	0	1	0	0	0	0	1
	Corwin	0	0	0	0	0	0	0	0	**1***	0	0	0	1	1	1
	FHT	0	0	0	0	0	0	0	0	0	**1***	0	0	1	1	1
	Closing Spread	0	0	0	0	0	0	0	0	0	0	**1***	0	0	1	1
	LIX	0	0	0	0	0	0	0	0	0	0	0	**1***	0	0	1
	Abdi	0	0	0	0	0	0	0	0	0	0	0	0	**1***	0	1
	VoV	0	0	0	0	0	0	0	0	0	0	0	0	0	**1***	1

1.4 Empirical Findings

1.4.1 Cross-Sectional Analysis

Table 1.6 shows the results for the cross-sectional correlations in levels. It reports the average number of stocks included in the monthly cross-sections, the time-series average of the monthly cross-sectional correlations (including the result of a t-test of the time-series average against zero), the percentage of months with a positive cross-sectional correlation and the percentage of month with a cross-sectional correlation that is significantly larger than zero at the 5% level. This information is provided for both benchmark measures, the percentage effective spread and the price impact.

Table 1.6: Monthly Cross-Sectional Correlations (Level)
Relative Effective Spreads are equally-weighted averages calculated from every trade of the TAQ dataset. Each **month** the cross-sectional correlation of those with the respective spread proxies is calculated.
N gives the average number of firms included in each monthly correlation. *Correlation* gives the mean cross-sectional correlation in percent and its significance (t-statistic after Fama and MacBeth (1973); *** 1%, ** 5% and * 10%) is indicated. *% ≥ 0* gives the percentage of monthly correlations that where larger or equal to 0 and *% ≥ 0 (5%)* gives the percentage of monthly correlations that where significantly greater than zero at 5% significance level. We repeat the analysis, but now correlate estimators to a 5-minute price impact measure. *N (PI)* and *Correlation (PI)* are calculated analogous to *N* and *Correlation*.

Measure	N	Correlation	> 0	> 0 (5%)	N (PI)	Correlation (PI)	> 0 (PI)	> 0 (5%) (PI)
Closing Spread CRSP	4493	87.42***	100.00	100.00	4550	36.25***	100.00	100.00
Roll 0	4461	1.30**	47.92	39.17	4521	-7.63	12.78	4.44
Roll 0 (ret)	4510	43.54***	99.58	99.58	4573	21.92***	100.00	100.00
Gibbs	4512	0.25	44.17	37.92	4574	-12.27	6.67	0.56
Zero	4514	39.52***	100.00	100.00	4576	16.29***	96.11	91.11
LOT	4513	46.97***	100.00	100.00	4575	22.33***	100.00	100.00
LOT y-split	4513	37.03***	100.00	100.00	4575	14.80***	99.44	98.33
FHT	4512	55.54***	100.00	100.00	4574	24.43***	100.00	100.00
Tobek FHT	4504	73.52***	100.00	100.00	4568	30.04***	100.00	99.44
Effective Tick	4515	57.91***	100.00	100.00	4577	29.01***	100.00	100.00
Corwin 0	4409	38.67***	99.58	99.17	4473	20.88***	100.00	98.89
Tobek Corwin 0	4409	33.11***	97.08	94.58	4473	17.11***	99.44	98.89
Abdi 2-day	4515	70.51***	100.00	100.00	4577	32.89***	100.00	100.00
Abdi monthly	4515	66.57***	100.00	100.00	4577	28.33***	100.00	100.00
VoV High-Low	4504	87.61***	100.00	100.00	4568	38.24***	100.00	100.00
VoV daily	4504	86.94***	100.00	100.00	4568	40.32***	100.00	100.00
VoV Sigma	4512	86.39***	100.00	100.00	4574	35.74***	100.00	100.00
Amihud	4514	64.79***	100.00	100.00	4576	20.78***	100.00	96.67
(-) Amivest	4513	25.25***	100.00	100.00	4575	13.20***	98.89	89.44
(-) LIX	4504	72.14***	100.00	100.00	4568	32.41***	100.00	99.44
(-) Gamma	4512	8.50***	95.00	87.92	4574	1.46***	62.78	29.44

We first consider the effective spread as benchmark measure. There are huge differences in the performance of the various low-frequency estimators. The four best estimators exhibit average cross-sectional correlations above 86%. The highest correlation (87.6%) is achieved by the version of the Tobek (2016) estimator that relies on daily high and low prices to estimate volatility (denoted VoV High-Low), closely followed by the CRSP closing spread (87.4%) and the two other versions of the Tobek (2016) estimator, the VoV daily estimator(86.9%) and the version that uses squared daily returns to estimate volatility (VoV sigma, 86.4%). All other estimators achieve markedly lower correlations. The Tobek (2016) version of the FHT estimator, the Abdi monthly and Abdi 2-day estimator, the LIX estimator and the Amihud (2002) illiquidity ratio are the "best of the rest", with average cross-sectional correlations ranging from 73.5%

to 64.8%. At the other end of the spectrum, three estimators (the Roll (1984) estimator based on price changes, the Hasbrouck (2009) Gibbs sampler and the Pástor and Stambaugh (2003) gamma) achieve average correlations below 10%. In addition, there are months in which the cross-sectional correlation between these estimators and the effective spread is actually negative.

Figure 1.4: Crosssectional Correlation
This figure shows the development of the 12 months rolling average of monthly crosssectional correlations over time.

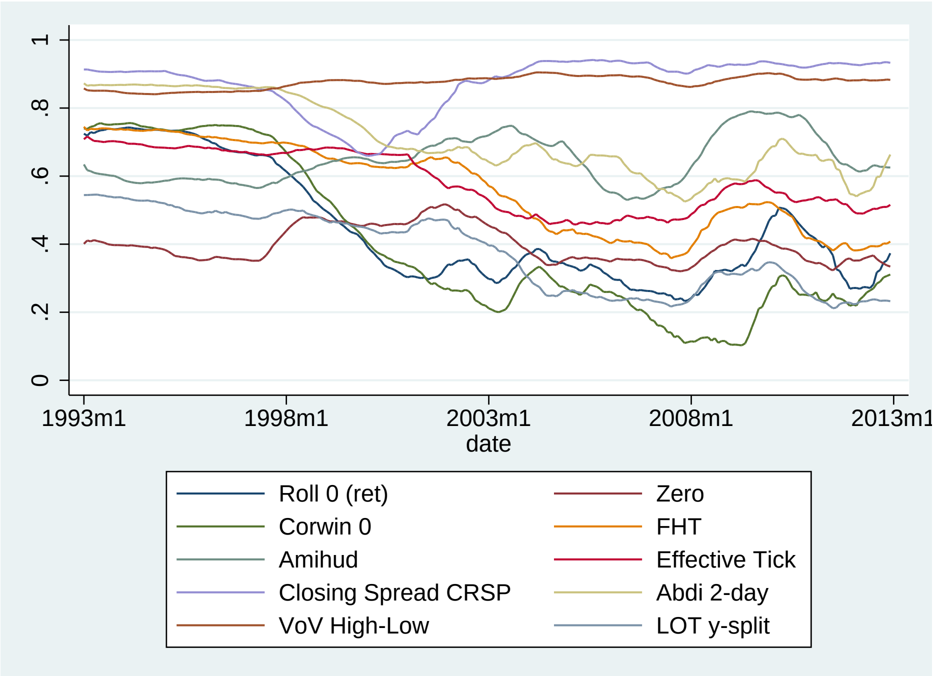


Figure 1.4 plots the cross-sectional correlation between ten of the low-frequency estimators and the effective spread for each month of the sample period. The VoV High-Low measure appears to be the most consistent estimator. It achieves correlations above 80% in every single month. The CRSP closing spread achieves higher correlation than the VoV High-Low measure in the beginning of the sample period (until 1997) and from 2003 onwards. Between 1998 and 2002 the performance of the CRSP closing spread deteriorates. The performance of some of the other low-frequency measures declines over time. This is particularly true for the Roll measure, the Abdi 2-day estimator and for the Corwin and Schultz high-low estimator. A potential explanation for this finding is that effective spreads have generally decreased over time[21] (partly because of decimalization), and that these estimators may perform worse in a low-spread environment. We return to this issue in section 1.4.5. In this context it is also interesting to note that the performance of some estimators appears to improve during the financial crisis. This is particularly true for the Amihud illiquidity ratio which achieves its best performance between November 2008 and January 2011.

The cross-sectional correlations based on first differences are much lower than those based on levels. However, as is documented in Table 1.7, the same four measures as before perform

[21] see Figure 1.2.

best, with the CRSP closing spread being the top performer (correlation 58.3%) followed by the three versions of Tobek's measure (correlations between 46.8% and 41.4%).

Columns 6-9 in Table 1.6 reveal that the cross-sectional correlations between the low frequency estimators and the price impact are much lower than those with the effective spread. This even holds for those estimators that are constructed as measures of price impact (the Amihud illiquidity ratio and the Pastor and Stambaugh gamma). The four best performing measures are again the CRSP closing spread and the three version of Tobek's measure, with the VoV daily measure being the top performer (average correlation 40.3%).

None of the low-frequency estimators performs well when first differences are benchmarked against the price impact. Even the best performing proxy, the Tobek daily measure, has an average cross-sectional correlation below 10%.

To summarize, there are remarkable differences in the performance of the low-frequency liquidity estimators. The best proxies capture the cross-sectional pattern of the effective spread levels very well (with average correlations above 86%), while the worst-performing proxies achieve values below 10%. The proxies do much worse when benchmarked against the price impact rather than the effective spread. Further, we find that the low-frequency liquidity estimators are much better at tracking levels than at tracking first differences. The best performing measures are the three version of Tobek's measure and the CRSP closing spread.

Table 1.7: Monthly Cross-Sectional Correlations (First Differences)
Relative Effective Spreads are equally-weighted averages calculated from every trade of the TAQ dataset. Each **month** the cross-sectional correlation of the first difference of those spreads with the first difference of the respective spread proxies is calculated.
N gives the average number of firms included in each monthly correlation. *Correlation* gives the mean cross-sectional correlation in percent and its significance (t-statistic after Fama and MacBeth (1973); *** 1%, ** 5% and * 10%). *% ≥ 0* gives the percentage of monthly correlations that where larger or equal to 0 and *% ≥ 0 (5%)* gives the percentage of monthly correlations that where significantly greater than zero at 5% significance level. *insignificantly different from* gives a list of those estimators that can not be significantly (t-test with 5%) distinguished from the regarded estimator in terms of their correlation with effective spreads. We repeat the analysis, but now correlate estimators to a 5-minute price impact measure. *N (PI)* and *Correlation (PI)* are calculated analogous to *N* and *Correlation*.

Measure	N	Correlation	> 0	> 0 (5%)	N (PI)	Correlation (PI)	> 0 (PI)	> 0 (5%) (PI)
Closing Spread CRSP	4319	58.34***	100.00	100.00	4388	6.65***	87.71	68.16
Roll 0	4276	6.00***	95.82	84.94	4344	0.19	50.84	5.59
Roll 0 (ret)	4344	17.86***	99.58	99.58	4422	3.02***	87.15	44.13
Gibbs	4344	9.89***	99.16	96.23	4420	0.39**	56.42	10.61
Zero	4348	-5.48	6.28	0.84	4424	-1.45	33.52	3.91
LOT	4347	8.91***	93.31	83.68	4424	1.65***	69.83	27.37
LOT y-split	4346	1.46***	59.83	46.03	4423	0.51**	59.22	16.20
FHT	4346	9.92***	91.63	81.17	4423	1.11***	62.01	26.82
Tobek FHT	4333	30.37***	100.00	100.00	4411	5.80***	87.71	66.48
Effective Tick	4349	4.97***	73.64	62.76	4425	0.18	49.72	23.46
Corwin 0	4209	21.67***	100.00	100.00	4278	3.64***	82.68	48.04
Tobek Corwin 0	4209	18.17***	100.00	97.49	4278	2.82***	74.86	40.78
Abdi 2-day	4349	31.19***	100.00	100.00	4426	4.84***	92.74	61.45
Abdi monthly	4349	22.64***	100.00	100.00	4426	3.17***	86.59	45.81
VoV High-Low	4333	42.70***	100.00	100.00	4411	8.41***	94.41	76.54
VoV daily	4333	46.77***	100.00	100.00	4411	9.87***	97.21	83.24
VoV Sigma	4346	41.35***	100.00	100.00	4423	7.08***	94.41	78.77
Amihud	4347	23.96***	100.00	99.58	4424	4.13***	82.12	53.07
(-) Amivest	4347	0.63***	74.90	0.84	4424	0.05	55.31	0.00
(-) LIX	4333	30.94***	100.00	100.00	4411	8.42***	97.21	85.47
(-) Gamma	4346	3.17***	76.99	51.05	4423	-0.12	47.49	17.88

1.4.2 Timeseries Analysis

Portfolio-Level Correlations

Table 1.8 shows the portfolio-level time series correlations. Two striking findings emerge immediately. First, the correlations are much higher than the cross-sectional correlations discussed in the previous section. Second, the results for some of the low-frequency proxies are extremely sensitive to the weighting scheme (i.e. equally-weighted versus value-weighted portfolios). This is particularly true for the Roll estimator, the two versions of the high-low estimator, the two versions of the Abdi and Ranaldo estimator and the Gamma estimator. These are precisely the measures that exhibit strongly decreasing cross-sectional correlation over time (see Figure 1.4). We have conjectured in the preceding section that these measures perform poorly in a low-spread environment. Because larger firms have lower spreads, these measures are likely to perform poorly when the liquidity of a value-weighted portfolio is considered.

When the effective spread is used as benchmark, the FHT estimator and the effective tick estimator perform very well both for equally-weighted and for value-weighted portfolios (correlations range from 97.7% to 98.7%). The CRSP closing spread, the zero estimator and the two versions of the LOT measure perform well for the equally-weighted portfolio but slightly less well for the value-weighted portfolio. The reverse is true for the LIX ratio.

The ranking of the measures changes considerably when we consider first differences instead of levels (see Table 1.9). Now the three versions of the Tobek measure perform best both for the equally-weighted and for the value-weighted portfolio. Correlations range from 75.2% to 87.8%. The CRSP closing spread performs reasonably well for the equally-weighted portfolio (correlation 78.9%) but does much less well for the value-weighted portfolio (37.4%).

The ranking of the low-frequency proxies changes yet again when we consider the price impact as benchmark measure. Now the return-based Roll measure performs best for the equally-weighted portfolio (correlation 80.5%) while the Abdi two-day measure comes out first for the value-weighted portfolio. As before, correlations drop when we consider first differences rather than levels. The Abdi two-day measure is still the best performing measure for the equally-weighted portfolio (59.0%). However, several other measures (most notably VoV daily, VoV sigma and the return-based version of the Roll measure, with correlations ranging from 40.3% to 38.8%) come out ahead for the value-weighted portfolio.

In summary, the results for the portfolio-based time-series approach are heterogeneous. The relative performance of the low-frequency proxies depends on the weighting scheme (equally versus value-weighted portfolio), on the benchmark measure (effective spread or price impact), and on whether levels or first differences are considered. None of the measures we analyze performs well under all conditions.

In our opinion the portfolio-level time-series correlation, even so it has been applied in several previous studies (see Table 1.5) is not a very good metric to assess the performance of the low-frequency liquidity estimators. The portfolio-level time-series correlation identifies low-frequency liquidity measures that capture the time-series variation of liquidity at the level of the entire market or at the level of a broadly diversified portfolio. However, in most applications we can think of, a researcher will either be interested in a measure that captures the cross-sectional

Table 1.8: Monthly Portfolio Time-Series Correlations (Level)
Relative Effective Spreads are equally-weighted averages calculated from every trade of the TAQ dataset. Each **month** the cross-section of firms is aggregated (equally- or market value-weighted) to one entity. The time-series correlation of the *aggregated* firm's effective spread with the respective spread proxies is calculated.
N gives the number of monthly observations, *Correlation* gives the correlation and significance for an equally-weighted cross-section, *Correlation (vw)* for a market value-weighted cross-section, respectively.
We repeat the analysis, but now correlate estimators to a 5-minute price impact measure (*PI*).

Measure	N	Correlation	Correlation (vw)	N (PI)	Correlation (PI)	Correlation (vw) (PI)
Closing Spread CRSP	240	98.39***	87.31***	180	45.75***	40.24***
Roll 0	240	32.76***	4.23	180	32.74***	49.00***
Roll 0 (ret)	240	59.99***	3.87	180	80.48***	73.64***
Gibbs	240	70.25***	30.92***	180	30.25***	49.10***
Zero	240	96.76***	93.01***	180	10.89	-11.96
LOT	240	97.21***	94.80***	180	42.92***	25.66***
LOT y-split	240	98.39***	92.17***	180	28.79***	-17.25
FHT	240	98.66***	98.19***	180	30.42***	5.78
Tobek FHT	240	86.59***	13.73**	180	69.28***	71.53***
Effective Tick	240	97.70***	98.77***	180	40.80***	14.38*
Corwin 0	240	85.73***	2.95	180	69.48***	74.08***
Tobek Corwin 0	240	88.34***	-0.00	180	65.88***	74.35***
Abdi 2-day	240	88.80***	12.57*	180	71.52***	75.09***
Abdi monthly	240	90.84***	17.11***	180	68.72***	65.02***
VoV High-Low	240	87.52***	83.93***	180	69.58***	50.28***
VoV daily	240	90.39***	85.25***	180	67.13***	50.70***
VoV Sigma	240	90.13***	85.13***	180	67.15***	49.44***
Amihud	240	83.35***	91.76***	180	63.16***	8.40
(-) Amivest	240	89.89***	95.48***	180	27.13***	15.73**
(-) LIX	240	94.32***	97.56***	180	41.92***	15.39**
(-) Gamma	240	82.70***	7.53	180	24.43***	-1.23

Table 1.9: Monthly Portfolio Time-Series Correlations (First Differences)
Relative Effective Spreads are equally-weighted averages calculated from every trade of the TAQ dataset. Each **month** the cross-section of firms is aggregated (equally- or market value-weighted) to one entity. The time-series correlation of the first-difference of *aggregated* firm's effective spread with the first-difference of the respective spread proxy is calculated.
N gives the number of monthly observations, *Correlation* gives the correlation and significance for an equally-weighted cross-section, *Correlation (vw)* for market value-weighted firms, respectively.
We repeat the analysis, but now correlate estimators to a 5-minute price impact measure (*PI*).

Measure	N	Correlation	Correlation (vw)	N (PI)	Correlation (PI)	Correlation (vw) (PI)
Closing Spread CRSP	239	78.85***	37.44***	179	55.62***	28.66***
Roll 0	239	21.93***	25.28***	179	3.20	11.72
Roll 0 (ret)	239	68.84***	61.17***	179	49.59***	38.77***
Gibbs	239	41.20***	45.01***	179	7.34	11.41
Zero	239	-27.97	-22.11	179	2.98	-2.94
LOT	239	27.24***	19.94***	179	33.37***	12.39*
LOT y-split	239	41.76***	-12.69	179	51.14***	3.10
FHT	239	56.09***	48.41***	179	46.85***	18.35**
Tobek FHT	239	78.95***	75.09***	179	49.90***	38.35***
Effective Tick	239	54.18***	62.16***	179	44.22***	25.15***
Corwin 0	239	67.40***	62.87***	179	55.47***	35.86***
Tobek Corwin 0	239	64.34***	59.08***	179	54.30***	35.16***
Abdi 2-day	239	76.17***	54.94***	179	59.01***	35.07***
Abdi monthly	239	55.12***	15.05**	179	48.34***	6.02
VoV High-Low	239	87.13***	81.98***	179	52.53***	36.37***
VoV daily	239	87.84***	80.32***	179	56.19***	40.33***
VoV Sigma	239	83.80***	75.15***	179	49.73***	39.47***
Amihud	239	45.14***	12.71**	179	23.48***	10.51
(-) Amivest	239	39.13***	23.88***	179	45.53***	30.60***
(-) LIX	239	73.09***	58.01***	179	47.11***	31.55***
(-) Gamma	239	10.55	0.02	179	3.40	-4.92

variation of liquidity, or in a measure that captures the time-series variation at the stock level. In the first case the choice of a measure should be based on cross-sectional correlations (discussed in the previous section) while in the second case it should be based on stock-level time-series correlations (to be discussed in the next section).

Stock-Level Correlations

The results presented in the previous section were obtained by estimating the correlation between (weighted) averages of liquidity measures. In this section we report (weighted) averages of correlations estimated at the stock level. We apply three different weighting schemes, an equally-weighted average, a value-weighted average and an average weighted by the number of stock-month observations available for a given stock. The latter weighting scheme puts less weight on stocks with missing data, but also on stocks which left the sample (e.g. because of a merger or because of bankruptcy) and on stocks which went public after the beginning of our sample period.

Table 1.10 shows the results when the correlations are estimated for the levels of the liquidity measures. The correlations are generally lower than the portfolio-level correlations reported in the previous section. Five estimators (the CRSP closing spread, all three version of Tobek's estimator and the LIX estimator) achieve average correlations above 60% irrespective of the weighting scheme that is applied. The CRSP closing spread performs best when equally-weighted and observation-weighted averages are considered (correlations 79.7% and 81.3%, respectively) while the VoV daily estimator performs best (72.0%) when value-weighted averages are considered. Of the remaining estimators, the effective tick estimator and the Amihud illiquidity ratio show a reasonably good and consistent performance.

Correlations obtained from first-differenced liquidity measures are considerably lower (Table 1.11). The same five measures as before perform best (with correlations ranging from 40.7% to 57.6%) when we consider equally-weighted or observation-weighted averages of stock-by-stock correlations. The Tobek measures and the CRSP closing spread continue to perform well (correlations between 33.5% and 52.8%) when value-weighted averages are considered while the LIX ratio (28.2%) does considerably worse in this case.

As in the preceding sections correlations are much lower when the price impact rather than the effective spread is used as benchmark. The largest value drops to 37.0%. The five measures listed above continue to perform relatively well. When first differences are used instead of levels the correlations drop even further, with the largest value now being 15.9%. The VoV high-low estimator and the VoV daily estimator are still among the top four measures.

All in all, the results are rather similar to those obtained for the cross-sectional correlations. We observe huge performance differences across the low-frequency measures, we find that correlations are higher in levels than in first differences, and we find that the low-frequency proxies are better able to track the effective spread than the price impact. The best performing measures are the two version of Tobek's measure (VoV high-low and VoV daily), the CRSP closing spread and the LIX ratio.

Table 1.10: Monthly Stock-by-Stock Time-Series Correlations (Level)
Relative Effective Spreads are equally-weighted averages calculated from every trade of the TAQ dataset. For each firm, we calculate the time-series correlation of the firm's effective spread with the respective spread proxies. Then the crosssectional average of those correlations is taken.
N gives the number of firms for which we were able to calculate a correlation, $\overline{\rho}$ gives the equally-weighted cross-sectional average correlation and significance (from a simple t-test), $\overline{\rho}$ *(by Size)* the market value-weighted average, respectively. $\overline{\rho}$ *(by Obs)* weights each firm by the number of monthly observations used to determine the time-series correlation. > 0 shows the fraction of firms that had a correlation above 0 and $> 0(5\%)$ the fraction that had a correlation that was significantly above 0 (at the 5% level).
We repeat the analysis, but now correlate estimators to a 5-minute price impact measure (PI).

	N	$\bar{\rho}$	$\bar{\rho}$ (by Size)	$\bar{\rho}$ (by Obs)	>0	>0 (5%)	N (PI)	$\bar{\rho}$ (PI)	$\bar{\rho}$ (PI by Size)	$\bar{\rho}$ (PI by Obs)	>0 (PI)	>0 (5%) (PI)
Closing Spread CRSP	13446	79.65***	68.06	81.33	97.97	94.00	11873	23.35***	32.24	24.75	75.84	44.72
Roll 0	13385	8.46***	1.49	6.99	60.58	22.86	11826	-1.84	2.62	-1.55	42.29	6.98
Roll 0 (ret)	13449	34.20***	23.10	32.36	87.79	60.23	11880	17.54***	21.49	19.28	74.87	34.53
Gibbs	13451	9.46***	7.35	12.17	61.40	31.75	11879	-3.59	7.52	-1.73	42.28	11.68
Zero	13406	21.20***	37.73	37.75	71.19	43.37	11845	0.93***	6.69	4.65	50.20	15.16
LOT	13449	33.12***	36.08	42.58	87.70	59.64	11877	10.31***	13.55	12.67	67.39	24.50
LOT y-split	13412	24.27***	28.17	34.85	78.54	47.44	11852	5.08***	5.36	6.44	56.24	17.37
FHT	13409	40.08***	43.76	51.41	89.48	65.39	11849	9.11***	11.97	11.17	63.63	23.63
Tobek FHT	13439	45.21***	33.97	43.58	92.38	72.88	11875	21.36***	27.34	22.91	76.29	40.65
Effective Tick	13451	51.75***	69.68	63.05	94.13	76.51	11880	15.99***	24.58	18.08	70.52	34.62
Corwin 0	13392	43.58***	29.55	40.61	90.28	70.23	11831	17.38***	20.38	18.94	70.89	35.90
Tobek Corwin 0	13386	38.79***	25.55	36.25	88.08	64.86	11828	14.81***	17.75	16.25	68.40	32.55
Abdi 2-day	13447	53.82***	30.64	51.27	94.45	79.70	11878	20.63***	22.81	22.26	76.96	40.31
Abdi monthly	13426	41.16***	15.54	40.53	89.65	66.06	11851	12.40***	8.68	13.65	70.15	27.16
VoV High-Low	13440	70.20***	69.33	72.97	98.21	92.29	11874	29.14***	36.49	32.66	82.71	53.07
VoV daily	13439	74.52***	71.96	76.80	98.46	93.70	11875	29.70***	37.02	33.03	83.33	53.58
VoV Sigma	13444	63.22***	62.56	67.90	97.60	88.18	11875	26.43***	34.83	30.15	81.73	49.89
Amihud	13448	53.91***	61.38	59.82	95.79	80.77	11877	18.90***	26.59	21.40	71.47	38.55
(-) Amivest	13445	40.34***	51.49	40.65	94.27	73.02	11879	13.43***	23.44	16.11	77.28	28.50
(-) LIX	13438	64.40***	67.51	70.21	96.91	88.33	11876	23.57***	30.23	27.75	79.92	46.62
(-) Gamma	13447	-0.64	0.90	-1.00	48.38	9.19	11879	-0.10	0.64	0.06	50.11	6.47

Table 1.11: Monthly Stock-by-Stock Time-Series Correlations (First Differences)
Relative Effective Spreads are equally-weighted averages calculated from every trade of the TAQ dataset. For each firm, we calculate the time-series correlation of the first-difference of the firm's effective spread with the respective first-difference of spread proxies. Then the crosssectional average of those correlations is taken.
N gives the number of firms for which we were able to calculate a correlation, $\overline{\rho}$ gives the equally-weighted cross-sectional average correlation and significance (from a simple t-test), $\overline{\rho}$ *(vw)* the market value-weighted average, respectively. $\overline{\rho}$ *(by Obs)* weights each firm by the number of monthly observations used to determine the time-series correlation. > 0 shows the fraction of firms that had a correlation above 0 and $> 0(5\%)$ the fraction that had a correlation that was significantly above 0 (at the 5% level).
We repeat the analysis, but now correlate estimators to a 5-minute price impact measure (PI).

	N	$\bar{\rho}$	$\bar{\rho}$ (by Size)	$\bar{\rho}$ (by Obs)	>0	>0 (5%)	N (PI)	$\bar{\rho}$ (PI)	$\bar{\rho}$ (PI by Size)	$\bar{\rho}$ (PI by Obs)	>0 (PI)	>0 (5%) (PI)
Closing Spread CRSP	13252	57.61***	33.45	52.60	97.59	85.76	11720	11.39***	7.63	7.79	67.24	20.64
Roll 0	13188	8.39***	6.07	7.92	69.38	15.68	11665	0.42**	0.34	0.19	50.14	5.21
Roll 0 (ret)	13252	23.10***	27.46	23.07	87.28	46.05	11721	7.35***	9.49	6.55	63.41	14.85
Gibbs	13254	10.44***	11.32	10.81	72.44	20.67	11722	0.69***	1.68	0.57	50.80	6.03
Zero	13223	-4.22	-2.11	-3.84	40.28	4.93	11699	-1.59	-1.35	-0.95	47.00	5.70
LOT	13254	9.63***	6.60	8.19	68.04	19.64	11723	3.32***	2.52	2.42	55.38	9.74
LOT y-split	13228	2.82***	-0.05	1.53	53.35	10.68	11706	1.34***	0.30	0.87	50.85	8.34
FHT	13224	10.35***	4.95	9.33	68.50	22.22	11701	2.21***	0.47	1.67	53.41	10.11
Tobek FHT	13244	33.27***	47.76	33.91	91.62	62.03	11718	11.45***	15.15	10.23	66.74	22.94
Effective Tick	13257	14.27***	14.24	12.50	74.99	28.46	11727	4.29***	3.18	2.67	55.43	11.89
Corwin 0	13154	29.26***	30.33	28.91	89.64	57.85	11638	6.81***	7.05	6.17	61.66	15.43
Tobek Corwin 0	13153	24.82***	25.64	24.70	86.92	50.58	11637	5.35***	5.66	4.92	59.47	13.23
Abdi 2-day	13257	34.70***	29.10	32.68	93.67	65.78	11727	8.38***	8.12	7.17	64.71	16.76
Abdi monthly	13244	20.85***	8.74	18.30	82.35	40.29	11712	3.37***	0.51	2.54	56.15	9.91
VoV High-Low	13244	49.93***	48.78	48.44	96.93	83.50	11717	14.33***	12.47	12.22	72.06	27.14
VoV daily	13244	56.86***	52.84	55.26	97.70	87.88	11718	15.86***	13.48	13.36	73.37	29.64
VoV Sigma	13252	38.80***	35.42	37.55	95.34	72.31	11720	11.83***	11.57	10.06	70.03	22.79
Amihud	13253	28.91***	21.52	26.28	88.66	54.41	11724	8.56***	5.89	6.22	62.76	18.14
(-) Amivest	13254	15.84***	8.11	9.81	87.01	19.28	11723	4.50***	2.67	2.96	65.87	5.64
(-) LIX	13242	40.74***	28.19	37.98	95.83	75.29	11717	11.16***	5.18	9.22	70.78	20.63
(-) Gamma	13252	0.31*	0.66	0.34	50.75	10.14	11723	-0.03	0.58	0.07	50.84	8.93

1.4.3 RMSE/MAE

The correlations discussed in the preceding sections indicate how well the various low-frequency proxies capture the cross-sectional and time-series dispersion of the benchmark measures, but they do not provide information on how close the low-frequency estimators are to the benchmark measures. Therefore we also calculate mean absolute errors (MAE) and root mean squared errors (RMSE). This analysis is confined to those low-frequency proxies that estimate the percentage effective spread. We proceed as follows. We calculate, for each of the low-frequency estimators included, the absolute difference and the squared difference between the proxy and the effective spread for each stock-month observation. These deviations are then aggregated across stocks and months to obtain the MAE and RMSE.

The results are presented in columns 2 and 3 of Table 1.12. The RMSEs are generally larger than the MAEs (mean 1.97% as compared to 1.57%). There are four measures with a mean absolute error below 1%, the Abdi 2-day estimator (0.86%), the VoV high-low estimator (0.91%), the VoV sigma estimator (0.97%) and the effective tick estimator (0.995%). Most of the other estimators have MAEs between 1.1% and 1.21%. Three estimators perform worse, with MAEs ranging from 1.56% (LOT y-split) to 5.86% (Roll 0 (ret)). The same four estimators that have the lowest MAEs also have the lowest RMSEs, and the same three measures that have the highest MAEs also have the highest RMSEs.

It is noteworthy that the CRSP closing spread, which performed very well in the correlation analysis, is not among the top estimators in terms of MAEs and RMSEs. This may be due to the relatively poor performance, documented in Figure 1.4, of the CRSP closing spread between 1998 and 2002. It should also be noted that the CRSP closing spread is a quoted spread, and quoted spreads are larger, on average, than effective spreads.

Table 1.12: RMSE / MAE
Every firm-month / firm-year, we calculate the absolute error between the effective spread and the respective spread proxy. We call this number AE (Absolute Error) and its square SE (Square Error). Foreach firm, we take the mean of these two figures. In case of SE, we additionally take the square root of that mean. We calculate the crosssectional mean of these numbers and call them MAE (Mean Average Error) and RMSE (Root Mean Square Error).
MAE and *RMSE* provide the MAE/RMSE in %.

Measure	MAE monthly	RMSE monthly	MAE yearly	RMSE yearly
Closing Spread CRSP	1.108	1.428	1.393	1.671
Roll 0 (ret)	5.857	7.016	7.122	7.665
LOT	2.821	3.889	3.139	3.631
LOT y-split	1.564	2.235	1.370	1.735
FHT	1.094	1.359	0.901	1.058
Tobek FHT	1.209	1.532	1.444	1.711
Effective Tick	0.995	1.258	0.947	1.105
Corwin 0	1.128	1.359	1.092	1.229
Tobek Corwin 0	1.210	1.443	1.161	1.293
Abdi 2-day	0.861	1.098	0.846	0.997
Abdi monthly	1.092	1.439	1.049	1.285
VoV High-Low	0.906	1.046	0.879	0.969
VoV daily	1.190	1.301	1.188	1.259
VoV Sigma	0.968	1.119	0.951	1.047

1.4.4 Yearly versus Monthly Aggregation

So far we have used liquidity measures at the stock-month level as our basic unit of observation. In many applications (e.g. panel studies with annual data) only a yearly measure of liquidity is needed. We therefore repeat the analysis using liquidity measures at the stock-year level as the basic unit of observation. Those yearly estimators are based on more (daily) observations and thus might be more precise. The main question we wish to address is whether the low-frequency estimators that perform best on monthly data also perform best when yearly data is used. We only present the results that we obtain when using the levels of the effective spread as benchmark measures.[22]

Table 1.13: Correlations: Monthly vs. Yearly
We repeat the analyses from tables 1.6, 1.8 and 1.10 respectively. However with yearly aggregated data instead of monthly data.
monthly repeats the correlation from above mentioned tables, *yearly* shows the correlations for the same approach using yearly data. In all three cases, results from the respective equal-weighted approach are shown here. The asterisks behind the yearly column show whether the difference between monthly and yearly data is significant. This test is conducted as a t-test assuming unequal variances for the Crosssection and Timeseries Stock-by-Stock and as a Fisher z-test for the Timeseries portfolio analysis.
Row *Spearman* provides the Spearman rank correlation coefficient between columns *Correlation monthly* and *Correlation yearly.*

	Crosssection		**Timeseries Portfolio**		**Timeseries Stock-by-Stock**	
Measure	monthly	yearly	monthly	yearly	monthly	yearly
Roll 0	1.30	12.78***	32.76	58.14	8.46	16.27***
Roll 0 (ret)	43.54	53.85***	59.99	57.97	34.20	36.15***
Gibbs	0.24	13.69***	70.21	90.92***	9.51	19.41***
Zero	39.52	57.14***	96.76	98.35	21.20	39.89***
LOT	46.97	60.65***	97.21	97.20	33.12	48.18***
LOT ysplit	37.03	48.31***	98.39	99.42**	24.27	39.89***
FHT	55.54	68.26***	98.66	99.05	40.08	57.89***
Tobek FHT	73.52	84.36***	86.59	88.84	45.21	51.63***
Effective Tick	57.91	71.97***	97.70	85.16***	51.75	64.93***
Corwin 0	38.67	46.47*	85.73	91.21	43.58	50.53***
Tobek Corwin 0	33.11	41.69*	88.34	93.46	38.79	47.12***
Abdi 2-day	70.51	78.26***	88.80	91.77	53.82	60.79***
Abdi monthly	66.57	78.98***	90.84	92.54	41.16	50.42***
VoV High-Low	87.61	90.60***	87.52	87.81	70.20	69.96
VoV daily	86.94	90.32***	90.39	91.84	74.52	76.27***
VoV Sigma	86.39	88.98***	90.13	88.80	63.22	63.50
Closing Spread CRSP	87.42	88.64	98.39	98.80	79.65	79.76
Amihud	64.79	71.65***	83.35	61.82*	53.91	65.55***
(-) Amivest	25.25	24.39	89.89	89.64	40.34	56.83***
(-) LIX	72.14	74.77***	94.32	94.57	64.40	71.47***
(-) Gamma	8.50	-17.55***	82.70	-76.37***	-0.64	-12.47***
Spearman		98.18		77.79		95.97

[22]Results with first differences of the effective spread and with the price impact as benchmark measures provide qualitatively similar results.

The results for the correlation analysis are shown in Table 1.13. For ease of comparison the correlations obtained from stock-month level data are repeated in the table. Columns 2 and 3 report the results for the cross-sectional correlation, columns 4 and 5 those for the time-series analysis at the (equally-weighted) portfolio level and columns 6 and 7 those for the time-series analysis at the stock-by-stock level (equally-weighted). Two main findings emerge. First, in most cases yearly liquidity measures result in higher correlations between the low-frequency proxies and the effective spread benchmark than monthly liquidity measures. Second, the ranking of the proxies is very similar for yearly and monthly data. For the cross-sectional correlation and the time-series correlations at the stock-by-stock level, the top-performing low frequency proxy is the same, and the measures on ranks 2 to 4 are also identical (although the ordering is slightly changed). For the portfolio-level time-series correlations, the top-three in the monthly analysis are also the top-three performers in the yearly analysis (although not in the same order).

The mean absolute errors (MAE) and root mean squared errors (RMSE) are shown in columns 4 and 5 of Table 1.12. They are very similar to the results obtained from monthly data shown in columns 2 and 3 of the same table.

To summarize, the results presented in Table 1.12 and Table 1.13 allow a simple conclusion. The choice of a low-frequency liquidity proxy can be made independent of the data frequency (i.e. monthly or yearly) at which the proxy is used.

1.4.5 Sample splits

The results presented previously suggest that the performance of some of the low-frequency estimators depends on the level of the bid-ask spread. To explore this issue further we subdivide the sample into five quintiles according to the size of the effective bid-ask spread. We resort the stocks every month. A stock can thus be sorted into different quintiles over time. Based on these quintile sorts we then estimate the cross-sectional and time-series correlations as before. Specifically, we calculate the cross-sectional correlation between the low-frequency estimators and the effective spread benchmark for each quintile and each month and then calculate, for each quintile, the time-series average of the cross-sectional correlations. Next, we calculate the (equally-weighted) average liquidity of all stocks in a given quintile for each month, and for both the benchmark measure and the low-frequency estimators, resulting in one portfolio-level time series for each measure and each quintile. Based on these time series we then calculate portfolio-level time-series correlations. Finally, we calculate the time-series correlation between each low-frequency proxy and the benchmark measure for each stock within a quintile and then average the correlations across the stocks in a quintile. In the following we show results for quintiles one, three and five.[23]

The results for the cross-sectional correlations are presented in Table 1.14. Three main findings emerge. First, there appears to be a pronounced u-shaped pattern across the quintiles. For most estimators the correlations are high in the quintile of stocks with the smallest spreads, then decrease and increase again in the quintile of stocks with the largest spreads. Second, when tracking the performance of the same estimator across the quintiles, we find that most

[23] Including quintiles 2 and 4 leads to similar results.

estimators perform best in the largest spread quintile. However, some estimators (for example the effective tick estimator and the Corwin and Schultz (2012) high-low estimator) perform best in the smallest spread quintile. Remarkably, none of the estimators we analyze performs best in the intermediate quintile. Third, some low-frequency estimators perform well in all quintiles. The three versions of Tobek's estimator (VoV high-low, VoV daily and VoV sigma) are among the top four estimators in all three quintiles shown in Table 1.14. The CRSP closing spread performs well in the large-spread quintile but does much less well in the small spread quintile. The LIX estimator, on the other hand, does well in the small-spread quintile but is not among the top estimators in the larger spread quintiles.

Table 1.14: Crosssectional Correlation (sorted by effective spread)
This table shows the same as column *Correlation* of table 1.6. However, the sample is split into quintiles based on relative effective spreads. Here we show the correlation for quintiles 1, 3 and 5.
Column *Small* shows the correlation for the firms with smallest relative spread levels in each given month, *Medium* for the middle and *Large* for the highest spread levels. *Large - Small* gives the difference in correlations between groups 1 and 5 and its significance (based on a t-test) is indicated.
Below the *Spearman Rank Correlation* between the different columns is provided.

Measure	Small	Medium	Large	Large - Small
Roll 0	-7.70	-2.17	12.99	20.69***
Roll 0 (ret)	24.71	8.43	39.40	14.68***
Gibbs	-13.55	-5.31	22.83	36.38***
Zero	11.72	7.91	16.56	4.85***
LOT	13.48	8.78	33.83	20.35***
LOT y-split	5.09	6.59	24.69	19.60***
FHT	17.31	11.49	38.55	21.24***
Tobek FHT	37.88	14.95	62.95	25.07***
Effective Tick	37.79	19.08	28.24	-9.55***
Corwin 0	29.73	16.90	21.68	-8.05***
Tobek Corwin 0	25.95	15.13	17.65	-8.30***
Abdi 2-day	27.40	18.88	58.45	31.05***
Abdi monthly	9.74	13.63	55.32	45.58***
VoV High-Low	59.05	35.75	70.62	11.57***
VoV daily	61.37	40.07	67.40	6.03***
VoV Sigma	52.71	28.23	71.80	19.09***
Closing Spread CRSP	38.49	33.26	78.49	40.00***
Amihud	24.95	16.56	54.19	29.24***
(-) Amivest	36.78	13.96	13.25	-23.52***
(-) LIX	49.48	27.28	55.67	6.18***
(-) Gamma	0.67	-0.40	9.80	9.13***
Spearman Rank Correlation				
Small		93.90	69.35	
Medium			73.64	

Table 1.15 shows the portfolio-level time-series correlations. The most consistent estimators, with correlations above 93% in all three quintiles, are the LOT and LOT y-split estimators, the FHT estimator and the effective tick estimator. While these estimators perform well in the small spread quintile (LOT, FHT and Effective Tick) and in the medium spread quintile (LOT y-split, FHT and Effective Tick), they are not among the best estimators in the large

spread quintile. Here, the CRSP closing spread performs best (correlation 99.3%), followed by the two versions of the Abdi and Ranaldo (2017) measure (99.2% and 99.1%, respectively). The different versions of Tobek's estimator, which performed well in the cross-sectional analysis, achieve correlations between 87.3% and 95.6% but are not among the top four estimators in any of the three quintiles. Comparing the results across the quintiles reveals that most estimators yield reasonably high correlations in the large spread quintile. However, the performance of some estimators deteriorates when the medium and low spread quintiles are considered. This is particularly true for the Roll estimator, the Corwin and Schultz (2012) high-low estimator and the two versions of the Abdi and Ranaldo (2017) estimator. The Amihud (2002) illiquidity ratio, on the other hand, performs well in the small and medium spread quintiles (correlations 91.3% and 96.7%, respectively) but does not very well in the large spread quintile (48.2%).

Table 1.15: Timeseries Portfolio Correlation (sorted by effective spread)
This table shows the same as column *Correlation* of table 1.8. However, the sample is split into quintiles based on relative effective spreads. Here we show the correlation for quintiles 1, 3 and 5.
Column *Small* shows the correlation for the firms with smallest relative spread levels in each given month, *Medium* for the middle and *Large* for the highest spread levels. *Large - Small* gives the difference in correlations between groups 1 and 5 and its significance (based on a Fisher z-test) is indicated.
Below the *Spearman Rank Correlation* between the different columns is provided.

Measure	Small	Medium	Large	Large - Small
Roll 0	-10.59	12.65	91.93	102.52***
Roll 0 (ret)	5.15	12.92	94.87	89.72***
Gibbs	22.61	57.20	92.88	70.27***
Zero	93.02	97.68	88.85	-4.17***
LOT	95.38	94.94	94.53	-0.85
LOT ysplit	91.89	98.90	92.47	0.58
FHT	97.76	98.72	93.63	-4.13***
Tobek FHT	6.82	62.86	92.42	85.60***
Effective Tick	98.41	99.40	93.06	-5.34***
Corwin 0	-11.28	48.42	95.93	107.20***
Tobek Corwin 0	-17.42	48.23	94.38	111.80***
Abdi 2-day	5.23	61.27	99.13	93.90***
Abdi monthly	0.92	73.51	99.24	98.32***
VoV High-Low	88.26	91.47	87.35	-0.92
VoV daily	88.83	93.47	95.60	6.77***
VoV Sigma	90.15	91.65	87.30	-2.85
Closing Spread CRSP	89.38	99.46	99.28	9.91***
Amihud	94.69	96.74	48.24	-46.46***
(-) Amivest	91.25	82.40	74.39	-16.87***
(-) LIX	96.50	94.58	82.70	-13.80***
(-) Gamma	-5.74	-16.91	37.94	43.68***
Spearman Rank Correlation				
Small		85.58	-26.36	
Medium			4.55	

The results for the stock-by-stock time series correlations are shown in Table 1.16. As was the case in the main analysis (see Tables 1.8 and 1.10) the stock-by-stock correlations are much lower than the portfolio-level correlations. On the other hand, the results for the stock-by-stock correlations are much more homogeneous than those for the portfolio-level correlations. This is true both when we consider the performance of different estimators in the same quintile and when we consider the performance of the same estimator across quintiles. Three estimators stand out. The VoV high-low estimator, the VoV daily estimator and the CRSP closing spread are the top-three estimators in all three quintiles. They achieve correlations between 51.8% and 72.5%. While VoV daily is the best estimator in the small spread quintile, the CRSP closing spread achieves the highest correlation in the medium and large spread quintiles. No other estimator achieves correlations above 50% in all quintiles.

Table 1.16: Timeseries Stock-by-Stock Correlation (sorted by effective spread)
This table shows the same as column $\bar{\rho}$ of table 1.10. However, the sample is split into quintiles based on relative effective spreads. Here we show the correlation for quintiles 1, 3 and 5.
Column *Small* shows the correlation for the firms with smallest relative spread levels in each given month, *Medium* for the middle and *Large* for the highest spread levels. *Large - Small* gives the difference in correlations between groups 1 and 5 and its significance (based on a t-test) is indicated.
Below the *Spearman Rank Correlation* between the different columns is provided.

Measure	Small	Medium	Large	Large - Small
Roll 0	3.56	5.21	16.21	12.65***
Roll 0 (ret)	21.97	19.67	34.32	12.35***
Gibbs	12.33	12.85	21.74	9.41***
Zero	17.38	18.54	13.76	-3.61***
LOT	17.57	20.06	29.50	11.93***
LOT y-split	10.75	17.03	21.47	10.73***
FHT	28.77	28.56	31.63	2.86***
Tobek FHT	34.52	31.17	40.42	5.90***
Effective Tick	51.16	41.58	31.72	-19.44***
Corwin 0	25.51	30.54	35.33	9.82***
Tobek Corwin 0	21.05	26.60	31.31	10.26***
Abdi 2-day	27.57	35.53	51.61	24.04***
Abdi monthly	7.19	20.94	44.11	36.92***
VoV High-Low	60.93	51.81	54.16	-6.77***
VoV daily	64.65	58.73	59.75	-4.90***
VoV Sigma	53.02	42.51	49.89	-3.12***
Closing Spread CRSP	58.01	68.01	72.49	14.48***
Amihud	52.53	41.33	38.91	-13.62***
(-) Amivest	42.41	35.82	28.29	-14.12***
(-) LIX	56.53	47.37	46.64	-9.89***
(-) Gamma	1.13	-1.55	0.76	-0.37
Spearman Rank Correlation				
Small		96.23	78.18	
Medium			85.19	

The results can be summarized as follows. Some estimators perform very differently in different spread quintiles. It may therefore be the case that an estimator produces reasonably good result in a sample of low-liquidity stocks while the same estimator may not perform well when applied to a sample of high-liquidity stocks (or vice versa). Tobek's VoV high-low and VoV daily estimators appear to be a very good choice overall. Both are among the top performers in all spread quintiles when either cross-sectional or stock-level time series correlations are considered.

1.4.6 NYSE versus Nasdaq

The performance of the low-frequency estimators may be affected by the trading protocol of the market in which a stock is traded. Consequently, both the absolute and the relative performance of the estimators may be different for NYSE and Nasdaq listed stocks. To explore this issue we perform a matched-sample analysis. We select, without replacement, a Nasdaq control stock for each NYSE stock.[24] We follow Hendershott and Moulton (2011) and select the control stocks such that the score

$$score = \frac{\left|\frac{Size_{NYSE}}{Size_{NASDAQ}} - 1\right| + \left|\frac{Spread_{NYSE}}{Spread_{NASDAQ}} - 1\right|}{2} \tag{1.17}$$

is minimized.[25] The matching is performed for the first month of the sample period. For NYSE stocks which are added to the CRSP database later, the matching is performed for the first month for which data is available. When a matched Nasdaq stock leaves the sample (e.g. because of a merger) we select a new Nasdaq match for the corresponding NYSE stock.[26] All other procedures are as described previously. We analyze cross-sectional correlations and time-series correlations at the individual stock level.[27] The results are presented in Table 1.17. Columns 1-4 show the average cross-sectional correlation between the low-frequency proxies and the effective stock for NYSE stocks (column 1), the average correlation for the matched Nasdaq stocks (column 2), the percentage of months in which the correlation is higher for the Nasdaq stocks (column 3), and the result of a t-test of the null hypothesis that the cross-sectional correlation is the same for NYSE and Nasdaq stocks. Columns 5-8 provide similar information on the stock-level time-series correlations.

The results for the cross-sectional and time-series correlations are very similar. While some of the low-frequency estimators (e.g. the Amihud illiquidity ratio and the effective tick estimator) perform better for NYSE stocks, the majority of the estimators perform better for Nasdaq stocks. The relative performance of the estimators is very similar in the two markets. The three measures that achieve the highest cross-sectional and time-series correlation for NYSE stocks (the CRSP closing spread, the VoV high-low estimator and the VoV daily estimator) also achieve the highest correlation for Nasdaq stocks. These three estimators are among those estimators that perform better for Nasdaq stocks.

To summarize, the results in this section indicate that the ranking of the estimators is similar for NYSE and Nasdaq stocks. Therefore, researchers can choose the same estimator for NYSE and Nasdaq samples.

[24] We select a NYSE stock randomly and then identify the best match from the sample of Nasdaq stocks. We then randomly select the next NYSE stock and identify the best match from the sample of remaining Nasdaq stocks. We proceed in this way until we have found a match for all NYSE stocks.

[25] We also implemented a version of the procedure where we required that the score is below 1. The results were very similar to those presented and are therefore omitted.

[26] When a NYSE stock has two (or more) Nasdaq matches we calculate two time-series correlations between the effective spread and the low-frequency estimators, one for the original match and one for the new match. We then calculate an observation-weighted average of these two correlations. This average is then compared to the time-series correlation between the effective spread and the low-frequency estimators for the NYSE stock.

[27] In both cases we present results for the equal-weighted correlations. Other weighting schemes lead to very similar results.

Table 1.17: Correlations: NYSE vs. NASDAQ (matched)

We repeat the analysis from tables 1.6 and 1.10 but only for matched NYSE and NASDAQ stocks. Matching is done based on the effective spread and the size of those companies. The matching approach is described in detail in text section 1.4.6.

We compare the crosssectional and stock-by-stock timeseries correlation. Results from the respective equal-weighted approach are shown here. *NYSE* and *NASDAQ* show the correlation in the respective market. *NASDAQ > NYSE* shows the fraction of observations with a NASDAQ correlation greater than the NYSE correlation. *Significance* indicates whether the difference between NYSE and NASDAQ data is significant. This test is conducted as a t-test assuming unequal variances.

Row *Spearman* provides the rank correlation coefficient between columns *NYSE* and *NASDAQ* and row *N* the number of observations.

	Crosssection				Timeseries Stock-by-Stock			
Measure	NYSE	NASDAQ	NASDAQ > NYSE	Significance	NYSE	NASDAQ	NASDAQ > NYSE	Significance
Closing Spread CRSP	81.29	89.41	92.50	***	66.82	79.00	63.60	***
Roll 0	-8.37	2.10	93.75	***	-1.19	8.26	63.93	***
Roll 0 (ret)	34.23	33.19	44.58		23.75	33.97	62.65	***
Gibbs	-12.41	-3.25	88.33	***	1.06	7.67	56.37	***
Zero	38.04	33.73	32.08	***	33.74	14.86	31.96	***
LOT	39.63	37.98	40.00		34.32	25.77	37.53	***
LOT y-split	30.58	30.38	50.42		27.80	16.73	37.71	***
FHT	49.61	46.67	29.17	**	44.20	30.52	34.32	***
Tobek FHT	63.24	67.50	74.58	***	36.89	45.65	59.26	***
Effective Tick	63.77	54.57	14.58	***	63.87	46.23	27.26	***
Corwin 0	38.77	32.97	25.42	***	35.16	50.25	63.36	***
Tobek Corwin 0	33.68	28.25	26.25	**	30.50	45.99	64.11	***
Abdi 2-day	54.84	63.49	81.25	***	38.67	52.72	63.81	***
Abdi monthly	42.86	59.00	99.17	***	23.47	36.82	65.03	***
VoV High-Low	82.35	87.00	89.17	***	66.34	70.28	54.29	***
VoV daily	83.24	86.40	81.25	***	71.15	75.24	55.12	***
VoV Sigma	77.94	84.35	94.58	***	58.06	59.87	49.58	***
Amihud	61.85	58.86	42.50	***	56.18	52.48	41.85	***
(-) Amivest	24.96	26.58	67.50	***	42.79	40.24	46.64	***
(-) LIX	65.50	72.06	93.33	***	63.60	62.87	44.32	
(-) Gamma	-2.16	4.81	69.17	***	-0.38	-1.10	47.50	
N				240				3341
Spearman				96.94				88.64

1.4.7 Regression Analysis

The results in sections 1.4.5 and 1.4.6 indicate that the performance of some of the low-frequency estimators depends on the size of the bid-ask spread. Other firm characteristics besides the spread may also affect the accuracy of the estimators. We explore this possibility by estimating cross-sectional regressions. We again start from the full set of stock-month observations. We calculate, for each stock, the time-series correlations between the effective spread benchmark and each of the low-frequency proxies. These correlations are the dependent variable in our regression analysis.[28] We include as independent variables the effective spread, the squared effective spread (to account for the non-linear pattern documented above), firm size (measured by the market value of equity) and the turnover ratio (defined as the ratio of daily dollar trading volume and market capitalization). These variables are calculated as time-series averages over the sample period. We further include the standard deviation of daily returns and the log of the age of the firm (measured from the first availability of data for the firm in the CRSP database). Finally, to account for the result reported in section 1.4.6 that the listing venue may also affect the performance of the liquidity estimators, we include dummy variables indicating whether the firm is listed on Nasdaq, the NYSE or AMEX.[29]

We estimate one cross-sectional regression for each low-frequency estimator. Because the number of time-series observations included in the correlation estimates and in the time-series averages differs across stocks we use weighted least squares with weights that reflect the number of time-series observations for each stock. The results are shown in Table 1.18. To enhance the readability of the Table we do not show results for all low-frequency estimators. Rather, for each group of conceptually similar estimators (e.g. the three versions of the VoV estimator) we report results for the estimator that performs best. The explanatory power of the regressions, measured by the adjusted regression R^2, ranges from 0.03 for the Pástor and Stambaugh (2003) gamma to 0.96 for the CRSP closing spread. The coefficient estimates indicate that the determinants of the time-series correlations between the effective spread and the low-frequency proxies differ widely between the different proxies. The most common pattern for the coefficients on the effective spread is a positive coefficient for the spread and a negative coefficient for the squared spread. This pattern is consistent with the u-shaped relation documented above. For three estimators (Zero, Effective Tick and LIX) both coefficients are negative, implying that these measures achieve higher time-series correlations for lower-spread stocks. No clear pattern emerges for the coefficients on firm size. Six coefficients are significantly negative while five coefficients are significantly positive. For most (but not all) low-frequency estimators, the time-series correlations are increasing in turnover, firm age, and volatility. The coefficients on the listing dummies indicate that all low-frequency estimators (with the exception of the Pástor and Stambaugh (2003) gamma) achieve higher correlations for Nasdaq stocks. This is a stronger result than the one we obtained from the matched-sample analysis in the previous section.

[28] The dependent variable can obviously only take on values between -1 and 1. Approximately 1% of the predicted values from the OLS regressions are outside of this range.

[29] Firms that changed their listing during our sample period are excluded. We calculated the variance inflation factors for all explanatory variables. They were all below the critical value of 10, indicating that multicollinearity is not an issue.

Table 1.18: Explaining Timeseries Correlations

We use the results from Table 1.10 to explain the differences in correlations between a given estimator and the effective spread across different firms:

Dependent variable is the timeseries stock-by-stock correlation between an estimator and the effective spread. For each independent variable the timeseries mean is calculated. *Size* is measured in billions and *Firm Age* is measured in log(years) between a given date and the CRSP begin date of that firm. AMEX, NASDAQ, NYSE are dummy variables that are equal to 1 if the fund was listed on that exchange.

We then conduct a simple crosssectional WLS regression with heteroskedasticity robust standard errors. As weight, the number of monthly observations in the stock-by-stock timeseries of the respective firm is used.

	(1) Roll 0 (ret)	(2) Zero	(3) Corwin 0	(4) FHT	(5) Amihud	(6) (-) Gamma	(7) Effective Tick	(8) CRSP Closing Spread	(9) LOT y-split	(10) (-) LIX	(11) Abdi 2-day	(12) VoV High-Low
Effective Spread	14.04***	-2.479***	12.76***	6.147***	-10.01***	1.434***	-4.138***	1.562***	2.860***	-3.538***	21.41***	2.330***
	(25.41)	(-3.62)	(19.25)	(10.86)	(-20.68)	(3.33)	(-7.97)	(4.70)	(4.94)	(-7.33)	(39.97)	(5.54)
Squared Effective Spread	-146.5***	-44.64***	-221.4***	-96.73***	94.34***	6.618	-25.03***	-58.77***	-46.89***	-13.79*	-308.4***	-69.17***
	(-19.88)	(-4.66)	(-23.36)	(-12.43)	(13.67)	(1.13)	(-3.43)	(-12.35)	(-5.83)	(-1.90)	(-41.29)	(-11.12)
Size	0.00229***	-0.00278***	-0.00105	-0.00350***	0.00115*	0.00142***	0.00170***	-0.00487***	-0.00352***	0.00118**	-0.00213***	0.00253***
	(3.63)	(-4.42)	(-1.50)	(-6.46)	(1.94)	(3.50)	(3.69)	(-8.40)	(-6.48)	(2.01)	(-3.04)	(4.09)
Turnover	-0.697	7.701***	2.076**	6.309***	3.228***	0.349	7.931***	4.634***	7.834***	2.053***	-3.186***	4.885***
	(-0.99)	(9.22)	(2.52)	(8.87)	(5.71)	(0.62)	(13.90)	(11.02)	(10.85)	(3.63)	(-4.42)	(11.16)
ln(Firm Age)	-0.0452***	0.161***	-0.0256***	0.117***	0.0285***	-0.00814***	0.0988***	0.0148***	0.130***	0.0400***	-0.0248***	0.00215
	(-17.49)	(53.87)	(-8.26)	(46.28)	(12.07)	(-4.44)	(43.40)	(7.13)	(49.66)	(17.43)	(-9.44)	(1.02)
Return Std.Dev.	-0.158***	0.0622***	0.0847***	-0.0596***	0.0410***	-0.0607***	0.0676***	0.0219***	0.100***	0.0804***	0.0169*	0.0436***
	(-15.98)	(4.99)	(7.19)	(-5.69)	(4.66)	(-7.36)	(7.17)	(3.67)	(9.16)	(9.50)	(1.70)	(6.11)
AMEX	0.332***	-0.192***	0.169***	0.0566***	0.586***	0.0434***	0.239***	0.560***	-0.242***	0.519***	0.353***	0.603***
	(21.03)	(-9.37)	(9.46)	(3.44)	(44.02)	(4.02)	(15.70)	(40.48)	(-14.03)	(39.97)	(25.16)	(52.97)
NASDAQ	0.416***	-0.0000814	0.352***	0.216***	0.616***	0.00936	0.393***	0.835***	-0.0646***	0.634***	0.437***	0.680***
	(35.03)	(-0.01)	(24.95)	(17.32)	(56.90)	(1.02)	(35.36)	(100.42)	(-5.10)	(61.22)	(38.35)	(74.01)
NYSE	0.327***	-0.0469***	0.182***	0.180***	0.539***	0.0435***	0.376***	0.622***	-0.106***	0.537***	0.279***	0.592***
	(29.62)	(-3.59)	(13.66)	(16.17)	(55.17)	(5.19)	(37.32)	(68.87)	(-9.32)	(57.15)	(25.48)	(69.05)
N	12115	12072	12058	12075	12114	12113	12116	12112	12078	12103	12112	12105
Adjust. R2	0.730	0.697	0.744	0.841	0.902	0.026	0.912	0.964	0.698	0.934	0.871	0.950

t statistics in parentheses

The results shown in Table 1.18 indicate that the time-series correlations between the effective spread and the low-frequency proxies can indeed be explained by firm characteristics. In principle, then, the predicted values from the regression can be used to predict the accuracy of a low-frequency estimator for a particular stock. However, when used in this way the regression should not include the effective spread on the right-hand side because researchers use the low-frequency estimators precisely because data on effective spreads is unavailable. We therefore now take the perspective of a researcher who has access (only) to the CRSP data base. All variables used on the right-hand side of our regression model except the effective spread are available in the CRSP data base. We therefore replace the effective spread by the CRSP closing spread and re-estimate our model. The results are shown in Table 1.19. The explanatory power, as measured by the adjusted R^2, is essentially unchanged. The coefficient estimates in Table 1.19 can thus be used to forecast the accuracy of the low-frequency estimators. Consider, for example, a 5-year old NYSE-listed firm with a CRSP closing spread (averaged over the sample period) of 0.02 (corresponding to 2%), a market capitalization of 1 billion dollars, an average daily turnover ratio of 0.006 and a standard deviation of daily returns of 0.9. Our regression results predict that the time-series correlation between the effective spread and the CRSP closing spread is 69.8%. The prediction for the VoV high-low estimator is a correlation of 68.1%. The high regression R^2 indicates that these predictions are precise.

One plausible way to make use of the results of the predictive regressions is to select, for each stock, the estimator which is expected to perform best. We therefore predicted the best estimator for each stock in our sample. The results are shown in Table 1.20. The CRSP closing spread is the clear winner. It is predicted to be the best estimator for 78.4% of the sample stocks, followed by the VoV high-low estimator (8.0%). All other estimators are rarely predicted to perform best. In the next step we analyze how the accuracy of low-frequency spread estimation can be improved when we use the predicted best estimator for each stock rather than using the same estimator for all stocks. We use the CRSP closing spread as the benchmark measure. It achieves average stock-level time-series-correlations between 68.1% (value-weighted average) and 81.3% (observation-weighted average). Using the best estimator for each stock improves upon this performance. The average value-weighted correlation increases from 68.1% to 79.6%. The improvement is more modest if one of the two other weighting schemes is applied (from 79.7% to 80.8% for the equally-weighted average and from 81.3% to 84.6% for the observation-weighted average).

Table 1.19: Predicting Timeseries Correlations

We repeat the analysis from table 1.18 and just replace effective spread and squared effective spread by CRSP closing spread and squared CRSP closing spread.

	(1) Roll 0 (ret)	(2) Zero	(3) Corwin 0	(4) FHT	(5) Amihud	(6) (-) Gamma	(7) Effective Tick	(8) CRSP Closing Spread	(9) LOT y-split	(10) (-) LIX	(11) Abdi 2-day	(12) VoV High-Low
CRSP Closing Spread	6.013***	-2.432***	4.598***	2.542***	-4.881***	1.330***	-2.396***	-0.568***	1.432***	-3.238***	7.351***	-0.211
	(25.20)	(-8.43)	(15.08)	(10.63)	(-23.10)	(7.32)	(-10.68)	(-3.68)	(5.88)	(-15.90)	(29.54)	(-1.16)
Squared CRSP Closing Spread	-32.17***	2.756	-39.62***	-17.02***	23.10***	-4.047***	1.551	-6.195***	-8.359***	8.087***	-53.40***	-7.468***
	(-19.68)	(1.44)	(-17.62)	(-10.41)	(14.93)	(-3.39)	(1.02)	(-5.40)	(-5.10)	(5.25)	(-28.95)	(-5.50)
Size	0.00202***	-0.00321***	-0.00158**	-0.00365***	0.00114*	0.00165***	0.00160***	-0.00532***	-0.00351***	0.000645	-0.00318***	0.00206***
	(3.22)	(-5.10)	(-2.28)	(-6.74)	(1.90)	(4.07)	(3.42)	(-9.29)	(-6.43)	(1.10)	(-4.44)	(3.39)
Turnover	-2.523***	8.608***	1.739**	6.830***	3.720***	0.386	9.732***	3.562***	8.743***	1.489***	-5.846***	4.036***
	(-3.71)	(10.27)	(2.14)	(9.66)	(6.72)	(0.70)	(16.73)	(8.67)	(12.13)	(2.70)	(-8.17)	(9.35)
ln(Firm Age)	-0.0489***	0.164***	-0.0265***	0.117***	0.0315***	-0.00930***	0.102***	0.0157***	0.130***	0.0426***	-0.0277***	0.00296
	(-18.53)	(53.99)	(-8.44)	(46.18)	(13.31)	(-5.06)	(43.42)	(7.60)	(49.59)	(18.57)	(-10.18)	(1.39)
Return Std.Dev.	-0.166***	0.0757***	0.0848***	-0.0716***	0.0606***	-0.0701***	0.0741***	0.0461***	0.0859***	0.111***	0.0285***	0.0632***
	(-16.12)	(5.83)	(6.89)	(-6.61)	(6.71)	(-8.19)	(7.44)	(7.27)	(7.65)	(12.65)	(2.69)	(8.41)
AMEX	0.383***	-0.180***	0.228***	0.0775***	0.561***	0.0368***	0.233***	0.589***	-0.238***	0.537***	0.462***	0.634***
	(24.88)	(-8.95)	(13.43)	(4.95)	(44.53)	(3.57)	(15.27)	(44.33)	(-14.37)	(43.05)	(33.90)	(58.73)
NASDAQ	0.505***	-0.0327**	0.402***	0.238***	0.557***	0.0186**	0.339***	0.843***	-0.0604***	0.613***	0.557***	0.691***
	(48.76)	(-2.50)	(32.22)	(21.88)	(57.66)	(2.31)	(33.79)	(116.34)	(-5.35)	(67.10)	(54.68)	(86.33)
NYSE	0.341***	-0.0472***	0.189***	0.181***	0.534***	0.0409***	0.366***	0.629***	-0.108***	0.543***	0.305***	0.600***
	(30.38)	(-3.57)	(14.06)	(16.36)	(55.07)	(4.85)	(35.47)	(71.81)	(-9.58)	(58.44)	(27.04)	(70.92)
N	12113	12070	12056	12073	12112	12111	12114	12112	12076	12101	12110	12103
Adjust. R2	0.725	0.691	0.740	0.841	0.902	0.024	0.909	0.964	0.698	0.934	0.863	0.949

t statistics in parentheses

Table 1.20: Predicted Best Estimator
We use predicted correlation values based on Table 1.19. using average firm characteristics as input.
Panel A shows the number/fraction of firms for which the respective estimator is predicted to perform best. The row *Predicted Mean Correlation* shows the predicted timeseries stock-by-stock correlation if one would always pick this best estimator.
Panel B shows the equal-, size- and observation-weighted average timeseries stock-by-stock correlation of the closing spread and a newly defined estimator. For each stock, this estimator is defined as the estimator that is predicted to perform best (see Panel A). Row *P-value* is the p-value of a ttest that tests whether the correlation of the combined estimator is higher than that of the Closing Spread. Row *Actual Max = Predicted Max* shows the fraction of firms for which the predicted best estimator is actually the best estimator.

PANEL A

Measure	**N**	**%**
Closing Spread CRSP	10027	78.44
Roll 0 (ret)	7	0.05
LOT y-split	1	0.01
FHT	16	0.13
Effective Tick	1035	8.10
Abdi 2-day	266	2.08
VoV High-Low	1019	7.97
Amihud	282	2.21
(-) LIX	48	0.38
Zero	0	0.00
Corwin 0	0	0.00
(-) Gamma	0	0.00
Missing	82	0.64
Predicted Mean Correlation		83.12

PANEL B

Measure	**Rho (equal-weighted)**	**Rho (size-weighted)**	**Rho (obs-weighted)**
Closing Spread CRSP	79.65	68.06	81.33
Maximum Predicted Correlation	80.77	79.59	84.60
P-value	.018		
Actual Max = Predicted Max	60.78		

In summary, the results in this section indicate that the accuracy of the low-frequency estimators depends on firm characteristics in a predictable way. This predictability can be exploited to forecast the accuracy of the low-frequency estimators. A potentially useful application is to determine which of the various low-frequency estimators is expected to perform best for a particular stock. Our results indicate that the accuracy of low-frequency spread estimation can indeed be improved when the predicted best estimator is used for each stock. The improvement is substantial when value-weighted averages of time-series correlations are considered while it is modest when equally-weighted or observation-weighted averages are considered. It should also be noted that the procedure proposed above is only feasible when one is interested in the time-series patterns of liquidity. The procedure is not applicable in a cross-sectional context.

1.4.8 Construction of a Composite Spread Estimator

The various low-frequency estimators that we analyze are conceptually very different. It is therefore conceivable that some combination of estimators may result in a liquidity measure that is superior to any individual estimator. In this section we explore this possibility. However, rather than including all low-frequency estimators in the investigation, we confine the analysis to the following estimators: the CRSP closing spread, the return-based Roll estimator, the Zero estimator, the Corwin and Schultz (2012) high-low estimator, the effective tick estimator, the FHT estimator, the Amihud illiquidity ratio, the Pástor and Stambaugh (2003) gamma, the LIX estimator, the Abdi 2-day estimator, the Tobek VoV high-low estimator and the LOT y-split estimator. These estimators were chosen such that the whole spectrum of estimation concepts is represented. Whenever there are several conceptually similar estimators (e.g. the different versions of the Tobek estimator) we select the one that performed best in the correlation analysis presented above.[30]

We implement two different approaches to construct a composite low-frequency liquidity measure. The first approach starts from the full set of stock-month observations and determines the first principal component of the low-frequency liquidity estimators listed above. We then construct a combined measure as a weighted average of the individual low-frequency estimators, using their loadings in the first principal component as weights.[31] We refer to this estimator as the principal component (PC) estimator. The second approach proceeds as follows. We again start from the full sample of stock-month observations and then calculate, for each month, the equally-weighted average effective spread and the equally-weighted average of the low-frequency estimators, resulting in one time series for the effective spread benchmark and one time series for each of the low-frequency estimators. We then construct a linear combination of the time series of the low frequency estimators and determine the weights such that the resulting time series has maximum correlation with the time series of effective spreads. We then use these weights to construct a composite liquidity estimator which we denote the equally-weighted maximum correlation (MC_{ew}) estimator. We repeat the procedure using a value-weighted instead of the equally-weighted average. The resulting estimator is denoted value-weighted maximum correlation (MC_{vw}) estimator.

We calculate the PC and MC estimators for each stock-month and then evaluate their performance based on the correlations with the effective spread benchmark. We proceed as follows. We first calculate the correlation between the composite estimator and the effective spread benchmark for each stock. We then calculate the average correlation across stocks using three weighting schemes, an equally-weighted average, a value-weighted average, and an observation-weighted average as described above.

The procedure described above is applied to the full sample and thus results in an in-sample evaluation of the composite estimators because we perform the evaluation on the same data set that was used to obtain the weights for the PC/MC estimators. We additionally perform two out-of-sample evaluations. For the first out-of-sample evaluation we split the sample in the middle of the sample period. We then use the first half (1993 to 2002) of the sample to obtain the weights for the composite estimators and use the second half (2003 to 2012) of the sample for the evaluation. For the second out-of-sample evaluation we randomly select 50% of the sample

[30] This implies that the estimators were selected with hindsight. However, even though we selected the components of our composite estimators with hindsight, the composite estimators do not perform better than the best of the individual estimators. Our conclusions are thus not affected by a hindsight bias.

[31] The approach is inspired by Baker and Wurgler (2006) who use a similar approach to construct a composite sentiment measure.

stocks. We then obtain the weights for the PC/MC estimators from the resulting sub-sample and use the other sub-sample to evaluate the estimators.

In order to put the correlations between the composite estimators and the effective spread into perspective, we compare them to the correlations between the CRSP closing spread and the effective spread benchmark. The CRSP closing spread is easily available and easily applicable.[32] If it results in correlations that are equal to, or higher than, those obtained for the composite estimators, then the latter are obviously not a recommendable choice.

The results for the PC estimator are shown in Panel A of Table 1.21. The equally-weighted average correlation between the PC estimator and the effective spread is 70.3%. The value- and observation-weighted averages are larger, at 77.6% and 71.1%. The corresponding correlations for the CRSP closing spread are 79.7%, 81.3% and 68.1%, respectively. We therefore conclude that the PC estimator is inferior to the CRSP closing spread when equally-weighted and observation-weighted averages are considered and slightly improves upon the CRSP closing spread when value-weighted average correlations are considered. However, as can be seen from Table 1.10, the CRSP closing spread is not the best of the individual low-frequency estimators when value-weighted average correlations are considered. The best estimator, the Tobek VoV daily estimator, achieves an average correlation of 72.0% and is thus better than the PC estimator. The out-of-sample performance of the PC estimator is not inferior to the in-sample performance. This is true irrespective of whether we split the sample by time or by randomly sorting the sample stocks into two groups. The out-of-sample average correlations range between 69.9% and 77.6%. However, it is again true that the PC estimator is inferior to the CRSP closing spread when equally-weighted or observation-weighted averages are considered.

Panel B of Table 1.21 shows the results for the MC estimator. They are unambiguous. No matter which weighting scheme is considered, and no matter whether the in-sample evaluation or the out-of-sample evaluation is considered, the MC estimator is inferior to the CRSP closing spread.[33]

The results of this section can be briefly summarized as follows. Both composite estimators that we analyze, the principal component estimator and the two versions of the maximum correlation estimator, are not better than the best of the individual low-frequency estimators. We therefore recommend against practical application of the composite estimators.

[32] We could, of course, use any other individual low-frequency estimator for comparison. Equally-weighted, value-weighted and observation-weighted average correlations for all estimators for the full sample are displayed in Table 1.10.

[33] This result may seem surprising given that (a) the MC estimator was constructed such that it has maximum correlation with the effective spread and that (b) the CRSP closing spread is included in the set of low-frequency estimators that enter the MC composite estimator. However, it should be kept in mind that the MC estimator maximizes the portfolio-level correlation between the effective spread and a linear combination of the low-frequency estimators. The evaluation, on the other hand, is based on the average of the stock-level correlations. In theory one could identify a maximum correlation estimator for each stock individually (though this would not be very informative).

Table 1.21: Composite Spread Estimator

Panel A shows the main results for the Principal Component Analysis:

We identify the first principal component in our monthly dataset using the below listed estimators. The right-hand side of Panel A provides the weight of the respective estimator in the first principal component in percent. *%* shows what fraction of the variation in the estimators can be explained by the first Principal Component. We next calculate the correlation between effective spreads and the principal component on a stock-by-stock basis. As benchmark for the performance of the Principal Component (*PC*), we correlate effective spreads with the Closing Spread from CRSP (*CRSP*). Panel A of this table shows the average Correlation Coefficient ($\bar{\rho}$) across all firms. This average is *equal-*, *value-* or *observation*-weighted. The *Overall* specification shows the results for the entire sample. In specifications *Firm* and *Time* we halved the sample into two equally-sized groups either by time (first period / second period) or by randomly assigning firms to each group. We then calibrate the PCA based on the first sample and test the correlation in the second sample. Variable definitions are identical to those in table 1.10.

Panel B shows results for the Maximum Correlation Estimator:

Based on the equal- or value weighted (*Weighting*) Portfolio Dataset (see Table 1.8), we calculate the correlation between the relative effective spread and a combined estimator $\hat{x}_t = \sum w_i x_{i,t}$ that is a linear combination of the below listed (standardized) estimators $x_{i,t}$. We regard the same samples as in Panel A.

We then try to maximize the thus calculated correlation by adjusting the weights, we put on each estimator: $\max_{w_i} \rho(s_t, \hat{x}_t) s.t \sum w_i = 1$.

The table shows the thus calculated weights in percent for different specifications on the right.

While the weights are calibrated using the Portfolio Dataset (due to computational limitations), we test the performance of the Maximum Correlation Estimator in the same stock-by-stock sample as the Principal component.

Panel A: PCA Estimator

Subsample	%	$\bar{\rho}$ PC	$\bar{\rho}$ (by Obs) PC	$\bar{\rho}$ (by Size) PC	$\bar{\rho}$ CRSP	$\bar{\rho}$ (by Obs) CRSP	$\bar{\rho}$ (by Size) CRSP	Weights: Roll 0 (ret)	Zero	Corwin 0	Closing Spread CRSP	Effective Tick	FHT	Amihud	(-) Gamma	LIX	Abdi 2-day	VoV High-Low	LOT y-split
Overall	56.37	70.33	77.63	71.13	79.65	81.33	68.06	8.82	7.36	9.07	10.57	9.71	10.47	5.84	0.30	7.83	10.66	9.94	9.44
by Time	57.73	71.01	75.03	74.65	76.88	77.04	61.17	8.99	6.38	9.16	10.31	9.69	10.50	6.50	0.29	7.93	10.69	10.19	9.39
by Firm	56.37	69.92	77.59	70.69	79.28	81.21	67.81	8.84	7.36	9.10	10.58	9.71	10.48	5.79	0.28	7.81	10.67	9.92	9.45

Panel B: Maximum Correlation Estimator

Subsample	Weighting	$\bar{\rho}$ PC	$\bar{\rho}$ (by Obs) PC	$\bar{\rho}$ (by Size) PC	$\bar{\rho}$ CRSP	$\bar{\rho}$ (by Obs) CRSP	$\bar{\rho}$ (by Size) CRSP	Weights: Roll 0 (ret)	Zero	Corwin 0	Closing Spread CRSP	Effective Tick	FHT	Amihud	(-) Gamma	LIX	Abdi 2-day	VoV High-Low	LOT y-split
Overall	equal	48.47	61.57	58.16	79.65	81.33	68.06	4.00	47.00	12.00	16.00	0	17.00	0	0	0	0	3.00	0
Overall	value	61.64	70.46	64.18	79.65	81.33	68.06	0	0	0	1.00	0	59.00	1.00	0	14.00	0	20.00	6.00
by Time	equal	38.95	42.18	30.10	73.36	71.89	59.50	14.35	46.87	0	1.21	0	8.42	0	0	29.15	0	0	0
by Time	value	54.81	55.63	40.98	73.36	71.89	59.50	0	0	0	2.55	0	42.59	0	0.59	25.42	0	17.76	11.09
by Firm	equal	52.30	64.44	61.76	80.02	81.45	68.32	5.40	46.01	9.41	20.23	0	15.01	0	0	3.94	0	0	0
by Firm	value	63.46	71.71	66.16	80.02	81.45	68.32	0	0	0	2.60	0	62.12	0.90	0.75	17.33	0	16.31	0

1.4.9 Estimator Performance in Different Regimes

During our sample period the trading protocols of the NYSE and Nasdaq underwent considerable change. Major changes include the adoption of the Nasdaq Order Handling Rules in 1997 (see McInish et al. (1998), Chung and Van Ness (2001)), the introduction of NYSE Open Book in 2002 (see Boehmer et al. (2005)) and the introduction of NYSE Hybrid in 2006/2007 (see Hendershott and Moulton (2011)). Further, the minimum tick size was reduced from eights to sixteenths and later to decimals. In this section we analyze whether the performance of the low-frequency estimators is affected by these changes. For each event we perform a difference-in-differences analysis using a matched control sample of firms that were not affected by the regime change under consideration.

For the two major changes on the NYSE (NYSE Open Book and NYSE Hybrid) we proceed as follows. We define a 6-months pre-event period (July-December 2001 for NYSE Open Book, April-September 2006 for NYSE Hybrid) and a 6-months post-event period (February-July 2002 for NYSE Open Book, February-July 2007 for NYSE Hybrid). The period during which the change took place (January 2002 for NYSE Open Book, October 2006-January 2007 for NYSE Hybrid) is discarded. We then select a Nasdaq match for each NYSE stock. The matching procedure is as described in section 1.4.6. The matching is performed for the first month of the pre-event period.

The reduction of the minimum tick size from sixteenths to decimals occurred in January 2001 for most NYSE stocks and in April 2001 for most Nasdaq stocks.[34] In order to avoid event contamination we define a six-months pre-event period and a two-months post-event period (July-December 2000 and February-March 2001, respectively) for the NYSE and a two-months pre-event period and a six-months post-event period (February-March 2001 and May-October 2001, respectively) for Nasdaq. The matching procedure is as described above.

The Nasdaq Order Handling Rules were introduced between January and October 1997. During this period both the NYSE and Nasdaq also reduced the minimum tick size from eights to sixteenths. The difference-in-differences analysis we perform thus compares the joint effect of the order handling rules and the tick size reduction on Nasdaq to the effect of a tick size reduction on the NYSE. The pre-event period extends from July-December 1996 and the post-event period from November 1997-April 1998. The matching procedure is as described above.

For all five events we perform a difference-in-differences analysis based on cross-sectional correlations. We calculate, for each month of the pre-event and the post-event period, and separately for the treatment and the matched control sample, the cross-sectional correlation between the low-frequency liquidity estimators and the effective spread benchmark. We then regress these correlations on a constant, a dummy variable that identifies the observations in the post-event period, a dummy that identifies observations from the treatment group, and the interaction between the post-event dummy and the treatment dummy. We confine the analysis to the subset of low-frequency estimators described in section 1.4.8. The results are displayed in Table 1.22.

[34] In both markets a small number of stocks was transferred to the new regime earlier. These stocks are completely discarded from our analysis. They are thus included neither in the treatment group nor in the control group.

Table 1.22: Event Compare Diff-in-Diff
We conduct a difference-in-differences analysis of five events: Nasdaq Order Handling Rule (*NASDAQ OHR* below), Nyse Tick Size change from 1/16 to decimals (*NYSE TICK* below), Nasdaq Tick Size change from 1/16 to decimals (*NASDAQ TICK* below), Nyse Open Book (*NYSE OB*) and *NYSE HYBRID.* The diff-in-diff approach is applied to the cross-section (*CS*) of liquidity estimators. For details of the methodology see Section 1.4.9. This table shows the $(Treatment_{Post} - Control_{Post}) - (Treatment_{Pre} - Control_{Pre})$-term. Asterisks indicate the results of a t-test which tests whether the diff-in-diff-term is significantly different from zero. N provides the number of firms in the sample.

	NASDAQ OHR	NYSE TICK	NASDAQ TICK	NYSE OB	NYSE HYBRID
Roll 0 (ret)	0.07**	-0.16**	0.01	-0.02	-0.02
Zero	0.15***	-0.01	0.02	-0.02	-0.02
Corwin 0	0.09***	-0.17*	0.05	-0.02	0.02
Closing Spread CRSP	-0.05***	-0.25**	0.07	-0.10	-0.08
Effective Tick	0.05**	0.21***	0.38***	-0.06*	0.02
FHT	0.12***	-0.11***	-0.01	-0.07	-0.02
Amihud	-0.03	0.02	0.02	-0.01	-0.15**
(-) Gamma	-0.05	0.05	-0.04	0.11	-0.10
LIX	0.04***	0.03	0.04***	0.03	0.05**
Abdi 2-day	0.12***	-0.21**	0.08	-0.05	0.01
VoV High-Low	0.01	-0.01	0.06*	-0.02	0.04
LOT y-split	0.11***	-0.12***	-0.03	-0.02	0.03
N	1415	1336	1307	1259	1252

The introduction of the Nasdaq Order Handling Rules has generally increased the ability of the low-frequency proxies to capture cross-sectional variation in spreads. Nine out of twelve coefficients are positive, and eight of them significantly so. A notable exception is the CRSP closing spread which displays significantly lower cross-sectional correlation after the introduction of the order handling rules.

The tick size reduction from sixteenths to decimals on the NYSE had an overall negative impact on the accuracy of the estimators. Only the performance of the effective tick estimator improves significantly. On the other hand, six estimators (the Roll measure, the high-low spread estimator, the CRSP closing spread, the FHT estimator, the Abdi 2-day estimator and the LOT y-split estimator) perform significantly worse after the tick size reduction. The effective tick estimator appears to generally perform better under a low tick-size regime. It also displays significantly improved performance after the tick size reduction in Nasdaq. The difference-in-differences coefficients for the other estimators are predominantly positive, but much smaller in magnitude than the coefficient for the effective tick estimator. Only two of them (the coefficients for the LIX and the VoV high-low estimators) are significant.

The introduction of NYSE Open Book and NYSE Hybrid did not have much impact on the accuracy of the low-frequency estimators. The majority of the coefficients for the introduction of NYSE Hybrid is negative, but only the coefficient for the effective tick estimator is significant. The results for the introduction of NYSE Hybrid are ambiguous. Six coefficients are positive (but only the coefficient for the LIX estimator is significant) and six are negative (but only the coefficient for the Amihud illiquidity ratio is significant).

Summarizing the results of this section, changes in the trading protocol can affect the performance of the low-frequency estimators. While the introduction of the Nasdaq Order Handling Rules has improved the performance of a majority of the estimators, the tick size reduction on the NYSE has predominantly resulted in lower performance.

1.4.10 Estimator Availability

The CRSP data base contains all data that is required to calculate the estimators considered in this chapter from 1992 onwards. Therefore, researchers using post-1992 US data can indeed select the low-frequency estimator that performs best in their specific application. This may be different when data for other countries or pre-1992 US data is used. In these cases reliable closing bid-ask spreads, daily high and low prices, or trading volume data may be unavailable. Consequently, data availability may be a limiting factor in the choice of an estimator.

In this section, we provide an overview of the data availability in the CRSP universe from December 1925 until December 2015. To this end, we retrieve the entire CRSP database and apply the filters described in Section 1.3.1 and Table 1.2. For each firm-month we then check whether the data necessary to calculate a specific estimator is available. We require at least ten days with non-missing values for the relevant variables in that month.[35] We then calculate the estimator availability ratio

$$EAR_{x,t} = \frac{C_{x,t}}{N_t} \tag{1.18}$$

where $C_{x,t}$ is the number of firms for which estimator x can be calculated in month t, and N_t is the total number of firms in month t. As data requirements for some of the estimators are very similar (see Table 1.1), EARs for those estimators, by definition, are almost identical. For ease of exposition we therefore combine estimators with very similar data requirements into one EAR.[36]

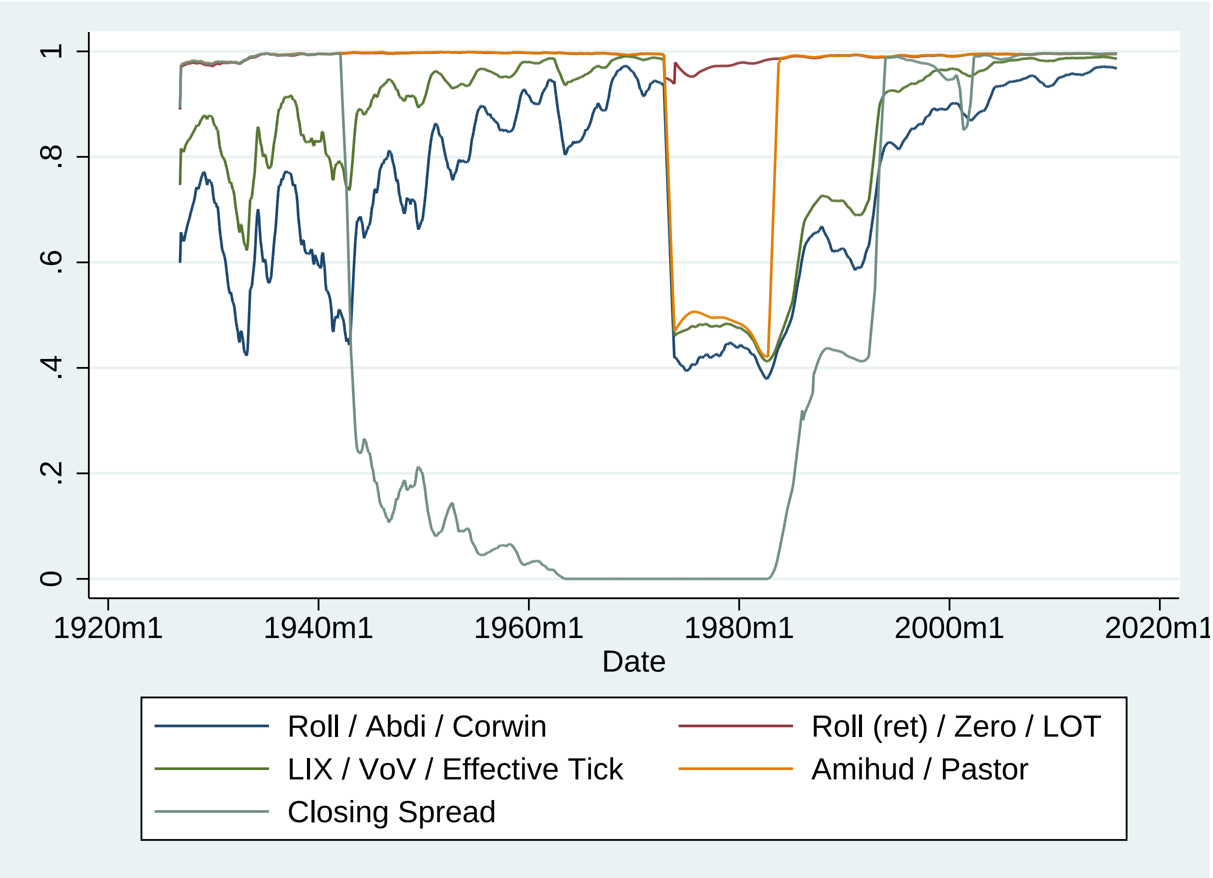
Figure 1.5 shows how the EARs evolve over time. The low-frequency estimators can be categorized into four main groups in terms of their data requirements. The Roll (ret) estimator, the two versions of LOT and the Zero estimator only require return data which is available for almost all firms over the entire sample period (1925-2015). These estimators thus have the best availability (but are, as has been extensively demonstrated in this chapter, not among the most accurate estimators). The Zero 2, Amihud (2002) and Pástor and Stambaugh (2003) estimators additionally require data on trading volume. We observe a sudden drop in the availability of those estimators in the period between December 1972 and October 1982. In December 1972 Nasdaq stocks were added to the CRSP universe. However, volume data on Nasdaq stocks was made available only from November 1982 onwards. The LIX ratio, the Tobek (2016) VoV measures, the Holden (2009b) effective tick estimator, the Roll (1984) measure based on closing prices as well as the Abdi and Ranaldo (2017) measures and the Corwin and Schultz (2012) estimator all require either closing prices or daily high/low prices. The availability of these

[35] The results are qualitatively similar when we require 15 days of non-missing data per stock-month.

[36] We only combine estimators when the time series correlation between their EAR ratios exceeds 95 % and when the mean absolute difference between the EAR ratios is below 5 %.

variables is lower than the availability of return data but steadily improves until December 1972, when the inclusion of Nasdaq stocks leads to a similar drop in data availability as described above for volume data. Finally, the CRSP closing spread measure obviously requires data on closing bid and ask prices. These are only available for specific periods. For NYSE/AMEX stocks they are available between December 1925 and February 1942 and since December 1992. For Nasdaq securities they are available since December 1982.[37]

Figure 1.5: Estimator Availability
This figure plots the estimator availability ratio, defined as $EAR_{x,t} = \frac{C_{x,t}}{N_t}$, with $C_{x,t}$ being the number of firms for which estimator x can be calculated in month t and N_t being the total number of firms in month t. We plot EAR for the entire CRSP universe from December 1925 to December 2015 (after applying the same filters as in our main analysis). When calculating $C_{x,t}$, we require a minimum of ten daily observations to calculate estimator x. The results do not change significantly if you require only one or even 15 days. To gain a better overview, we combine estimators with very similar data requirements into one EAR. We assure that estimator x and y are only combined if $cor(EAR_x, EAR_y) > 0.95$ and the MAE is below 5%.



In summary, the accuracy and availability of the low frequency estimators appear to be inversely related. Specifically, the estimators with the best overall performance, the Tobek (2016) VoV estimators and, in particular, the CRSP closing spread have the lowest availability within the CRSP universe.

[37]For details see Chung and Zhang (2014).

1.5 Conclusion

In this chapter we perform a comprehensive comparative analysis of low-frequency measures of liquidity. Our main objective is to provide researchers with clear guidelines for the selection of the best liquidity estimator in a specific research application. The cornerstone of our analysis is a horse race between a comprehensive set of low-frequency liquidity estimators (including the CRSP closing spread) proposed in the literature.

Among the most important determinants of a specific research application are data availability (e.g. only daily returns, closing prices and daily volume, or prices, volume and high-low prices) and the sample at hand (e.g. large-caps or small-caps). Further, researchers may be primarily interested in the bid-ask spread or in the price impact, and they may be interested in levels or in first differences of the variable of interest. Finally, in some applications the cross-sectional differences in liquidity are of prime importance while in other applications the time-series properties of liquidity are most important.

In order to capture all these aspects we implement several approaches aiming to compare the low-frequency liquidity measures. Specifically, we consider both time-series correlations and cross-sectional correlations, we apply different weighting schemes, we calculate mean absolute and root mean squared errors, and we use both the effective spread and the price impact (both in levels and in first differences) as benchmark measures. We further analyze how stock characteristics such as firm size and market characteristics such as the minimum tick size regime or the level of transparency affect the performance of the low-frequency liquidity proxies. Finally, we develop two composite low-frequency estimators and test whether they perform better than the best of the individual estimators.

We implement our analysis on a broad sample of more than 10,000 US stocks listed on the NYSE, AMEX and Nasdaq and covering 1993-2012. A central finding is that both the absolute and the relative performance of many of the low-frequency estimators is highly dependent on the specific setting and on the criterion used to evaluate the performance of the estimators.

In spite of these differences several general patterns emerge. First, the estimators are generally better at explaining levels than at explaining first differences, and they are better at explaining the effective spread than the price impact. On the other hand, the data aggregation (i.e. the question whether the low-frequency estimators are calculated at the stock-month level or the stock-year level) does not materially affect the relative performance of the estimators. The composite estimators that we develop do not improve upon the performance of the best individual estimators. The introduction of the Nasdaq Order Handling Rules has improved the performance of a majority of the estimators while the tick size reduction on the NYSE has predominantly resulted in lower performance. Other changes in the trading protocol, namely the introduction of NYSE Open Book or NYSE Hybrid, did not have first-order effects on the performance of the low-frequency liquidity proxies.

The estimators that display the highest cross-sectional and stock-level time-series correlation with the benchmark measures are the estimators recently proposed by Tobek (2016) and the CRSP closing spread. The estimator that results in the smallest mean absolute and root mean squared error, on the other hand, is the Abdi 2-day estimator proposed by Abdi and Ranaldo

(2017). The Roll (1984) (ret) as well as the Zero and LOT measure proposed by Lesmond et al. (1999) have the lowest data requirements. They can thus be calculated for almost the entire CRSP universe back until 1925. On the other hand, the best performing estimators, the Tobek (2016) VoV estimators and the CRSP closing spread, have higher data requirements and, correspondingly, lower availability.

Figure 1.1 provides a brief summary of our results and may guide researchers' selection of an appropriate estimator in a specific research setting. It should be noted, though, that the recommendations given in Figure 1.1 are based on evidence from the US. The extent to which our results are valid for other countries is an open issue that may be explored in future research.

Appendix to Chapter 1

A The effective tick estimator on a decimal price grid

Holden (2009b) develops a version of the effective tick estimator specifically for a minimum tick size of \$ $\frac{1}{8}$ but provides the necessary modifications to accomodate any other price grid in Holden (2009a). Our sample period covers three minimum tick size regimes: eighths, sixteenths, and decimals. We here derive a version of the Holden (2009b) model for a decimal price grid with possible spreads: $s_1 = 0.01$, $s_2 = 0.05$, $s_3 = 0.1$, $s_4 = 0.25$, $s_5 = 0.5$ and $s_6 = 1.00$. Each day, we calculate the probability that a given closing price C_t was generated by above spreads. Next, we weight the different spreads by their respective probability to arrive at the effective tick spread estimator.

The model takes into account that on zero volume days, the data field of closing prices will contain the average of bid and ask during that day. Therefore, the model differentiates between trading and no trading days.
Let A_j be the total number of possible trade prices, which may result from spread s_j ($j \in \{1, 2, 3, 4, 5, 6\}$). Let A_{6+j} be the number of midpoints measured for non-trading days. For a 0.01-spread on a zero volume day one could then encounter every odd half cent price. Let B_j and B_{6+j} be the number of "special" prices/midpoints that can be generated by the jth spread but not by any larger spread. Let O_{jk} be the number of price increments of the jth spread that overlap with price increments of the kth spread ($k < j$) and do not overlap with the prices that can be generated by spreads between the jth and the kth spread. Table A1.1 summarizes those variables for the decimal grid.

Table A1.1: A_j, B_j, O_{jk} for a decimal price grid in the style of Holden (2009a, p.6)

j	Spread	Price/Midpoint	A_j	B_j	O_{jk}				
1	0.01	Price	100	80					
2	0.05	Price	20	8	$O_{21} = 20$				
3	0.10	Price	10	8	$O_{31} = 0$	$O_{32} = 10$			
4	0.25	Price	4	2	$O_{41} = 0$	$O_{42} = 2$	$O_{43} = 2$		
5	0.50	Price	2	1	$O_{51} = 0$	$O_{52} = 0$	$O_{53} = 0$	$O_{54} = 2$	
6	1.00	Price	1	1	$O_{61} = 0$	$O_{62} = 0$	$O_{63} = 0$	$O_{64} = 0$	$O_{65} = 1$
7	0.01	Midpoint: 0.005	100	80					
8	0.05	Midpoint: 0.025	20	16	$O_{87} = 20$				
9	0.10	Midpoint: 0.050	10	8	$O_{97} = 0$	$O_{98} = 0$			
10	0.25	Midpoint: 0.125	4	4	$O_{10,7} = 0$	$O_{10,8} = 4$	$O_{10,9} = 0$		
11	0.50	Midpoint: 0.250	2	2	$O_{11,7} = 0$	$O_{11,8} = 0$	$O_{11,9} = 2$	$O_{11,10} = 0$	
12	1.00	Midpoint: 0.500	1	1	$O_{12,7} = 0$	$O_{12,8} = 0$	$O_{12,9} = 0$	$O_{12,10} = 0$	$O_{12,11} = 0$

Let's first have a look at the B_j's. In a 1 cent grid 100 price endings can be generated ($A_1 = 100$). But some of those 100 increments could also have been generated by larger spreads. All prices ending on X.Y5 or X.Y0 could also have been generated by the 0.05 spread. Those 20 increments are thus not "special" to the 0.01 spread. The other 80 spreads ending on 1,2,3,4,6,7,8 or 9 can not be generated by any other of the regarded spreads. Observing one of those, we can infer that they could not be generated by any larger spread. As 0.01 is the lowest spread we also know that no smaller spread can generate those and thus all of those 80 price endings are generated by a 0.01 spread.

Next, consider the 0.05 spread, which can generate X.Y5 and X.Y0 endings ($A_2 = 1.00/0.05 = 20$). The 10 X.Y0 endings can also be generated by a spread of 0.10 which reduces the set to ten candidates for being "special". Of those, X.25 and X.75 could be the result of a 0.25 spread, which leads to $B_2 = 8$ in table A1.1: X.05, X.15, X.35, X.45, X.55, X.65, X.85, X.95. As every of those 8 prices can also be generated by a 0.01 spread, we can not directly conclude that these prices were generated by a 0.05 spread.
The same considerations apply to midpoints. However, the "bisection" of the spread may change the relation of increments (it does not need to hold that $B_j = B_{6+j}$). Consider for example the midpoints of the 0.05 spread: 0.025, 0.075, ... While $2 * 0.05 = 0.1$, $\frac{0.05}{2} + 0.05 \neq \frac{0.1}{2}$. Thus, 16 0.05 midpoints are "special", as only X.125, X.375, X.625 and X.875 can be the result of a 0.25-spread.

Next, let's consider the O_{jk}s. We already noted, that observing a price of X.25, we can not directly conclude that this price was generated by a 0.25 spread as larger spreads usually "include" the lower ones, meaning that this price could also be a result of the smaller spreads 0.05 or 0.01, but not 0.10. O_{jk} measures this kind of relationship between prices. Of the 4 prices generated by the 0.25 spread, (X.25, X.50, X.75, X.00) two (X.50, X.00) could also be generated by a 0.1 spread and all of the four prices could follow from a 0.05 spread. By definition of O_{jk} those prices that are already mapped to the 0.1 spread are excluded from the count for the 0.05 spread.

For each firm-month, let N_j be the number of observed "special" prices for spread j. Then $F_j = \frac{N_j}{\sum_{j=1}^{12} N_j}$ is the fraction of closing trades that is generated by the jth or any smaller spread.
Note that we divide by the total number of days, that could result from either trading or non-trading days.

With A_j, B_j, O_{jk} and F_j at hand one can now determine the conditional probability of the jth spread, given observed price .XX.
For simplicity assume that there were no zero volume days. We already noted that $P(S_t = s_1 | C_t \text{ is ending on } 1,2,3,4,6,7,8,9) = 1$. One would now be tempted to propose that $P(S_t = s_1) = 1 * F_1$ But what about prices ending on 5 or 10, which also could have been generated by a 0.01 spread. Holden (2009b) addresses this issue by assuming a uniform price distribution over the grid, resulting in $P(S_t = s_1) = 1 * F_1 * \frac{A_j}{B_j} = F_1 * \frac{100}{80}$. This simplified example carries

over to the generalized pricing formula:

$$U = \begin{cases} \left(\frac{A_1}{B_1}\right) F_1 + \left(\frac{A_7}{B_7}\right) F_7 & j = 1 \\ \left(\frac{A_j}{B_j}\right) F_j - \sum\limits_{k=1}^{j-1} \left(\frac{O_{j,k}}{B_k}\right) F_k + \left(\frac{A_{6+j}}{B_{6+j}}\right) F_{6+j} - \sum\limits_{k=1}^{j-1} \left(\frac{O_{6+j,k}}{B_{6+k}}\right) F_{6+k} & j = 2, 3, ..., 12 \end{cases} \tag{1.19}$$

For a spread of 0.01, this formula look exactly the way we just derived it, except that we now add the probability of zero volume days with 0.01 spreads to that of trading days. For higher order price grids, e.g. the 0.25 spread, The first term is identical. But knowing that any X.00, X.25, X.50 or X.75 price could be the result of a smaller spread (here the 0.01, 0.05 or 0.10 spread) this term would overestimate the probability of 0.25 spread grids. One thus needs to subtract the probability that this price was generated by any lower spread. $\frac{O_{4,3}}{B_3} F_3 = \frac{2}{8} F_3$ is the probability that the two increments X.00 or X.50 were actually generated by a 0.10 or lower grid.

As F_js are based on a small sample of closing prices U_js might fall outside the range between 0 and 1. Therefore Holden (2009b) imposes constraints on the empirical probabilites of specific price grids $\hat{\gamma}_j$s:

$$\hat{\gamma}_j = \begin{cases} min\left[max\left(U_j; 0\right); 1\right] & j = 1 \\ min\left[max\left(U_j; 0\right); 1 - \sum\limits_{k=1}^{5} \hat{\gamma}_k\right] & j = 2, 3, ..., 12 \end{cases} \tag{1.20}$$

Effective Ticks then are calculated as

$$EffectiveTick = \frac{\sum\limits_{j=1}^{6} \hat{\gamma}_j s_j}{\bar{P}}, \tag{1.21}$$

Chapter 2

May I have your Attention, Please: The Market Microstructure of Investor Attention

2.1 Introduction

Attention is a scarce cognitive resource and attention-constrained investors have to be selective while processing information (Kahneman (1973)). This challenge might even have been exacerbated in recent years by the increased information availability through the Internet and social media. Too little attention towards important news might lead to delayed reaction times while too much attention towards stale information might lead to an overreaction (see Barber and Odean (2013)). Theory suggests that attention has an important influence on asset prices (Peng and Xiong (2006)), risk taking (Bordalo et al. (2012)) and volatility (Andrei and Hasler (2014)). It is the purpose of this study to clarify the impact of daily active investor attention on a stock's trading dynamics as measured by liquidity, turnover, volatility, and returns. Furthermore, this study explains the underlying dynamics of informed and uninformed trading in an attention-trading model based on Easley et al. (1996).

The analysis shows that attention, as measured by daily Google Search Volume, increases both volatility and turnover in the German stock market but has only weak or no influence on daily stock returns and liquidity. The relation between attention and trading dynamics is stronger for large stocks, stocks with a generally lower level of cross-sectional attention, and stocks with a higher proportion of retail trading. Our findings are robust to a large variety of regression methodologies, subsample sorts, and endogeneity tests.

We find evidence for increased trading by both uninformed and informed traders on high attention days. As increases in uninformed trading are not entirely offset by increases in informed trading, high attention results in a lower probability of informed trading on high attention days.

This chapter contributes to the existing literature by establishing a refined and more precise measure of daily investor attention, namely *daily* Google Search Volume. A novel and sophisticated download methodology is developed which allows to retrieve a time series of eight years of *daily* Google Search Volume. Most of the literature is limited to weekly Google Search Volume and thus to the weekly relation between attention and liquidity/returns, as Google limits data downloads to weekly time series for longer time horizons.[1,2] This chapter establishes that the daily Google Search Volume has distinct features that are different from the weekly search volume and from other attention proxies like Wikipedia page views and Bloomberg search frequencies. Furthermore, it is the first to show that an attention index, retrieved from Google trends, is highly correlated with actual daily search requests. This correlation suggests that the retrieved time series of daily Google Search Volume is an adequate measure of attention that can be used in further research. The presented methodology opens the Google Search Volume to a new set of applications in financial research. Additionally, the Search Volume download is refined by using the firm names and by using the feature offered by Google to filter for those searches that are only related to 'Finance'.

This chapter aims to better understand the market microstructure implications of varying investor attention. In contrast to the existing literature, changes in attention are related to measures of market quality derived from intraday data (daily volatility, spreads, market depth and price impact), allowing for an analysis of the multiple dimensions of liquidity and insights into market dynamics that could not be derived from data on a daily frequency. Also, the chapter contributes to the understanding of the trading dynamics and the price-formation process in a market with heterogeneously informed investors with varying levels of attention. In particular, the dynamics of informed and uninformed trading on high attention days and their influence on liquidity are unraveled in an attention-adjusted market microstructure model based on the theoretical models of Glosten and Milgrom (1985) and Easley et al. (1996). The model helps to better understand the strategic decisions of informed and uninformed traders, their influence on the adverse-selection costs, and the liquidity of a stock. Finally, in contrast to many other studies in this field, the identification strategy in this study relies on the within-firm time-series variation of attention. We do not limit our analysis to specific firm events, like e.g. earnings announcements, but want to understand the impact of every-day fluctuations in investor attention.

This work is the first to analyze the daily attention trading dynamics in the German stock market.[3] This setting not only helps to provide external validity to the existing literature that mainly focuses on US equity markets[4] but also allows us to exploit some peculiarities of the German equity market: With Stuttgart Stock Exchange Germany has a marketplace that is

[1]Exceptions from this are Drake et al. (2012), who use daily Google search volume in disconnected time intervals of three months in an event study setup and Da et al. (2014).

[2]In this study, the daily search volume offers additional, more precise information as shown e.g. by the higher correlation between traditional attention measures and the Google Search Volume.

[3]Another study, analyzing attention based trading in the German market can be found in Bank et al. (2011). This chapter differs from their approach by using more precise liquidity measures (intraday spreads vs. weekly Amihud (2002)) on a higher frequency (daily vs. weekly). Additionally, the evidence of the microstructure model in this paper illustrates a decision making process that is fundamentally different from the one in Bank et al. (2011) (see Section 2.2). As a consequence, and in contrast to Bank et al. (2011) we find no signifincant relation between attention and liquidity (see Section 2.6).

[4]Several studies have shown differences in culture and market structure between the US and Germany that impact trading outcomes: Examples are differences in overconfidence(Jlassi et al. (2014)), home bias (Chan et al. (2005)), risk aversion (Rieger et al. (2014)) and the degree of algorithmic trading (Boehmer et al. (2015)).

specifically tailored to retail traders. Previous literature identifies attention as a retail trading phenomenon (Barber and Odean (2008), Da et al. (2011)). We use trading data from Stuttgart Stock Exchange to observe the attention-trade dynamics relation in a retail trader environment.[5] Also, we use local holidays in some regions of Germany to better identify the impact of attention on trading dynamics.

Section 2.2 presents the related literature and develops hypotheses. Section 2.3 describes the model that relates informed and uninformed trading T high attention days. Section 2.4 presents the dataset (most importantly the algorithm to arrive at a robust daily measure of Google search volume) and variable descriptions. Daily Google Search Volume is compared and evaluated against other attention measures in section 2.5. In Section 2.6, results of the model estimation are provided. Afterwards, trade dynamics on high investor attention days are analyzed. The developed relationships are tested for robustness in various settings. Section 2.7 analyzes possible endogeneity issues in the relation between attention and the different measures of trade dynamics. Section 2.8 concludes.

2.2 Literature Review and Hypotheses

Investor attention is an important behavioral concept. Merton (1987) finds that if investor attention is directed to a certain stock, this stock becomes a part of their investment choice set. As, in their investment decisions, investors are constrained to the stocks that capture their attention, not all information is immediately processed and incorporated into stock prices as assumed by the theoretical asset pricing theories such as the Capital Asset Pricing model by Sharpe (1964) and Lintner (1965). Attention-constrained investors will consider attention-grabbing stocks first, which will in turn influence the demand and prices of these assets.

Empirically testing the influence of attention on market outcomes became possible with the emerge of new data sources over the last decade. Since then researchers have established various attention proxies and related them to market outcomes: Barber and Odean (2008) identify attention-grabbing stocks by their news coverage, abnormal returns and abnormal trading volume on the previous trading day. Grullon et al. (2004) and Lou (2014) proxy the attention a firm receives by its marketing expenditures and Kent and Allen (1994) measure attention based on brand familiarity. Kim and Meschke (2011) measure attention by counting CEO interviews on TV and general news coverage. Others (Seasholes and Wu (2007), Li and Yu (2012), Yuan (2015)) proxy attention by extreme return events. Bazley et al. (2017) show that market outcomes presented in the colour red reduce risk taking by investors. DellaVigna and Pollet (2009) and deHaan et al. (2015) find less investor attention on Fridays, after market closure and on days with distracting events. All the proposed measures and identification strategies presented above are assumed to be likely drivers of attention, but are rather indirect. Choi and Varian (2012), Mondria et al. (2010) and Da et al. (2011) propose a more direct measure of investor attention using search frequency in Google. Once the investors' interest in a certain stock is raised, it becomes part of their choice set, and they will directly allocate attention to the stock

[5] https://www.boerse-stuttgart.de/en/company/about-us/

via an inexpensive Google search request. If someone is googling a term, this directly implies a minimum degree of interest. Other more direct attention measures employed by the literature are logins to retirement accounts (Sicherman et al. (2015)) and Wikipedia page views (Ungeheuer (2017) and Focke et al. (2016)). Active attention of institutional investors is proxied by download numbers from SEC's EDGAR database (Drake et al. (2017)) and Bloomberg article searches (Ben-Rephael et al. (2017)). While this study establishes a refined version of the Google search volume, we devote a section of this chapter to the comparison of these different attention measures.

Attention obviously is a consequence of the interplay of a variety of attention drivers. Likely candidates for determinants of attention are, for example, all above listed indirect attention measures. In this study, we focus on attention as the driver of market outcomes and are rather impartial to the potential causes of attention. For the understanding of this work, it is nevertheless helpful to get an overview on potential attention drivers. Ungeheuer (2017) specifically addresses this question and finds that stocks being ranked as daily winners or losers experience large spikes in attention. Lou (2014), Madsen and Niessner (2016) and Focke et al. (2016) show that attention is driven by a firm's advertising expenditures. Fang and Peress (2009), Engelberg et al. (2012), Solomon et al. (2014) and Hillert et al. (2014) show that attention is related to media coverage.

Theoretical and empirical research has identified several consequences of increased attention that shall be discussed in the following section: Many studies have related attention to stock returns and trading volumes: In Merton (1987) attention is a necessary condition for trading and thus should be related to trading volume. Also, higher attention might lead to higher dispersion in opinion and thus foster trading (see Hong and Stein (1999)). Assuming that retail investor attention should not fundamentally affect prices, any price reaction should be temporary and price corrections should depend on limits to arbitrage considerations. Empirically, Gervais et al. (2001) shows that stocks with abnormally high volume show positive returns over the following month. Huberman and Regev (2001) present case study evidence of a newspaper article that did not provide any new fundamental information but anyways positively influenced stock prices. Barber and Odean (2008) were one of the first to find that attention has a positive short-term effect on stock prices. They show empirically that attention-grabbing stocks have a higher turnover and volume but perform badly in the long run. Additionally, they find an asymmetry in the influence of attention on the trading patterns in buys and sells. They hypothesize that the possible attention effect is stronger for buyers as compared to sellers because retail investors can only sell the stocks they already own. This short-term positive and long-term negative relation between attention and returns is confirmed by Da et al. (2011) who show that stocks with higher abnormal Google Search volume outperform within a 2-week window followed by a return reversal within one year. Seasholes and Wu (2007) find a similar return pattern in the Shanghai market. Bank et al. (2011) provide confirming results for the German stock market, also documenting a positive effect of attention on trading volume. Latoeiro et al. (2013) document a negative return effect for European large caps and Vozlyublennaia (2014) a short-lived relation between attention and index returns. Yuan (2015) shows that market-wide attention shocks negatively influence market returns. Kumar et al. (2018) provide evidence that stocks ranked as daily winners and losers attract investor attention, resulting in retail traders' buying pressure that leads to those stocks being overpriced. In line with the attention-induced overpricing hypothesis, Joseph et al. (2011) show that the short-term positive relation is weaker for stocks that are easier to arbitrage. Others have tested the implications of attention on stock prices around specific firm events: DellaVigna and Pollet (2009) and Hirshleifer et al. (2009) show that earnings announcements are connected to a weaker immediate and stronger delayed response if investors pay less attention (proxied by a higher number of concurrent earnings announcements or announcements on Fridays).[6] In line with this, Drake et al. (2012) show that higher pre announcement Google Search Volume leads to a more immediate response to earnings news. In line with empirical evidence, Gödker and Lukas (2017) show in an experimental setting that higher attention leads to higher buying volume.

Taken together, above evidence predicts a positive short-term relation between attention and returns / trading volume.

Hypothesis 1: *Trading volume is higher on high attention days.*

Hypothesis 2: *Returns are higher on high attention days.*

It should be noted however, that, in contrast to above studies, we employ a daily attention measure and observe daily returns (as opposed to weekly or monthly returns). Also, we clearly differentiate between buying and selling volume. Our study thus adds to the understanding of the short-term effects of attention on market outcomes.

Fewer studies have related attention to stock market volatility. Andrei and Hasler (2014) show theoretically that stock return variance and risk premia should increase with attention. In their model, news on low attention days will only be gradually incorporated into prices which reduces volatility. Vlastakis and Markellos (2012) using a sample of 30 US large caps show that attention and volatility are positively related on a weekly frequency after controlling for information supply. Dimpfl and Jank (2016) find that Google searches for the term 'dow' are positively correlated with realized volatility of the Dow Jones Industrial Average index. Foucault et al. (2011) find that trading by retail investors induces higher levels of volatility. In line with the theoretical predictions of Andrei and Hasler (2014) and the intuition that more attention of retail traders leads to more noise trading and thus higher volatility, those papers predict a positive relation between attention and volatility.

Hypothesis 3: *Volatility is higher on high attention days.*

We add to this evidence by presenting results on a broader firm sample using a daily measure of realized volatility derived from intraday data.

Theoretical market microstructure models (see Kyle (1985)) suggest that in a market with heterogeneously informed investors a relatively higher fraction of uninformed traders should improve liquidity. If attention positively influences the arrival rate of uninformed traders this

[6] deHaan et al. (2015) and Niessner (2015) find that managers strategically release bad news on low-attention days.

might have positive effects on liquidity. Empirical evidence is largely in line with this conjecture: Corwin and Coughenour (2008) show that limited attention from NYSE specialists reduces their liquidity provision. Bank et al. (2011) provide evidence for Germany that illiquidity (measured by the Amihud (2002) illiquidity ratio) is negatively related to Google Search volume. This is confirmed by Ding and Hou (2015) for a sample of US stocks. Jacobs and Hillert (2015) show that stocks that appear near the top of an alphabetical listing (and thus might catch more attention) have higher liquidity compared to stocks at the bottom of that list.

Hypothesis 4: *Liquidity is higher on high attention days.*

As presented above, many studies have already analyzed the relationship between attention and volumes, returns, volatility and liquidity. Against this background, our study makes several contributions: First, the measures of attention and market quality employed in this study come at a higher frequency than those employed by the existing literature and thus allow to identify the short-term influence of attention. Second, we account for multiple dimensions of liquidity (spreads, depth and price impact). Third, in contrast to most studies, identification is derived from within-firm fluctuations of attention over time. Most other studies have concentrated on cross-sectional differences in attention.

The market microstructure literature identifies three main components of trading costs (see e.g., Huang and Stoll (1997)): Order processing costs, inventory holding costs, and adverse selection costs. Adverse selection costs represent the largest cost component (Stoll (1989); Huang and Stoll (1997)) and stem from investor heterogeneity. As market makers cannot differentiate between informed and uninformed investors, they will expect to incur a loss when trading with informed investors, who will have more information about the true value of the asset. Therefore, a market maker needs to increase the bid-ask spread to compensate for expected losses.[7] This problem of adverse selection was first discussed in the models by Bagehot (1971), Copeland and Galai (1983), Glosten and Milgrom (1985) and Kyle (1985). Barber and Odean (2008), Da et al. (2011) and Bank et al. (2011) assume that a Web search for information by uninformed investors reduces the costs of asymmetric information. They argue that uninformed investors become more informed, which in turn reduces adverse selection cost and increases liquidity. An alternative theory could be the following: Assuming semi-strong efficient markets, one could argue that internet searches do not provide any valuable information but only increase the arrival rate of uninformed traders to the market. This leads to two competing hypotheses: First, uninformed traders are influenced in their decision making by their level of attention. They trade more aggressively on high attention days. Everything else being equal, this behavior would lead to more natural liquidity in the market. However, if more uninformed attention traders are in the market (and this is known by insiders), informed traders themselves may strategically adjust their behavior. The larger uninformed order flow makes it more difficult for the market maker to detect insider trading on high attention days. Therefore insiders may trade more frequently and aggressively as they can camouflage their trades within uformed order flow. In this scenario, on

[7] In a typical market-maker market, this spread represents the gross proceeds of the market maker, as he buys stocks at the bid and sells them at the ask price. The higher the bid-ask spread set by the market maker, the higher the cost of trading for market participants.

high attention days, the effect of the increased uninformed trading is reduced or even reversed.

Hypothesis 5: *Both, informed and uninformed traders, trade more on high attention days.*

The model presented in Section 2.3 offers a tool for quantifying both effects by estimating uninformed and informed arrival rates on high and low attention days separately.

2.3 Model of Informed and Uninformed Trading on Attention Days

Easley et al. (1996) develop an empirically testable model that describes and tests the dynamics and channels of the trading behavior of informed and uninformed trading. They develop an empirically testable microstructure model, based on the framework by Glosten and Milgrom (1985), to identify the probability of informed trading (the proportion of informed over all traders on a certain day) in a stock. In this chapter, the Easley et al. (1996) is estimated for low and high attention days separately. In the following, the Easley et al. (1996) and the underlying Glosten and Milgrom (1985) model are explained and the model adjustments are presented.

Every trading day, nature determines if a news event occurs that influences the value of the risky asset or not. The probability for a news event is α. The probability that the news is bad/good equals δ or $(1 - \delta)$ respectively. There are three types of market participants in the Glosten and Milgrom (1985) model world: uninformed traders who randomly buy and sell assets due to some exogenous trading need, informed traders who (prior to the other market participants) receive some signal about the value of an asset and trade based on this information, and finally a competitive market maker that stands ready as a counterparty of trade for the two previously named trader types. The market maker faces some adverse selection costs due to the chance that his counterparty could be an informed trader. Therefore, he demands a fee (the spread) from anyone who trades with him (uninformed as well as informed traders, as they cannot be distinguished by the market maker). The buy and sell trades of the informed and uninformed traders on days with good, bad, and no news follow three mutually independent Poisson processes.[8]

Up to this point, our proposed model does not differ from the Easley et al. (1996) model. The only adjustment that is made is the replacement of the unknown exogenous stimulus, which determines the uniformed trader's market arrival, by the uninformed trader's attention towards the asset. The arrival rate of the uninformed investor is not constant as in the original model of Easley et al. (1996) but depends on his attention. Furthermore, the arrival rate of the informed investor does not just depend on the news events but also on the level of attention of the uninformed investor.[9] Subsequently, the behavior of uninformed and informed traders

[8]Note that we apply this model to a limit order market.

[9]Admati and Pfleiderer (1988), Lei and Wu (2005), and Duarte and Young (2009) question the trading motives (information and exogenous liquidity needs) of informed and uninformed traders as proposed by Easley et al. (1996). Admati and Pfleiderer (1988) find theoretically that uninformed traders coordinate their trading to reduce transaction costs. They also find that with a higher uninformed coordination, more informed traders are in the market. Lei and Wu (2005) model the arrival rates of uninformed traders based on time-varying market variables and let the informed traders strategically adjust their behavior. Their model is closest to the presented

on high/low attention days is specifically modeled. In the empirical implementation of the model, the uninformed arrival rate may take two states (high attention/low attention), which are proxied by the instrument of Google Search Volume.[10]

As in Easley et al. (1996) the uninformed buy arrival ($\varepsilon_t^{b,ha}, \varepsilon_t^{b,la}$) and sell arrival ($\varepsilon_t^{s,ha}, \varepsilon_t^{s,la}$) rates are distinguished. The buy and sell arrival rates are allowed to be different on high (ha) and low (la) attention days. There is no restriction implemented to ensure that high-attention day arrival rates are greater than low-attention day arrival rates, although this would be in line with our hypotheses. The arrival of the informed traders is measured by μ_t^{ha} and μ_t^{la}. We assume that informed traders know about the attention in the market at the beginning of the trading day (as they can observe previous days' and contemporaneous Google Search Volume). Thus, they can adjust their level of aggressiveness as a function of uniformed traders' attention. Changes in μ could be both, a reaction to changes in ε or a reaction to an information event that, at the same time, affects attention of uninformed investors. The informed trader is expected to trade more actively based on his informational advantage if he can better hide his trades in the order flow of uninformed traders on high-attention days.[11] Again, this behavior is not enforced by the model, and μ_t^{ha} and μ_t^{la} could take any value (e.g., be equal to each other). In addition to informed and uninformed trading on high and low attention days, the probability for news (α) and bad news events (δ) are allowed to vary freely. This allows for testing whether more news events happen if attention is high.[12] Figure A2.1 in the Appendix exemplifies the whole process. The extended model allows for testing whether and how attention influences the arrival rates of the uninformed and informed trading by looking at the difference of the parameters in the low and high attention states.

The trading process is estimated in a maximum likelihood framework. The intuition of this approach is that the order imbalance between buys and sells tells something about the participating trader types. The model parameters are estimated per company for all assets of the sample (see Section 2.4). The likelihood function takes the daily buys, sells, and Google search volume as input parameters and provides estimates of $\hat{\theta} = \alpha^{ha}, \alpha^{la}, \delta^{ha}, \delta^{la}, \varepsilon_t^{b,ha}, \varepsilon_t^{b,la}, \varepsilon_t^{s,ha}, \varepsilon_t^{s,la}, \mu_t^{ha}, \mu_t^{la}$ per stock.[13] In the maximum likelihood estimation, the α and δ parameters are restricted to lie in the closed interval between 0 and 1. The ε and μ parameters are required to be larger than or equal to zero. The starting values of the optimization are a critical choice. Yan and Zhang (2012) find that they have an influence on the optimal solution of the problem and, specified correctly, help to prevent the optimization ending up in a boundary solution for α or δ. The optimization follows the approach of Yan and Zhang (2012) and runs the maximization from

model. Duarte and Young (2009) find that PIN does ignore the positive correlation between buy and sell arrival rates. They develop a measure of symmetric order flow shocks that could conceptionally be explained by investor attention. Their findings are in line with the results in this model.

[10] Googling the asset will not provide the investor with insider information (in this case he would become an informed trader); however his information demand potentially indicates a higher likelihood of trading.

[11] An additional interpretation of the informational advantage of the informed trader could be that he is a high-frequency trader. Low latency traders would typically increase their trading in high attention times, characterized by higher natural liquidity, to better exploit their trading speed advantage. Chakrabarty et al. (2018) show that market inefficiencies around low-attention earnings announcements are reduced in the presence of high frequency traders.

[12] One could expect that investors' attention is high in expectation of news events.

[13] For details on the estimation procedure and derivation of the likelihood function, see Easley et al. (1996).

different starting values. The initial parameters depend on the mean buys ($\bar{B}$) and sells ($\bar{S}$) per firm on high and low attention days and are specified as follows[14]:

$$\alpha^0 = \alpha_i,\ \delta^0 = \delta_j,\ \varepsilon_b^0 = \gamma_k \bar{B},\ \mu^0 = \frac{\bar{B} - \varepsilon_b^0}{\alpha^0(1-\delta^0)}\ and\ \varepsilon_s^0 = \bar{S} - \alpha^0\delta^0\mu^0 \tag{2.1}$$

Parameters α_i,δ_j,γ_k take values from the grid (0.1, 0.3, 0.5, 0.7, 0.9) and consequently there are 125 combinations of starting parameters per firm. Of the 125 combinations per high and low attention day, only the non-boundary solution with the highest likelihood value is taken.

From the parameter estimates, the probability of informed trading (PIN) measure is derived as in Easley et al. (1996). This measure can be derived separately for the high and low attention states as:

$$\begin{aligned} PIN_t^{low\ attention} &= \alpha^{la}\mu_t^{la}/(\varepsilon_t^{b,la} + \varepsilon_t^{s,la} + \alpha^{la}\mu_t^{la}) \\ PIN_t^{high\ attention} &= \alpha^{ha}\mu_t^{ha}/(\varepsilon_t^{b,ha} + \varepsilon_t^{s,ha} + \alpha^{ha}\mu_t^{ha}) \end{aligned} \tag{2.2}$$

The sample likelihood function, exemplary for the high attention state, is shown below. The likelihood of observing B buy trades and S sell trades is

$$\begin{aligned} a(s_t^{ha}) = {} & (1-\alpha^{ha})exp(-\varepsilon_t^{b,ha} - \varepsilon_t^{s,ha})\frac{(\varepsilon_t^{b,ha})^{B_t}}{B_t!}\frac{(\varepsilon_t^{s,ha})^{S_t}}{S_t!} \\ & + \alpha^{ha}\delta^{ha}exp(-\varepsilon_t^{b,ha} - \varepsilon_t^{s,ha} - \mu_t^{h})\frac{(\varepsilon_t^{b,ha})^{B_t}}{B_t!}\frac{(\varepsilon_t^{s,ha} + \mu_t^{h})^{S_t}}{S_t!} \\ & + \alpha^{ha}(1-\delta^{ha})exp(-\varepsilon_t^{b,ha} - \varepsilon_t^{s,ha} - \mu_t^{ha})\frac{(\varepsilon_t^{b,ha} + \mu_t^{ha})^{B_t}}{B_t!}\frac{(\varepsilon_t^{s,ha})^{S_t}}{S_t!} \end{aligned} \tag{2.3}$$

The high and low attention day observations are derived from the Google Search Volume of the day. All search volume observations per firm are sorted into terciles. High attention days are all days with a Google Search Volume in the highest tercile, whereas low attention days are all observations from the lowest tercile.

2.4 Data and Descriptives

We collect data for all stocks that were listed in one of the four major German stock indices (Dax, MDax, SDax and TecDax)[15] from January 1^{st} 2004 until December 31^{st} 2011.[16] Those stocks make up about 75% of the market cap of the German equity market.[17] For those firms, we collect intraday data, daily stock information and Search Volume data.

[14] A detailed derivation of the initial parameter grid can be found in Yan and Zhang (2012)

[15] The inclusion of even smaller firms in the sample is not useful as those companies are usually less known and thus search volumes would be missing.

[16] This includes firms that went bankrupt during that time as well as firms that were introduced into the index.

[17] The reference equity market for this statistic is the German CDax.

Intraday Data In this study, most measures of trading dynamics and market quality[18] are derived from intraday data. Former studies (e.g. Bank et al. (2011)) were able to establish a relationship between Google search frequency and liquidity estimators such as the Amihud (2002) illiquidity ratio on a weekly frequency. While these low frequency liquidity proxies correlate with actual trading costs (see Goyenko et al. (2009) and Chapter 1 in this thesis), these measures are less precise than those derived from intraday data. Additionally they are not available on a daily basis. Investor attention, however, is highly volatile on a day-to-day basis.[19] This study computes quoted spreads, effective spreads, price impact (5-minute, 60-minute), market depth (complete, bid-side, ask-side), trade (number of trades, buys, sells, order imbalance), and volatility measures (number of volatility interruptions,[20] midpoint volatility), from millisecond trade and quote data of the Xetra market. This data is available from January 2004 until December 2011 for German stocks.

Additionally, warrant trading data from Stuttgart Stock Exchange from April 2009 to March 2011 is used.[21] The main target group of the Stuttgart Stock Exchange are retail traders, and therefore the dataset offers a unique setting for analyzing retail trader behavior. The data provides information about underlying, option type (call/put), strike price, and maturity date of the products. Also, price, quantity and trade direction[22] are known for each trade. The dataset contains about 54,194 warrants (43,263 calls and 10,931 puts). The average (median) trading volume per call (put) is about 5,000 Euro (1,800 Euro). The warrants are based on 98 underlyings from the Dax and MDax indices. The trades in those products are matched with their underlyings from the Xetra dataset.[23]

Daily Data Daily data (closing prices, daily returns[24], daily consolidated volume, number of common stock, and market capitalization) are collected from Thomson Reuters Datastream.[25] News Event data is retrieved from Deutsche Gesellschaft für ad-hoc Publizität (DGAP[26]). Section 15 of the German Securities Trade Act[27] requires firms to immediately publish any information that might affect the price of a security. DGAP is a German organization that provides a platform to all German companies to fulfill those disclosure requirements. The dataset consists of 3,563 events for 159 firms (about 3 events per firm-year) with a variety of event types: dividend announcements, quarterly reports, personnel decisions, mergers and acquisitions, etc..

[18] The construction of intraday measures is explained in detail in Appendix B.

[19] The daily standard deviation is 20 for a Google SVI attention variable scaled between 1 and 100 (see summary statistics, Table 2.3).

[20] Xetra has several circuit breakers in place to assure price continuity. Those breakers are triggered if the price leaves some predefined static of dynamic price channel and are followed by an unscheduled intraday call auction of random length. On each stock day, several volatility interruptions may happen.

[21] We thank Stuttgart Stock Exchange for the provision of the dataset.

[22] One distinct advantage of the trading data is that buys and sells are directly flagged. The Lee and Ready (1991)-algorithm is thus not needed here.

[23] 84 firms can be matched.

[24] The Datastream return index is used to measure returns, which artificially reinvests dividends and ignores stock splits.

[25] Due to potential data problems in Datastream, the return and market capitalization corrections as in Ince and Porter (2006) and Schmidt et al. (2017) are applied to the dataset. However, results are robust to not adjusting the data.

[26] www.dgap.de

[27] Wertpapierhandelsgesetz WpHG.

From the interaction of those events with Google Search Volume, we can, to some degree, account for differences between information and non-information induced attention. For a robustness check, data on German local holidays and information about the number of people/households affected by those holidays is collected. In Germany, some holidays are only relevant in some of the German federal states.

Google Search Volume As a direct measure of investor attention, the relative search volume from Google Trends is used.[28] Google Trends does not provide the absolute number of search requests, but only a relative Google Search Volume Index (SVI) that is scaled by some (unknown) average search term that shall correct for any timeseries patterns in aggregate search behavior. Thus SVI measures relative, rather than absolute attention. The measurement of relative attention ensures a time series comparability of the data.[29]

Google Trends allows filtering by several categories. The term 'adidas' might be entered by someone who wants to invest in the firm, but it is far more likely that this person simply wants to buy new clothes or shoes. Former studies were unable to differentiate between these two search types.[30] Google category filters can ensure a clear separation of different search intentions. Implicitly, Google checks which search queries a specific user started and which links he clicked before and after googling the term of interest. If he googled for 'dax' and 'stock' or clicked on several financial data providers, this might be a good indicator of his interest in financial information concerning 'adidas'. By selecting the category filter 'Finance' and using firm names instead of tickers, the direct attention towards the stock is captured more precisely.[31]

The firm names used in this study are collected from Datastream. All corporate form acronyms such as 'AG' are removed. The firms' names are manually shortened by eliminating parts of the companies' names that are not necessary for a clear identification. Using shorter names such as 'INFINEON' instead of 'INFINEON TECHNOLOGIES AG' will deliver better search results as the output automatically includes all combinations with the term, e.g., also its longer name.

As already mentioned, Google search volumes are rather volatile in the short-run. Hence, an observation of monthly or weekly changes in Google SVI might not appropriately capture the dynamics of day-to-day changes in people's attention. Except for Drake et al. (2012), who applied a daily attention measure of SVI over a short horizon, researchers using Google search volumes, so far, have only analyzed long-term attention changes. Google offers daily SVI values for requests up to a period of three months.[32] Each inquiry is standardized to a scale between

[28] http://www.google.com/trends/

[29] Many empirical studies (see Da et al. (2011), Drake et al. (2012), Dimpfl and Jank (2016)) use Google Search Volume data from an older version of Google Trends. The main advantage of this data compared to the current dataset was that it offered a fixed-scaling option, which basically ensured that each index value was expressed relatively to the average search volume during January 2004. This ensured a time series comparability of different values. Due to that fixed-scaling option on former Google Trends, one could simply append those files to arrive at a longer daily time series. This procedure is not available any more.

[30] Da et al. (2011) and Li et al. (2011) avoid this problem by searching for ticker symbols instead of firm names. However, using tickers is rather atypical in Germany, and only professional market participants would use ISIN, WKN or tickers to search for a stock of interest.

[31] No correlation between tickers as search term and other attention proxies can be found.

[32] As used by Drake et al. (2012).

0 and 100, where 100 is the day with the maximum relative search volume for the entered time period. A zero search volume does not imply that nobody searched for that specific term on a day but that the number of search requests was below a certain, but for the user unknown, threshold. Google Trends allows a search for five different time intervals at the same time. Thus it is possible to span a time interval of 15 months (five 3-month intervals) all being scaled by the same day of maximum search volume. Unfortunately, it is not directly possible to link two 15-month-intervals, as they are standardized based on different reference points. A longer time series however permits a more thorough analysis. A novel 4-step solution algorithm to extract longer periods of daily data is developed in this chapter.

First, for every company-year combination, the day with the maximum relative search volume in that specific year[33] is determined. In a second step, the four identified yearly maxima determine in one request the global relative search volume maximum. With eight years of data (2004 - 2011), steps number one and two have to be repeated twice, as only four years of data can be related to each other. In step three, the two four-year maxima are compared and the eight-year maximum is determined.[34] Finally, yearly requests including the found global maximum in any request are executed. This ensures that every search volume will now be scaled by this global maximum and therefore one may append the different firm-years (2004-2011) to each other without loosing scalability.[35] Figure A2.2 in the appendix exemplifies this process.

The robustness of the algorithm is verified by analyzing whether the changes in the SVI (ΔSVI) are systematically different for 'request' jumps[36] compared to other monthly jumps. If the algorithm did not work in the desired way, one would expect to encounter abrupt SVI changes on request change dates as one does if one simply appends two three-month windows.[37] A stock-wise mean-comparison t-test is applied and the null hypothesis of equal mean ΔSVI cannot be rejected in 98% of the cases at 99% significance level.[38] This result provides evidence for the appropriateness of the applied algorithm.

The described algorithm for arriving at an unbiased within-company time series of data can be transformed to infer a cross-sectional ordering of companies. Here, it is not the maximum attention quarter for one company that is identified, but rather the maximum attention firm within a quarter.[39] Thus, firms can be ordered by their cross-sectional attention over the entire time series (2004-2011) based on their average weekly search volume. This cross-sectional ordering is used in later analysis.

[33] Per year, one needs to have four 3-month intervals: January-March, April-June, July-September and October-December.

[34] Now, the day at which the relative interest for the given firm was highest can be clearly identified.

[35] The algorithm could easily be adjusted to longer time series. However this would increase the number of required search queries. Also note that a cross-sectional comparison of attention levels is not possible when applying this algorithm.

[36] First days of January, April, July, October.

[37] Event dates are dropped in this analysis as those should influence attention and thus would possibly falsify the comparison.

[38] 92% for 95% significance and 85% for the 90% significance level.

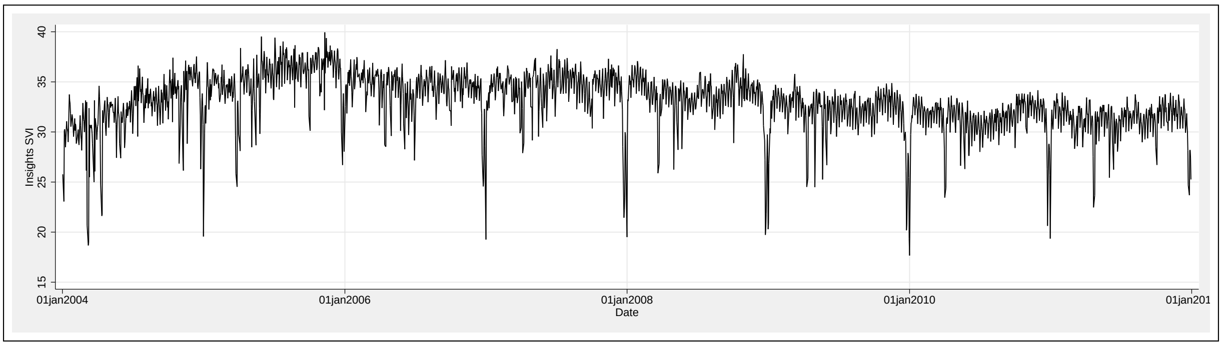
[39] This is achieved by a stepwise comparison of sets of five (maximum number of terms that can be compared in Google Trends) companies. The one company with the highest search volume in each of these sets 'survives'. The remainder of surviving companies is compared in sets of five against each other. This procedure is repeated until the maximum attention company is identified.

2.4.1 Descriptives

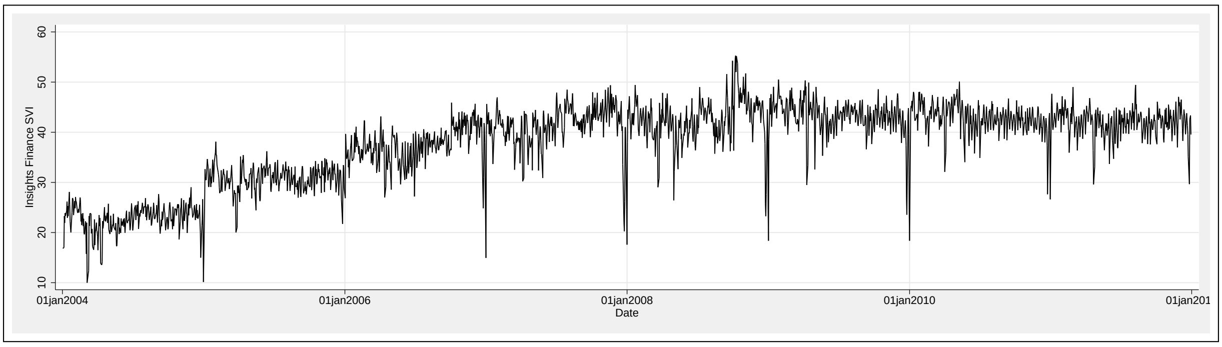
Figure 2.1 shows the time series development of equally-weighted Google SVI over all sample stocks. The average SVI is below 50 for both, the filtered and non-filtered data. The reason

Figure 2.1: Average Time Series SVI from Google Trends
This figure shows the equally-weighted daily time series of weekday-corrected normalized search volume for all constituents of Dax, MDax, SDax and TecDax during 2004 to 2011. Panel A shows the plot for Google Search Volume without use of a category filter, Panel B for Google Search Volume with category filter ’Finance’.

Panel A: Average Trends SVI



Panel B: Average Trends Finance SVI



for this can be found in the data handling by Google: One extreme outlier in attention, will be assigned a value of 100 and as all other observations are scaled by this value, they are ”‘pushed”’ to low SVI values. Even on this aggregated scale, SVI is very volatile. SVI increases until 2006 and then decreases. Due to its relative scaling property, this decrease in SVI does not necessarily imply an decrease in absolute search volume but rather that it did not grow as fast as the average search term on Google. The pattern is different for category-filtered SVI, which rises until 2008 and stays relatively constant afterwards. Filtered SVI seems to measure something different from overall SVI. SVIs are generally lower around Christmas, which is intuitively explained by the dominance of other stimuli over financial news and closed markets during that time.

Table 2.1 enriches the previous analysis by presenting the two different attention measures across years. First, note that the use of a category filter significantly reduces the sample size to 28.5% of the Trends sample (which can be seen as a clear disadvantage of the filtered data). By limiting the Google Trends search to finance-related requests, the absolute number of queries with non-missing observations is significantly reduced. A value of 306,742 daily observations over a sample of 150 stocks that contain at least one non-missing information on Google SVI means that those firms on average contain information on 1,614 trading days (77% of 2,086 total trading days). In contrast, we only have finance-filtered data for 62 firms with a coverage of about 67% of all trading days within these firms. Due to the low number of observations, the finance-filtered data is only used in robustness checks.

Table 2.1: *Summary Statistics Google SVI Across Years*
The Table provides summary statistics for the equally-weighted *SVI* across the years 2004 to 2011 for constituents of the 4 major German stock indices Dax, MDax, SDax, TecDax. The search volume is from Google Trends without use of a category filter (*Trends*) and with category filter Finance (*Trends Finance*). *N* provides the total number of non-missing daily observations. Additionally *Mean, Median, Standard Deviation, Skewness* and *Kurtosis* are provided.

Year	Variable	N	Mean	Median	SD	Skewness	Kurtosis
2004	Trends	29318.00	31.89	33.00	23.19	0.08	2.05
	Trends Finance	8486.00	22.65	21.00	23.92	0.47	1.87
2005	Trends	31228.00	35.34	37.00	20.89	-0.04	2.32
	Trends Finance	7610.00	30.88	35.00	22.77	-0.14	1.82
2006	Trends	34681.00	34.43	35.00	19.48	0.08	2.39
	Trends Finance	8267.00	37.35	41.00	22.48	-0.37	2.23
2007	Trends	38621.00	34.38	34.00	19.24	0.23	2.45
	Trends Finance	10192.00	41.39	43.00	21.42	-0.28	2.67
2008	Trends	40673.00	33.57	32.00	19.30	0.33	2.44
	Trends Finance	11596.00	42.52	43.00	20.55	-0.29	2.64
2009	Trends	43120.00	32.18	31.00	19.25	0.36	2.45
	Trends Finance	12983.00	43.36	44.00	20.55	-0.25	2.63
2010	Trends	44510.00	31.39	29.00	19.47	0.47	2.56
	Trends Finance	13768.00	42.89	43.00	20.11	-0.08	2.58
2011	Trends	44591.00	31.31	29.00	20.02	0.58	2.65
	Trends Finance	14495.00	42.19	42.00	20.76	-0.04	2.29
Total	Trends	306742.00	32.95	32.00	20.05	0.27	2.40
	Trends Finance	87397.00	39.08	41.00	22.30	-0.22	2.35

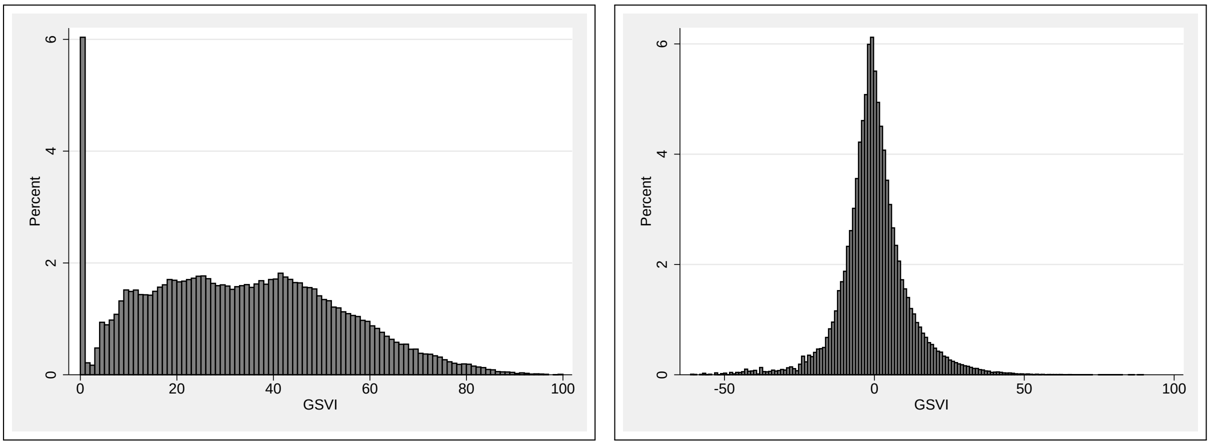
Generally, category-filtered data has a significantly higher average SVI than non-filtered data, while having the same variance. The normality for both variables is generally refused at 1% significance over all indices and SVI measures using Shapiro-Wilk and Shapiro-Francia tests.

While the applied download algorithm solves the problem of differing reference points, it generates a non-normal dataset as one extreme attention outlier pushes the rest of the sample to lower SVI levels. *Panel A* of Figure 2.2 shows the resulting SVI distribution for the complete sample without a category filter. If attention were to be equally distributed, one would expect a density of 1% for each interval. However, the percentage of zero observations (6%) is much higher as the SVI values are set to zero for all days where the absolute search volume was too low to be reported. Additionally, it is important to note that the SVI is issued on a discrete scale. This implies some unwanted data aggregation.[40]

Before the SVI data is used in the empirical analysis, several adjustments are applied to the data. Drake et al. (2012) and DellaVigna and Pollet (2009) provide some evidence that attention might vary across the week. These intra-week fluctuations can also be confirmed for this sample.[41] As results should not be affected by this day-of-the-week effect, residuals of the regression of SVI on weekday dummies are used. Those residuals are standardized by subtracting the mean and dividing by the standard deviation. *Panel B* of Figure 2.2 shows the resulting new density distribution. This standardized measure is used as attention proxy.

Figure 2.2: Density Distribution of Google Search Volume Index
This Figure shows the aggregated Density Distribution of Google Search Volume Index for all stocks from 2004 to 2011. Stocks are equally weighted. Panel A shows the unadjusted search volume. Panel B shows the weekday adjusted and normalized search volume.

Panel A: Distribution raw SVI **Panel B**: Corrected raw SVI



Intraday, Datastream, and Google data are available for 190 of the 256 companies that were part of the four major German stock indices during the analyzed period. In total there are 394,683 firm-day observations across all four indices. To evaluate the data availability, Table 2.2 summarizes the different sample sizes across all variables.

Table 2.2: ***Companies in Indices***
The Table provides summary statistics on the number of companies in the respective major German stock indices Dax, MDax, SDax, TecDax per year. All Indices give the number of unique companies (without considering index changes) in the indices per year. The TOTAL column gives the number of unique firms in the respective index over the whole timeperiod.

Index	2004	2005	2006	2007	2008	2009	2010	2011	TOTAL
Dax	35	36	36	37	38	36	35	35	39
MDax	36	45	53	56	59	64	62	62	75
SDax	43	43	47	53	57	60	62	67	77
TecDax	15	19	21	29	29	29	28	28	36
All Indices	107	118	128	144	151	154	153	157	188

The last row of Table 2.2 shows the number of firms fulfilling the data requirements and

[40] Additionally, Google does not search the entire database to produce the outputs but only a grab sample of the data. Therefore SVI values might slightly differ for two identical requests at different points in time.
[41] For more details see Figure A2.3 in the Appendix to this Chapter.

included in the respective index from 2004 to 2011. It can be seen that the number of firms for which price, intraday, and Google information are available increases over time, which is mainly due to an increased usage of search engines and thus an increased availability of the SVI measure. The 39 firms included in the Dax during this period imply that 9 firms must have been dropped from the index and have been replaced by other companies during this period.[42]

Table 2.3 provides summary statistics of all variables used in the study.[43]

In terms of market value, the fraction of penny stocks, and the number of daily trades, buys and sells, the four indices show the expected ordering among each other. Dax index stocks are on average the most traded and have the highest market value, followed by MDax, TecDax, and SDax. The liquidity measures effective spread, market depth, and price impact show a similar ordering. In some cases the ordering between TecDax and SDax is reversed. It is not surprising that Dax is the most liquid among the four indices. The proportion of small buys is highest for Dax and TecDax companies. The number of volatility interruptions[44] is highest for TecDax companies followed by Dax and MDax companies. The midpoint volatility is highest for the TecDax companies followed by the SDax and Dax companies.

Next, alternative attention measures proposed by the literature, namely trading volume, the DGAP event dummy, and squared returns, are considered. Consolidated trading volume from Datastream shows the expected ordering. It is by far highest for Dax companies followed by MDax and TecDax. Average daily squared returns are highest for TecDax followed by SDax and MDax. Events happen most often for Dax and TecDax companies. Across all indices, events occur only at about 1% of the days in the sample.

Trends SVI and Trends Finance SVI have a higher mean and median value for the larger indices. Standard deviation is nearly identical across indices. These findings are confirmed by the weekday-adjusted SVIs.[45]

[42]The dataset therefore can be considered to be free of any survivorship bias.

[43]Summary statistics are presented for each index separately as index membership is related to the cross-sectional attention towards stocks. For example, the market capitalization of Dax companies and the appealing business model of TecDax companies are linked to higher investor attention.

[44]Whenever the potential execution price deviates to much from previously determined (static and dynamic) reference prices, i.e. if the market is to volatile, a so-called circuit breaker is triggered. Continuous trading is interrupted by an unscheduled auction price determination process.

[45]The cross-sectional comparison needs to be interpreted with care as the relative SVI needs to be sorted cross-sectionally for comparison.

Table 2.3: Descriptive Statistics

The Table provides daily *Mean* (equally-weighted), *Median* and *Standard Deviation* of several variables for stocks from the four indices *Dax, MDax, SDax, TecDax* from 2004 to 2011. Additionally the number of total observations (*N*) and the number of firms for which this variable is filled (*Firms*) is provided. *Market Value* is the daily Market Value calculated as Price times Shares Outstanding. *% below 1 Euro* gives the percentage of daily trades in a given stock with a price below one Euro. The search volume comes from Google Trends without use of a category filter (*Trends SVI*) and with category filter Finance (*Trends Finance SVI*). Furthermore, both SVI measures are also shown as standardized and weekday corrected. *Consolidated Volume* is the number of shares traded per day on all German Exchanges (from Datastream). *% Event Days* provides the percentage of days on which an event happens. *Squared Stock Return* is the stock's squared return. *# Trades* is the total number of daily trades and *# Buys/Sells* is the daily number of buyer-/seller-initiated trades (calculated from Xetra Intraday Data). *Prop of Small Buys/Sells* gives the proportion of daily trades that were among the smallest 10% of all buys/sells. *Order Imbalance* is the equal-weighted mean difference between buys and sells on a day divided by total trades. *Relative Effective Spread* is equal-weighted mean of twice the absolute difference between trading price and midpoint divided by midpoint during a day. *Relative Quoted Spread* is the time-weighted average difference between bid and ask price during a day. *Market Depth* is the average quantity available for trade at the best bid/ask respectively. *Price Impact* is the equally-weighted relative difference between the midpoint and the midpoint 5 and 60 minutes later. *Midpoint Volatility* is the volatility of the midpoint price over a day. *# Volatility Interruptions* is the number of volatility interruptions during a day (detailed description in data section). *Daily Stock Return* is the daily stock return. The *Excess Return* by subtracting the CDax index return from the stock return. *Daily Stock (Excess) Return, Prop of Small Buys/Sells, Relative Effective/Quoted Spread, Price Impact, Order Imbalance, Squared Return, Event Dummy* and *Midpoint Volatility* are given in percentage terms. For a more detailed definition of all variables, see Appendix B.

	Dax					**MDax**					**SDax**					**TecDax**				
Variable	Mean	Median	Std.Dev.	N	Firms	Mean	Median	Std.Dev.	N	Firms	Mean	Median	Std.Dev.	N	Firms	Mean	Median	Std.Dev.	N	Firms
Market Value	23.19	23.18	1.08	70,117	38	21.02	21.05	1.24	138,219	74	19.46	19.65	1.39	132,857	73	19.79	19.69	1.32	58,536	33
% below 1 Euro	0.13	0.00	0.65	78,713	39	3.35	0.00	12.57	149,165	76	4.81	0.00	14.11	153,870	78	2.56	0.00	6.80	68,510	36
SVI	38.37	37.00	19.89	75,553	39	31.91	31.00	20.06	118,333	76	32.50	32.00	19.65	118,133	78	29.44	29.00	19.75	54,687	36
Finance SVI	41.42	42.00	20.09	39,328	25	35.04	38.00	22.83	31,050	24	36.52	39.00	23.57	26,862	20	50.54	51.00	17.76	7,499	5
SVI (weekday)	0.00	-0.55	9.40	75,553	39	0.00	-0.42	11.08	118,333	76	0.00	-0.51	12.22	118,133	78	0.00	-0.56	11.45	54,687	36
Finance SVI (weekday)	0.01	-0.11	13.33	39,328	25	0.01	-0.44	14.57	31,050	24	0.01	-0.77	17.42	26,862	20	0.00	-0.29	15.77	7,499	5
Consolidated Volume	4,082.77	1,894.10	7,476.75	76,653	39	485.99	183.70	1,379.52	125,281	76	103.88	25.10	405.85	123,331	78	393.09	159.30	883.57	57,185	34
% Event Days	1.03	0.00	10.09	80,962	39	0.88	0.00	9.32	157,962	76	0.91	0.00	9.51	162,708	78	1.00	0.00	9.94	74,013	36
Squared Stock Return	5.47	0.86	72.35	78,308	39	8.13	1.21	49.16	128,373	76	10.65	1.28	105.68	131,701	78	13.53	2.11	86.58	60,872	36
# Trades	3,519.21	2,555.00	3,543.69	76,652	39	738.19	410.00	999.80	124,159	76	134.23	47.00	241.38	125,925	78	425.05	181.00	743.01	58,386	36
# Buys	1,752.04	1,254.00	1,803.16	76,652	39	368.92	203.00	507.73	124,159	76	67.71	23.00	123.82	125,925	78	212.64	87.00	382.90	58,386	36
# Sells	1,767.13	1,284.00	1,766.26	76,652	39	369.26	202.00	501.60	124,159	76	66.52	22.00	121.68	125,925	78	212.39	89.00	368.05	58,386	360
% Small Buys	8.26	6.16	7.32	67,795	39	19.96	14.29	17.30	122,010	76	34.08	28.00	23.65	104,215	78	29.81	25.29	20.12	53,275	36
% Small Sells	9.19	6.83	7.70	67,881	39	20.70	14.81	17.95	122,892	76	33.90	28.09	23.38	105,156	78	30.78	26.42	20.20	53,704	36
Order Imbalance	-1.23	-0.94	12.56	76,576	39	-1.56	-0.36	25.54	122,335	76	-1.19	0.00	40.73	119,268	78	-2.79	-1.23	28.27	58,007	36
Relative Effective Spread	0.10	0.07	0.10	76,016	39	0.37	0.20	0.65	120,419	76	0.97	0.63	1.26	117,117	78	0.72	0.43	1.29	57,499	36
Relative Quoted Spread	0.11	0.08	0.11	76,652	39	0.42	0.23	1.26	124,159	76	1.03	0.65	1.69	125,925	78	0.73	0.43	1.04	58,386	36
Market Depth	4,114.43	1,100.24	53,044.97	76,016	39	3,596.28	633.64	54,932.53	120,419	76	2,811.85	532.80	35,580.40	117,117	78	3,051.67	1,041.21	24,772.96	57,499	36
Market Depth (Ask)	3,772.26	1,090.49	21,489.71	76,016	39	3,394.01	621.87	42,030.90	120,425	76	2,854.99	510.15	38,994.79	117,145	78	2,956.43	1,012.65	22,273.20	57,499	36
Market Depth (Bid)	4,456.60	1,092.41	93,505.37	76,016	39	3,798.38	614.46	83,101.19	120,422	76	2,768.04	500.00	37,357.03	117,126	78	3,146.85	1,002.30	29,737.05	57,500	36
5-min Price Impact	0.04	0.03	0.04	76,016	39	0.12	0.08	0.19	120,419	76	0.24	0.15	0.45	117,117	78	0.20	0.13	0.29	57,499	36
60-min Price Impact	0.04	0.03	0.06	76,016	39	0.12	0.07	0.22	120,419	76	0.26	0.16	0.48	117,117	78	0.21	0.13	0.34	57,499	36
Midpoint Volatility	0.04	0.02	0.16	76,092	39	0.06	0.03	0.25	122,010	76	0.09	0.03	0.95	121,845	78	0.10	0.04	0.48	57,856	36
# Vola Interruptions	0.43	0.00	1.14	46,343	39	0.34	0.00	0.90	74,493	74	0.47	0.00	1.16	63,752	74	0.50	0.00	1.11	33,872	34
Daily Stock Return	0.05	0.00	2.34	78,308	39	0.04	0.00	2.85	128,373	76	0.05	0.00	3.26	131,701	78	0.05	0.00	3.68	60,872	36
Daily Stock Excess Return	0.02	-0.01	1.93	78,308	39	0.02	-0.02	2.57	128,373	76	0.02	-0.04	3.18	131,701	78	0.03	-0.11	3.41	60,872	36

2.5 Comparison of Alternative Attention Measures

Several other attention measures have been proposed in the literature: As stated above Barber and Odean (2008) propose the abnormal volume, abnormal returns and news events[46] as attention measures. Ungeheuer (2017) uses Wikipedia firm page views to measure investor attention and Ben-Rephael et al. (2017) use news searching activity on Bloomberg to measure instituional attention. We replicate their methodology to arrive at those alternative attention measures and later compare them to Google search volumes.

Hourly Wikipedia page views for all our sample stocks (if Wikipedia firm pages are available) and the 'Dax' index are retrieved from 2008 (when the Wikipedia sample starts) to 2011. We strictly follow the methodology described in Appendix B of Ungeheuer (2017) and aggregate hourly search volumes to the daily level (using Central European Time). Wikipedia page views offer several advantages compared to Google SVI: First, they are easier to retrieve and do not require a complex download algorithm as described in this work. Second, they come at hourly frequency and in absolute numbers and thus do not face the problem of relative scaling connected to Google Search volumes. Third, a Wikipedia page is unambiguously related to one firm, while firm names can have multiple meanings. We address this issue by relying on the Google machine learning algorithm that assigns searches for the same term to different categories. However, it is not clear that Wikipedia is the primary source of information for investors who are interested in trading a stock. While Google is by far the most prominent search engine (see Da et al. (2011)) and thus very likely to be included in the information gathering process of investors, only a selected subsample of those might use Wikipedia as opposed to company and financial news websites. Additionally, our sample includes small firms from the SDax for which Wikipedia pages do not exist. Wikipedia pages only exist for about 75% of the firms in our sample. Thus, in the German setting, Wikipedia page views can only serve as an attention measure for sufficiently large firms.

The measure of institutional attention was introduced by Ben-Rephael et al. (2017). It is based on the user search and reading activity on Bloomberg. Bloomberg translates those into a categorial variable of abnormal attention, ranging from 1 to 4. It is available since February 2010, so it covers only a small fraction of our sample period.[47]

Table 2.4 shows the correlations between different attention measures. Four different versions of the Google search volume are considered. First, SVI might be filtered or unfiltered. Second, it might be adjusted for the weekday effect or left unadjusted.

The correlation among most measures is significantly positive as expected. It can be confirmed that most variables seem to be proxies for the same unobserved concept. However, as they are not perfectly correlated, it seems as if they might measure different components of the attention concept. The rather low correlation between SVI and the indirect attention measures (especially the event dummy) suggests that attention is not exclusively information-triggered. Thus it might make sense to consider several attention proxies to describe trade dynamics.[48]

[46]In contrast to Barber and Odean (2008), who use the Dow Jones News feed, this study relies on actual disclosure information from DGAP. News of any kind should be the major trigger for investors' attention.

[47]For details on the methodology, see Ben-Rephael et al. (2017).

[48]The indirect attention measures are included as controls in all regression specifications.

Table 2.4: Attention Measure Correlations

This Table provides average stock-by-stock correlations between different attention variables for the sample of all Dax, MDax, SDax and TecDax stocks between 2004 and 2011. *Previous Day Event* is a dummy variable, which takes value 1 if an event happens one day before. *Previous Day Consolidated Volume* is the number of shares traded the previous day on all German stock exchanges (from Datastream). *# Trades* is the total number of daily trades and *# Buys/Sells* is the daily number of buyer-/seller-initiated trades. *Previous Day squared return* is the squared stock return lagged by one day. *Bloomberg* is the categorial Bloomberg search and reading variable ranging from 1 to 4. *Wikipedia* is the number of Wikipedia frim page views per day. The search volume is from Google without use of a category filter (*GSVI*) and with category filter Finance (*GSVI Finance*). Both variables are additionally corrected for weekday effects (Weekday). For a more detailed definition of all variables, see Appendix B ***, ** and * indicate that the mean correlation coefficient across all stocks is significant at a 1%, 5% and 10% significance level, respectively.

	Previous Day Event Dummy	Previous Day Consolidated Volume	# Trades	# Buys	# Sells	Previous Day Squared Return	GSVI	GSVI Finance	GSVI (Weekday)	GSVI Finance (Weekday)	Bloomberg	Wikipedia
Previous Day Event Dummy	100.00%											
Previous Day Consolidated Volume	10.45% ***	100.00%										
# Trades	6.87% ***	42.83% ***	100.00%									
# Buys	6.59% ***	41.45% ***	96.14% ***	100.00%								
# Sells	6.63% ***	41.18% ***	96.24% ***	85.43% ***	100.00%							
Previous Day Squared Return	8.28% ***	33.96% ***	22.77% ***	22.27% ***	21.77% ***	100.00%						
GSVI	4.09% ***	9.60% ***	10.99% ***	10.63% ***	10.74% ***	4.73% ***	100.00%					
GSVI Finance	-0.53%	7.11% ***	14.58% ***	13.91% ***	14.53% ***	6.44% ***	35.62% ***	100.00%				
GSVI (Weekday)	4.15% ***	9.74% ***	11.19% ***	10.85% ***	10.91% ***	4.79% ***	99.15% ***	34.60% ***	100.00%			
GSVI Finance (Weekday)	-0.42%	6.92% ***	14.59% ***	13.96% ***	14.49% ***	6.30% ***	34.43% ***	99.23% ***	34.94% ***	100.00%		
Bloomberg	-0.21%	1.34% *	28.02% ***	28.02% ***	26.01% ***	0.27%	12.49% ***	7.52% ***	11.79% ***	6.45% ***	100.00%	
Wikipedia	-0.82% **	0.19%	14.25% ***	13.61% ***	14.03% ***	-0.31%	17.30% ***	10.54% ***	16.40% ***	10.06% ***	20.94% ***	100.00% ***

This is also true for the relation between filtered and unfiltered SVI. While the correlation of about 35% is highly significant, it is far from perfect. As expected, the correlation between the weekday-adjusted and original SVI series is close to 100%. Institutional Attention seems to only have a low, though positive relation with retail investor attention. This finding is in line with the results in Ben-Rephael et al. (2017). In line with Ungeheuer (2017) Wikipedia page views are positively and significantly related to Google SVI. Surprisingly, they are not related to the indirect attention measures proposed by Barber and Odean (2008).

Overall, the *direct* SVI seems to be related to traditional attention triggers. At the same time, correlations are not perfect, which implies that the SVI as retrieved here might offer some additional insights compared to the *indirect* measures.

One major shortcoming of the existing literature that uses Google Trends as an attention measure is that the construction of SVI remains a black-box to users. The data adjustments that transfer actual search queries into SVI are not known to the researchers that use SVI. Thus it is not ultimately clear that SVI is what it claims to be. In this section, the quality of the SVI and other attention measures will be objectively evaluated by comparing it to actual clicks on Google. For a small subsample of 58 days, actual clicks and impressions from Google for the search term 'Dax' are available.[49] Impressions count the number of times people googled for the term 'Dax' while clicks count the number of people clicking on links after googling for the term. This dataset allows for a verification of the quality of the Trends SVI and its suitability as an attention proxy. Also the data download algorithm applied in this chapter can objectively be compared to e.g., a weekly attention measure as used in many other studies.

Table 2.5 *Panel A* shows the correlation with the daily SVI as used in this study, whereas *Panel B* shows correlations for weekly SVIs as used by e.g., Da et al. (2011). For the daily data, correlations of Trends SVI variables, clicks and impressions are positive and highly significant. While it is not entirely transparent how the SVI is constructed, it actually correlates with people's clicks. Also the applied algorithm does not seem to bias the data in an unexpected way. For the weekly data, correlations are positive as well. Significance should not be overstated here as correlations are actually based on only 13 weeks of data. Still, it can be seen that also the weekly index does an appropriate job in measuring the actual search behavior of people. In line with the idea that institutional traders do not use Google for information search, Bloomberg requests seem to be unrelated to Google Searches. Wikipedia page views are highly positively related with the number of Google searches which provides evidence of their suitability as attention measure.

In summary, data from Google trends and Wikipedia are highly correlated and both positively related to actual search requests. Correlations for SVI with indirect attention measures and actual search requests are slightly higher compared to Wikipedia page views.

[49] We arrive at this sample by running an online marketing campaign, which provides us with access to data from Google Analytics.

Table 2.5: Intraday Attention Correlation with Trends SVI
This table shows the daily (*Panel A*) and weekly (*Panel B*) correlations between different Google attention measures for a non-continuous time series of 58 days from August 2013 to January 2014 for the search term 'Dax'. *Clicks* is the number of people that clicked on a link after googling with the term 'Dax' included in the search string, whereas *Impressions* is the number of search requests. The terms in quotation marks all are retrieved from Google Trends and adjusted by the algorithm described in Section 2.4. *Finance* implies the application of a Finance-filter.

Panel A: Daily Correlations

	Clicks	Impressions	'Dax'	'Dax' (Finance)	'DAX Index'	'DAX Index' (Finance)	Bloomberg	Wikipedia
Clicks	1							
Impressions	62.3% ***	100%						
'Dax'	50.0% ***	51.7% ***	100%					
'Dax' (Finance)	36.1% ***	62.9% ***	51.4% ***	100%				
'DAX Index'	45.2% ***	75.8% ***	63.1% ***	78.3% ***	100%			
'DAX Index' (Finance)	26.3% **	61.4% ***	55.4% ***	85.0% ***	76.7% ***	100%		
Bloomberg 'Dax'	-10.2%	16.3%	16.9%	7.3%	11.3%	22.7%	100%	
Wikipedia 'Dax'	32.2% **	46.9% ***	16.4%	26.0% *	42.9% ***	25.2% *	15.2%	100%

Panel B: Weekly Correlations

	Clicks	Impressions	"Dax"	"Dax" (Finance)	"DAX Index"	"DAX Index" (Finance)	Wikipedia	Bloomberg
Clicks	100%							
Impressions	57.7% **	100%						
"Dax"	55.2% *	48.3% *	100%					
"Dax" (Finance)	8.3%	56.0% **	39.7%	100%				
"DAX Index"	42.0%	75.8% ***	73.4% ***	71.2% ***	100%			
"DAX Index" (Finance)	29.4%	61.3% **	41.5%	75.1% ***	79.3% ***	100%		
Bloomberg 'Dax'	-8.1%	33.3%	50.4% *	72.2% ***	76.8% ***	67.8% ***	100%	
Wikipedia 'Dax'	45.7%	71.0% **	7.7%	53.7% *	64.2% **	75.0% ***	19.8%	100%

2.6 Empirical Results

In the following, the main empirical analysis as well as several subsorts and robustness checks are presented. The optimization results of the attention-trading model serve as introductory evidence for the dynamics of attention-based trading. Afterwards the dynamics are regarded in a panel data analysis in greater detail.

2.6.1 Estimation Results of the Attention-Adjusted Trading Model

Table 2.6 presents the estimation results of the Maximum Likelihood estimation of the attention-adjusted trading model as described in Section 2.3. All stocks (192 firms) for which the Google Search Volume and trading data (buys/sells) are available are used in this analysis. The optimization converges for 179 firms.

Panel A of Table 2.6 shows the estimates of $\alpha, \delta, \varepsilon^{buy}, \varepsilon^{sell}, \mu$ and PIN for the subsamples of high and low attention days. As described in Section 2.3, the days are sorted into terciles of high and low attention respectively, defined by the Google Search Volume measure of the trading day. Only the highest and lowest attention tercile are used here.

Table 2.6: ***Optimization Results***
This Table shows the estimation results $\hat{\theta} = \alpha, \delta, \mu, \varepsilon_t^{buy}, \varepsilon_t^{sell}$ of the Maximum Likelihood estimation of the attention-adjusted model as described in section 2.3 for the low and high attention terciles. Furthermore, the Probability of Informed trading is derived for the high and low attention states as $PIN_t^{low\ attention} = \alpha^{la}\mu_t^{la}/(\varepsilon_t^{b,la} + \varepsilon_t^{s,la} + \alpha^{la}\mu_t^{la})$ and $PIN_t^{high\ attention} = \alpha^{ha}\mu_t^{ha}/(\varepsilon_t^{b,ha} + \varepsilon_t^{s,ha} + \alpha^{ha}\mu_t^{ha})$. The model is estimated for 179 stocks out of the total sample for which Google Search Volume is available. In Panel B the parameter estimates of the stocks are sorted into size terciles, in Panel C into relative effective spread terciles and in Panel D into Cross-Sectional Attention Terciles. ***, ** and * indicate that the parameter estimate across all stocks is significant at a 1%, 5% and 10% significance level, respectively. *T-value* is the test statistic of a matched two-sided t-test to verify that the difference in coefficients *High-Low* is different from 0.

Panel A: Attention

Attention Day Tercile	α	δ	μ	ε^{buy}	ε^{sell}	PIN	# firms
High	0.29***	0.38***	667.49***	386.93***	411.31***	0.22	179
Low	0.31***	0.40***	610.96***	342.75***	380.83***	0.25	179
High-Low	-0.02	-0.01	56.53	44.18	30.48	-0.03	
T-value	-1.24	-0.52	0.45	0.63	0.41	-2.83***	

Panel B: Attention / Size Sort

Attention Day Tercile	Size Tercile	α	δ	μ	ε^{buy}	ε^{sell}	PIN	# firms
High	1	0.27***	0.34***	115.69***	53.11***	60.04***	0.26	57
Low	1	0.25***	0.40***	91.38***	34.47***	36.40***	0.29	57
High-Low		0.02	-0.06	24.31	18.63	23.64	-0.02	
T-value		0.81	-1.38	1.49	1.81	2.26**	-1.54	
High	2	0.31***	0.44***	416.90***	231.42***	221.08***	0.21	57
Low	2	0.30***	0.42***	480.05***	195.49***	197.68***	0.24	57
High-Low		0.01	0.02	-63.15	35.93	23.40	-0.02	
T-value		0.34	0.48	-0.45	0.86	0.57	-1.27	
High	3	0.31***	0.37***	1379.68***	878.94***	962.47***	0.17	56
Low	3	0.40***	0.37***	1338.85***	832.25***	949.59***	0.23	56
High-Low		-0.08	0.01	40.84	46.69	12.87	-0.05	
T-value		-1.93*	0.11	0.13	0.26	0.07	-2.23**	

Panel C: Attention / Spread Sort

Attention Day Tercile	Spread Tercile	α	δ	μ	ε^{buy}	ε^{sell}	PIN	# firms
High	1	0.27***	0.37***	795.01***	405.97***	451.44***	0.21	60
Low	1	0.35***	0.40***	636.32***	450.24***	467.22***	0.26	60
High-Low		-0.08	-0.03	158.69	-44.26	-15.78	-0.06	
T-value		-2.24**	-0.59	0.75	-0.34	-0.11	-2.61***	
High	2	0.30***	0.40***	797.13***	475.74***	510.26***	0.23	60
Low	2	0.27***	0.40***	721.90***	321.68***	393.07***	0.25	60
High-Low		0.03	0.00	75.23	154.06	117.19	-0.02	
T-value		1.13	0.04	0.27	1.03	0.74	-1.24	
High	3	0.30***	0.38***	405.97***	277.25***	269.88***	0.22	59
Low	3	0.32***	0.39***	472.35***	254.88***	280.54***	0.23	59
High-Low		-0.02	-0.02	-66.38	22.38	-10.65	-0.02	
T-value		-0.66	-0.39	-0.48	0.34	-0.16	-0.92	

Panel D: Attention / Cross-Sectional Attention Sort

Attention Day Tercile	Cross-Sectional Attention Tercile	α	δ	μ	ε^{buy}	ε^{sell}	PIN	# firms
High	1	0.28***	0.39***	369.98***	245.88***	222.37***	0.22	56
Low	1	0.31***	0.39***	250.50***	168.03***	152.56***	0.26	56
High-Low		-0.02	0.00	119.48	77.84	69.81	-0.04	
T-value		-0.96	0.11	1.08	1.23	1.40	-2.33**	
High	2	0.30***	0.36***	472.57***	247.69***	271.14***	0.23	57
Low	2	0.28***	0.42***	634.29***	229.51***	263.76***	0.27	57
High-Low		0.02	-0.06	-161.71	18.18	7.38	-0.04	
T-value		0.56	-1.27	-0.87	0.24	0.08	-1.72*	
High	3	0.29***	0.42***	1198.86***	685.49***	759.50***	0.21	55
Low	3	0.35***	0.39***	982.85***	657.70***	744.52***	0.22	55
High-Low		-0.06	0.03	216.01	27.78	14.98	-0.01	
T-value		-1.73*	0.63	0.67	0.15	0.07	-0.52	

Overall, the α estimates, which give the probability of an information event, are quite stable at around 30% for both high and low attention days. The probability of a bad-news event δ is about 39% for high and low attention days.[50] The arrival rates for uninformed buys and sells ($\varepsilon_t^{buy}, \varepsilon_t^{sell}$) as well as for informed trading (μ) are higher on high attention days. While the difference in coefficients between high and low attention days is not statistically significant, as evidenced by a two-sided t-test, numbers indicate an increase of about 10% in both, informed and uninformed trading, on high attention days. The increased trading on high attention days is in line with Hypothesis 5. The Probability of Informed trading measure, as determined in Section 2.3, is about 3% lower on high attention days compared to low attention days. This difference is significant at the 1% level. The reduced PIN on high attention days supports the hypothesis that the asymmetric information is reduced and liquidity could be improved.

Panel A compounds a cross-section of stocks with quite diverse characteristics. *Panel B* presents the same analysis with firms being split into size terciles according to their market capitalization. The size of a company is an important factor that has an influence on its recognition. Larger firms are more in the focus of the attention-constrained investor. Within size terciles, coefficient estimates show a similar ordering between high and low attention days as in *Panel A*, without sorting. With the exception of μ for the medium sized firms, $\varepsilon^{buy}, \varepsilon^{sell}$ and μ are higher on high attention days for all subsets. For companies in size tercile three (the largest companies), we document a difference in the probability of informed trading of about 5% (significant at the 5% level). On high attention days, there is a lower probability of informed trading in large firms. The difference in PIN for the other size terciles remains insignificant. Furthermore, the difference in the α between high and low attention days is significantly negative at the 10% level for large firms. There seem to be more news events on low attention days. This could hint at strategic news dissemination on low attention days.

Panel C of Table 2.6 shows the results for all the companies if they are sorted into relative effective spread terciles. This sort mirrors the results of the size sort, which is not surprising knowing that size and liquidity are closely related. Companies with a low spread (tercile 1) have a significantly (at the 1% level) lower PIN on high attention days. Furthermore, these companies have significantly more (at the 5% level) information events on low attention days.

Panel D exhibits the results for companies sorted according to their cross-sectional mean attention level over the entire sample. In companies with a generally lower attention, the PIN is significantly lower on high attention days. There seem to be relatively less informed traders in low (cross-sectional) attention companies on high (time series) attention days.

As expected, high attention days seem to exhibit more overall trading of informed(μ) and uninformed traders (ε) and less risk of adverse selection as measured by PIN. This result is confirmed for larger and more liquid firms as well as for firms with a generally lower attention in the subsample sorts. This indicates that spreads should not increase and maybe even be lower on high attention days. The results support Hypothesis 5 that there is both, more uninformed and informed trading on high attention days. Given these findings, one would expect a higher trading volume, liquidity, and volatility on high attention days. To resolve potential endogeneity

[50] One might interpret this as indication that attention is not necessarily information driven.

in the model setup, untabulated results use the previous day's SVI to define high and low attention days. Using the previous day's SVI solves the potential problem that attention could be influenced by same day's trading behavior. Results are qualitatively and quantitatively the same in this additional specification.

2.6.2 Attention and Trade Dynamics

In this section the trade dynamics in terms of liquidity, turnover, volatility, and returns and their relation with the Google Search Volume attention measure are analyzed. All regressions are estimated with firm-fixed effects and firm-clustered standard errors as well as year dummies. The inclusion of firm-fixed effects is necessary due to the firm-dependent level of Google Search Volume as described in Section 2.4 and to adress potential unobserved time-invariant firm characteristics. Year dummies control for overall market trends (there is e.g. an increase in liquidity measures from 2004 until 2011).[51] The Google Search Volume is weekday-corrected and normalized as described in Section 2.4. Also, all other dependent and independent variables are standardized within a firm.[52] Coefficients thus can be interpreted as the effect of a one standard deviation change in the independent variable.

There are two regression specifications for every dependent variable. One specification with only the attention variable as explanatory variable and one specification with the attention variable and all control variables. Control variables are lagged trading volume, lagged squared excess returns[53], and an event dummy based on DGAP publications.[54] All these measures could potentially serve as an attention measure. In line with Barber and Odean (2008), the attention variables are lagged by one day. Additionally the dependent variable is lagged by one day and included as a regressor.[55] However, for the SVI, it is not clear whether it should be lagged or not as the time between an active search and a trading decision is unknown. First, the contemporaneous relation is analyzed. Table 2.7 summarizes the results of all regression specifications.

Panel A of Table 2.7 shows how the Google Search Volume influences the different liquidity dimensions. In line with the findings of the previous section and the literature that motivated hypothesis 4, we expect a positive relation between attention and liquidity. Regressions (1) and (3) in Table 2.7 show a negative but insignificant influence of the Google Search Volume on the Relative Quoted and Effective Spread Measure. This relation remains negative and insignificant

[51] In addition, the regressions are estimated with firm and time clustered standard errors as described in Petersen (2009). Furthermore, the relation is estimated using the Fama and MacBeth (1973) method. The methodology of Fama and MacBeth (1973), however, is reversed by first running a time series and later a cross-sectional regression. Results generally stay the same using those methodologies.

[52] $x^{std} = \frac{x-\bar{x}}{\sigma_x}$, with x being any dependent or independent variable in the regression model.

[53] The excess return is calculated by subtracting the CDax index return from the stock return.

[54] In untabulated results, we also include Wikipedia page views and Bloomberg Institutional Attention in our regression. We refrain from generally using those two variables as they are only available since 2008 (for Wikipedia) and 2010 (for Bloomberg) and thus would reduce our sample by a lot. Also, Wikipedia pages only exist for about 75% of our sample firms. Results for the GSVI-trading dynamics relation are however largely unaffected by the inclusion of those two variables. Generally, we find evidence that Wikipedia page views and Bloomberg Institutional Attention influence trading volume and volatility (in addition to GSVI).

[55] Nickell (1981) finds that the inclusion of the lagged dependent variable in the fixed effects regression creates a bias in the estimation. However, the bias is negligible in a dataset with a long enough time series T as in this chapter.

if additional lagged attention measures, year dummies, and the lagged spread measures are included as control variables in the regression. Thus, if anything, stocks become more liquid if attention is high. It is also interesting to see that less direct attention proxies, such as lagged volume and events on the previous day, seem to drive spreads up. Lagged squared returns are not only a proxy for attention but also for volatility in the market, which is why a significant positive coefficient might not be surprising. As another liquidity dimension, market depth measures the available quantity for trade at the current bid-ask spread. The larger the market depth, the larger is the quantity one may trade without influencing the market price. Therefore market depth should be large in liquid markets. The overall market depth is insignificantly increased with a higher level of investor attention. The market depth on the bid and ask side are significantly positively related to the Google Search Volume at the 10% level. However, the significance is lost if the control variables are included in the regression. The relation to the other attention proxies is comparable to the previous findings. Volume and events seem to positively affect liquidity while squared excess returns have a negative influence. However, significance is, at most, weak. Price Impact measures the response of market prices to trading. Stock prices should only react to trades if those might be informative (see Kyle (1985)). Thus, the price impact of a stock is important as it is strongly related to the costs of adverse selection. The 5-min and 60-min price impact measures show an inconclusive and insignificant relation with the Google Search Volume. Including all control variables, the Google Search Volume has a positive but insignificant influence on the price impact.

Overall, the relation between Google Search Volume and liquidity related measures is economically small and usually insignificant. This result is not in line with the findings by Bank et al. (2011). It must be noted, however, that the liquidity measure employed in their paper strongly differs from the measures used in this study: First, the Amihud (2002) illiquidity ratio is a proxy for the price impact of a stock. While we as well regard the price impact, we additionally examine other dimensions of liquidity. Second, the Amihud illiquidity ratio is not defined for zero volume days (which we observe frequently for small cap firms), while our measures of liquidity are still available at those days with presumably extremely low attention. Third, while a weak relationship between the Amihud illiquidity ratio and intraday measures is documented in the literature (see e.g. Goyenko et al. (2009) and Chapter 1 of this thesis) intraday measures are more precise measures of actual trading costs. Finally, their analysis is conducted on weekly frequency, which might explain the difference in results. Also, the Amihud illiquidity measure is very noisy on a weekly frequency being based on not more than five daily observations.

In summary, one does not find a significant and economically meaningful relationship between the direct attention measure and liquidity. Hypothesis 4 must be rejected. This result however is in line with the model results presented earlier. If not only uninformed retail traders but also informed traders react to attention, then liquidity could be unaffected in equilibrium. However, one would expect turnover to increase significantly on both sides of the market.

Table 2.7: ***Attention and Trade Dynamics***

This Table provides firm-fixed effects regressions with robust, company-clustered standard errors of liquidity measures, turnover, volatility and returns as dependent variables and Google Search Volume as explanatory variable. The sample contains all Dax, MDax, SDax and TecDax firms from 2004 to 2011. Control variables are: Year Dummies, Lagged Event Dummy, Lagged Squared Excess Returns, Lagged Trading Volume as well as the Lagged Dependent Variable. For a more detailed definition of all variables, see Appendix B. All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. T-Statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

Panel A: Liquidity

	(1) Quoted Spread	(2) Quoted Spread	(3) Effective Spread	(4) Effective Spread	(5) Depth	(6) Depth	(7) Depth on Bid Side	(8) Depth on Bid Side	(9) Depth on Ask Side	(10) Depth on Ask Side	(11) 5-min Price Impact	(12) 5-min Price Impact	(13) 60-min Price Impact	(14) 60-min Price Impact
GSVI	-0.0208	-0.00752	-0.0235	-0.00991	0.0368	0.00872	0.0428*	0.0108	0.0402*	0.0118	-0.00235	0.000592	0.00419	0.00557
	(-1.02)	(-1.47)	(-1.25)	(-1.08)	(1.60)	(0.97)	(1.95)	(1.15)	(1.88)	(1.23)	(-0.18)	(0.07)	(0.46)	(0.75)
Lagged Consolidated Volume		-0.0162***		-0.0420***		0.00571		0.0130**		0.0180***		-0.0272***		-0.0279***
		(-4.58)		(-7.33)		(0.96)		(2.18)		(3.02)		(-4.00)		(-4.95)
Lagged Squared Excess Return		0.0155***		0.0456***		-0.00214		-0.00219		-0.00483*		0.0634***		0.0617***
		(6.53)		(17.24)		(-0.82)		(-0.84)		(-1.73)		(16.72)		(11.80)
Lagged Event Dummy		-0.0373***		-0.0457***		0.0360**		0.0127		0.0441**		-0.0505**		0.0486**
		(-2.75)		(-2.63)		(2.02)		(0.72)		(2.23)		(-2.44)		(2.21)
Lagged Dependent Variable		0.741***		0.489***		0.560***		0.513***		0.490***		0.336***		0.153***
		(61.17)		(24.14)		(27.64)		(27.40)		(24.27)		(31.72)		(19.16)
Constant	-0.0336***	0.114***	-0.0282***	0.186***	-0.0140***	0.156***	-0.0117***	0.155***	-0.0135***	0.183***	-0.0124***	0.0886***	-0.0110***	0.113***
	(-32.60)	(5.11)	(-29.88)	(4.81)	(-12.21)	(4.53)	(-10.63)	(4.44)	(-12.55)	(4.95)	(-19.06)	(3.10)	(-24.09)	(3.98)
Observations	255863	246973	245984	237944	245984	237944	245990	237945	246007	237945	245984	237944	245984	237944
Year Dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
R-squared	0.00	0.60	0.00	0.30	0.00	0.36	0.00	0.30	0.00	0.29	0.00	0.18	0.00	0.06

Panel B: Turnover

	(1) Consolidated Volume	(2) Consolidated Volume	(3) # Trades	(4) # Trades	(5) # Buys	(6) # Buys	(7) # Sells	(8) # Sells	(9) Order Imbalance	(10) Order Imbalance
GSVI	0.110***	0.0650***	0.0887***	0.0530***	0.0871***	0.0546***	0.0859***	0.0526***	0.00551	0.00340
	(7.17)	(7.92)	(3.58)	(7.38)	(3.57)	(7.14)	(3.56)	(6.96)	(0.71)	(0.60)
Lagged Consolidated Volume		0.458***		-0.0518***		-0.0122		-0.0129*		0.0282***
		(44.09)		(-7.63)		(-1.63)		(-1.72)		(6.67)
Lagged Squared Excess Return		0.0322***		0.00312		0.00322		0.0108**		0.00317
		(5.74)		(0.62)		(0.68)		(2.05)		(1.62)
Lagged Event Dummy		0.224***		0.146***		0.144***		0.150***		0.0119
		(5.07)		(4.24)		(4.24)		(4.29)		(0.70)
Lagged Dependent Variable				0.674***		0.618***		0.613***		0.233***
				(56.57)		(49.13)		(45.65)		(27.27)
Constant	0.0142***	-0.110***	0.0437***	-0.188***	0.0431***	-0.200***	0.0426***	-0.215***	-0.00250***	0.0631***
	(18.26)	(-4.78)	(34.92)	(-8.33)	(34.99)	(-8.48)	(34.99)	(-9.07)	(-6.64)	(3.26)
Observations	255163	250200	255863	246973	255863	246973	255863	246973	249629	240986
Year Dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
R-squared	0.01	0.26	0.01	0.49	0.01	0.45	0.01	0.46	0.00	0.06

Table 2.7: Attention and Trade Dynamics (ctd.)

Panel C: Volatility

	(1) # Volatility Interruptions	(2) # Volatility Interruptions	(3) Midpoint Volatility	(4) Midpoint Volatility
GSVI	0.0484***	0.0479***	0.0486***	0.0322***
	(3.75)	(5.63)	(4.07)	(5.85)
Lagged Consolidated Volume		0.0132		0.0213***
		(1.57)		(3.89)
Lagged Squared Excess Return		0.0286***		0.0749***
		(4.54)		(8.21)
Lagged Event Dummy		-0.0248		-0.0603**
		(-0.65)		(-1.96)
Lagged Dependent Variable		0.335***		0.372***
		(24.27)		(26.99)
Constant	0.00273***	-0.151***	0.0113***	-0.0969***
	(12.37)	(-18.48)	(18.28)	(-6.83)
Observations	157480	148086	250767	242268
Year Dummy	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.00	0.18	0.00	0.24

Panel D: Return

	(1) Stock Return	(2) Stock Return	(3) Excess Return	(4) Excess Return
GSVI	-0.00109	-0.00317	-0.00126	-0.00431*
	(-0.44)	(-1.29)	(-0.53)	(-1.69)
Lagged Consolidated Volume		0.0140***		0.0201***
		(3.16)		(4.72)
Lagged Squared Excess Return		0.0140**		0.0126**
		(2.38)		(2.00)
Lagged Event Dummy		-0.0467*		-0.0377
		(-1.67)		(-1.21)
Lagged Dependent Variable		-0.0329***		-0.0615***
		(-6.42)		(-11.58)
Constant	-0.000344***	0.0181***	0.00116***	0.0213***
	(-4.53)	(3.26)	(15.99)	(3.51)
Observations	265442	254939	265442	254939
Year Dummy	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.00	0.00	0.00	0.00

Panel B of Table 2.7 displays the relation between the Google Search Volume and several turnover variables. The Google Search Volume has a strong positive significant influence on the consolidated euro volume, number of trades, buys, and sells. It is also economically meaningful. If attention changes by one standard deviation the number of trades increases by about 0.09 standard deviations, which implies a change of $2,265.95 * 0.09 \approx 204$ trades[56] for the average firm in the sample. This relation remains robust if control variables and fixed effects are included. The order imbalance variable is not significantly influenced by the Google Search Volume variable. This result shows that attention has an omnidirectional influence on trades. Buys and sells likewise increase.[57] Results are in line with the estimation results of the modified Easley et al. (1996) model, earlier research and confirm Hypothesis 1. Complementing the existing literature, we find that this relation is contemporaneous, hinting at the decision making process of individual traders.

[56]The mean standard deviation of trades for the average firm is 2,265.95 in Table 2.3.

[57]The positive sign of the GSVI coefficient from the order imbalance regression might be attributed to the fact that it is easier to buy than to short sell an asset (Barber and Odean (2008)). However, results are insignificant. The results are qualitatively the same if volume or dollar-volume weighted order imbalance measures are used.

Panel C of Table 2.7 documents the relation between the Google Search Volume and volatility in the market. In the model presented earlier volatility mainly stems from the trading of uninformed traders. Insiders trade directionally and therefore should only have a small influence on intraday price fluctuations. Therefore one should expect that uninformed traders who become more active in times of high attention, drive volatility. This is in line with retail traders acting mainly as noise traders as proposed by Foucault et al. (2011). Volatility is measured by midpoint volatility and the number of volatility interruptions per day. Both midpoint volatility as well as the circuit breakers are positively and significantly (1% level) driven by attention in all specifications. A one standard deviation increase in Google Search volume increases the likelihood of a volatility interruption by more than 10% (compared to the average). Dimpfl and Jank (2016) also find this positive relation, however, based on weekly volatility observations and not for single stocks. Our findings confirm Hypothesis 3 and are in line with the idea that retail traders drive volatility (Foucault et al. (2011)).

Panel D of Table 2.7 exhibits the relation between stock returns and Google Search Volume. Barber and Odean (2008), Da et al. (2011) and Drake et al. (2012) study this relationship and find a positive short-term influence of search volume on stock returns. Those studies, however, either only regard specific events[58] or only regard a subset of the market[59]. In that sense, this study takes a different stand by looking at an 'unselected' time series of stock returns. In contrast to the mentioned studies, the results in regressions (1)-(4) indicate a negative influence of search volume on stock returns. The influence of search volume on excess returns, however, is only significant for regression (4) at the 10% level. The differences to the results of Da et al. (2011) or Bank et al. (2011) can also be explained by the different time horizons of the studies: While those studies analyze average weekly search volume changes and their influence on weekly returns, this study is interested in the influence of daily search volume. Hypothesis 2 must be rejected for very short horizons.

Overall, the trading dynamics results indicate no significant influence of the attention measure on the liquidity measures. Only the market depth seems to be significantly increased. The turnover and volatility measures are all positively related to the Google attention measure. The short-term stock returns are unrelated to the search volume. This result might be due to the fact that attention is a non-directional concept. In general, attention seems to increase both informed and uninformed trading such that overall liquidity is unaffected. Turnover and volatility increase on high attention days due to the increased activity of market participants.[60]

[58] Da et al. (2011) look at IPO returns and Drake et al. (2012) analyze earnings announcements.

[59] Barber and Odean (2008) concentrate on the portfolios of individual investors.

[60] As stated earlier, the same analysis is repeated with the Fama and MacBeth (1973) estimation method. The results are presented in Table A2.3 in the Appendix. Findings stay qualitatively the same, only the overall significance is increased. Also, in addition to the fixed-effects regression with firm-clustered standard errors, the attention-trade dynamics relation is estimated with fixed-effects and firm-time clustered standard errors. Again, the untabulated results are qualitatively the same.

Lagged Google Search Volume

One possible concern of the analysis in the contemporaneous relation between Google Search Volume and trade dynamics measures could be that they mutually influence each other. Also, as noted earlier, it is not clear how much time individual investors need from their active information search to a trading decision. To mitigate these concerns, the regressions of the previous analysis are repeated with a one day lagged Google Search Volume. It seems rather unlikely that today's liquidity, volatility, turnover, and prices drive yesterday's attention. The results of this estimation can be found in Table A2.1 in the Appendix.

The directions of the relations, size of coefficients, and significance of the lagged attention-liquidity relation are similar to the main regression. The results for the turnover and volatility variables are confirmed with the lagged attention variable. The relation is positive and highly significant, as in the contemporaneous regressions. Only the size of the effects is slightly reduced for the lagged Google Search Volume. The relation between search volume and stock returns remains qualitatively the same as well. However, the significance of the relation increased (now at the five percent level), and the coefficients are more negative. While the negative influence of attention on returns before was not significant, lagged results provide some evidence in favor of lower returns after high attention days. Overall, the attention-trade dynamics relation seems robust to lags in the attention variable.

Search Volume - Category Finance Filter

Table A2.2 in the Appendix shows the attention-trade dynamics relation for the category finance-filtered Google Search Volume. The finance-filtered search volume is derived as described in Section 2.4. While the filtered data might offer some advantages due to less noise in search traffic, there are fewer observations for the Google finance-filtered variable than for the general Google Search Volume. As noted in Section 2.4, while being positively related, unfiltered and filtered SVI behave differently. So the results from this table can be considered as a further robustness check for the relation between attention and trade dynamics. The results of the finance-filtered attention-trade dynamics relation are in line with previous findings, as can be seen in all panels. The positive relation between turnover/volatility and attention is quite robust.

2.6.3 Subsample Sorts

In this section, several sample splits are applied to the regression presented in Section 2.6.2. The goal of this section is to provide additional robustness checks and to understand whether the attention-trade dynamics relationship is stable over time and firm characteristics. To this end, the methodology of the previous section is applied to several subsamples.[61]

[61]In the following paragraphs, we use sample splits to observe the influence of various firm characteristics. Including the sorting variables as independent variables into our regression and interacting them with SVI however yields very similar results.

Subperiods

Table 2.8 presents fixed-effects regressions of the attention-trade dynamics relation with robust, company-clustered standard errors, year dummies and control variables as in the main regression. The two subperiods are from 2004 until 2007 and from 2008 until 2011. There are several reasons for choosing these subperiods. First, in the first subperiod, the Google search engine was used less than in the later subperiod. Second, the later subperiod can be understood as a time of financial crisis and market turmoils. Third, in 2007 the Markets in Financial Instruments Directive (MiFID) was introduced in European financial markets, and thus the second subperiod can be understood as a phase of new market regulation with more fragmented markets (see Chapter 3 in this thesis). Finally, the second subperiod is characterized by increased high-frequency trading (see e.g. Boehmer et al. (2015)).

Panel A of Table 2.8 shows the attention-liquidity relation. Generally, the insignificant relation between attention and liquidity measures can (with some exceptions) be confirmed for both subsamples. The quoted and effective spread react more negatively to the search volume in the early subperiod, from 2004 until 2007, than in the later subperiod. The quoted spread is significantly negatively influenced at the 1% level. This influence could potentially be explained by the lower high frequency trader presence in earlier years of the sample (see Boehmer et al. (2015)). As described earlier, high frequency traders can be interpreted as insiders. With relatively fewer insiders in the earlier years, it is not surprising that attention has a more positive effect on liquidity. The market depth, however, seems to increase more with the attention measure in the later subperiods. The search volume has a significant positive influence on the 5min and 60min price impact in the later subperiod, whereas the relation is negative and insignificant in earlier periods. Overall, the mixed results again show that it is important to consider the multidimensionality of liquidity. It seems that spreads did improve in earlier subperiods while price impact and market depth increase for higher attention in the later period.

Panel B of Table 2.8 shows the results of the turnover attention relation. In both subperiods the relation is significantly positive. However, the coefficients of the Google Search Volume are higher in the second subperiod. This finding can not be explained by a general increase in trading volume as the model controls for time trends by the use of year dummies.

The results in *Panel C* of Table 2.8 confirm the positive and significant relation between search volume and volatility variables for both subperiods. The coefficient in the midpoint volatility-search volume regression is larger for the second subperiod.

The stock return-search volume relation remains insignificant in all subsamples as shown in *Panel D* of Table 2.8. The relation is positive for the first subperiod and negative for the second subperiod. Overall, the volatility and turnover relations are robust in all subsamples.[62]

[62] The subperiod results remain robust for Fama and MacBeth (1973) regressions and panel fixed-effects regressions with firm-time clustered standard errors

Table 2.8: ***Attention Subperiods and Trade Dynamics***
This Table provides firm-fixed effects regressions with robust, company-clustered standard errors of liquidity measures, turnover, volatility and returns as dependent variables and Google Search Volume as explanatory variable. The sample contains all Dax, MDax, SDax and TecDax and is split in two subperiods (2004-2007) and (2008-2011). Control variables are: Year Dummies, Lagged Event Dummy, Lagged Squared Excess Returns, Lagged Trading Volume as well as the Lagged Dependent Variable. For a more detailed definition of all variables, see Appendix B. All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. T-Statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

Panel A: Liquidity

	Quoted Spread		Effective Spread		Depth		Depth on Bid Side		Depth on Ask Side		5-min Price Impact		60-min Price Impact	
	04 - 07	08 - 11	04 - 07	08 - 11	04 - 07	08 - 11	04 - 07	08 - 11	04 - 07	08 - 11	04 - 07	08 - 11	04 - 07	08 - 11
GSVI	-0.0121**	-0.00224	-0.00872	0.00372	0.000166	0.0119	0.00149	0.0107	-0.00208	0.0160*	-0.00751	0.0200**	-0.00198	0.0301***
	(-2.52)	(-0.46)	(-1.62)	(0.35)	(0.03)	(1.55)	(0.24)	(1.32)	(-0.31)	(1.91)	(-1.42)	(2.20)	(-0.38)	(3.89)
Observations	107793	139180	104836	133108	104836	133108	104837	133108	104836	133109	104836	133108	104836	133108
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.44	0.63	0.32	0.23	0.23	0.33	0.19	0.27	0.18	0.26	0.08	0.20	0.03	0.06

Panel B: Turnover

	Consolidated Volume		# Trades		# Buys		# Sells		Order Imbalance	
	04 - 07	08 - 11	04 - 07	08 - 11	04 - 07	08 - 11	04 - 07	08 - 11	04 - 07	08 - 11
GSVI	0.0511***	0.112***	0.0436***	0.0945***	0.0463***	0.0968***	0.0430***	0.0921***	0.00604	0.0124**
	(7.12)	(7.93)	(6.74)	(7.98)	(6.54)	(7.80)	(6.64)	(7.93)	(1.18)	(2.15)
Observations	109878	140322	107793	139180	107793	139180	107793	139180	105019	135967
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.19	0.28	0.41	0.43	0.36	0.40	0.39	0.40	0.05	0.05

Panel C: Volatility

	# Volatility Interruptions		Midpoint Volatility	
	04 - 07	08 - 11	04 - 07	08 - 11
GSVI	0.0576***	0.0529***	0.0133***	0.0768***
	(5.10)	(5.06)	(3.31)	(6.47)
Observations	27759	120327	106528	135740
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
Controls	Yes	Yes	Yes	Yes
R-squared	0.06	0.20	0.10	0.24

Panel D: Return

	Stock Return		Excess Return	
	04 - 07	08 - 11	04 - 07	08 - 11
GSVI	0.00252	-0.00612	0.00129	-0.00534
	(0.82)	(-1.01)	(0.42)	(-0.91)
Observations	111892	143047	111892	143047
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
Controls	Yes	Yes	Yes	Yes
R-squared	0.00	0.00	0.00	0.00

Size Sort

In this analysis, firms are sorted into size terciles. The regression setup again is the same as in the full sample analysis, only that it is applied to the terciles of smallest and largest firms based on the previous year's market cap. Thus a firm can switch between terciles across years. There are several reasons why size is an important factor in the attention-trading dynamics relation. First, a cross-sectional size sort can be seen as a proxy for attention as large firms should usually also attract more attention. It is of interest to understand whether time series fluctuations in attention are only a relevant determinant for small, rather unknown firms or whether they also play a role for trading dynamics in larger stocks that are continuously in the news. Second, transparency as well as liquidity are higher for those stocks. They are covered by more analysts and traded by institutional investors. Altogether, this might lead to more efficient pricing in those stocks. Also the Probability of Informed Trading should be lower for those stocks as seen in the results of the model in Section 2.6.1.

The results in the liquidity-search volume relation in *Panel A* of Table 2.9 are mainly insignificant but differ between small and large firms. In large firms, the spread measures and the depth and price impact measures are (if anything) increased. In contrast, for the small firms, the effective spreads and price impact measures are decreased. This result could indicate that attention only plays a role for liquidity if the firm is relatively small or unknown. These results in the size sorts are later supported in the cross-sectional attention sort. If everybody already knows of a firm in the first place a higher attention does not necessarily influence investors' behavior (as it was already part of their choice set, see Kahneman (1973)). Also, the relative impact of retail traders can be much higher in smaller stocks. The turnover and volatility specifications in *Panel B* and *Panel C* of Table 2.9 remain significant and positive in the large and small firm subsamples. The search volume has a slightly larger effect on volatility and turnover in the sample of large firms. The return-attention relation remains negative as shown in *Panel D* of Table 2.9. It is, however, only significant at the ten percent level for large firms.[63]

Extreme Attention Day Sort

This analysis sorts the attention days per firm into high and low attention deciles. Of these deciles, only the highest and lowest are kept for the analysis. Thus only 20% of the sample are considered. These extreme search volume observations in the high and low attention deciles should have a stronger impact on the trade dynamics. The results of this analysis are presented in Table 2.10.

Panel A of Table 2.10 shows the attention-liquidity relation. On extreme attention days, the influence of the search volume on the spread measures is negative. The relation between market depth and search volume is mixed positive and insignificant on extreme attention days. The coefficient of the search volume on the 5min and 60min price impact measure is positive on extreme attention days. Overall, the attention-liquidity relation has the same direction as in the main regression and is still insignificant.

[63] The size sort results remain robust for Fama and MacBeth (1973) regressions and panel fixed-effects regressions with firm-time clustered standard errors.

Table 2.9: ***Attention and Trade Dynamics: Size Sort***
This Table provides firm-fixed effects regressions with robust, company-clustered standard errors of liquidity measures, turnover, volatility and returns as dependent variables and Google Search Volume as explanatory variable. The sample contains all Dax, MDax, SDax and TecDax and is split in size terciles. A firm's size is measured by its previous year's market capitalization. The Table shows the small and large size tercile (excluding medium sized companies). Control variables are: Year Dummies, Lagged Event Dummy, Lagged Squared Excess Returns, Lagged Trading Volume as well as the Lagged Dependent Variable. For a more detailed definition of all variables, see Appendix B. All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. T-Statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

Panel A: Liquidity

	Quoted Spread		Effective Spread		Depth		Depth on Bid Side		Depth on Ask Side		5-min Price Impact		60-min Price Impact	
	SMALL	LARGE	SMALL	LARGE	SMALL	LARGE	SMALL	LARGE	SMALL	LARGE	SMALL	LARGE	SMALL	LARGE
GSVI	-0.0137*	0.00315	-0.0141	0.00713	0.00104	0.0121	0.00526	0.0126	-0.00120	0.0223	-0.00389	0.0123	-0.00309	0.0243*
	(-1.66)	(0.51)	(-1.43)	(0.42)	(0.09)	(0.70)	(0.49)	(0.73)	(-0.11)	(1.26)	(-0.44)	(0.85)	(-0.34)	(1.77)
Observations	59929	80962	56299	79343	56299	79343	56300	79343	56299	79343	56299	79343	56299	79343
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
R-squared	0.53	0.72	0.40	0.17	0.26	0.47	0.18	0.45	0.19	0.43	0.12	0.27	0.07	0.05

Panel B: Turnover

	Consolidated Volume		# Trades		# Buys		# Sells		Order Imbalance	
	SMALL	LARGE	SMALL	LARGE	SMALL	LARGE	SMALL	LARGE	SMALL	LARGE
GSVI	0.0635***	0.0829***	0.0508***	0.0630***	0.0518***	0.0639***	0.0513***	0.0623***	-0.00213	-0.00311
	(4.96)	(4.74)	(4.15)	(4.38)	(4.00)	(4.28)	(3.98)	(4.23)	(-0.29)	(-0.29)
Observations	60538	81208	59929	80962	59929	80962	59929	80962	57138	80304
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
R-squared	0.25	0.25	0.41	0.54	0.36	0.52	0.36	0.52	0.04	0.09

Panel C: Volatility

	# Volatility Interruptions		Midpoint Volatility	
	SMALL	LARGE	SMALL	LARGE
GSVI	0.0398***	0.0517***	0.0298***	0.0447***
	(2.71)	(3.33)	(3.23)	(3.99)
Observations	32330	58646	58301	79779
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.15	0.22	0.12	0.34

Panel D: Return

	Stock Return		Excess Return	
	SMALL	LARGE	SMALL	LARGE
GSVI	-0.00279	-0.0101*	-0.00554	-0.0108*
	(-0.65)	(-1.79)	(-1.15)	(-1.92)
Observations	62122	82367	62122	82367
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.01	0.00	0.01	0.00

Panel B and *Panel C* of Table 2.10 show a positive and significant relation between the turnover and volatility measures and Google Search Volume on extreme attention days. This result supports the findings of the main analysis (as expected coefficients are even slightly larger). Overall, the relation between turnover and volatility is robust on high attention days.

Panel D of Table 2.10 shows again an insignificant negative relation between stock returns and the attention measure on extreme attention days.[64]

Table 2.10: ***Attention and Trade Dynamics: Extreme Attention Sort***
This Table provides firm-fixed effects regressions with robust, company-clustered standard errors of liquidity measures, turnover, volatility and returns as dependent variables and Google Search Volume as explanatory variable. The sample contains all Dax, MDax, SDax and TecDax and is split into time series attention deciles. The Table shows the two most extreme attention deciles. For each firm only the days with lowest and highest attention are considered. Control variables are: Year Dummies, Lagged Event Dummy, Lagged Squared Excess Returns, Lagged Trading Volume as well as the Lagged Dependent Variable. For a more detailed definition of all variables, see Appendix B. All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. T-Statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

Panel A: Liquidity

	(1) Quoted Spread	(2) Effective Spread	(3) Depth	(4) Depth on Bid Side	(5) Depth on Ask Side	(6) 5-min Price Impact	(7) 60-min Price Impact
GSVI	-0.00553	-0.00400	0.00658	0.00789	0.00837	0.00292	0.00797
	(-1.22)	(-0.63)	(0.94)	(1.12)	(1.12)	(0.41)	(1.24)
Observations	48353	46395	46395	46396	46396	46395	46395
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.58	0.39	0.36	0.29	0.30	0.15	0.05

Panel B: Turnover

	(1) Consolidated Volume	(2) # Trades	(3) # Buys	(4) # Sells	(5) Order Imbalance
GSVI	0.0712***	0.0584***	0.0600***	0.0575***	0.00297
	(8.75)	(8.31)	(8.02)	(8.11)	(0.71)
Observations	49024	48353	48353	48353	47063
Year Dummy	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company
Controls	Yes	Yes	Yes	Yes	Yes
R-squared	0.26	0.47	0.43	0.44	0.05

Panel C: Volatility

	(1) # Volatility Interruptions	(2) Midpoint Volatility
GSVI	0.0542***	0.0361***
	(4.97)	(6.34)
Observations	23088	47211
Year Dummy	Yes	Yes
Fixed Effects	Yes	Yes
SE	Company	Company
Controls	Yes	Yes
R-squared	0.19	0.21

Panel D: Return

	(1) Stock Return	(2) Excess Return
GSVI	-0.00492	-0.00545*
	(-1.49)	(-1.64)
Observations	50922	50922
Year Dummy	Yes	Yes
Fixed Effects	Yes	Yes
SE	Company	Company
Controls	Yes	Yes
R-squared	0.00	0.00

Cross-Sectional Attention Sort

In this analysis, the companies are sorted according to their cross-sectional level of attention into terciles (see Section 2.4). One can hypothesize that firms with a generally lower level of average

[64] The extreme attention day results remain robust for Fama and MacBeth (1973) regressions and panel fixed-effects regressions with firm-time clustered standard errors.

attention should experience a stronger shift in their trading dynamics if the time series of their attention moves. One potential reason can be found in Merton (1987): If an investor's attention is drawn to a certain stock, it becomes part of his or her investment choice set. This effect should be more relevant for rather unknown companies as prominent firms are part of the choice set anyways. At the same time, retail traders should exhibit greater impact on more unknown stocks as the general trading volume of those is usually lower. Note that the cross-sectional attention sort and the size sort result in surprisingly different portfolios. Only 40% (45%) of the small (large) stocks are also low (high) attention stocks. We find that small business-to-customer firms generally receive a high level of cross-sectional attention while large business-to-business companies do not. As in the previous analyses, the regression setup is unchanged. Only the firms that experience the highest and lowest overall level of cross-sectional attention are considered.[65] Table 2.11 shows the results of the mean cross-sectional attention sort.[66]

Panel A of Table 2.11 displays the attention-liquidity relation. The influence of the search volume on the quoted and effective spread is significantly negative at the 1% level for firms that have a low general level of attention. This finding is in line with the idea that firms that are not in the focus of investors experience stronger attention-related shocks. For these firms, the liquidity in terms of the spread significantly improves. The relation between market depth and search volume is mostly insignificant for high and low attention firms. Only the coefficient of the bid-side depth in low attention firms is significantly negative (at the 10% level), which is puzzling and not in line with Hypothesis 1. The coefficient of the search volume on the 5min and 60min price impact measure is negative for low attention companies. Overall, the attention-liquidity relation shows a significant improvement in liquidity, in terms of spread, for low attention firms. This result is in line with the hypotheses that these type of firms should experience the strongest attention effects.

Panel B of Table 2.11 shows a positive and highly significant (at the 1% level) relation between the turnover measures and search volume in low attention firms. In high attention firms, this relation is also significantly positive at the 10% level. Yet the coefficients are much more positive in low attention firms, confirming the idea that the attention effect is stronger for low attention firms.

Panel C of Table 2.11 shows the same pattern for the volatility-attention relation as for the turnover-attention relation. The volatility increases with a higher search volume for low and high attention firms, but the effects are stronger in low attention companies.

Panel D of Table 2.11 shows the insignificant negative relation between stock returns and the attention measure for both high and low attention firms, as found in the main regression.

Overall, the relation between turnover and volatility is robust for high and low attention firms and particularly strong in low attention firms. The liquidity, in terms of the spread measure, is improved in low level attention firms on high attention days.

[65] To address concerns of a potential look-ahead bias, we repeat the analysis with firms being sorted according to a weekly changing cross-sectional attention measure instead of the mean attention over the whole time series. Results are qualitatively unchanged.

[66] The cross-sectional attention sort results also remain robust for Fama and MacBeth (1973) regressions and panel fixed-effects regressions with firm-time clustered standard errors.

Table 2.11: ***Attention and Trade Dynamics: Cross-Sectional Attention***

This Table provides firm-fixed effects regressions with robust company-clustered standard errors of liquidity measures, turnover, volatility and returns as dependent variables and Google Search Volume as explanatory variable. The sample contains all Dax, MDax, SDax and TecDax and is split in cross-sectional attention terciles. The Table shows the lowest and highest attention tercile. Control variables are: Year Dummies, Lagged Event Dummy, Lagged Squared Excess Returns, Lagged Trading Volume as well as the Lagged Dependent Variable. For a more detailed definition of all variables, see Appendix B. All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. T-Statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

Panel A: Liquidity

	Quoted Spread		Effective Spread		Depth		Depth on Bid Side		Depth on Ask Side		5-min Price Impact		60-min Price Impact	
	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH
GSVI	-0.0208***	0.00424	-0.0257***	0.00906	-0.0126	0.0229	-0.0171**	0.0269	-0.00238	0.0283	-0.0127	0.00823	-0.00583	0.0123
	(-3.58)	(0.45)	(-2.78)	(0.43)	(-1.43)	(1.25)	(-2.00)	(1.48)	(-0.24)	(1.44)	(-1.30)	(0.49)	(-0.61)	(0.87)
Observations	49972	99648	48486	95808	48486	95808	48486	95809	48486	95808	48486	95808	48486	95808
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
R-squared	0.64	0.63	0.40	0.23	0.27	0.40	0.21	0.38	0.20	0.33	0.18	0.20	0.08	0.05

Panel B: Turnover

	Consolidated Volume		# Trades		# Buys		# Sells		Order Imbalance	
	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH	LOW	HIGH
GSVI	0.0993***	0.0330**	0.0943***	0.0239*	0.0969***	0.0244*	0.0937***	0.0238*	-0.00135	0.00712
	(6.52)	(2.24)	(7.16)	(1.95)	(7.12)	(1.86)	(6.91)	(1.81)	(-0.18)	(0.66)
Observations	50025	101072	49972	99648	49972	99648	49972	99648	49245	96817
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
R-squared	0.28	0.24	0.45	0.51	0.41	0.47	0.42	0.47	0.04	0.07

Panel C: Volatility

	# Volatility Interruptions		Midpoint Volatility	
	LOW	HIGH	LOW	HIGH
GSVI	0.0663***	0.0271**	0.0419***	0.0192**
	(4.67)	(2.27)	(4.09)	(2.42)
Observations	38112	54893	49123	97678
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.16	0.21	0.19	0.28

Panel D: Return

	Stock Return		Excess Return	
	LOW	HIGH	LOW	HIGH
GSVI	-0.00258	-0.000869	0.000227	-0.00387
	(-0.47)	(-0.25)	(0.04)	(-1.02)
Observations	50785	103084	50785	103084
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.00	0.00	0.01	0.00

2.6.4 Attention and Retail Trading

Most studies using SVI as an attention measure take it for granted that SVI measures the attention of retail traders while professionals would use more elaborated information sources e.g., Bloomberg Professional. Retail traders are more prone to the attention bias, have a higher demand for information, and will use the Google search engine before they trade. Therefore, the attention-trade dynamics relations should be stronger for a sample with a higher proportion of retail trades. Da et al. (2011) find supportive evidence by showing that order types that are likely to be used by retail traders are strongly related to SVI. In the following sections, we intend to add further robustness to their findings and provide clear indication for SVI being a retail trader attention measure.

Small Trade Quintiles

The following analysis builds on the assumption that small trades are usually conducted by retail traders (see e.g., Kumar and Lee (2006)). In line with this conjecture, we find in untabulated results that the average trade size (the fraction of small trades) is significantly negatively (positively) related to Google SVI. Against this assumption stands the increase of algorithmic trading and smart order routing in the last years.[67] Algorithmic traders use small and frequent trades (see e.g., Chordia et al. (2011)). Therefore, the following results should not be overstated.[68] Even though small trades, as instrument for retail trades, nowadays have a lower validity, the instrument is still used for two reasons: In the first years of the data sample (2004-2007), algorithmic trading was not yet utilized that much (see Boehmer et al. (2015)). Furthermore, previous authors, e.g., Da et al. (2011), also used the small trades as instrument for retail investors in the context of the Google Search Volume. If small trades proxy for retail trader presence the attention-trade dynamics relation should be stronger on days with a higher fraction of small trades.

This analysis again uses the same fixed-effect regression setup as in Section 2.6.2. The data sample is divided into quintiles defined by the proportion of small trades. A trade is classified as small if the trade size in Euro terms is among the smallest 5% of all trades for a given firm-year. Other classification algorithms, however, generate similar orderings.[69] The proportion of small trades is calculated for each stock-day. Finally, stocks are sorted into terciles on a yearly basis according to their average proportion of small trades.[70] The results of the analysis can be found in Table 2.12.

[67] An analysis of algorithmic and high frequency trading in more than forty countries, including the German Xetra market, can be found in Boehmer et al. (2015).

[68] In untabulated results, we document qualitatively similar results sorting stocks based on their institutional ownership from Thomson Reuters Eikon. We refrain from presenting these results as ownership information is only available for 60% of our sample stocks.

[69] Trades are classified as small relative to the average trade size over all firms or relative to a fixed Euro amount, e.g. 10,000 Euro.

[70] Tercile (1) holds stocks with the smallest proportion of small trades (i.e., mainly large trades), tercile (3) stocks with the highest proportion of small trades.

Table 2.12: ***Attention and Trade Dynamics: Small Trade Sort***
This Table provides firm-fixed effects regressions with robust, company-clustered standard errors of liquidity measures, turnover, volatility and returns as dependent variables and Google Search Volume as explanatory variable. The sample contains all Dax, MDax, SDax and TecDax companies and is split into small trade terciles. A trade is classified as small if he is among the smallest 5% of trades for a specific firm-year. Per company a proportion of small trades is calculated each day and based on this proportion companies are sorted into terciles. The Table shows the terciles with high and low proportion of small trades (medium proportion days are omitted). Control variables are: Year Dummies, Lagged Event Dummy, Lagged Squared Excess Returns, Lagged Trading Volume as well as the Lagged Dependent Variable. For a more detailed definition of all variables, see Appendix B. All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. T-Statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

Panel A: Liquidity

	Quoted Spread		Effective Spread		Depth		Depth on Bid Side		Depth on Ask Side		5-min Price Impact		60-min Price Impact	
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
GSVI	-0.00200	-0.0179***	0.00835	-0.0132*	0.00152	-0.00383	0.00637	-0.00253	0.00164	-0.00208	0.0166	-0.00266	0.0203**	0.00572
	(-0.22)	(-2.94)	(0.58)	(-1.66)	(0.10)	(-0.41)	(0.42)	(-0.27)	(0.11)	(-0.20)	(1.31)	(-0.28)	(1.98)	(0.63)
Observations	78595	69330	75155	65676	75155	65676	75155	65677	75156	65676	75155	65676	75155	65676
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.51	0.54	0.19	0.41	0.31	0.30	0.26	0.23	0.27	0.23	0.14	0.13	0.03	0.06

Panel B: Turnover

	Consolidated Volume		# Trades		# Buys		# Sells		Order Imbalance	
	Low	High	Low	High	Low	High	Low	High	Low	High
GSVI	0.0648***	0.0879***	0.0441***	0.0663***	0.0465***	0.0681***	0.0412***	0.0656***	0.0128	0.00393
	(4.94)	(6.05)	(4.27)	(5.34)	(4.28)	(5.11)	(3.88)	(5.31)	(1.34)	(0.58)
Observations	79825	69730	78595	69330	78595	69330	78595	69330	76376	66542
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.24	0.25	0.48	0.39	0.45	0.35	0.45	0.35	0.06	0.04

Panel C: Volatility

	# Volatility Interruptions		Midpoint Volatility	
	Low	High	Low	High
GSVI	0.0406***	0.0637***	0.0292***	0.0502***
	(3.10)	(3.53)	(3.18)	(3.96)
Observations	46314	39302	76652	67808
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
Controls	Yes	Yes	Yes	Yes
R-squared	0.12	0.16	0.24	0.13

Panel D: Return

	Stock Return		Excess Return	
	Low	High	Low	High
GSVI	0.00200	-0.00489	-0.00137	-0.00348
	(0.50)	(-0.81)	(-0.33)	(-0.60)
Observations	81465	71383	81465	71383
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
Controls	Yes	Yes	Yes	Yes
R-squared	0.00	0.00	0.00	0.01

Panel A of Table 2.12 shows the results for the liquidity measures. The quoted and effective spreads measures do not significantly react to attention changes on days with a low proportion of small trades. However, for days with a high proportion of small trades, a significant negative relation can be identified. The depth measures are not related to the search volume variable in small and large trades. The search volume only has a significant influence on the 60min price impact in large trades. Altogether, results provide weak indication of liquidity improving on days with a high proportion of retail traders.

Panel B and *Panel C* of Table 2.12 show the relation of the turnover and volatility relation to the attention measure. In every specification, the search volume coefficients are significant and positive. In the subsample with a higher proportion of small trades, however, the coefficients are larger than in the low proportion subsample. Thus, the effects on turnover and volatility also exist in environments with less retail trader presence (assuming that trades size really proxies for those) but are enforced if the market impact of retail traders is relatively increased.

In *Panel D*, the return relation is again negative and insignificant in all subsamples. Overall, assuming trade size is a suitable proxy for retail trader presence, it can be stated that the general effects of attention on spreads, volatility, and trades are amplified on days with more retail trading. This finding is consistent with herding behavior of retail traders (Barber et al. (2008)).

Retail Trading Products

An additional test to analyze the influence of attention days on the trading dynamics and its relation to retail trading is shown in this section. This analysis is based on an additional dataset from the Stuttgart Stock Exchange as described in Section 2.4. The sample includes warrant trades (calls/puts) on Dax and MDax underlyings from April 2009 to March 2011. The Stuttgart Stock Exchange advertises itself as being 'the' trading platform for all German retail investors. Trades in this market are mainly undertaken by retail investors. If the attention effect is mainly due to retail traders, then the Google Search Volume should have a strong impact on the trading dynamics in this market.

Due to the characteristics of the dataset (many different and often illiquid warrants with no quote data available), only the relation between the Google Search Volume and the daily trading volume is analyzed. Every trade is assigned to the respective underlying such that the number of call and put buys/sells per day and underlying can be determined. In Table 2.13, the daily number of buying transactions is regressed on the SVI.[71] All the regressions presented in this section are conducted with fixed-effects, year dummies, and company clustered standard errors.

Table 2.13 shows that the number of call buys, put buys, and overall buying trades in warrants is positively and significantly related to the search volume. As in the Xetra sample, the imbalance remains insignificant.[72]

[71] In the regression, only buying transactions of options are considered due to the conjecture that retail traders' selling transactions might be motivated by means other than attention, e.g., the realization of profits/losses.

[72] Untabulated results also show that results are robust if buying quantity and buying volume (Euro) are used instead of a simple trade count.

Table 2.13: ***Attention and Retail Trading***
This Table provides firm-fixed effects regressions robust, company-clustered standard errors. The sample contains warrant buys (Calls / Puts) from the Stuttgart Stock Exchange between 2009-2011 as dependent variable and Google Search Volume as explanatory variable. Control variables are: Year Dummies, Lagged Event Dummy as well as the Lagged Dependent Variable. Lagged variables are lagged by one day. For a more detailed definition of all variables, see Appendix B. T-Statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

	(1) Call Buys	(2) Put Buys	(3) Buys	(4) Put/Call Buy Imbalance
GSVI	0.295*	0.511*	0.380**	-0.0249
	(1.80)	(1.85)	(2.04)	(-1.00)
Lagged Dependent Variable	0.555***	0.161***	0.552***	0.363***
	(20.69)	(5.26)	(20.91)	(5.57)
Lagged Event Dummy	0.696	1.818	1.058	0.155**
	(0.82)	(0.90)	(1.60)	(2.06)
Constant	2.223***	1.920***	2.170***	0.180**
	(4.06)	(3.78)	(3.71)	(2.45)
Observations	4063	1027	4850	600
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.34	0.06	0.33	0.15

The attention-trading volume relation can thus be confirmed in a setting with only retail traders. Together with the findings from the small-trade analysis, this finding confirms that attention is an important determinant of trade dynamics in a pure retail trader environment. Besides the analysis of a mere retail trader market (Stuttgart Stock Exchange) and a mixed market with both professional and retail traders (Xetra), future research could further elaborate on the attention effect of professional traders (see Ben-Rephael et al. (2017)).

2.7 Endogeneity

There is a potential endogeneity problem in the contemporaneous relation between the trading dynamics and attention. The direction of influence in the relation is not entirely clear. Does attention have an influence on a stock's trading dynamics or is there a reverse causality in a sense that highly traded, liquid, volatile assets with high returns attract more investor attention? The previous analysis with the lagged Google Search Volume already tackled this problem in the sense that yesterday's attention influenced tomorrow's trading dynamics. To further address potential concerns about edogeneity, two additional analyses are presented.

Attention on Weekends

In this analysis, the mean Google Search Volume on weekends is used as attention variable. In the following regressions, the Monday trade dynamics are related to the search volume on the weekend before. The results of the regressions are presented in Table 2.14.

Table 2.14: ***Attention on Weekends and Trade Dynamics***

This Table provides firm-fixed effects regressions with robust, company-clustered standard errors of liquidity measures, turnover, volatility and returns on Mondays as dependent variables and Google Search Volume on Weekends (Average of Saturday and Sunday) as explanatory variable. The sample contains all Dax, MDax, SDax and TecDax. Control variables are: Year Dummies, Lagged Event Dummy, Lagged Squared Excess Returns, Lagged Trading Volume as well as the Lagged Dependent Variable. For a more detailed definition of all variables, see Appendix B. All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. T-Statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

Panel A: Liquidity

	(1) Quoted Spread	(2) Quoted Spread	(3) Effective Spread	(4) Effective Spread	(5) Depth	(6) Depth	(7) Depth on Bid Side	(8) Depth on Bid Side	(9) Depth on Ask Side	(10) Depth on Ask Side	(11) 5-min Price Impact	(12) 5-min Price Impact	(13) 60-min Price Impact	(14) 60-min Price Impact
Weekend GSVI	0.000931	-0.00551	-0.00365	0.00154	0.0498**	0.00730	0.0527**	0.00782	0.0540**	0.0113	0.00188	0.00808	0.00596	0.00636
	(0.04)	(-0.88)	(-0.17)	(0.19)	(2.15)	(0.71)	(2.39)	(0.77)	(2.47)	(1.03)	(0.13)	(0.80)	(0.56)	(0.73)
Lagged Consolidated Volume		-0.0235***		-0.0363***		0.00854		0.0117		0.0217**		-0.0324***		-0.0187**
		(-5.02)		(-6.74)		(0.85)		(1.39)		(2.10)		(-4.08)		(-2.48)
Lagged Squared Excess Return		0.00593		0.0179***		-0.00314		-0.00325		-0.00542		0.0531***		0.0562***
		(1.35)		(4.23)		(-0.72)		(-0.70)		(-1.14)		(7.42)		(5.73)
Lagged Event Dummy		-0.0324		-0.0895***		0.0542		-0.00189		0.0563		-0.145***		-0.0736
		(-1.02)		(-3.45)		(1.10)		(-0.03)		(1.38)		(-3.24)		(-1.53)
Lagged Dependent Variable		0.734***		0.645***		0.511***		0.501***		0.435***		0.326***		0.163***
		(53.78)		(36.45)		(13.06)		(19.76)		(11.85)		(24.21)		(14.16)
Constant	-0.0190***	0.126***	-0.0165***	0.166***	-0.0358***	0.132***	-0.0333***	0.119***	-0.0330***	0.162***	-0.00918***	0.125***	0.0105***	0.201***
	(-19.18)	(4.80)	(-16.76)	(5.06)	(-33.00)	(3.36)	(-32.22)	(3.18)	(-32.25)	(4.00)	(-13.54)	(3.61)	(21.17)	(5.95)
Observations	50205	48139	48412	46547	48412	46547	48412	46547	48415	46547	48412	46547	48412	46547
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
R-squared	0.00	0.62	0.00	0.48	0.00	0.35	0.00	0.31	0.00	0.26	0.00	0.17	0.00	0.06

Panel B: Turnover

	(1) Consolidated Volume	(2) Consolidated Volume	(3) # Trades	(4) # Trades	(5) # Buys	(6) # Buys	(7) # Sells	(8) # Sells	(9) Order Imbalance	(10) Order Imbalance
Weekend GSVI	0.0684***	0.0412***	0.0422*	0.0399***	0.0413*	0.0398***	0.0398*	0.0393***	0.000741	-0.000224
	(5.05)	(5.07)	(1.87)	(5.47)	(1.87)	(5.38)	(1.81)	(5.13)	(0.08)	(-0.03)
Lagged Consolidated Volume		0.399***		-0.0445***		-0.0252**		0.00500		0.0226***
		(19.32)		(-3.61)		(-2.11)		(0.36)		(3.38)
Lagged Squared Excess Return		0.0331***		-0.0131		-0.0123		-0.00795		0.0112**
		(3.31)		(-1.60)		(-1.58)		(-0.93)		(2.17)
Lagged Event Dummy		0.0948		0.0887		0.0706		0.104		-0.0766
		(1.18)		(1.03)		(0.82)		(1.24)		(-1.62)
Lagged Dependent Variable				0.627***		0.592***		0.565***		0.235***
				(47.05)		(36.24)		(38.93)		(22.35)
Constant	-0.0767***	-0.183***	-0.0444***	-0.250***	-0.0455***	-0.264***	-0.0416***	-0.265***	-0.0117***	0.00927
	(-121.99)	(-8.00)	(-43.91)	(-11.19)	(-45.99)	(-10.73)	(-42.14)	(-11.68)	(-29.20)	(0.38)
Observations	50162	48835	50205	48139	50205	48139	50205	48139	49125	47105
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
R-squared	0.01	0.26	0.00	0.46	0.00	0.43	0.00	0.41	0.00	0.05

Table 2.14: Attention on Weekends and Trade Dynamics (ctd.)

Panel C: Volatility

	(1) # Volatility Interruptions	(2) # Volatility Interruptions	(3) Midpoint Volatility	(4) Midpoint Volatility
Weekend GSVI	0.00941	0.0390***	0.0229**	0.0199***
	(0.63)	(3.15)	(2.11)	(2.86)
Lagged Consolidated Volume		0.00643		0.0303***
		(0.43)		(3.16)
Lagged Squared Excess Return		0.0113		0.0375***
		(0.66)		(3.47)
Lagged Event Dummy		-0.0797		-0.130
		(-1.25)		(-1.34)
Lagged Dependent Variable		0.323***		0.308***
		(18.36)		(16.91)
Constant	-0.00481***	-0.175***	-0.0225***	-0.114***
	(-9.88)	(-12.54)	(-43.88)	(-5.53)
Observations	31327	29164	49206	47272
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.00	0.19	0.00	0.20

Panel D: Return

	(1) Stock Return	(2) Stock Return	(3) Excess Return	(4) Excess Return
Weekend GSVI	-0.00617	-0.00815	-0.00507	-0.00504
	(-1.11)	(-1.46)	(-0.97)	(-0.91)
Lagged Consolidated Volume		0.00241		0.00246
		(0.30)		(0.31)
Lagged Squared Excess Return		0.00353		0.00718
		(0.31)		(0.65)
Lagged Event Dummy		-0.0620		-0.0246
		(-0.64)		(-0.26)
Lagged Dependent Variable		-0.0172		-0.0600***
		(-1.59)		(-6.36)
Constant	-0.00186***	0.0123	-0.000218	0.0347***
	(-11.03)	(1.08)	(-1.39)	(2.82)
Observations	53010	50008	53010	50008
Year Dummy	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.00	0.01	0.00	0.00

This setup solves the endogeneity problem as the attention of the weekend cannot be influenced by the trading dynamics on a Monday. Moreover, investors with a high attention on the weekend must wait until Monday to trade. Finally, firms will produce less value-relevant information, so that SVI should be less information-driven. Again, all the regressions are with fixed-effects, year dummies, and company clustered standard errors.

The results in *Panel A* are not qualitatively different from those in the main analysis. The Google Search Volume has a significant positive influence on the depth while its relation to other liquidity measures is at best weak.

Panel B and *Panel C* also show the significant positive coefficients found in the main analysis. The same is true for returns, as they remain insignificant as confirmed by *Panel D*.

Altogether, this result confirms that the results of the main analysis are fairly robust and seem not to be due to some uncontrolled endogeneity in the model.

Local Holidays and Attention

An additional way to control for the endogeneity problem is to use German regional holidays as an instrument for attention as proposed by Jacobs and Weber (2012). In Germany there exist regional holidays that are non-business days in some, but not all, of the 16 federal states. On those days, stock exchanges are not closed. So people could still trade if they wanted to. Presumably people from holiday states should be less focused on trading stocks and the general attention towards a stock should be lower on these days, as they are 'distracted' by their holiday activities. This said, the local holiday might qualify as an instrument for the Google Search Volume variable. If the relation between search volume and trading dynamics still survives on these low attention days in this instrumental variable setup, this would further alleviate endogeneity concerns. Before the local holidays[73] can be used as an instrument, tests must be performed on whether they correlate with the Google Search Volume. Table A2.4, in the Appendix, shows a regression of the Google Search Volume on a holiday dummy. The local holiday measure is significantly negatively related to the Google Search Volume measure. People seem to google less on local holidays. Therefore, the local holiday dummy qualifies as an instrument for Google Search Volume. At the same time, it is very likely that those days also are days with less news. One thus could be concerned that the instrument actually measures low-information rather than low-attention. We however find that local holidays are not significantly related to the number of DGAP announcements and that the results, presented hold if we only keep firms with headquarters outside the local holiday states.

In the following, the regression from Section 2.6.2 is repeated with the only difference that the local holiday dummy serves as an instrument for the SVI. The results of the instrumental variable regression are presented in Table 2.15. *Panels A* to *D* show the results of the attention-trade dynamics relation as specified in the main regression. F-tests as specified by Cragg and Donald (1993) are used to ensure that the local holiday dummy is no weak instrument. In all specifications, F-values are a lot higher than the critical values derived in Stock and Yogo (2005).

In *Panel A* the weak relation between attention and liquidity can be confirmed. If anything, liquidity improves with higher attention as indicated by the significantly increased market depth and decreased 5min price impact on local holiday days.

In *Panel B* the turnover is significantly increased. A new insight is that sells increase more than buys as the order imbalance coefficient is significantly negative.

Panel C shows that the midpoint volatility significantly increases with attention. Although the number of volatility interruptions is not significantly influenced, evidence tends to confirm prior findings of a positive attention-volatility relation. Finally, *Panel D* shows that stock returns decrease with attention.

Overall, the instrumental variable regression confirms prior results. The positive relation between attention and both turnover and volatility can be confirmed. Also, evidence hints at a weakly negative relation between attention and concurrent returns.

[73] The presented analysis includes all local holidays that could be identified, e.g. Epiphany, All Saints' Day, Reformation Day. Robustness tests with only specific holidays yield qualitatively the same results.

Table 2.15: ***Regional Holiday and Trade Dynamics***
This Table provides firm-fixed effects instrumental-variable regressions robust, company-clustered standard errors of liquidity measures, turnover, volatility and returns as dependent variables and Google Search Volume as explanatory variable. Google Search Volume is instrumented by a regional German holiday dummy. The sample contains all Dax, MDax, SDax and TecDax companies. Control variables are: Year Dummies, Lagged Event Dummy, Lagged Squared Excess Returns, Lagged Trading Volume as well as the Lagged Dependent Variable. For a more detailed definition of all variables, see Appendix B. All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. T-Statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively. F gives the statistic from the Cragg and Donald (1993) test for weak instruments as explained in Stock and Yogo (2005).

Panel A: Liquidity

	(1) Quoted Spread	(2) Effective Spread	(3) Depth	(4) Depth on Bid Side	(5) Depth on Ask Side	(6) 5-min Price Impact	(7) 60-min Price Impact
GSVI	-0.0610	0.0364	0.126**	0.117*	0.0847	-0.124*	-0.119
	(-1.26)	(0.57)	(2.01)	(1.80)	(1.28)	(-1.76)	(-1.56)
Lagged Consolidated Volume	-0.0122***	-0.0455***	-0.00342	0.00489	0.0124**	-0.0174***	-0.0182***
	(-3.18)	(-8.77)	(-0.66)	(0.93)	(2.28)	(-2.97)	(-2.87)
Lagged Squared Excess Return	0.0161***	0.0450***	-0.00313*	-0.00310*	-0.00545***	0.0647***	0.0630***
	(11.48)	(23.74)	(-1.77)	(-1.69)	(-2.93)	(31.25)	(28.21)
Lagged Event Dummy	-0.0246	-0.0570**	0.00791	-0.0128	0.0266	-0.0203	0.0785***
	(-1.46)	(-2.52)	(0.36)	(-0.56)	(1.14)	(-0.81)	(2.92)
Lagged Dependent Variable	0.739***	0.490***	0.560***	0.512***	0.490***	0.335***	0.152***
	(406.52)	(193.50)	(323.50)	(270.49)	(269.06)	(155.28)	(68.49)
Observations	246972	237944	237944	237945	237945	237944	237944
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model	IV	IV	IV	IV	IV	IV	IV
Cragg and Donald (1993)-F	176.38	176.94	178.23	177.69	178.28	177.27	177.21

Panel B: Turnover

	(1) Consolidated Volume	(2) # Trades	(3) # Buys	(4) # Sells	(5) Order Imbalance
GSVI	0.450***	0.444***	0.389***	0.447***	-0.358***
	(6.28)	(7.08)	(6.18)	(6.92)	(-4.54)
Lagged Consolidated Volume	0.430***	-0.0665***	-0.0264***	-0.0293***	0.0565***
	(74.78)	(-20.16)	(-7.56)	(-8.30)	(8.64)
Lagged Squared Excess Return	0.0289***	0.00196	0.00222	0.00932***	0.00614***
	(14.21)	(1.14)	(1.29)	(5.26)	(2.78)
Lagged Event Dummy	0.132***	0.0560***	0.0672***	0.0588***	0.0972***
	(5.24)	(2.58)	(3.08)	(2.62)	(3.53)
Lagged Dependent Variable		0.650***	0.599***	0.589***	0.233***
		(140.87)	(140.14)	(131.33)	(110.20)
Observations	250200	246972	246972	246972	240985
Year Dummy	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Model	IV	IV	IV	IV	IV
Cragg and Donald (1993)-F	188.31	184.57	184.28	184.06	179.04

Table 2.15: Regional Holiday and Trade Dynamics (ctd.)

Panel C: Volatility

	(1) # Volatility Interruptions	(2) Midpoint Volatility
GSVI	-0.0231	0.166**
	(-0.23)	(2.34)
Lagged Consolidated Volume	0.0181**	0.0112**
	(2.49)	(1.98)
Lagged Squared Excess Return	0.0294***	0.0743***
	(12.14)	(36.40)
Lagged Event Dummy	-0.00885	-0.0922***
	(-0.27)	(-3.70)
Lagged Dependent Variable	0.336***	0.370***
	(121.26)	(167.60)
Observations	148086	242268
Year Dummy	Yes	Yes
Fixed Effects	Yes	Yes
Model	IV	IV
Cragg and Donald (1993)-F	141.23	179.43

Panel D: Return

	(1) Stock Return	(2) Excess Return
GSVI	-0.100	-0.178**
	(-1.19)	(-2.10)
Lagged Consolidated Volume	0.0216***	0.0338***
	(3.11)	(4.81)
Lagged Squared Excess Return	0.0149***	0.0141***
	(6.54)	(6.22)
Lagged Event Dummy	-0.0236	0.00364
	(-0.83)	(0.13)
Lagged Dependent Variable	-0.0338***	-0.0625***
	(-15.74)	(-30.19)
Observations	254938	254938
Year Dummy	Yes	Yes
Fixed Effects	Yes	Yes
Model	IV	IV
Cragg and Donald (1993)-F	158.50	158.30

2.8 Conclusion

The aim of this chapter was to offer an integral description of the relation between investor attention in a stock and its trading dynamics. This relation is multidimensional and driven by the strategic decision making of different investor types (informed/uninformed). The trading dynamics are modeled in an attention-adjusted microstructure model based on the seminal work of Easley et al. (1996). In line with the previous literature and the model implications, we find evidence consistent with increased trading by uninformed retail traders on high attention days. The daily Google Search Volume is significantly positively related to daily turnover and volatility of a stock. This relation is robust to several model specifications and endogeneity tests. It is stronger for large stocks, stocks with a low general level of cross-sectional attention and stocks with a higher proportion of retail trading. In other words: The effect of attention on market outcomes depends on firm and market characteristics. Especially rather unknown firms and firms with a larger fraction of retail trading should be concerned about attention-induced volatility and turnover. The liquidity of a stock is positively but in general not significantly affected by investor attention. This is explained by a strategic reaction of informed traders to the higher natural liquidity on high attention days. Results are consistent with informed traders trading more aggressively on high attention days, leading to only slightly improved liquidity measures and reduced probability of informed trading on high attention days. The short-term returns of a stock are negatively but insignificantly affected by the Search Volume.

The findings of this chapter have implications for the market microstructure and asset pricing literature and contribute to the understanding of retail investors' decision making under attention constraints. The extensive dataset of daily Google Search Volume Data is new and was previously unavailable. The daily Google measure is correlated with existing indirect attention measures and actual Google search requests but offers additional explanatory power. The search volume, as derived in this chapter, can be used in various future research settings as a daily active attention measure. This study has implications for general market outcomes and the trading of retail investors in the presence of attention.

The results of the study have implications for many market participants: Investors should consider the turnover and volatility increasing effect of attention during their investment decision. Stock exchanges will profit from increased turnover on high attention days. Market makers and designated sponsors should generally be aware that attention influences adverse selection risks and consider it in their pricing.

Appendix to Chapter 2

A Additional Analyses and Robustness Checks

Figure A2.1: Trading Dynamics on Attention Days Model
This Figure depicts the trading dynamics model. Every trading day it its determined if it is a high or low attention day based on the relative Google Search Volume of the day. On the beginning of every trading day, nature decides if it is a news or no news day. The probability for a news event on trading day t is depicted as α. The probability of bad news is δ and good news $(1-\delta)$. The buy and sell trades of the informed and uninformed on no news, good and bad news days follow three mutually independent Poisson processes as in the original model of Easley et al. (1996) (EKOP). The EKOP model is then estimated for high and low attention days (ha/la) separately. This allows to derive a probability of informed trading for high and low attention days and to analyze the informed and uninformed trading.

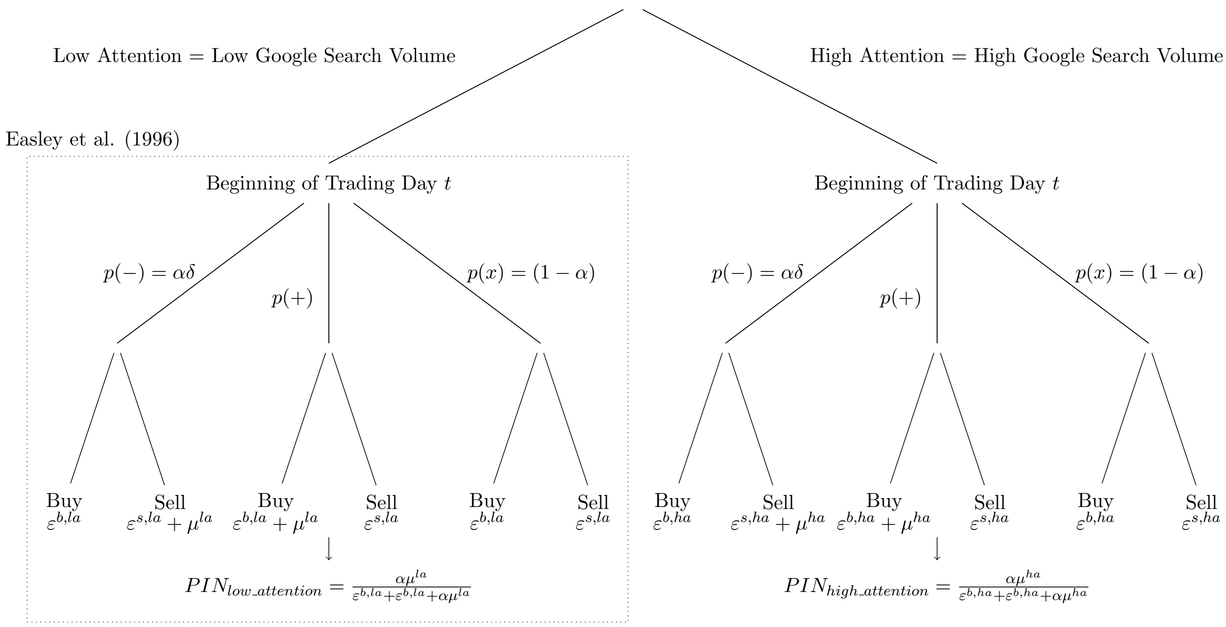


Figure A2.2: Google Search Volume Download Algorithm
This Figure demonstrates the 4 steps necessary for the generation of the Google Search Volume dataset for a time interval of more than 15 months. To get a connected timeline of eight years of search volume data, one has to submit 19 download requests per stock to Google Trends.

Step 1: Find yearly maxima. In this step, 8 download requests are needed

2004 Q1	2004 Q2	2004 Q3	2004 Q4	2008 Q1	2008 Q2	2008 Q3	2008 Q4
	x					x	
2005 Q1	2005 Q2	2005 Q3	2005 Q4	2009 Q1	2009 Q2	2009 Q3	2009 Q4
x				x			
2006 Q1	2006 Q2	2006 Q3	2006 Q4	2010 Q1	2010 Q2	2010 Q3	2010 Q4
		x				x	
2007 Q1	2007 Q2	2007 Q3	2007 Q4	2011 Q1	2011 Q2	2011 Q3	2011 Q4
		x		x			

Step 2: Find maxima of four year subperiods. In this step, 2 download requests are needed

2004 Q2	2005 Q1	2006 Q3	2007 Q3	2008 Q3	2009 Q1	2010 Q3	2011 Q1
	x				x		

Step 3: Find global maxima. In this step, 1 download requests are needed

2005 Q1	2009 Q1
	x

Step 4: Include global maximum in yearly requests. In this step, 8 download requests are needed

1)	2004 Q1	2004 Q2	2004 Q3	2004 Q4	2009 Q1
2)	2005 Q1	2005 Q2	2005 Q3	2005 Q4	2009 Q1
3)	2006 Q1	2006 Q2	2006 Q3	2006 Q4	2009 Q1
4)	2007 Q1	2007 Q2	2007 Q3	2007 Q4	2009 Q1
5)	2008 Q1	2008 Q2	2008 Q3	2008 Q4	2009 Q1
6)	2009 Q1	2009 Q2	2009 Q3	2009 Q4	2009 Q1
7)	2010 Q1	2010 Q2	2010 Q3	2010 Q4	2009 Q1
8)	2011 Q1	2011 Q2	2011 Q3	2011 Q4	2009 Q1

Figure A2.3: Average Weekday SVI Levels
This figure shows the average Trends SVI level by weekday. For each firm the unfiltered SVI is regressed on weekday dummies (Mon-Fri), separately for unfiltered and category filtered SVI. The regression coefficients of the SVI variable are plotted in the graph.

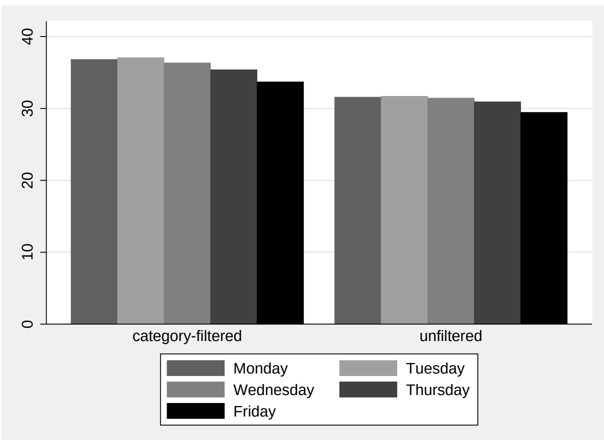


Table A2.1: ***Lagged Attention and Trade Dynamics***

This Table firm-fixed effects regressions with robust, company-clustered standard errors of liquidity measures, turnover, volatility and returns as dependent variables and Lagged Google Search Volume as explanatory variable. The sample contains all Dax, MDax, SDax and TecDax firms from 2004 to 2011. Control variables are: Year Dummies, Lagged Event Dummy, Lagged Squared Excess Returns, Lagged Trading Volume as well as the Lagged Dependent Variable. For a more detailed definition of all variables, see Appendix B. All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. T-Statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

Panel A: Liquidity

	(1) Quoted Spread	(2) Quoted Spread	(3) Effective Spread	(4) Effective Spread	(5) Depth	(6) Depth	(7) Depth on Bid Side	(8) Depth on Bid Side	(9) Depth on Ask Side	(10) Depth on Ask Side	(11) 5-min Price Impact	(12) 5-min Price Impact	(13) 60-min Price Impact	(14) 60-min Price Impact
Lagged GSVI	-0.0193	-0.00537	-0.0236	-0.0111	0.0323	0.00262	0.0390*	0.00672	0.0355*	0.00502	-0.00524	-0.00378	-0.00339	-0.00289
	(-0.96)	(-1.04)	(-1.28)	(-1.21)	(1.44)	(0.29)	(1.82)	(0.72)	(1.69)	(0.52)	(-0.41)	(-0.45)	(-0.38)	(-0.39)
Lagged Consolidated Volume		-0.0162***		-0.0416***		0.00610		0.0132**		0.0183***		-0.0269***		-0.0272***
		(-4.60)		(-7.26)		(1.03)		(2.22)		(3.08)		(-3.96)		(-4.84)
Lagged Squared Excess Return		0.0155***		0.0457***		-0.00209		-0.00218		-0.00483*		0.0634***		0.0618***
		(6.55)		(17.33)		(-0.80)		(-0.84)		(-1.73)		(16.73)		(11.81)
Lagged Event Dummy		-0.0376***		-0.0447**		0.0374**		0.0132		0.0459**		-0.0475**		0.0514**
		(-2.76)		(-2.56)		(2.10)		(0.75)		(2.33)		(-2.29)		(2.34)
Lagged Dependent Variable		0.741***		0.489***		0.560***		0.513***		0.490***		0.336***		0.153***
		(61.20)		(24.16)		(27.64)		(27.40)		(24.26)		(31.74)		(19.20)
Constant	-0.0342***	0.114***	-0.0287***	0.187***	-0.0135***	0.156***	-0.0111***	0.155***	-0.0129***	0.183***	-0.0124***	0.0889***	-0.0108***	0.114***
	(-39.66)	(5.11)	(-36.83)	(4.81)	(-14.24)	(4.55)	(-12.30)	(4.45)	(-14.57)	(4.98)	(-22.99)	(3.12)	(-28.60)	(4.02)
Observations	255812	247062	245934	238029	245934	238029	245940	238030	245957	238030	245934	238029	245934	238029
Year Dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
R-squared	0.00	0.60	0.00	0.30	0.00	0.36	0.00	0.30	0.00	0.29	0.00	0.18	0.00	0.06

Panel B: Turnover

	(1) Consolidated Volume	(2) Consolidated Volume	(3) # Trades	(4) # Trades	(5) # Buys	(6) # Buys	(7) # Sells	(8) # Sells	(9) Order Imbalance	(10) Order Imbalance
Lagged GSVI	0.0879***	0.0321***	0.0701***	0.0205***	0.0672***	0.0207***	0.0695***	0.0233***	0.00199	0.000171
	(6.33)	(4.81)	(2.97)	(3.46)	(2.90)	(3.26)	(3.01)	(3.58)	(0.26)	(0.03)
Lagged Consolidated Volume		0.459***		-0.0520***		-0.0119		-0.0134*		0.0286***
		(43.53)		(-7.55)		(-1.58)		(-1.78)		(6.81)
Lagged Squared Excess Return		0.0319***		0.00279		0.00296		0.0105**		0.00317
		(5.66)		(0.56)		(0.63)		(1.97)		(1.62)
Lagged Event Dummy		0.232***		0.154***		0.152***		0.158***		0.0127
		(5.23)		(4.47)		(4.46)		(4.50)		(0.75)
Lagged Dependent Variable				0.676***		0.619***		0.614***		0.233***
				(56.62)		(49.22)		(45.63)		(27.28)
Constant	0.0163***	-0.106***	0.0455***	-0.184***	0.0449***	-0.196***	0.0443***	-0.212***	-0.00272***	0.0635***
	(27.41)	(-4.73)	(44.91)	(-8.16)	(45.17)	(-8.32)	(44.81)	(-8.91)	(-8.84)	(3.27)
Observations	255112	250290	255812	247062	255812	247062	255812	247062	249578	241072
Year Dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
R-squared	0.01	0.25	0.00	0.49	0.00	0.45	0.00	0.45	0.00	0.06

Table A2.1: Lagged Attention and Trade Dynamics (ctd.)

Panel C: Volatility

	(1) # Volatility Interruptions	(2) # Volatility Interruptions	(3) Midpoint Volatility	(4) Midpoint Volatility
Lagged GSVI	0.0244**	0.0166***	0.0327***	0.0101**
	(2.25)	(2.74)	(3.03)	(2.24)
Lagged Consolidated Volume		0.0152*		0.0221***
		(1.82)		(4.04)
Lagged Squared Excess Return		0.0288***		0.0746***
		(4.55)		(8.17)
Lagged Event Dummy		-0.0186		-0.0542*
		(-0.49)		(-1.76)
Lagged Dependent Variable		0.335***		0.372***
		(24.33)		(26.98)
Constant	0.00328***	-0.145***	0.0125***	-0.0946***
	(36.02)	(-18.36)	(26.07)	(-6.83)
Observations	157528	148137	250718	242356
Year Dummy	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.00	0.18	0.00	0.24

Panel D: Return

	(1) Stock Return	(2) Stock Return	(3) Excess Return	(4) Excess Return
Lagged GSVI	-0.00455**	-0.00297	-0.00220	-0.00551**
	(-2.27)	(-1.55)	(-1.07)	(-2.52)
Lagged Consolidated Volume		0.0142***		0.0205***
		(3.24)		(4.84)
Lagged Squared Excess Return		0.0139**		0.0125**
		(2.38)		(1.99)
Lagged Event Dummy		-0.0467*		-0.0371
		(-1.67)		(-1.19)
Lagged Dependent Variable		-0.0329***		-0.0615***
		(-6.42)		(-11.58)
Constant	-0.000601***	0.0182***	0.00114***	0.0214***
	(-9.82)	(3.27)	(18.11)	(3.53)
Observations	265288	254996	265288	254996
Year Dummy	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.00	0.00	0.00	0.00

Table A2.2: ***Attention (Finance) and Trade Dynamics***

This Table provides firm-fixed effects regressions with robust, company-clustered standard errors of liquidity measures, turnover, volatility and returns as dependent variables and Google Finance Search Volume as explanatory variable. The sample contains all Dax, MDax, SDax and TecDax firms from 2004 to 2011. Control variables are: Year Dummies, Lagged Event Dummy, Lagged Squared Excess Returns, Lagged Trading Volume as well as the Lagged Dependent Variable. For a more detailed definition of all variables, see Appendix B. All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. T-Statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

Panel A: Liquidity

	(1) Quoted Spread	(2) Quoted Spread	(3) Effective Spread	(4) Effective Spread	(5) Depth	(6) Depth	(7) Depth on Bid Side	(8) Depth on Bid Side	(9) Depth on Ask Side	(10) Depth on Ask Side	(11) 5-min Price Impact	(12) 5-min Price Impact	(13) 60-min Price Impact	(14) 60-min Price Impact
GSVI, category: Finance	0.0113	0.00234	0.0249	0.00996	-0.0577	0.0149	-0.0347	0.0247*	-0.0621	0.0139	0.0441**	0.0150	0.0270*	0.0178
	(0.33)	(0.30)	(0.81)	(0.53)	(-1.32)	(1.17)	(-0.77)	(1.94)	(-1.57)	(0.98)	(1.97)	(1.24)	(1.77)	(1.55)
Lagged Consolidated Volume		-0.0134**		-0.0336**		0.0106		0.0143		0.0289**		-0.00698		-0.0162
		(-2.11)		(-2.50)		(0.78)		(1.19)		(1.99)		(-0.42)		(-1.37)
Lagged Squared Excess Return		0.0168***		0.0572***		-0.0127***		-0.0127***		-0.0156***		0.0678***		0.0680***
		(3.01)		(10.57)		(-3.82)		(-4.06)		(-3.97)		(9.77)		(5.19)
Lagged Event Dummy		-0.0393*		-0.0128		0.0267		0.0129		0.0367		-0.0792**		0.108***
		(-1.68)		(-0.60)		(1.03)		(0.50)		(1.28)		(-1.96)		(2.67)
Lagged Dependent Variable		0.755***		0.402***		0.595***		0.578***		0.502***		0.356***		0.121***
		(31.38)		(9.85)		(13.11)		(16.51)		(11.21)		(21.40)		(7.27)
Constant	-0.0233***	0.0604*	-0.00926***	0.106	-0.0490***	0.247***	-0.0519***	0.246***	-0.0458***	0.318***	0.00335***	0.0272	-0.00113*	0.0542
	(-17.48)	(1.82)	(-7.84)	(1.62)	(-29.36)	(4.83)	(-30.30)	(5.04)	(-30.34)	(5.75)	(3.92)	(0.65)	(-1.95)	(1.27)
Observations	71203	69067	67640	66166	67640	66166	67640	66166	67651	66167	67640	66166	67640	66166
Year Dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
R-squared	0.00	0.63	0.00	0.24	0.00	0.43	0.00	0.42	0.00	0.34	0.00	0.22	0.00	0.05

Panel B: Turnover

	(1) Consolidated Volume	(2) Consolidated Volume	(3) # Trades	(4) # Trades	(5) # Buys	(6) # Buys	(7) # Sells	(8) # Sells	(9) Order Imbalance	(10) Order Imbalance
GSVI, category: Finance	0.0856***	0.0520***	0.161***	0.0437***	0.158***	0.0449***	0.158***	0.0425***	0.0420**	0.0267**
	(2.98)	(4.21)	(3.74)	(3.59)	(3.74)	(3.53)	(3.74)	(3.27)	(2.38)	(2.26)
Lagged Consolidated Volume		0.456***		-0.0534***		-0.0259**		-0.0215		0.0300***
		(19.87)		(-4.55)		(-2.40)		(-1.61)		(3.30)
Lagged Squared Excess Return		0.0274***		0.00740		0.00684		0.0149		0.0128***
		(2.92)		(0.80)		(0.92)		(1.36)		(4.18)
Lagged Event Dummy		0.192***		0.143***		0.141***		0.153***		-0.0371
		(3.30)		(3.05)		(3.11)		(2.93)		(-1.08)
Lagged Dependent Variable				0.693***		0.654***		0.640***		0.249***
				(30.68)		(32.33)		(24.88)		(14.38)
Constant	-0.00907***	-0.0172	0.0468***	-0.131***	0.0490***	-0.136***	0.0444***	-0.162***	0.0113***	0.0664*
	(-8.62)	(-0.41)	(28.15)	(-3.08)	(29.97)	(-3.11)	(27.17)	(-3.70)	(16.92)	(1.93)
Observations	71819	70177	71203	69067	71203	69067	71203	69067	68774	67098
Year Dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company	Company	Company	Company	Company	Company	Company
R-squared	0.01	0.26	0.03	0.51	0.03	0.48	0.03	0.48	0.00	0.07

Table A2.2: Attention (Finance) and Trade Dynamics (ctd.)

Panel C: Volatility

	(1) # Volatility Interruptions	(2) # Volatility Interruptions	(3) Midpoint Volatility	(4) Midpoint Volatility
GSVI, category: Finance	0.0585***	0.0399***	0.101***	0.0397***
	(3.26)	(3.54)	(5.59)	(5.55)
Lagged Consolidated Volume		0.00238		0.00540
		(0.18)		(0.75)
Lagged Squared Excess Return		0.0310***		0.0869***
		(2.63)		(4.02)
Lagged Event Dummy		0.115		0.0260
		(1.38)		(0.33)
Lagged Dependent Variable		0.372***		0.444***
		(12.97)		(20.54)
Constant	-0.00312	-0.160***	0.0121***	-0.0694***
	(-0.86)	(-11.38)	(17.05)	(-2.99)
Observations	45184	43532	69279	67442
Year Dummy	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.00	0.22	0.01	0.31

Panel D: Return

	(1) Stock Return	(2) Stock Return	(3) Excess Return	(4) Excess Return
GSVI, category: Finance	-0.00365	-0.00231	-0.00149	-0.00283
	(-0.86)	(-0.58)	(-0.33)	(-0.59)
Lagged Consolidated Volume		0.00994		0.0127**
		(1.59)		(1.96)
Lagged Squared Excess Return		0.0253*		0.0221
		(1.69)		(1.40)
Lagged Event Dummy		-0.0668		-0.0369
		(-1.13)		(-0.52)
Lagged Dependent Variable		-0.00671		-0.0419***
		(-0.70)		(-3.87)
Constant	-0.000610***	0.0223**	0.00282***	0.0273**
	(-9.15)	(2.24)	(39.94)	(2.36)
Observations	74483	71740	74483	71740
Year Dummy	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	Company	Company	Company	Company
R-squared	0.00	0.00	0.00	0.00

Table A2.3: ***Attention and Trade Dynamics (FMB)***

This Table provides Fama-MacBeth (FMB) regressions of liquidity measures, turnover, volatility and returns as dependent variables and Google Search Volume as explanatory variable. The methodology of Fama and MacBeth (1973), however, is reversed by first running a time series and later a cross-sectional regression. The sample contains all Dax, MDax, SDax and TecDax firms from 2004 to 2011. Control variables are: Year Dummies, Lagged Event Dummy, Lagged Squared Excess Returns, Lagged Turnover as well as the Lagged Dependent Variable. All variables are standardized ($\frac{x-mean_x}{\sigma_x}$). Lagged variables are lagged by one day. Robust t-Statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

Panel A: Liquidity

	(1) Quoted Spread	(2) Quoted Spread	(3) Effective Spread	(4) Effective Spread	(5) Depth	(6) Depth	(7) Depth on Bid Side	(8) Depth on Bid Side	(9) Depth on Ask Side	(10) Depth on Ask Side	(11) 5-min Price Impact	(12) 5-min Price Impact	(13) 60-min Price Impact	(14) 60-min Price Impact
GSVI	-0.0415**	-0.00660	-0.0390**	0.00412	0.0340*	0.00841	0.0420**	0.00663	0.0310*	0.00965	-0.00506	0.0147**	0.00259	0.0225***
	(-2.13)	(-1.20)	(-2.10)	(0.54)	(1.86)	(1.18)	(2.42)	(1.41)	(1.76)	(1.22)	(-0.41)	(2.41)	(0.28)	(3.60)
Lagged Consolidated Volume		-0.00956***		-0.0162**		0.0428***		0.0432***		0.0481***		-0.00587		-0.00715
		(-3.46)		(-2.57)		(4.04)		(4.14)		(3.87)		(-1.10)		(-1.34)
Lagged Squared Excess Return		0.0132***		0.0401***		-0.0281		-0.0197		-0.0365		0.0485***		0.00828
		(3.83)		(7.81)		(-1.33)		(-1.09)		(-1.60)		(4.07)		(0.19)
Lagged Event Dummy		-0.0210		-0.0201		0.0330**		0.0230		0.0487**		0.00125		0.0367
		(-1.11)		(-1.20)		(1.96)		(1.11)		(2.42)		(0.05)		(1.58)
Lagged Dependent Variable		0.595***		0.360***		0.389***		0.346***		0.335***		0.238***		0.102***
		(41.51)		(25.69)		(25.71)		(24.62)		(23.12)		(25.48)		(15.35)
Constant	-0.0329*	0.138***	-0.0134	0.257***	0.0208	0.143***	0.0168	0.101***	0.0136	0.153***	-0.0132	0.0682***	-0.0109	0.0714***
	(-1.94)	(5.41)	(-0.77)	(2.97)	(1.21)	(3.93)	(1.12)	(3.26)	(0.86)	(3.32)	(-1.07)	(2.87)	(-1.11)	(3.17)
Observations	255863	246973	245984	237944	245984	237944	245990	237945	246007	237945	245984	237944	245984	237944
Year Dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB
R-squared	0.06	0.62	0.05	0.41	0.05	0.43	0.05	0.36	0.05	0.35	0.02	0.22	0.01	0.10

Panel B: Turnover

	(1) Consolidated Volume	(2) Consolidated Volume	(3) # Trades	(4) # Trades	(5) # Buys	(6) # Buys	(7) # Sells	(8) # Sells	(9) Order Imbalance	(10) Order Imbalance
GSVI	0.133***	0.0932***	0.130***	0.0762***	0.126***	0.0785***	0.125***	0.0710***	0.00763	0.0122**
	(8.51)	(8.86)	(5.78)	(9.67)	(5.68)	(9.64)	(5.73)	(9.48)	(0.93)	(2.20)
Lagged Consolidated Volume		0.369***		-0.0243**		0.0307***		0.0191*		0.0216***
		(40.32)		(-2.51)		(2.96)		(1.79)		(5.12)
Lagged Squared Excess Return		0.0489***		0.0433**		0.0397**		0.0497***		0.0164*
		(3.92)		(2.24)		(2.06)		(2.70)		(1.80)
Lagged Event Dummy		0.194***		0.160***		0.143***		0.164***		-0.0208
		(4.85)		(5.09)		(4.85)		(4.99)		(-0.88)
Lagged Dependent Variable				0.509***		0.444***		0.446***		0.185***
				(43.04)		(38.55)		(35.10)		(29.41)
Constant	0.00183	-0.0638***	0.0374**	-0.111***	0.0370**	-0.106***	0.0362**	-0.120***	-0.0146*	0.0119
	(0.20)	(-3.19)	(2.51)	(-4.34)	(2.56)	(-4.04)	(2.53)	(-4.48)	(-1.75)	(0.54)
Observations	255163	250200	255863	246973	255863	246973	255863	246973	249629	240986
Year Dummy	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB	FMB
R-squared	0.05	0.30	0.09	0.52	0.08	0.49	0.08	0.49	0.01	0.09

Table A2.3: Attention and Trade Dynamics (FMB) (ctd.)

Panel C: Volatility

	(1) # Volatility Interruptions	(2) # Volatility Interruptions	(3) Midpoint Volatility	(4) Midpoint Volatility
GSVI	0.0432***	0.0499***	0.0628***	0.0484***
	(2.81)	(3.79)	(4.14)	(4.56)
Lagged Consolidated Volume		0.0529		0.0124**
		(1.26)		(2.06)
Lagged Squared Excess Return		0.0646**		0.0753***
		(2.30)		(5.62)
Lagged Event Dummy		-0.0288		-0.0149
		(-0.90)		(-0.43)
Lagged Dependent Variable		0.288***		0.331***
		(13.32)		(23.78)
Constant	-0.0196**	0.0370	0.00998	0.00451
	(-2.21)	(1.01)	(0.98)	(0.24)
Observations	157480	148086	250767	242268
Year Dummy	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	FMB	FMB	FMB	FMB
R-squared	0.02	0.21	0.02	0.28

Panel D: Return

	(1) Stock Return	(2) Stock Return	(3) Excess Return	(4) Excess Return
GSVI	-0.00241	-0.00402	-0.00350	-0.00652
	(-0.58)	(-0.65)	(-0.87)	(-1.08)
Lagged Consolidated Volume		0.0393**		0.00810
		(2.07)		(0.39)
Lagged Squared Excess Return		0.00803		0.00489
		(1.06)		(0.61)
Lagged Event Dummy		-0.0170		-0.0113
		(-0.53)		(-0.32)
Lagged Dependent Variable		-0.0413***		-0.0703***
		(-8.07)		(-15.21)
Constant	-0.00371	0.00297	-0.00138	0.00595
	(-1.54)	(0.41)	(-0.59)	(0.78)
Observations	265442	254939	265442	254939
Year Dummy	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes
SE	FMB	FMB	FMB	FMB
R-squared	0.00	0.01	0.00	0.01

Table A2.4: ***Regional Holiday Instrument Test***
This Table provides a regression of Google search volume on Lagged Event Dummy, Lagged Squared Excess Returns, Lagged Trading Volume as well as a German local holiday dummy. Holidays are Epiphany, Reformation Day, All Saints' Day, Assumption of Mary, Repentance Day and Corpus Christi. Robust t-statistics are shown in parentheses. ***, ** and * indicate significance at a 1%, 5% and 10% significance level, respectively.

	(1) GSVI
Lagged Consolidated Volume	0.0785***
	(5.74)
Lagged Squared Excess Return	0.00821
	(1.60)
Lagged Event Dummy	0.236***
	(8.28)
Holiday Dummy	-0.180***
	(-7.99)
Constant	0.120
	(1.08)
Observations	254961
Year Dummy	Yes
Fixed Effects	Yes
SE	Company
R-squared	0.02

B Data & Variable Definitions

As described in the Section 2.4, the dataset from this study is mainly retrieved from four sources: Datastream, Xetra (Deutsche Börse), Stuttgart Stock Exchange and Google. The Google variables are already explained in detail in the Data Section. Variables generated from the other datasets are described in this Section.

Datastream

First, Datastream is used to collect monthly historical constituents' lists for the regarded indices Dax, MDax, SDax and TecDax. Those lists are verified by comparing them to similar lists from Bloomberg and Compustat. The use of historical constituents' lists excludes the risk of a survivorship bias in the data. Second, Datastream is used as a source of daily stock information. The following variables are used:

- Market Value is the Market Value of Common Stock only, based on the data item *MV*.
- Return is calculated based on the Return Index data item *RI*.[74]
- Volume is the consolidated trading volume across all exchanges available in Datastream, based on the data item *VC*.

Xetra

Xetra Exchange Data is derived from best bid/ask- and trade-information from the Deutsche Börse.[75] The Data is provided at a frequency of one hundredth of a second. Several filters[76] (e.g., exclude intraday auctions, eliminate negative prices and volumes) are applied to control for data imperfections. Finally, several intraday measures are calculated and aggregated on a daily basis.[77] In the following those measures will be presented in greater detail:

The index i is used for a firm $i \in I$ (total number of firms), $t \in T$ for a trading day from 2004-2011, index $j \in J$, where J is the total number of quote updates/trades at a given day t. The quote midpoint can then always be calculated as $M_{itj} = \frac{Bid_{itj}+Ask_{itj}}{2}$, where Bid and Ask are the best bid and ask prices at quote j.

1. Liquidity

   - Time-weighted relative quoted spread:

   $$prop\_quoted_{itj} = \frac{A_{itj} - B_{itj}}{M_{itj}} \tag{2.4}$$

   In contrast to the other measures the different relative quoted spreads across a day here are weighted by the time they were available in the order book.

[74]As already said, adjustments as in Ince and Porter (2006) and Schmidt et al. (2017) are applied beforehand.
[75]For more detail visit Deutsche Börse Data Shop: http://datashop.deutsche-boerse.com/1017/en
[76]A detailed list of filters can be found in the technical documentation to the Market Microstructure Database Xetra.
[77]Aggregation is generally done by equally-weighting every trade of a given day. However, the results remain robust to a value-weighted average based on the number of units traded per trade.

- Relative Effective Spread:

$$prop\_effective_{itj} = \frac{2 * |P_{itj} - M_{itj}|}{M_{itj}} \tag{2.5}$$

  with P_{itj} being the trade price at j

- Market Depth: (Mean of) Units available at the best bid/ask price
- Price Impact: Let M_{itj}^{5min} be the midpoint five minutes after a trade with midpoint M_{itj} and let

$$q_{itj} = \begin{cases} 0 & \text{if trade } itj \text{ is a buy} \\ -1 & \text{if trade } itj \text{ is a sell} \end{cases}$$

$$PriceImpact_{itj} = \frac{\left(M_{itj}^{5min} - M_{itj}\right) * q_{itj}}{M_{itj}} \tag{2.6}$$

  Also, the price impact for a lag of 60 minutes is calculated.

2. Turnover

- # Buys/Sells/Trades: Total number of (buyer/seller-initiated) trades (after filtering)[78]
- OIB: If B_{it} is defined as the number of transactions that are buyer-initiated (sells A_{it}), then order Imbalance (OIB) is the absolute difference between buys and sells relative to the number of total transactions. Thus:

$$OIB_{it} = \frac{|B_{it} - A_{it}|}{B_{it} + A_{it}} \tag{2.7}$$

3. Volatility

- # Volatility Interruptions: Total number of volatility auctions on a given day
- Midpoint Volatility: Let M_{itf}^{5min} be the last midpoint of a five minute interval f with a total number of daily five minute intervals without missing midpoint F.

$$midpoint\_vola_{it} = \frac{1}{F}\sum_{f=1}^{F}\left(\frac{M_{itf}^{5min} - M_{it(f-1)}^{5min}}{M_{it(f-1)}^{5min}}\right)^2 \tag{2.8}$$

[78] Lee and Ready (1991)'s algorithm is used to classify trades into buys and sells. A trade is classified as buy if the trading price is above the midpoint. If the trading price equals the midpoint, the trade is classified as buy if the trading price is larger than the previous [different] trading price. The opposite holds for sells.

Chapter 3

Quasi-dark trading: The effects of banning dark pools in a world of many alternatives

3.1 Introduction

Dark pools – venues that provide no pre-trade transparency – are routinely used by investors, especially large buy-side institutions, to manage order exposure costs. These venues are highly controversial due to three main concerns: (i) a lack of level playing field vis-à-vis public markets, (ii) inadequate disclosures concerning order routing decisions,[1] and (iii) a potential to impair public markets' price discovery mechanism. In combination with recent increases in dark pools' market shares[2,3] these arguments have put dark pools at the forefront of regulatory scrutiny. Regulators in the EU, Canada, and Australia have all implemented restrictions or caps on dark trading.[4] The intention of these regulations is to ensure efficient price discovery and to maintain high levels of liquidity in public markets by keeping the majority of trading on transparent public markets.

Most theoretical and empirical literature explores a dichotomy of lit markets versus dark pools or transparent versus non-transparent trading. This dichotomy however oftentimes is an oversimplification of the reality of today's complex market landscape, which instead involves a wide spectrum of pre-trade transparency or "shades of grey". Besides dark pools and transparent

[1] Anand et al. (2019) provide empirical evidence that in such an opaque setting brokers might route orders to markets associated with higher trading costs for their client.

[2] Healthy Markets (2010), citing data from Rosenblatt Securities, report that the market share of US dark pools increased from 4% in 2008 to 18% in 2015. Petrescu and Wedow (2017) report that, in 2016, European dark pools had a market share of approximately 12%, 8%, and 7% for stocks listed in London, Paris, and Frankfurt, respectively.

[3] Another recent development is a decrease in dark pool trade sizes. Dark pools were originally conceived as mechanisms best suited for *large* natural liquidity traders to trade directly with each other while minimizing information leakage. But CFA Institute (2012) and Foley and Putniņš (2016) observe that dark pool and lit market trade sizes in the US and Canadian markets are comparable. Petrescu and Wedow (2017) report that, in the EU, more than 50% of dark pool trades are smaller than €50,000 and only two dark pools actively restrict trading to large block orders.

[4] We refer to "dark trading" for any mechanism that provides no or only little pre trade information.

public markets, there exist several other mechanisms that all offer varying degrees of opacity and provide an alternative to trading in dark pools. We refer to these mechanisms as "quasi-dark". Quasi-dark venues include internalization platforms, the over-the-counter market and periodic auction markets, i.e., venues conducting repeated call auctions throughout the day.[5]

This complex trading landscape raises several important questions: What happens when restrictions or limits are placed on only one form of dark trading? Does dark volume migrate to other (quasi-)dark mechanisms? If so, what does the volume migration reveal about which trading mechanisms are viewed as the closest substitutes to dark pool trading? Do volume spill-overs to quasi-dark venues mitigate the effects of dark trading regulation? What are the effects of such regulations on market quality? And should transparency policies be broader and take into consideration the spectrum of quasi-dark alternatives?

We shed light on these questions using a quasi-natural experiment provided by the European Commission's (EC) Markets in Financial Instruments Directive (MiFID II). The new regulation imposes a complete ban on small trades in dark pools for stocks that historically traded more than 8% of their volume in such venues (henceforth referred to as "the ban"). Using a large cross-section of stocks that differ in terms of their size, index membership, liquidity, tick size, and primary listing market, we show that indeed quasi-dark trading plays a significant role in today's markets and impacts the effectiveness of dark trading regulations.

Our analyses reveal complex shifts in trading activity in multiple directions upon the mechanical elimination of small trades in dark pools. Continuous lit markets gain about 1% market share suggesting that the regulation is only partially successful in inducing a shift in trading activity towards lit markets. However, investors – attempting to avoid the (potentially) higher costs associated with information leakage in continuous lit markets – shift almost thrice as much order flow towards block trading venues, periodic auctions, and internalizing dealers. These three (quasi-)dark markets gain approximately 0.6%, 1.3%, and 0.8% market share respectively. The ban's impact on market quality is largely negligible. Liquidity, proxied by quoted and effective bid-ask spread and top-of-book depth, remains unchanged and price efficiency deteriorates slightly. These results are not surprising considering most trading in response to the ban does not shift towards the lit market but instead to alternative quasi-dark venues. Using event study methodology, we show that investors had a positive expectation on the ban's implications, evidenced by a positive announcement return experienced by banned stocks. Consistent with the ban's largely insignificant effect on market quality, this announcement return is reversed with the actual implementation of the ban.

We compute the above-mentioned effects by employing two quasi-experimental techniques: Semiparametric Difference-in-Differences (SP-DID) developed by Abadie (2005) and Regression Discontinuity Design (RDD). A standard DID estimator relies on the strong assumption that outcomes for firms in the treatment and control group follow parallel trends. However, this assumption is unlikely to hold in our setting as dark pool activity is correlated with several firm characteristics, liquidity conditions, and the tick size (Kwan et al., 2015; Gomber et al.,

[5]The US equity market, as of September 2018, is characterized by competition between twelve lit exchanges on the one hand, and 42 Alternative Trading Systems (ATS) encompassing a diverse set of mechanisms on the other hand.

2016). SP-DID modifies the standard estimator by adjusting the weights of individual firms for their propensity to be banned, which is estimated as a function of observable covariates. For robustness purposes, we also employ an RDD estimator that focuses on stocks close to the 8% cap. To further alleviate concerns about a causal interpretation of our results, we conduct placebo tests using a subset of 24 stocks that were not treated due to inadequate and/or erroneous reporting by trading venues to ESMA.

This chapter contributes to the literature on dark market fragmentation by exploiting a regulatory event that had the effect of banning small trades in mid point dark pools. Classical theories of market fragmentation such as Pagano (1989) and Mendelson (1987) argue that consolidation of trading onto a single (or fewer) venue(s) leads to improvements in market quality due to positive network externalities. Harris (1993) however argues that a fragmented market can emerge in equilibrium as heterogeneous agents optimize their venues choices based on their need for anonymity, immediacy, and transparency. Theories of dark pool trading such as Hendershott and Mendelson (2000), Zhu (2014), Buti et al. (2017), Ye (2011), and Brolley (2016) derive equilibrium strategies for heterogeneously informed investors as a function of the execution probability in dark pools (typically vis-à-vis lit markets), the price improvement offered by dark pools, the type of information traders possess (short-term versus long-term), and other agents' (typically uninformed and/or noise traders) strategies.

The empirical literature on the impact of dark trading on market quality provides conflicting results. Comerton-Forde and Putniņš (2015) evaluate the impact of dark trading on price discovery by examining the effect of rule changes affecting dark trading activity in the Australian market. They find that, at moderate levels, dark trading is beneficial, whereas beyond 10% of total volume it harms price efficiency. Conrad et al. (2003) find that institutional order execution costs are substantially lower in mid-quote dark pools. Buti et al. (2016) examine the determinants of activity in eleven US dark pools and find that increased dark pool activity is associated with higher liquidity. Foley and Putniņš (2016) rely on regulatory decisions requiring minimum price improvement in Australian and Canadian dark pools as an instrument to causally examine the impact of dark trading on market quality. They find that dark limit order books positively impact market quality. In contrast, they do not find consistent evidence for an impact of mid-point dark pools on market quality. Farley et al. (2018) evaluate the exogenous reduction in dark trading observed for one treatment group of the US tick size pilot and find no effect on market quality.

The conflicting results in empirical research likely arise for three reasons. First, the relationship between market quality and trading in dark pools is endogenous with bi-directional causality. Most studies rely on regulatory/rule changes as an identification strategy for causal inference. These rules are typically applied uniformly across all stocks. In contrast, our setting involves cross-sectional heterogeneity in the imposition of the ban. Second, dark pools encompass a variety of market models in terms of their order matching rules, type of ownership, permissible trade sizes, clientèle they cater to, etc.[6] For example, some dark pools operate as independent limit order books, others rely on derivative pricing and match orders at lit market

[6] Mittal (2008) provides a taxonomy of dark pools.

best or mid quotes. Existing studies either differ in the specific market model they analyze or subsume different market models under the dark market label. For example, Farley et al. (2018) focus on dark limit order books and internalizing platforms. Our setting is specific in that we analyze a ban on mid-point dark pools. Furthermore, Hatheway et al. (2017) find that dark pool trade sizes affect the impact of dark trading on market quality. Our setting is unique in that it includes market places that specifically cater to large or small trade sizes and in that the ban only applies to small trades in dark pools. Finally, the level of fragmentation and the regulatory setting (tick sizes, minimum price improvements, etc.) around dark trading differ substantially across markets. Our setting involves multiple competing trading mechanisms with different levels of pre-trade transparency.

Our analysis has clear policy implications. It sheds light on the extent to which the restrictions were successful in achieving the regulator's dual objective of shifting trading towards lit venues and improving the efficiency of stock prices. Our results highlight that in a market with several shades of dark venues (pre-trade transparency), restricting trading in one dark market mostly shifts investors to other close, albeit imperfect, substitutes. These shifts can have unintended consequences contrary to regulatory expectations.

The remainder of the chapter is structured as follows. Section 3.2 provides an overview of the institutional setting, specifically involving (quasi-)dark markets, around the implementation of MiFID II. In Section 3.3, we derive hypotheses on the ban's effects on the share of alternative trading mechanisms and market quality. In Section 3.4, we provide a description of the sample and the variables used in the analysis along with some descriptive statistics. Section 3.5 lays down the empirical methodology we employ to test our hypotheses. Section 3.6 presents the results. In Section 3.7, we investigate the announcement effects on asset prices in an event study framework. Finally, we conclude in Section 3.8.

3.2 Institutional Background

The implementation of the Markets in Financial Instruments Directive (MiFID) in November 2007 kick-started competition in the trading services industry by allowing exchanges and other venues to compete with each other for order flow. At the same time, MiFID also imposed pre-trade (and post-trade) transparency requirements on trading venues to mitigate potential adverse consequences associated with order flow fragmentation. These requirements include an obligation for venues to make quotes (bid and ask prices) and related depths publicly available.

MiFID also provides specific exemptions from these requirements to certain orders and/or trading venues by instituting four pre-trade transparency waivers: (i) the reference price waiver; (ii) the negotiated trade waiver; (iii) the large-in-scale waiver; and (iv) the order management facility waiver. The *reference price waiver* is used by trading systems that rely on the derivative pricing rule to execute trades at a widely published price obtained from another system. The *negotiated trade waiver* applies to bilaterally negotiated trades that are priced either within the (volume-weighted) bid-ask spread or are subject to conditions other than the current market price. This waiver is most relevant for trading systems handling retail orders, trades attached with special conditions such as Volume-Weighted Average Price (VWAP), portfolio, give-up, special ex/cum dividend trades, and trades involving a non-standard settlement. The *large-in-scale waiver* is applicable to block trades defined as those that are greater than the large in-scale size threshold, which is computed annually based on the average turnover of a stock and ranges from €15,000 to €650,000. Finally, the *order management facility waiver* applies to orders, such as hidden and iceberg orders, held by exchanges in their systems before being disclosed to the market.[7]

3.2.1 Dark, Quasi-Dark and Lit Trading

In this chapter we differentiate between seven different market mechanisms that can be categorized into three shades of pre-trade transparency: Dark pools relying on the reference price waiver and dark pools relying on the large-in-scale (LIS) waiver are markets that offer no pre-trade transparency at all. Lit markets, on the contrary, offer information on the number of orders and volume for several price levels. Traditional auctions, systematic internalizers (SIs), over-the-counter (OTC) markets and periodic auctions only offer a limited degree of transparency and are categorized as quasi-dark mechanisms in this chapter.

Dark pools are fully non-transparent multilateral markets that rely on the reference price waiver and/or the large-in-scale waiver to execute orders at midpoint prices derived from the lit markets. On the other end of the transparency distribution, public continuous limit order book markets that offer real-time information on current orders and quotes are represented by lit incumbent exchanges and other lit markets (such as Cboe BXE (formerly Bats), Cboe CXE (formerly Chi-X), and Turquoise).

In between those two extremes of complete/no opacity, quasi-dark mechanisms offer a limited degree of pre-trade transparency: Most incumbent exchanges in Europe start and end trading in the continuous limit order book by a call auction phase. On London Stock Exchange and Deutsche Börse Xetra those are complemented by an intraday auction in the middle of the trading day. Finally, continuous trading can be interrupted by circuit breakers whenever prices leave pre-specified price bands. In such a case prices are determined in an auction before trading in the continuous limit order book resumes. Throughout this chapter, we refer to the set of open, close, intraday and volatility auctions as traditional call auctions. These auctions concentrate liquidity at specific times during the day when buyers and sellers are brought together to trade at a single price. During the call phase usually lasting between two and five minutes, orders are collected in a central limit order book and traders can enter, change and delete orders/quotes. Only aggregated information on the current order situation is published. Indicative prices/volumes reveal the conditions at which auction trades would execute if the auction ended at that time. The auction clears at the uncrossing price that maximizes the trading volume that can be executed. Only providing indicative prices, auctions offer less pre-trade information compared to lit markets.

SIs are operated by broker-dealers and high-frequency trading firms to execute client orders against their own inventory on a frequent and substantial basis. An SI thus operates a bilateral

[7] Further information about these waivers is available in ESMA's report on Waivers from Pre-Trade Transparency (https://www.esma.europa.eu/sites/default/files/library/2015/11/2011-241g_u_compilation_of_esma_opinions_and_cesr_positions_on_pre-trade_waivers_21082015.pdf).

system and is not allowed to match third party buying and selling interests. While SIs have to publish bid and offer prices for small volumes and thus provide more pre-trade transparency than auction markets, large orders can be executed at prices other than the current quotes.

The OTC market – primarily involving dealers that execute client trades on an ad-hoc basis – is a residual category encompassing all trading not classified under any of the above categories. No public quotes are available but traders receive pre-trade information during the bilateral negotiation process.

Finally, Periodic auctions operate very similar to the traditional call auctions described above.[8] The key differences are: (i) Auctions do not take place at pre-specified times but, depending on the exact specification of the venue operator, either whenever there is an order in the order book or every time the order book is crossed. Thus, periodic auctions can trade several times during the day. (ii) The auction phase is much shorter, typically lasting for less than one second. During this phase these venues provide pre-trade transparency in the form of indicative prices and volumes. As a consequence of these characteristics, periodic auctions are considered as lit markets under MiFID even though they are opaque outside the auction phase.

3.2.2 Implementation of the Ban

In June 2014, the European Commission (EC) adopted the revision to MiFID (called MiFID II) and the Markets in Financial Instruments Regulation (MiFIR) with a focus on, among other areas, non-equity markets such as derivatives and fixed income markets. The equity market specific provisions primarily aim to correct the unintended consequences of MiFID perceived as such by the EC. Most of these rules came into force on 3 January 2018. One of the most significant rules is the introduction of so-called Double Volume Caps (DVCs) on trading in venues that rely on the reference price waiver and/or the negotiated trade waiver.[9] Specifically, any individual venue cannot use either of these two waivers to execute trades in a specific stock for six months if it was responsible for more than 4% of the stock's trading volume in the previous 12 months. Similarly, no venue can use the two waivers to trade a stock for six months if the total trading volume across all venues using the waivers comprised more than 8% of the stock's trading volume in the previous 12 months. The restrictions only apply to small trades defined as trades below the Large In-Scale threshold. Block trades, i.e. trades equal to or greater than the LIS threshold, are exempt from these restrictions in the sense that they are not considered in the DVC computations and are themselves not subject to the ban. We exclusively focus on the 8% cap because, in response to a ban on only one dark pool, investors could easily route their orders to other dark pools, potentially negating any economic effect of the ban. Focusing on a *complete* ban allows for a cleaner estimation of the effects of a prohibition on dark pools. Furthermore, 97.5% of the bans in our sample are due to a breach of the 8% threshold.

The implementation of the dark trading suspensions is based on historical market share data

[8] Budish et al. (2015) model a similar mechanism of call auctions happening frequently at fixed intervals during the day.

[9] Other important equity market specific provisions of MiFID II include introduction of a harmonised tick size regime, specific obligations on firms and exchanges relying on algorithmic and high-frequency trading, a revamp of the regulatory architecture applicable to systematic internalizers, and changes to trade reporting obligations.

computed by ESMA which relies on volume reports by all registered trading venues. ESMA decides whether to include a stock in the report based on data completeness criteria defined relative to all venues, the most relevant venue, and all dark pools.[10] While the ban was supposed to be effective from January 2018 (along with other provisions of MiFID II), the implementation was delayed until March 2018 due to data quality and completeness issues. This deferral allows us to separate the implementation of the ban from other provisions of MiFID II / MiFIR.

Table 3.1 provides a timeline of the ban's implementation. Our analysis is based on reports published by ESMA on 7 March 2018 and 10 April 2018. Based on the reports published in March-2018 (based on trading for twelve months ending January-2018 and February-2018), dark trading in 736 firms was suspended due to the 8% cap starting 12 March 2018. On 10 April 2018 a new report (based on trading for twelve months ending March-2018) suspended dark trading in 797 stocks starting 13 April 2018. In addition, the April-2018 report updated the January-2018 and February-2018 reports due to (i) now sufficiently complete data being reported for stocks that were earlier excluded; and (ii) trading venues submitting corrected data for some stocks. Due to these updates, additional instruments that breached the DVCs were banned and bans for certain stocks implemented in March-2018 were lifted.

Table 3.1: DVC Implementation Timeline
This table lists the important dates relevant for the implementation of the Double Volume Caps (DVCs) on dark trading imposed by MiFID II.

Date	Event Description
12 June 2014	MiFID II and MiFIR are adopted by the European Commission with the original implementation date of 3 January 2017
May 2016	The European Council and European Parliament agree to postpone the implementation by one year with a new implementation date of 3 January 2018
9 January 2018	ESMA decides to delay the publication of the data on DVCs for January-2018
7 March 2018	ESMA publishes the DVC data for the month of January-2018 and February-2018
12 March 2018	Dark trading bans kick-in for stocks identified in the January-2018 and February-2018 reports
10 April 2018	ESMA publishes the DVC data for the month of March-2018 and updates the January-2018 and February-2018 reports
13 April 2018	Dark trading ban kicks-in for stocks identified in the March-2018 report. Additionally, dark trading resumes for stocks incorrectly banned based on the January-2018 and February-2018 reports

3.2.3 MiFID II and Changes in Market Structure

Venue operators, anticipating the implementation of the ban, initiated several changes to existing markets and also introduced new quasi-dark trading mechanisms. Carlens and Higgins (2017) summarize several such initiatives undertaken by industry participants. First, since MiFID II, we have seen a rise in periodic auctions as alternative quasi-dark market mechanism. Second, several dark pool operators applied for an exemption from pre-trade transparency obligations

[10] Further details on the implementation of the ban are available at https://www.esma.europa.eu/double-volume-cap-mechanism.

under the LIS waiver in addition to the reference price waiver. Furthermore, new block trading venues such as Turquoise Plato Block Discovery emerged. These two industry initiatives allowed market participants willing to execute large blocks to trade in the dark even after the ban kicked in.

In addition to the (quasi-)dark mechanisms already in place, these changes in market structure offer various close alternatives to trading in reference price waiver dark pools.

3.3 Hypotheses

The ban's impact on market outcomes likely depends on the changes in investors' equilibrium strategies around the imposition of the ban. Existing theories of investors' order routing decisions in fragmented markets provide insights on this question. These studies typically model a market consisting of a dark pool on the one hand and a dealer, specialist or limit order market on the other. Our analysis is complicated by the fact that quasi-dark trading mechanisms coexist alongside lit and dark venues. We thus extend the models' implications by comparing the different market structures along three dimensions – pre-trade transparency, immediacy, and access restrictions – and their specific regulatory setting to generate hypotheses about changes in trading activity and market quality. Pre-trade transparency captures the level of information available to market participants before they submit their orders; immediacy refers to investors' ability to trade a given quantity in short time with a high degree of certainty; and access restrictions refer to venues' ability to prohibit certain investors from accessing their liquidity. Access restrictions depend on whether a particular trading mechanism is organized as a bilateral or multilateral system; the former (latter) are (are not) allowed to impose restrictions.[11]

Models of dark pools incorporating asymmetric information such as Hendershott and Mendelson (2000), Zhu (2014), Ye (2011), and Buti et al. (2017) derive equilibrium order submission strategies for informed and uninformed investors and conclude that dark pools are likely used by patient traders who are willing to forgo immediacy and/or wish to minimize information leakage while potentially obtaining cost savings associated with a mid-quote execution. Investors who are impatient and/or possess short-term information likely avoid dark pools due to their high execution risk. Ye (2011) shows that informed traders prefer to hide in dark pools when the share of liquidity traders trading in dark pools is given exogenously. Zhu (2014) however argues that, when both informed and liquidity traders trade strategically, the former have a lower execution probability in dark pools as they cluster on the same side of the order book. In Hendershott and Mendelson (2000), informed traders possessing long-lived information trade opportunistically in dark pools whereas those possessing short-lived information trade directly in the dealer market. Empirical evidence also suggests that execution probability (or fill rates) in dark pools are low such that the opportunity costs associated with non-execution can sometimes offset the price improvements offered by them (Næs and Ødegaard, 2006). Buti et al. (2017) examine the trading strategies of heterogeneous agents possessing differential private values in a market consisting of a dark pool and a limit order book. In their model, the liquidity in the

[11] We distinguish access restrictions from market segmentation as in Harris (1993), where investors self-select into their preferred venues based on their trading motives and the markets' design features.

limit order book, tick size constraints, and agents' private valuations determine both limit and market orders migration to the dark pool. Menkveld et al. (2017) rank traders' preference as a pecking order from low-cost-low-immediacy venues to high-cost-high-immediacy venues and show that mid-point dark pools (lit markets) rank at the top (bottom) of this pecking order and dark limit order books rank in the middle.

We hypothesize that traders who cannot access dark pools using the reference price waiver due to the ban will switch to close substitutes. Dark venues that rely on the LIS waiver are probably the closest substitutes. Neither provide any pre-trade transparency or impose any access restrictions but the latter potentially provide lower immediacy due to their large trade size requirement. In the presence of restrictions on small dark trades, LIS dark venues allow (institutional) investors to continue trading in the dark in case they are willing to trade large blocks.

Hypothesis 1: *Trading volume and market share of dark venues operating under the LIS waiver increase for suspended stocks.*

Conversely, investors preferring smaller trade executions or those unwilling to trade in LIS dark pools have to rely on liquidity in lit and quasi-dark trading mechanisms. OTC and SI dealers are two sources of quasi-dark liquidity for investors wanting to stay away from public markets with full pre-trade transparency. These bilateral mechanisms can restrict access to uninformed and/or retail orders (Seppi, 1990; Madhavan and Cheng, 1997; Hatheway et al., 2017) by relying on their counterparties' identity. Other trader types, like, e.g., HFTs, might not be able to access these markets. Periodic auction markets are presumably very attractive to patient traders – especially those who find it difficult to access liquidity in the OTC or SI markets – as they potentially offer similar cost savings as dark pools with limited, albeit higher, pre-trade transparency. In other words, periodic auctions likely act as a close substitute to dark pools (Carlens and Higgins, 2017). Finally, traditional, scheduled auctions also provide a valuable source of liquidity if investors are prepared to trade at fixed points during the day. These arguments lead to the following hypothesis:

Hypothesis 2: *Trading volume and market share of quasi-dark venues (OTC, SI, periodic auctions, and traditional auctions) increase for banned stocks.*

Considering the types of investors attracted to dark pools in the first place, we expect little shift in natural liquidity towards lit venues. Such investors likely rely on lit markets only if they cannot fulfill their liquidity needs from other less transparent venues. However, the ban effectively imposes a higher level of transparency on the market as a whole, potentially allowing HFTs and other short term traders to more frequently and more precisely identify the presence of natural liquidity. These short-term traders likely exploit this information (back-running) by increasing their participation in lit markets.[12] To the extent this does not reduce participation by natural liquidity traders, we obtain the following hypothesis:

[12] van Kervel and Menkveld (2018) find that HFTs initially provide liquidity to large institutional traders by "leaning against the wind" but later employ back running strategies and trade "with the wind".

Hypothesis 3: *Trading volume and market share of continuous lit markets increase for banned stocks.*

Article 5(1) of MiFIR argues that the ban is implemented *"to ensure that the use of the [reference price and negotiated trade waivers] does not unduly harm price formation."* However, the ban's impact on market quality is likely driven by the above-mentioned shifts across different market mechanisms. Furthermore, knowledge about the presence, direction, and magnitude of natural liquidity can lead to increased adverse selection costs and order flow toxicity for liquidity suppliers due to fast traders employing back-running strategies in the lit markets. At the same time, increased transparency due to reduced uncertainty about the fundamental value likely leads to improvements in liquidity and price efficiency as it allows liquidity providers to quote more aggressively in the lit markets.[13] Hence, we formulate the following competing hypotheses for liquidity:

Hypothesis 4A: *Liquidity improves (bid-ask spreads decrease and/or order book depth increases) for banned stocks.*

Hypothesis 4B: *Liquidity deteriorates (bid-ask spreads increase and/or order book depth decreases) for banned stocks.*

The impact on price efficiency depends on how informed traders and back-running HFTs react to the increased transparency resulting from the ban. Chowdhry and Nanda (1991) and Madhavan (1995) argue that profit-maximizing informed traders trade slowly in a (more) transparent market to disguise their trades. Yang and Zhu (2017) argue that, for this reason, back-running initially harms price discovery (due to reduced trading intensity of the informed trader) but subsequently enhances it (as the back-runner trades alongside the informed trader).[14] This leads to the following competing hypotheses for price discovery:

Hypothesis 5A: *Price discovery improves for banned stocks.*

Hypothesis 5B: *Price discovery deteriorates for banned stocks.*

Finally, as asset prices are positively correlated with liquidity (Acharya and Pedersen, 2005b; Amihud and Mendelson, 1986b), we expect stock returns to react around the publication of DVCs by ESMA if the market correctly predicts the ban's effect on liquidity. Hence, we formulate the following competing hypotheses:

Hypothesis 6A: *Banned stocks experience positive cumulative abnormal returns on the DVC announcement date in anticipation of a positive effect on liquidity.*

Hypothesis 6B: *Banned stocks experience negative cumulative abnormal returns on the DVC announcement date in anticipation of a negative effect on liquidity.*

[13] In the HFT literature, the impact of HFT in the presence of asymmetric information depends on the HFTs' trading strategies (Budish et al., 2015), speed differentials across different HFTs (Ait-Sahalia and Saglam, 2013; Biais et al., 2015b; Rosu, 2018), and the proportion of liquidity-driven and information-driven trading (Menkveld and Zoican, 2017).

[14] The key variable in their model is precision of the back-runner's signal. If it is sufficiently high, the informed traders, in addition to trading slowly, also randomize their trades.

3.4 Stock Selection, Data, Variables, and Descriptives

3.4.1 Stock Selection

We obtain our sample of stocks from the January-2018 and February-2018 ESMA reports published on 7 March 2018 as well as from the updates to these reports published on 10 April 2018. For each stock, these reports contain information about the Relevant Competent Authority (RCA), total EU-wide volume, market shares of trading under the reference price and negotiated trade waivers, the sum of which we refer to as waiver percentage, and the start and end dates of suspensions. These reports altogether include 20,920 stocks. Table 3.2 describes the different filters applied to obtain the final list of stocks.

Table 3.2: Stock Selection
This table lists the filters sequentially applied to the stock included in the ESMA DVC reports. *Main sample* includes stocks in the January-2018 and February-2018 reports published on 7 March 2018. *Placebo sample* includes stocks whose suspension status changed due to the (updated) ESMA January-2018, February-2018 and March-2018 reports published on 10 April 2018. Figures in parentheses indicate a change in status due to incomplete or erroneous reporting by trading venues in the January-2018 and/or February-2018 reports. † flags firms incorrectly not suspended in March-2018 that are the focus of our placebo analyses.

Filtering	Main Sample	Placebo Sample
Firms in the ESMA DVC reports	20,920	
Firms affected by the 8% cap only	20,888	
Equity type = Shares	18,437	
Liquidity status = Liquid	1,315	
2017 EU-wide volume > 5 million	1,311	
RCA reported in ESMA reports in BE, DE, DK, ES, FI, FR, GB, IT, NL, NO, PL, SE	1,246	
No delistings, stock splits or corporate actions	1,216	
Primary listing inside the EU or majority market share in an EU venue	1,183	
Exclude Swiss firms	1,168	
Exclude lower volume A/B stock	1,149	
Exclude/Keep firms that change status	1,082	67 (25)
Suspended	614	–
Not Suspended	468	–
Suspended to Not Suspended	–	1 (1)
Not Suspended to Suspended	–	21 (11†)
Not in Report to Suspended	–	18 (13†)
Not in Report to Not Suspended	–	17 (0)

First, we eliminate securities partially banned based on the 4% cap. As mentioned earlier, the vast majority of suspensions implemented are due to total dark trading exceeding the 8% threshold. Next, we remove exchange-traded funds, share warrants, and other share-like securities from our sample. We further exclude stocks that are not classified as "Liquid" for the purpose of MiFID II. This status governs the application of pre-trade and post-trade transparency rules.[15] Next, we eliminate firms that have a 2017 EU-wide trading volume of less than €5 million. Subsequently, we restrict our sample to stocks from countries that make up at least 2% of the filtered stock list (based on the stocks' RCA). The countries fulfilling this criterion are: Belgium, Germany, Denmark, Finland, France, Italy, Netherlands, Norway, Poland, Spain, Sweden, and the United Kingdom. Furthermore, we eliminate stocks that experience corporate actions, stock splits, or delistings during our sample period. Next, we drop stocks with a primary listing outside the European Economic Area (EEA) and less than 50% market share in the EEA. We exclude Swiss stocks because the SIX Swiss Exchange does not fall under the regulatory scope of MiFID II.[16] Finally, if multiple share classes of a company are part of our sample, we keep only the most liquid one. This leaves us with a final sample of 1,149 firms. While these steps reduce our sample from 20,920 to 1,149 firms, it still includes 614 of the 736 suspended firms.[17]

We differentiate between three different suspension states: "suspended", "not suspended" and "not in report". 67 firms change their status based on the April-2018 publication. We exclude these firms from our main analysis and focus on the March-2018 publication using the suspension date (12 March 2018) in this report as the event date. Our filtered sample (henceforth referred to as the "main sample") thus includes 1,082 stocks of which 614 were suspended.

Of the 67 stocks that changed their status, one stock switched its status from suspended to not suspended, 21 from not suspended to suspended, 18 from not in report to suspended, and the balance 17 from not in report to not suspended. The change in status to suspended can be due to: (i) the March-2018 report triggering a stock's ban; (ii) or an update to the January-2018 and February-2018 reports triggering the suspension. The latter group includes stocks that would have been suspended already in March if ESMA had obtained the correct/complete volumes in time. We use this group of 24 stocks (henceforth referred to as the "placebo sample") in a separate analysis.

[15] A stock is classified as having a liquid market if it has (i) a free float of at least €100 million; (ii) at least 250 average daily number of transactions; (iii) and an average daily turnover of €1 million.

[16] Previous steps do not eliminate all Swiss firms as sometimes an EEA national regulator is their RCA.

[17] These 1,149 firms make up 85% of the EU trading volume of all firms in the ESMA reports.

3.4.2 Variable Description

Our sample period extends from 3 January 2018 – the implementation date of MiFID II – to 11 May 2018. For every stock in the main and placebo samples, we obtain intraday trades and best quotes data from Thomson Reuters Tick History (TRTH) for the stock's most relevant market. We focus on the continuous trading session to measure effects of dark trading restrictions on market quality. Hence, we exclude the period before (after) the end (start) of the opening (closing) auction. We also exclude all trades reported to these markets but not executed on their limit order books. Using this data, we generate estimates of trading activity, liquidity and price efficiency for every stock-day.

For stock i and day t, we capture trading activity by computing the trading volume in euros and the number of trades. We capture quoted liquidity by computing the bid-ask spread and top-of-book depth. Specifically, denoting the time of a quote update on day t as t', the best bid and ask quotes as $Bid_{t'}$ and $Ask_{t'}$, the associated quantities as $BidQ_{t'}$ and $AskQ_{t'}$, and the mid-quote at time t' as $M_{t'}$, we compute:

$$QuotedSpread_{t'} = \frac{Ask_{t'} - Bid_{t'}}{M_{t'}}$$
$$QuotedDepth^{Bid}_{t'} = Bid_{t'} * BidQ_{t'}$$
$$QuotedDepth^{Ask}_{t'} = Ask_{t'} * AskQ_{t'}$$

We compute time-weighted averages of these measures for each trading day t.

Next, we compute three measures of trading liquidity: effective spread, realized spread, and price impact. The effective spread captures the actual transaction costs paid by the trader submitting a market order, the realized spread the compensation earned by the limit order trader after adjusting for any losses associated with adverse selection, and the price impact the information content of a transaction. For a trade at time t' we compute:

$$EffectiveSpread_{t'} = \frac{2 \cdot D_{t'} \cdot (P_{t'} - M_{t'})}{M_{t'}}$$
$$RealizedSpread_{t'} = \frac{2 \cdot D_{t'} \cdot (P_{t'} - M_{t'+\Delta})}{M_{t'}}$$
$$PriceImpact_{t'} = \frac{2 \cdot D_{t'} \cdot (M_{t'+\Delta} - M_{t'})}{M_{t'}}$$

where $P_{t'}$ is the transaction price, $D_{t'}$ is the direction of a trade ($+1$ for a buy and -1 for a sell), and Δ is the time taken for the information associated with a trade to be fully impounded into the mid-quote. We obtain three versions of realized spread and price impact associated with $\Delta \in \{10, 30, 60\}$ seconds. All three measures are weighted by the trade size in euros.

To understand the impact of the ban on price efficiency, we construct measures based on autocorrelation and variance ratios at different time intervals. These measures capture deviations of returns from a random walk and thus act as a proxy for short term price efficiency (Boehmer and Kelley, 2009). First, denote $r^{\Delta}_{t'} = ln(M_{t'}) - ln(M_{t'-\Delta})$ as the Δ-second log returns based on the mid-quote. For each stock i and day t, we compute the first order autocorrelation of return measured at interval Δ, denoted by $AutoCorr(r_{t'}^{\Delta})$ and the ratio of return variance calculated over an interval of length m, $r_{t'}^{m}$, to return variance over an interval of length n, $r_{t'}^{n}$, both scaled by the respective time periods, denoted by $VR(n,m)$. We measure daily price efficiency as $|AutoCorr(r_{t'}^{\Delta})|$ and $|1 - VR(n,m)|$. We use absolute values as we are interested in deviations from a random walk in either direction. We compute both measures for different time windows to ensure that our results are robust. Specifically, we use $\Delta \in \{10, 30, 60, 300\}$ and $(n,m) \in \{(30,10),(60,10),(300,10),(60,30),(300,30),(300,60)\}$.

Finally, we compute intraday volatility as the standard deviation of one-minute returns per day, $r_{t'}^{60}$ and the relative tick size for each quote update at time t' as

$$RelativeTick_{t'} = \frac{Tick_{t'}}{M_{t'}}$$

where $Tick_{t'}$ is the tick size (defined by the MIFID II regulation and based on historical price and the average number of trades per day). We also define a variable that takes a value 1 if the bid-ask spread is one tick, and 0 otherwise. The last two measures are averaged through each trading day by time weighting every quote update.

In order to capture shifts in trading activity to different lit, quasi-dark and dark mechanisms, we supplement the above information with weekly snapshots of trading volume from Fidessa in all lit, OTC, SI, traditional and periodic auction markets as well as dark pools. Additionally, we also collect information on block trades in dark pools from Fidessa and from TRTH.[18,19] We combine the block trade data and the dark market data to disentangle dark pool trades under the reference price waiver from those under the LIS waiver.[20]

We use daily exchange rates from Thomson Reuters Eikon to convert all relevant variables into Euros. We also collect information from Thomson Reuters Eikon on daily prices and returns (used in Section 3.7 for the event study), share classes and industries (used in the filtering process), and constituents of the main European indices as a potential predictor of investors' trading behavior. Table 3.3 provides an overview of the different variables used in this chapter.

[18] The block trade definition is applied based on realized trading activity. In other words, multiple child orders each smaller than the LIS threshold belonging to a single parent order are not reported as block trades even if the parent order is larger than the LIS threshold.

[19] These data are available at http://fragmentation.fidessa.com/fragulator/ and http://fragmentation.fidessa.com/blocks/.

[20] See Appendix A to this chapter for the steps taken to obtain the two Fidessa datasets and to match them with each other.

Table 3.3: Variable Definitions
This table defines the variables used in our analyses. *Unit* is the unit of measurement, *Source* is the original data source, *Frequency* is the frequency of measurement (daily/weekly/static) in our final dataset, and *Definition* provides a short definition.

Variable	Unit	Source	Frequency	Definition
Panel A: Stock Characteristics and Trading Activity				
Market Value	mio	Eikon	Daily	$P \cdot MV$
Total Trading Volume	mio	Fragulator	Weekly	Total Euro volume across all trading mechanisms
Trading Volume (Most Relevant Market)	mio	TRTH	Daily	Total Turnover on the Most Relevant Market during continuous trading
Waiver Percentage	%	ESMA	Static	Fraction of trading under the negotiated trade and reference price waivers across EU
Percentage Negotiated Trade Waiver	%	ESMA	Static	Fraction of trading under the negotiated trade waivers across the EU
Percentage Reference Price Waiver	%	ESMA	Static	Fraction of trading under the reference price waiver across the EU
Suspension Dummy	%	ESMA	Static	1 if Waiver Percentage > 8%
Main Index Constituent	%	Eikon	Daily	1 if Stock is Constituent of index I on day t, I element of (AEX25 BEL20 CAC40 FTSE100 DAX30 IBEX35 FTSE MIB40 OMXC 20 OMXH 25 OMXS 30 OSEAX WIG 20)
Panel B: Liquidity				
Quoted Spread	bp	TRTH	Daily	Difference between best quotes divided by the mid-quote, time-weighted through the day
Effective Spread	bp	TRTH	Daily	Actual transaction costs paid by the trader submitting a market order
Depth	thousands	TRTH	Daily	Average of the euro depth at the best quotes, time-weighted through the day
Midpoint Volatilty (1 Minute)	bp	TRTH	Daily	Standard deviation of log returns measured at 1-minute interval
Price Impact	bp	TRTH	Daily	The information content of a transaction measured over 10, 30, and 60 seconds
Realized Spread	bp	TRTH	Daily	The compensation earned by the limit order trader after adjusting for any losses associated with adverse selection, measured over 10, 30, and 60 seconds
Relative Tick Size	bp	TRTH	Daily	Ratio of tick size over mid-quote, time-weighted through the day
Tick Constraint	%	TRTH	Daily	Indicator variable equal to 1 if difference between best quotes is 1 tick and 0 zero otherwise, time-weighted through the day
Panel C: Price Efficiency				
Midpoint Autocorrelation ($\lvert AutoCorr(r_{t'}^{\Delta})\rvert$)	%	TRTH	Daily	Absolute return first-order correlation based on Δ-second log returns where $\Delta \in \{10, 30, 60, 300\}$
Variance Ratio ($\lvert 1 - VR(n, m)\rvert$)	%	TRTH	Daily	Ratio of return variance calculated over intervals of length m, $r_{t'}^{m}$, to return variance over intervals of length n, $r_{t'}^{n}$, both scaled by the respective time periods. $(n, m) \in$ {(30, 10), (60, 10), (300, 10), (60, 30), (300, 30), (300, 60)}
Panel D: Market Shares				
Market Share (j)	%	Fragulator	Weekly	Fraction of Total Trading Volume (defined above) in trading mechanism j. j is Auction, Periodic Auction, Dark LIS, Dark REF, Lit, OTC, or SI

3.4.3 Descriptive Statistics

Table 3.4 provides descriptive statistics for the 1,082 (24) firms in the main (placebo) sample. These are calculated for our entire sample period and thus include both the pre and post event period. We report the (equal-weighted) mean, median and the 5th/95th percentiles for the main sample and the mean and median for the placebo sample. Our sample is broadly representative of the European equity landscape even though our filtering procedure eliminates the most illiquid securities.

Table 3.4: Descriptive Statistics
This table contains the descriptive statistics for the variables used in our analysis. For details and definitions of the different variables, see Subsection 3.4.2 and Table 3.3. Descriptives are shown for the main and placebo sample separately. We report the distribution of different variables over the full sample period (January 3, 2018 to May 11, 2018) and across stocks. *Unit* provides the unit of measurement, *Mean* the equal-weighted mean across all firm-days/weeks and *P(x)* the 5th/50th(median)/95th percentiles of the variables.

		Main Sample				Placebo Sample	
	Unit	Mean	P(5)	P(50)	P(95)	Mean	P(50)
Panel A: Stock Characteristics and Trading Activity							
Market Value	mio	7,957.06	381.73	2,581.83	36,615.18	9,785.62	2,638.35
Total Trading Volume	mio	61.39	0.94	14.07	290.61	69.41	13.75
Trading Volume (Most Relevant Market)	mio	14.55	0.26	3.93	64.41	13.88	4.33
Waiver Percentage	%	8.58	1.24	8.64	14.92	9.58	8.22
Percentage Negotiated Trade Waiver	%	2.54	0.32	1.96	6.05	4.28	4.09
Percentage Reference Price Waiver	%	6.02	0.73	5.95	10.84	6.44	6.62
Suspension Dummy	%	56.75	0.00	100.00	100.00	100.00	100.00
Main Index Constituent	%	32.62	0.00	0.00	100.00	58.33	100.00
Panel B: Liquidity							
Quoted Spread	bp	16.73	3.42	12.82	41.20	14.75	13.60
Depth	thousands	21.63	4.06	14.68	57.54	25.19	19.61
Effective Spread	bp	14.84	2.73	10.59	39.59	11.81	11.50
Realized Spread (10 sec.)	bp	1.41	-5.52	0.03	13.38	1.83	0.92
Price Impact (10 sec.)	bp	13.44	2.09	10.10	34.87	9.98	8.92
Midpoint Volatilty (1 Minute)	bp	7.02	3.22	5.99	13.98	6.48	5.55
Relative Tick Size	bp	7.05	2.07	5.57	17.96	7.91	6.95
Tick Constraint	%	27.49	0.42	21.41	76.40	36.51	32.72
Panel C: Price Efficiency							
Autocorrelation (10 sec.)	%	4.25	0.26	3.21	11.49	4.43	3.42
Variance Ratio (10/30 sec.)	%	7.59	0.46	5.67	20.73	7.90	5.99
Variance Ratio (30/300 sec.)	%	19.85	1.49	16.30	49.86	19.75	16.27

The average (median) stock in the main sample has a firm size of €8.0 (€2.6) billion. There is substantial cross-sectional dispersion, as evidenced by the 5th and 95th percentiles. The stocks in the placebo sample seem to be similar to those in the main sample in terms of their size. The wide size distribution leads to a skewed distribution of trading activity as evidenced by the large difference between mean and median daily trading volume (€61.39 million versus €14.07 million). The median firm trades about 28% of its entire volume on the primary listing market. 33% and 58% of the firms in the main and placebo sample, respectively, are constituents of one of the main European indices. Waiver percentages range between 1.2% and 14.9% for the 5th and 95th percentile, indicating a huge cross-sectional dispersion in pre-event dark pool trading across stocks. The 8% cut-off seems to naturally divide the sample into two groups of firms with nearly equal size (see Suspension Dummy).[21] About 23% of the median firm's waiver percentage originates from trades utilizing the negotiated trade waiver.[22]

The main sample also exhibits substantial dispersion in its market quality characteristics. Mean (median) quoted spreads and top-of-book depth are 16.73bps (12.82bps) and €21,630 (€14,680). Again, firms in the placebo sample do not seem very different. Unsurprisingly, effective spreads are smaller than quoted spreads as traders' time their market orders when liquidity is high. Median realized spreads are close to zero suggesting a high level of competition among liquidity providers. Median price impact is approximately 10bps. Mean intraday volatility for an average stock-day is 7bps. The mean (median) relative tick size is 7.05bps (5.57bps). The minimum tick size is binding in about 27% of the quote updates, but percentiles indicate that this measure also exhibits wide dispersion. We also observe autocorrelation in prices and variance ratios substantially different from zero, indicating some degree of short-term inefficiency in the market. These measures, again, vary widely across stocks.

In Table 3.5, we report the market shares of the different trading mechanisms for the main and placebo sample separately. For the main sample we report the mean market share for suspended/non-suspended stocks and the pre-ban/post-ban period separately. To begin with, we observe that a substantial amount of trading is conducted away from the lit markets in venues that offer lower transparency.[23] The pre-ban market share traded under the reference price waiver of 5.25% (2.80%) for suspended (non-suspended) stocks is lower than previous 12-month-average of 6.02% (see Table 3.4) based on which the suspension status was determined. This indicates that order routing already shifted away from dark pools. This is most likely because traders change the equilibrium routing behavior in anticipation of the ban. We also observe the mechanical elimination of trading (from 5.25% to zero) under the reference price waiver for the suspended stocks. Interestingly, continuous lit market share decreases after the ban for suspended stocks though non-suspended firms experience a much larger decrease. Suspended stocks also experience a larger increase in the share of traditional auctions and quasi-dark markets like periodic auction, SI and OTC venues as compared to non-suspended firms.[24] Most notably, periodic auction market share increases by 3.7 (1.6) times for suspended (non-suspended) firms.

These unconditional shifts provide a first indication of the limited success of the ban in moving trading towards continuous lit markets. They also highlight the need to control for market-wide changes in trading activity that are unrelated to the ban. Finally, suspended

[21]The placebo sample has a 100% suspension rate by construction as we only select firms suspended on April 13, 2018.

[22]Negotiated trade waiver and reference price waiver percentages do not fully add up to the total waiver percentage due to rounding in the ESMA reports.

[23]In untabulated results, we also observe that: (i) the average size of a transaction in these (quasi-)dark markets is generally higher; (ii) and there is substantial dispersion in the market shares of all trading mechanisms across stocks.

[24]OTC (SI) market share has decreased (increased) since the implementation of MiFID II. This is because the trading venues' discretion to classify themselves as SIs under MiFID no longer exists. As a result, venues that were earlier reporting their trades in the OTC category now report them as SI.

Table 3.5: Market Shares
This table contains the market shares of the different trading mechanisms. Market shares are shown for the main and placebo sample separately. For the main sample, they are calculated separately for *Suspended/Not Suspended* stocks and for the *Pre* (January 3 - March 9) and *Post* (March 12 - May 11) period. For the placebo sample, they are calculated separately for the *Pre* (January 3 - March 9) , *Mid* (March 12 - April 13) and *Post* (April 16 - May 11) period. We report the mean market shares of all stocks over the specified time periods for all trading mechanisms.

Panel A: Main Sample	Suspended		Not Suspended	
	Pre	Post	Pre	Post
Dark Ref. Price	5.25	0.00	2.80	2.67
Dark LIS	2.37	2.86	0.87	0.87
Periodic Auctions	0.66	2.43	0.37	0.61
Continuous Lit	46.45	43.91	57.91	53.69
Call Auction	6.35	7.80	4.73	5.42
SI	18.85	21.30	14.48	16.77
OTC	20.06	21.65	18.84	19.97

Panel B: Placebo Sample	Pre	Mid	Post
Dark Ref. Price	5.28	4.47	0.00
Dark LIS	2.93	3.06	2.26
Periodic Auctions	0.60	0.98	2.10
Continuous Lit	48.66	46.63	44.50
Call Auction	5.06	6.36	4.80
SI	18.74	19.63	24.23
OTC	18.73	18.87	22.09

firms, compared to non-suspended ones, do not just have a larger share of trading under the reference price waiver but also have a higher overall (quasi-)dark market share (54% versus 42%) suggesting that their composition is likely different to begin with. The last two points motivate the choice of empirical techniques we employ (see Section 3.5) to estimate the ban's effect on market outcomes.

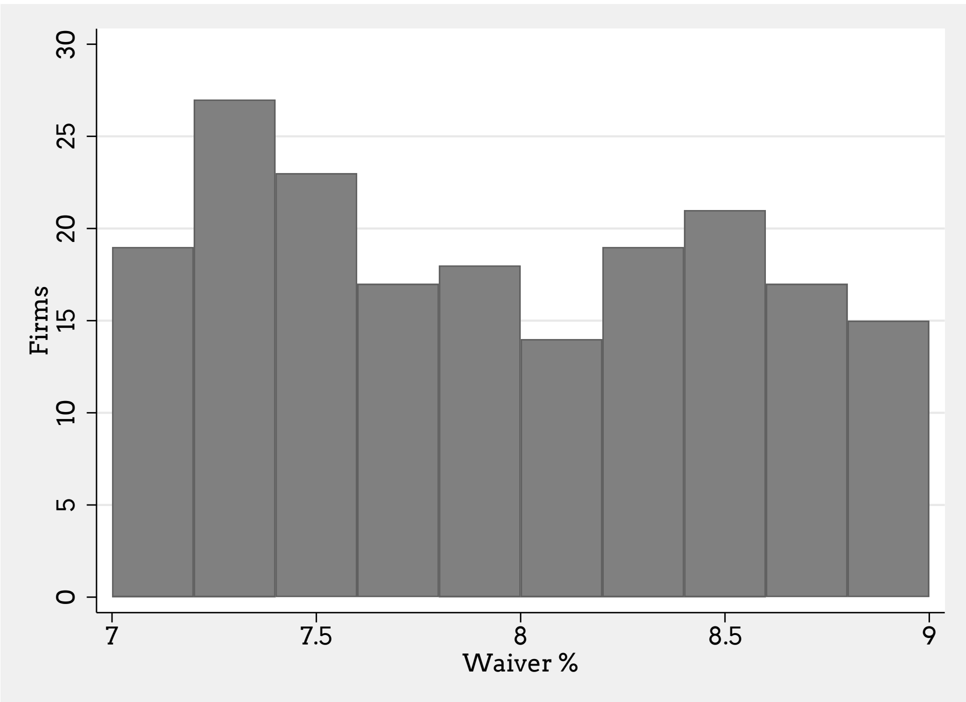
Panel B of Table 3.5 shows the mean market shares of the placebo stocks for three time periods: (i) the phase before the ban kicks in based on the January-/February-2018 reports; (ii) the period in between the January/February-2018 and March-2018 reports; and (iii) the period after the March-2018 report becomes operational. Stocks in the placebo sample, by construction, are not suspended in the first two phases and are suspended in the third phase. Moreover, in the second phase, the not suspended status is due to incorrect/incomplete data in the January-/February-2018 reports. Pre ban market shares of the placebo sample are quite similar to those of the main sample. While we observe a strong reaction of market shares for the suspended stocks after the ban kicks in (see Panel A), placebo stocks react much less intensely albeit in the same direction. However, when the ban (correctly) becomes effective in April, trading under the reference price waiver is halted and, similar to the main sample, volume shifts towards quasi-dark venues such as periodic auctions, SI and OTC markets.

3.5 Empirical Approach

Our objective is to understand the causal effect of the ban on volumes and market shares of the different trading mechanisms as well as the liquidity and price efficiency on the primary market. For this purpose, we employ two quasi-experimental techniques: The Abadie (2005) semi-parametric difference-in-differences estimator (SP-DID), and a robust Regression Discontinuity Design (RDD) estimator as specified by Calonico et al. (2014).

One concern that affects these techniques is the potential for market participants and/or trading venues to strategically increase (decrease) dark pool activity over the measurement period for selected stocks in order to game the ban's outcome. This concern is more likely to affect stocks near the 8% threshold. We plot the number of stocks in different buckets of historical dark pool market share near the 8% threshold in Figure 3.1 and do not observe any obvious discontinuity. This is unsurprising considering such strategic behavior is likely very expensive as traders need to ensure that a stock remains above or below the 8% threshold on a rolling twelve monthly basis. While individual dark pools may be able to constrain activity on their platform to ensure uninterrupted trading, it is unlikely that all venues collude to achieve such an outcome.[25]

Figure 3.1: Firms Around the 8% Threshold
This figures plots the number of firms in each 0.2% waiver percentage bucket around the cutoff of 8%. *Waiver percentage* is defined as the maximum of the waiver percentages as reported in the January-2018 and February-2018 ESMA reports published on 7 March 2018. These reports determine the waiver percentage based on EU-wide trading in the reference price and negotiated trade waiver in the twelve month prior to the respective report, i.e., January 2017 to December 2017 and February 2017 to January 2018.



[25] The stocks affected by the 4% cap applicable to individual dark pools – which we do not investigate – are more likely to be affected by such gaming concerns.

3.5.1 Semi-parametric Difference-in-Differences (SP-DID)

While there is no evidence that the assignment of stocks to the treatment or control is manipulated, observable variables likely predict the probability of a stock being banned. This is already evident in high (low) overall dark pool market share for suspended (not suspended) firms.We provide evidence of this in Subsection 3.6.1. We therefore use an enhanced version of the standard difference-in-differences (DID) estimator suggested by Abadie (2005). It adjusts for potentially non-parallel trends by re-weighting the differences of post- and pre-event averages of stocks in the control group based on their propensity score, i.e., their probability of being treated, to generate a more credible estimate of the Average Treatment Effect on the Treated (ATT).Specifically, in a first stage regression, we predict the probability of treatment using the following logit regression:

$$P_{ban}(X) = \Lambda\Big(\gamma_0 + \sum_{i=1}^{k} \gamma_i x_i\Big) \tag{3.1}$$

where Λ is the logit operator and X is a vector of observable covariates used to predict the treatment. X contains averages of the following variables measured in the pre-event period for each stock i: relative tick size, tick constraint, the natural logarithm of the market value, the percentage of trading under the reference price waiver, dummy variables indicating membership of the countries' main stock indices, and dummy variables for the RCAs. We define the pre-event period as beginning on 15 January and ending on 9 March. We exclude the first two weeks of 2018 to allow market participants to adjust their behavior to other MiFID II rules that came into effect on January 3. The post-event period begins on 12 March 2018 and ends on 11 May 2018.[26] For each stock and period, we compute the simple average of all variables of interest.

In the second stage, we employ a modified DID estimator, where we estimate the difference in outcomes between treated and untreated groups controlling for treatment probability. This works by weighting-down (weighting-up) control firms with over-represented (under-represented) values of the covariates. In other words, we assign a high (low) weight to control firms with high (low) propensity scores. This approach can lead to noisy, imprecise estimates if the estimated propensity scores are very close to zero or one. Hence, we restrict the estimation sample to stocks with estimated propensity scores between 5 and 95 percent.

The estimation approach we employ additionally allows for the estimation of heterogeneous treatment effects, i.e., whether the ban's impact differs conditional on the observed covariates. To do so, we center our explanatory variables around zero such that our estimation output still allows us to see the unconditional effect. We include all previously used covariates other than the dummy variables in these regressions.

[26] In untabulated results, we leave a two week gap around the ban's implementation date, to allow for an adaptation period. Thus, we end the pre-event window on 2 March and begin the post-event period on 19 March. Our results are unaffected by this choice.

3.5.2 Regression Discontinuity Design (RDD)

As another empirical approach, we employ the RDD technique and exploit the discontinuity in the application of the treatment vis-à-vis the running variable – which in our case is the historical waiver percentage – to estimate a Local Average Treatment Effect (LATE). Stocks with a historical waiver percentage just below 8% are eligible for trading under the reference price and negotiated trade waivers, whereas those just above 8% are not.[27] We thus focus our analysis on the sample of stocks whose historical waiver percentage lies close to the 8% threshold. Following Calonico et al. (2018), we include covariates to improve the precision of our estimates and exploit the panel structure of our data. Specifically, we estimate the ban's effect using the following linear regression specification:

$$Y_{it} = \alpha + \beta Suspension_{it} + \gamma \bar{y}_i^{pre} + \delta WaiverPercentage_i + \varepsilon_{it} \tag{3.2}$$

where Y_{it} are the different variables of interest, $Suspension_{it}$ is a dummy variable equal to one if stock i has historical waiver percentage greater than 8% and zero otherwise, and β is the main coefficient of interest measuring the causal impact of the ban on Y_{it}. $\bar{y}_i^{pre}$ is the mean value of the dependent variable in the pre-event window. ε_{it} is the residual term and we cluster standard errors by stock. We also estimate an RDD without $\bar{y}_i^{pre}$ and with the dependent variable being the stock-level difference in pre- and post-event mean.

A key identifying assumption underlying a RDD is that stocks near the 8% threshold are almost randomly assigned their suspension status due to exogenous variation in the waiver percentage. In other words, stocks around the cut-off should be similar with respect to other observable characteristics, market participants and venues should not be able to strategically game the running variable, and, except for discontinuity in the treatment, any variation in other relevant variables should be continuous and smooth. To test this assumption, we first estimate the above equation with historical market capitalization, relative tick size and tick constraints as the dependent variables and find that the β coefficient is insignificant in these cases, suggesting that stocks near the 8% threshold do not to differ in terms of these variables. Additionally, as discussed above, Figure 3.1 alleviates any concerns related to gaming on the part of investors and/or market operators.

One issue in any RDD analysis is the choice of an optimal bandwidth around the threshold used to obtain the estimation sample. A narrower bandwidth allows for more accurately measuring the treatment effect whereas a wider bandwidth improves the statistical power of our estimations due to the inclusion of a larger number of stocks. We employ the bias-corrected Calonico et al. (2014) bandwidth with a triangular kernel.[28]

[27] See Lee and Lemieux (2010) and Imbens and Lemieux (2008), for a general discussion of RDD in economics.

[28] Fan and Gijbels (1996) show the triangular kernel to be optimal for our purpose of estimating local linear regressions at the boundary. As a robustness check, we also employ a rectangular kernel and find that our results remain qualitatively unchanged.

3.6 Results: Implementation Effects

In this section, we discuss the ban's impact on market outcomes based on the SP-DID and RDD estimations. It is worthwhile to highlight that the SP-DID and RDD estimators are not directly comparable as the former (latter) provides an estimate of the ATT (LATE). Put differently, the RDD describes the ban's impact for the average firm in the local sample near the threshold, whereas the SP-DID estimates the ban's impact for the average firm in the entire treatment group.

3.6.1 Which Stocks Are Banned?

Before examining the effects of the ban, we consider what predicts whether a stock will be banned. Table 3.6 provides an overview of the characteristics of suspended and non-suspended stocks. Panel A shows, besides the obvious fact that suspended stocks trade relatively more under the negotiated trade and reference price waivers, they are of a smaller size and trade lower volumes than non-suspended stocks. Panel B shows that suspended stocks have smaller quoted and effective spreads as well as smaller price impacts and realized spreads, though their depth is also smaller. Suspended stocks trade at a smaller relative tick size, too, such that the average tick constraint is similar across the two samples. Differences in the price efficiency measures, displayed in Panel C, are negligible.

Table 3.6: Pre-Ban Differences
This table contains the pre-ban (January 3 - March 9, 2018) mean for the variables used in our analysis, reported separately for *Suspended/Not Suspended* stocks of the main sample. For details and definitions of the different variables, see Table 3.3. *Unit* provides the unit of measurement.

	Unit	**Suspended**	**Not Suspended**
Panel A: Stock Characteristics and Trading Activity			
Market Value	mio	6,165.52	10,357.27
Total Trading Volume	mio	42.36	79.11
Trading Volume (Most Relevant Market)	mio	11.11	20.36
Waiver Percentage	%	11.33	4.98
Percentage Negotiated Trade Waiver	%	3.39	1.42
Percentage Reference Price Waiver	%	7.92	3.52
Main Index Constituent	%	31.60	33.97
Panel B: Liquidity			
Quoted Spread	bp	15.13	18.88
Effective Spread	bp	12.83	17.72
Depth	thousands	19.09	24.92
Midpoint Volatilty (1 Minute)	bp	7.08	7.18
Price Impact (10 sec.)	bp	12.31	14.83
Realized Spread (10 sec.)	bp	0.53	2.90
Relative Tick Size	bp	6.59	7.63
Tick Constraint	%	26.66	27.17
Panel C: Price Efficiency			
Autocorrelation (10 sec.)	%	4.17	4.27
Variance Ratio (10/30 sec.)	%	7.48	7.57
Variance Ratio (30/300 sec.)	%	20.01	19.81

Besides these differences in stock characteristics, we report the distribution of banned firms by country and membership of the main national stock market indices in Figure 3.2 and Figure 3.3. Stocks contained in different indices and from different countries strongly differ in their probability of being suspended. For example, constituents of the German, Spanish, and Polish main stock market indices are less likely to be banned, whereas constituents of the main index of the UK and Scandinavian countries have a higher ban probability. Similarly, a small (large) fraction of firms from Germany (UK) are banned.

Figure 3.2: Dark Trading Bans by Stock Index
We plot the fraction of stocks banned from dark trading due to a breach in the 8% DVC for constituents of the main stock market index of each country included in our sample. The total number of stocks in each index is adjusted for stocks missing in the ESMA reports due to incomplete reporting by trading venues.

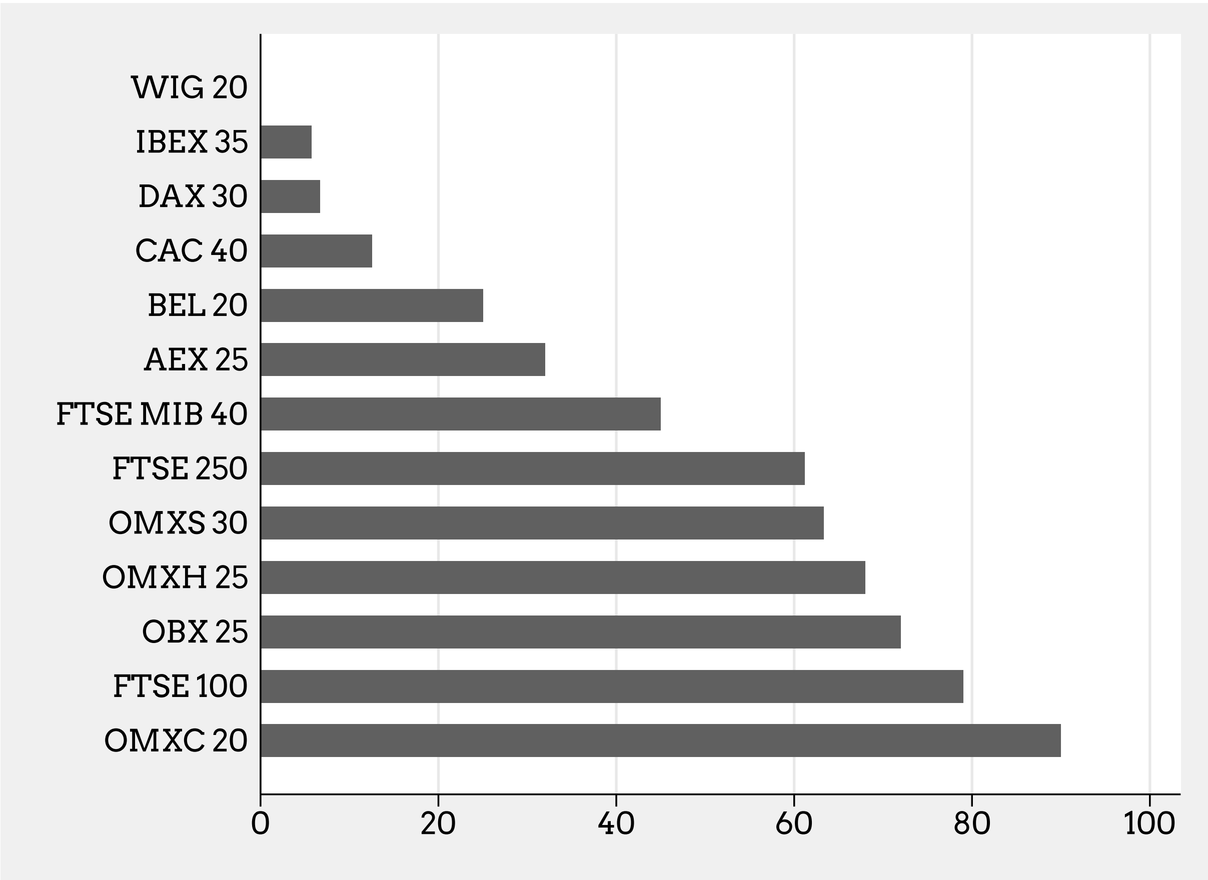
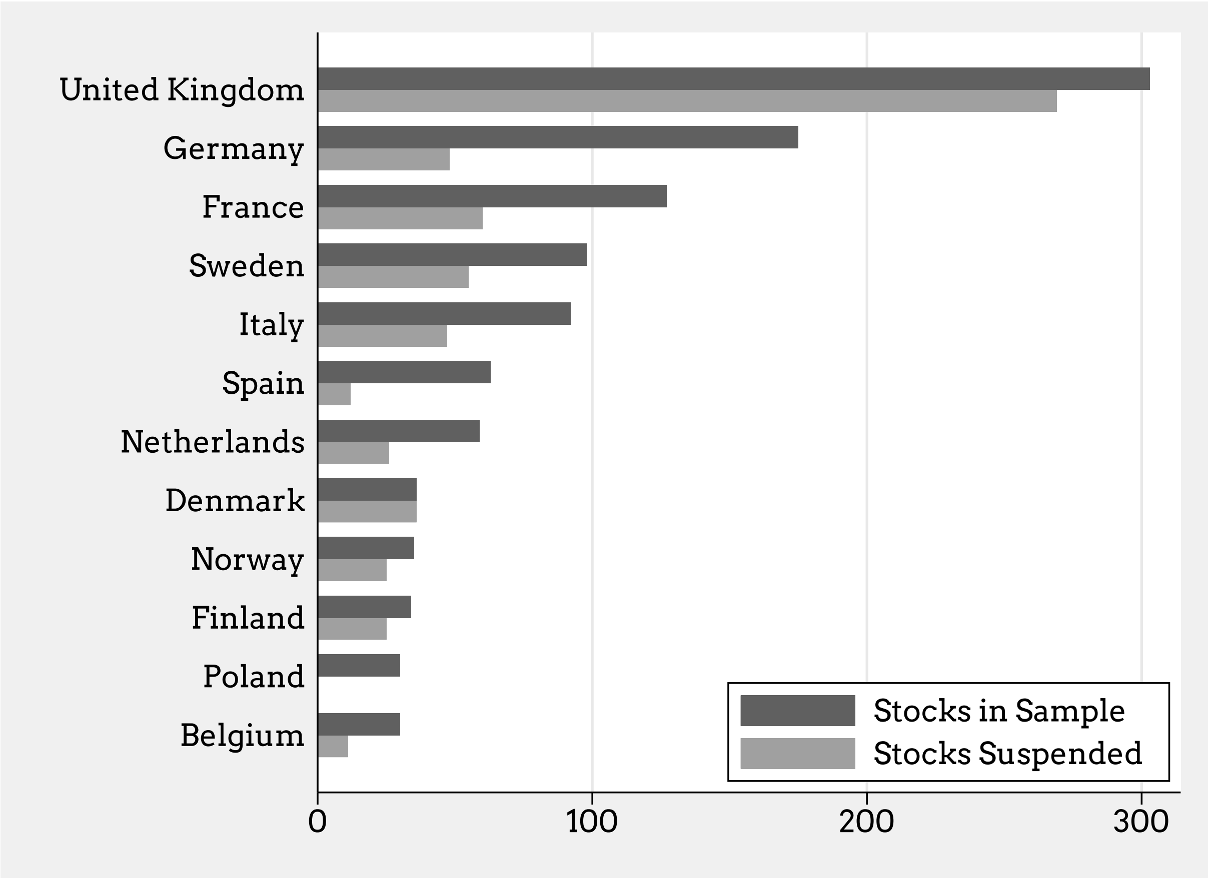


Figure 3.3: Dark Trading Bans by Country
We plot the the total/banned number of stocks in our main sample for each relevant competent authority.



The above differences motivate our choice of covariates when estimating the propensity scores using Equation 3.1. The estimated propensity scores are used to determine the weights of individual observations in estimating the second stage difference-in-difference Abadie (2005) estimator and remain constant for the different dependent variables. Table 3.7 contains the results of this first stage regression. The fraction of trading conducted under the reference price waiver is the strongest predictor of a stock's suspension status. A one standard deviation increase (about 3%) in the fraction of trading under the reference price waiver predicts a 19.5 percentage points increase in the ban probability. This is to be expected because it has a strong positive correlation with the historical total waiver percentage contained in the ESMA reports. However, this link is not completely mechanical because the explanatory variable refers to trading activity spanning only the pre-event period between 15 Jan 2018 and 11 Mar 2018, and thus covering only a small part of the period used to determine the waiver percentage. The insignificant coefficients for relative tick size and tick constraint may seem surprising considering the existing theoretical and empirical evidence to the contrary Buti et al. (2017); Gomber et al. (2016). We obtain this result because the measurement period for the ban mostly falls in 2017 and, starting 2018, EU-wide tick size regimes were changed due to the implementation of MiFID II. A one standard deviation change in log firm size is associated with a 5.3 percentage point increase in treatment probability. Finally, we find that index membership and country dummies have strong effects on the propensity to cross the 8% threshold. In particular, indices such as the CAC40, DAX30, and IBEX35 have a negative effect on the propensity score. The country dummies are expressed relative to the base category, which is Italy. In comparison, German stocks are less likely and British stocks are more likely to experience the ban.[29]

Table 3.7: Semi-parametric DID: First Stage
This table presents the average marginal effects from the first stage logit estimation in the Abadie (2005) semi-parametric DID for all main sample stocks. The dependent variable is a dummy variable that equals to one if a stock is banned and zero otherwise. The independent variables are defined in Table 3.3. All independent variables are mean values from the pre-event period (January 3 - March 9). *N* is the number of observations. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Marginal Effect	T-Statistic
Rel. Tick Size	-2.062	(-0.87)
Tick Constraint	-1.640	(-0.85)
log(MV)	5.268**	(2.25)
% Ref. Price Waiver	19.468***	(13.26)
FTSE MIB40	0.259	(0.04)
AEX25	-17.396**	(-1.98)
BEL20	-9.361	(-0.91)
CAC40	-36.197***	(-4.65)
FTSE250	-6.599	(-0.79)
FTSE100	14.920	(1.27)
DAX30	-24.142**	(-2.17)
IBEX35	-39.667***	(-3.31)
OBX	-1.897	(-0.15)
OMXH25	-2.172	(-0.19)
OMXS30	9.552	(1.15)
Netherlands	-4.178	(-0.50)
Belgium	0.396	(0.04)
Germany	-23.832***	(-3.88)
Finland	3.211	(0.26)
United Kingdom	21.141**	(2.35)
Spain	-5.012	(-0.57)
Norway	12.264	(1.08)
France	-2.397	(-0.37)
Sweden	-7.276	(-1.05)
N	1016	

[29] Our results remain qualitatively unchanged when we additionally include liquidity and trading volume in the first (and second) stage regression. This is in line with our expectations as these variables are correlated with firm size and relative tick size.

3.6.2 Shifts in Trading Activity: Winners and Losers

The application of the ban mechanically eliminates small dark pool trades for the affected stocks. We start by examining whether the ban was successful in its primary objective of shifting order flow from the dark to lit markets. In Section 3.3, we develop hypotheses for three distinct sets of trading venues: Dark LIS, quasi-dark, and continuous lit markets. We test these hypotheses by estimating the SP-DID and RDD with $Y_{i,t}$ being the market share of these trading mechanisms. Furthermore, our SP-DID regressions enable us to test the cross-sectional effects of the ban. Table 3.8, Table 3.9, and Figure A3.1 in the Appendix contain the results from these estimations. In untabulated results, we show that the ban had no significant influence on the total turnover, implying that an increase in the market share of a trading mechanism is equivalent to an increase in its volume.

The results are consistent with Hypothesis 1. We observe an increase in the market share of dark LIS trades which is statistically significant independent of the estimation approach. The results range between 0.65 and 1.37 percentage points. This also shows that the increase in block trades is smaller than the magnitude of the eliminated trades based on the reference price and negotiated trade waivers, which suggests small and large dark pool trades are no perfect substitutes.

We also obtain evidence in support of Hypothesis 2 for two quasi-dark mechanisms. The coefficients for periodic auctions and SI based on the SP-DID estimations are positive and significant. The coefficients for these two mechanisms based on the RDD are also positive but only significant for periodic auctions. There are no significant changes in the market share of traditional call auctions[30] and the OTC market. The magnitude of the impact on periodic auction market share ranges between 0.9 and 1.3 percentage points. The results for both dark LIS and periodic auctions are economically large compared to their pre-event averages.

Finally, we find mixed evidence for Hypothesis 3. Both approaches show an increase in lit continuous market trading of similar magnitude, though the SP-DID (RDD) point estimate is significant (insignificant). The estimates range from 0.9 to 1.2 percentage points, which is of a similar magnitude compared to the shifts towards dark LIS and periodic auctions, but substantially smaller relative to the pre-event average.

In summary, while we do observe some migration of trading towards lit markets, almost thrice as much volume migrated to dark LIS, periodic auctions and SI. Thus, we conclude that the regulation was only partially successful in shifting order flow towards lit markets. At the same time, quasi-dark markets secure the highest relative gains in market shares. These findings are not affected by cross-sectional differences in firm characteristics.

[30] This is true for the aggregate of traditional call auctions, but also confirmed for opening, intraday, closing and volatility auctions separately in untabulated results.

Table 3.8: Semi-parametric DID: Second Stage: Market Shares
This table shows the effects of the ban on the market shares of different trading mechanisms for the affected (main sample) stocks based on a semi-parametric difference-in-differences estimations (Abadie, 2005). The table presents the output from the second stage estimation (first stage results are reported in Table 3.7). Independent variable, as defined in Table 3.3, are centered around zero, such that *Unconditional* provides the unconditional effect of the ban. t-statistics are shown in parentheses. N is the number of observations. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Dark LIS	Periodic Auction	Continuous Lit	Call Auction	SI	OTC
Relative Tick Size	0.395	0.186	0.690	0.722	0.653	-3.814
	(0.33)	(0.98)	(0.31)	(1.23)	(0.42)	(-1.32)
Tick Constraint	-0.234	-0.250*	1.044	-0.995*	-1.059	1.445
	(-0.43)	(-1.86)	(0.77)	(-1.66)	(-1.01)	(0.93)
log(MV)	0.395	0.009	-0.493	0.737	1.579	-2.602
	(0.49)	(0.05)	(-0.21)	(1.16)	(0.99)	(-1.25)
% Reference Price Waiver	0.546	0.215	1.388	-0.081	-2.526	-1.622
	(0.32)	(1.10)	(0.69)	(-0.15)	(-0.71)	(-0.36)
Unconditional	0.649***	1.256***	1.175**	0.056	0.803**	-0.040
	(3.47)	(23.38)	(2.37)	(0.32)	(2.27)	(-0.09)
Observations	792	792	792	792	792	792

Table 3.9: RDD Results: Market Shares
This table shows the effects of the ban on the market shares of the different trading mechanisms for affected (main sample) stocks based on the RDD estimation. *Panel* denotes a panel RDD only controlling for the mean value of the dependent variable in the pre-event window. *Post–Pre* denotes a simple RDD where the dependent variable is the difference in market shares around the event date. A triangular kernel is employed while estimating the local linear regression. All estimates are computed using nearest neighbor heteroskedasticity-robust variance estimators. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *p-Values* are shown in parentheses. *Bandwidths* used are data-driven MSE-optimal and the resulting lower / upper cutoffs of the waiver percentage are shown in the table. N provides the number of observations to the left and right of the 8% threshold.

		Dark LIS	Periodic Auction	Continuous LIT	Call Auction	SI	OTC
Panel	Coef.	1.3728***	.9393***	.9003	-.4126	.2162	.5085
	p-Value	(.0039)	(0)	(.6066)	(.5702)	(.8739)	(.6837)
	Bandwidth	4.41 | 11.59	2.49 | 13.51	4.48 | 11.52	4.48 | 11.52	5.03 | 10.97	4.34 | 11.66
	N	2691 | 2988	3348 | 4392	2682 | 2925	2682 | 2925	2358 | 2484	2763 | 3060
Post - Pre	Coef.	1.0633**	.9432***	1.0819	-.1546	-.1462	.6745
	p-Value	(.0147)	(0)	(.5224)	(.8404)	(.9186)	(.6142)
	Bandwidth	3.66 | 12.34	2.09 | 13.91	4.44 | 11.56	4.67 | 11.33	5.14 | 10.86	4.28 | 11.72
	N	329 | 408	380 | 518	298 | 327	290 | 311	252 | 263	309 | 347

3.6.3 Market Quality Implications

In this subsection, we investigate effects of the ban on measures of lit market quality. This includes liquidity and short-term price efficiency of the primary listing venue for each stock. As noted in the previous section, the ban induces an increase in the market share of lit venues. The effects of this increase on market quality will depend on the kind of order flow that moved to lit markets. Furthermore, the ban also increases the level of market-wide transparency allowing limit order traders to incorporate information from quasi-dark markets such as periodic auctions in their quoting behavior on lit markets. This will further have implications for the lit market quality. In Tables 3.10 and 3.11 and in Appendix Figure A3.2, we report the liquidity results. Tables 3.12 and 3.13 and Figure A3.3 in the Appendix show the price efficiency results.

Overall, there is no unambiguous evidence for any effect of the ban on liquidity as all unconditional results are statistically insignificant, allowing no firm conclusion with respect to Hypothesis 4A or Hypothesis 4B. Our findings, at least with respect to the SP-DID estimates, do not result from a high degree of noise or a lack of power in our data: our 95% confidence intervals for quoted spread, effective spread, realized spread, and price impact range from less than 0.7 basis points on either side of zero, and the confidence interval for depth excludes changes of more than approximately 0.5%. These insignificant results can be attributed to the relatively low increase in lit market shares and the unclear implications of the ban for the equilibrium order flow composition in lit markets.

Almost all price efficiency point estimates are positive suggesting an increase in deviations from a random walk or reduction in price efficiency. However, only few of these estimates are statistically significant. Altogether, the results thus provide some support for Hypothesis 5B. We do not find evidence of systematic cross-sectional differences based on the stock characteristics under consideration as all coefficients aiming to capture such effects are statistically insignificant for liquidity and price efficiency.

Table 3.10: Semi-parametric DID: Second Stage: Liquidity
This table shows the effects of the ban on the primary market liquidity for the affected (main sample) stocks based on a semi-parametric difference-in-differences estimations (Abadie, 2005). The table presents the output from the second stage estimation (first stage results are reported in Table 3.7). Independent variable, as defined in Table 3.3, are centered around zero, such that *Unconditional* provides the unconditional effect of the ban. t-statistics are shown in parentheses. N is the number of observations. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Quoted Sp	Log Depth	Eff Sp	Real Sp 10s	P Imp 10s
Relative Tick Size	0.014	4.131	0.011	0.003	0.008
	(0.41)	(0.36)	(0.35)	(0.26)	(0.26)
Tick Constraint	-0.016	0.969	-0.014	-0.009	-0.005
	(-0.65)	(0.17)	(-0.65)	(-0.98)	(-0.28)
log(MV)	0.025	-6.895	0.025	0.012	0.014
	(0.59)	(-0.84)	(0.62)	(1.01)	(0.37)
% Reference Price Waiver	-0.027	21.977	-0.038	-0.003	-0.035
	(-0.72)	(0.86)	(-0.84)	(-0.17)	(-0.74)
Unconditional	-0.002	-0.174	-0.003	-0.003	-0.000
	(-0.69)	(-0.09)	(-0.98)	(-1.27)	(-0.09)
Observations	792	792	792	792	792

Table 3.11: RDD Results: Liquidity
This table shows the effects of the ban on the primary market liquidity for the affected (main sample) stocks based on the RDD estimation. *Panel* denotes a panel RDD only controlling for the mean value of the dependent variable in the pre-event window. *Post–Pre* denotes a simple RDD where the dependent variable is the difference in market shares around the event date. A triangular kernel is employed while estimating the local linear regression. All estimates are computed using nearest neighbor heteroskedasticity-robust variance estimators. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *p-Values* are shown in parentheses. *Bandwidths* used are data-driven MSE-optimal and the resulting lower / upper cutoffs of the waiver percentage are shown in the table. N provides the number of observations to the left and right of the 8% threshold.

		Quoted Sp	Log Depth	Eff Sp	Real Sp 10s	P Imp 10s
Panel	Coef.	.1442	.0284	-.2447	.1224	-.2829
	p-Value	(.8507)	(.5674)	(.6845)	(.7814)	(.6526)
	Bandwidth	4.92 | 11.08	2.87 | 13.13	4.86 | 11.14	4.58 | 11.42	4.1 | 11.9
	N	11461 | 11999	15106 | 19326	11710 | 12401	12255 | 13103	13135 | 15351
Post - Pre	Coef.	.2157	.0183	-.2709	.0434	-.2985
	p-Value	(.7864)	(.7218)	(.6798)	(.9309)	(.6595)
	Bandwidth	4.64 | 11.36	2.87 | 13.13	4.48 | 11.52	4.19 | 11.81	4.54 | 11.46
	N	292 | 312	361 | 464	298 | 325	312 | 358	294 | 319

Table 3.12: Semi-parametric DID: Second Stage: Price Efficiency
This table shows the effects of the ban on the short-term efficiency of primary market mid-quote for the affected (main sample) stocks based on a semi-parametric difference-in-differences estimation (Abadie, 2005). The table presents the output from the second stage estimation (first stage results are reported in Table 3.7). Independent variable, as defined in Table 3.3, are centered around zero, such that *Unconditional* provides the unconditional effect of the ban. t-statistics are shown in parentheses. N is the number of observations. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	AC 10s	AC 30s	AC 300s	VR 10/30s	VR 10/300s	VR30/300s
Relative Tick Size	0.213	-0.110	0.535	-0.275	-0.367	-0.947
	(0.33)	(-0.33)	(0.83)	(-0.27)	(-0.22)	(-0.57)
Tick Constraint	-0.554	-0.110	-0.176	-0.791	-0.461	-0.013
	(-1.11)	(-0.38)	(-0.49)	(-1.03)	(-0.57)	(-0.01)
log(MV)	0.475	-0.080	0.831	0.603	-0.437	-1.364
	(0.55)	(-0.21)	(1.36)	(0.49)	(-0.31)	(-0.72)
% Reference Price Waiver	-0.650	-0.062	-0.660	-2.116	2.595	2.614
	(-0.80)	(-0.15)	(-0.59)	(-0.92)	(0.90)	(0.84)
Unconditional	0.094	0.193*	-0.016	0.056	0.792**	0.586*
	(0.77)	(1.65)	(-0.11)	(0.25)	(2.02)	(1.74)
Observations	792	792	792	792	792	792

Table 3.13: RDD Results: Price Efficiency
This table shows the effects of the ban on the short-term efficiency of the primary market mid-quote for the affected (main sample) stocks based on the RDD estimation. *Panel* denotes a panel RDD only controlling for the mean value of the dependent variable in the pre-event window. *Post–Pre* denotes a simple RDD where the dependent variable is the difference in market shares around the event date. A triangular kernel is employed while estimating the local linear regression. All estimates are computed using nearest neighbor heteroskedasticity-robust variance estimators. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *p-Values* are shown in parentheses. *Bandwidths* used are data-driven MSE-optimal and the resulting lower / upper cutoffs of the waiver percentage are shown in the table. N provides the number of observations to the left and right of the 8% threshold.

<table>
<tr><th></th><th></th><th>AC 10s</th><th>AC 30s</th><th>AC 300s</th><th>VR 10/30s</th><th>VR 10/300s</th><th>VR 30/300s</th></tr>
<tr><td>Panel</td><td>Coef.</td><td>.3996</td><td>.1004</td><td>.3718</td><td>.7952*</td><td>1.9853</td><td>.5522</td></tr>
<tr><td></td><td>p-Value</td><td>(.1139)</td><td>(.6933)</td><td>(.2594)</td><td>(.0928)</td><td>(.1051)</td><td>(.5447)</td></tr>
<tr><td></td><td>Bandwidth</td><td>5.01 | 10.99</td><td>4.2 | 11.8</td><td>2.73 | 13.27</td><td>5.39 | 10.61</td><td>5.47 | 10.53</td><td>5.01 | 10.99</td></tr>
<tr><td></td><td>N</td><td>11082 | 11622</td><td>13053 | 14913</td><td>15396 | 19821</td><td>9491 | 9922</td><td>9365 | 9469</td><td>11082 | 11622</td></tr>
<tr><td>Post - Pre</td><td>Coef.</td><td>.1904</td><td>-.0452</td><td>.5948</td><td>.7791*</td><td>1.5029</td><td>.5406</td></tr>
<tr><td></td><td>p-Value</td><td>(.4566)</td><td>(.8566)</td><td>(.211)</td><td>(.0729)</td><td>(.2664)</td><td>(.6256)</td></tr>
<tr><td></td><td>Bandwidth</td><td>3.94 | 12.06</td><td>3.2 | 12.8</td><td>4.2 | 11.8</td><td>4.62 | 11.38</td><td>5.08 | 10.92</td><td>4.75 | 11.25</td></tr>
<tr><td></td><td>N</td><td>318 | 381</td><td>350 | 443</td><td>312 | 358</td><td>293 | 312</td><td>256 | 270</td><td>287 | 305</td></tr>
</table>

3.6.4 Placebo Tests

We repeat the SP-DID analyses for the placebo sample of 24 stocks that should have been banned in March-2018 but were not because of insufficient or incorrect data provided to ESMA. These stocks were eventually banned in April-2018. If the results observed in the previous subsections are attributable to the ban, we should observe a delayed reaction consistent with the previous analyses for these stocks. In other words, we should observe no significant change in market outcomes in March-2018, and a reaction consistent with our main analyses in April-2018. We estimate two sets of regressions. In the first one, we set the event date to 12 March 2018, the pre-event period to that used in the main analysis, the post-event period to one month between the reports published in March-2018 and April-2018, and the control group to firms not suspended on the event date. In the second regression, we set the event date to 13 April 2018, the pre-event window to the one month between the publication of the two reports, the post-event window to the period between the event date and the end of our sample period, and the control group to firms suspended on 12 March 2018. We focus our analysis on the unconditional effect and do not attempt to explain cross-sectional differences because of our limited sample size. Tables 3.14 and 3.15 show the SP-DiD second stage results for market shares, liquidity, and price efficiency for the March-2018 and April-2018 report respectively. For brevity, we exclude the first stage results.

Table 3.14: Placebo Semi-parametric DID: Second Stage: March Report
This table shows the effects of the ban on the market shares (Panel A), primary market liquidity (Panel B) and price efficiency (Panel C) of different trading mechanisms for the incorrectly not banned stocks when these stocks erroneously did not get banned on 12 March 2018 based on a semi-parametric difference-in-differences estimations (Abadie, 2005). The table presents the output from the second stage estimation. t-statistics are shown in parentheses. N is the number of observations. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Market Shares

	Dark LIS	Periodic Auction	Continuous Lit	Call Auction	SI	OTC
Uncond.	0.165	-0.083	-2.115	0.270	0.979	1.041
	(0.18)	(-0.60)	(-1.58)	(0.37)	(0.87)	(0.84)
N	113	113	113	113	113	113

Panel B: Liquidity

	Quoted Sp	Log Depth	Eff Sp.	Real Sp 10s	P Imp 10s
Uncond.	-0.014	1.462	-0.010	0.000	-0.011*
	(-1.24)	(0.21)	(-1.34)	(0.05)	(-1.65)
N	113	113	113	113	113

Panel C: Price Efficiency

	AC 10s	AC 30s	AC 300s	VR 10/30s	VR 10/300s	VR 30/300s
Uncond.	-0.500	0.368	0.279	-0.755	0.732	0.898
	(-1.11)	(0.85)	(0.49)	(-1.05)	(0.43)	(0.48)
N	113	113	113	113	113	113

Panel A of Table 3.14 shows that changes in market shares are different from those observed for the main sample. The magnitude of the change in periodic auction volume and LIS dark pool volume is much smaller. Furthermore, and in contrast to the main sample, there is a reduction in the share of lit continuous order books and periodic auctions. However, all these changes are statistically insignificant. The effect on liquidity (Panel B) is also insignificant with the exception of a weakly significant reduction in price impacts. The price efficiency results (Panel C), again contrary to the main sample results, show no clear pattern, with both positive and negative coefficients, but are insignificant.

The results in Table 3.15 are similar to those in the main analyses: the market share of periodic auctions increases significantly, as does the SI market share. We find no significant effect on liquidity and there is some evidence of a short-term price efficiency worsening, as evidenced by the autocorrelation of midpoint returns which is significant at 10 percent. Altogether, the placebo analysis confirms that the effects observed for the main sample indeed result from the ban itself and not from other confounding changes to the stocks.

Table 3.15: Placebo Semi-parametric DID: Second Stage: April Report
This table shows the effects of the ban on the market shares (Panel A), primary market liquidity (Panel B) and price efficiency (Panel C) of different trading mechanisms for the previously incorrectly not banned stocks when these stocks get banned on 13 April 2018 based on a semi-parametric difference-in-differences estimations (Abadie, 2005). The table presents the output from the second stage estimation. t-statistics are shown in parentheses. *N* is the number of observations. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Market Shares

	Dark LIS	Periodic Auction	Continuous Lit	Call Auction	SI	OTC
Uncond.	-1.144	0.625**	-0.397	0.142	4.563***	0.110
	(-0.86)	(2.38)	(-0.19)	(0.29)	(2.87)	(0.05)
N	130	130	130	130	130	130

Panel B: Liquidity

	Quoted Sp	Log Depth	Eff Sp.	Real Sp 10s	P Imp 10s
Uncond.	-0.003	11.913	-0.002	0.000	-0.002
	(-0.74)	(1.62)	(-0.44)	(0.04)	(-0.41)
N	130	130	130	130	130

Panel C: Price Efficiency

	AC 10s	AC 30s	AC 300s	VR 10/30s	VR 10/300s	VR 30/300s
Uncond.	0.499*	-0.099	0.011	0.409	1.426	1.418
	(1.77)	(-0.28)	(0.02)	(0.88)	(1.11)	(1.04)
N	130	130	130	130	130	130

3.7 DVC Ban Announcement Returns

In the previous section we document a positive effect of the ban on the market share of lit venues. Simultaneously, market liquidity remains unchanged and price efficiency slightly deteriorates. Against this background and to test Hypothesis 6A/6B, we explore how market participants evaluate the introduction of the ban by conducting an event study analyzing the returns of affected stocks after the first DVC report's publication on March 7, 2018. We use daily stock returns for all stocks in our main sample from January 2 to March 15. Expected returns are computed using a Carhart (1997) 4-factor-model with country-specific factors from Andrea Frazzini's data library[31,32] We use the period between January 3 and March 2 as our estimation window. As the report was published after trading hours on March 7, we select March 8 as the event date ($t = 0$). The actual ban of suspended stocks started on March 12 ($t = 2$). Abnormal returns on March 8 and March 9 should capture investors' expectations about market liquidity, while abnormal returns starting March 12 will capture investors' learning after having observed the ban's actual impact on market quality.

As we intend to analyze both the announcement effect (before the ban kicks in) and the actual effect (after the ban is implemented), we use $(-1; +6)$ as the event window around March 8, such that it contains one week of trading with the ban in force. Figure 3.4 shows the Cumulative Abnormal Returns of suspended stocks and non-suspended stocks separately. Returns for suspended stocks are significantly more positive by about 25 basis points on the announcement day.[33] This finding is in line with the conjecture that traders on average anticipated a positive effect of the ban on market quality. The positive announcement effect is fully reversed with the actual implementation of the ban on day 2. The difference between CAR(-1,2) for suspended and non-suspended stocks is insignificantly different from zero. This finding is in line with investors learning that market quality largely remains unchanged after the ban kicks in.

To further understand the drivers of announcement and implementation effect, we perform a cross-sectional regression with the following specification:

$$CAR(t_1, t_2)_i = \alpha + \beta Suspension_i + \gamma Dist_i + \delta Suspension_i \cdot Dist_i \; + \varepsilon_i \tag{3.3}$$

where $CAR(t_1, t_2)_i$ is the cumulative abnormal return for stock i from day t_1 to day t_2, $Suspension_i$ is a dummy variable equal to one for the treatment stocks and zero for the control stocks, $Dist_i$ measures the absolute distance between the actual waiver percentage and 8%, and ε_i is the residual term. As we expect that the news of the ban is more likely to come as a surprise for firms closer to the 8% threshold,[34] we include the interaction term $Suspension_i \cdot Dist_i$.[35]

[31] Available at http://people.stern.nyu.edu/afrazzin/data_library.htm.

[32] In untabulated results, we also employ the constant mean return model, index adjusted return model, Fama-French 3-factor model using factors from Ken French's homepage and the 4-factor model with European factor loadings. Results remain largely unaffected by these choices.

[33] This finding's statistical significance is confirmed by parametric as well as non-parametric test statistics.

[34] For example, the news that most of the FTSE100 stocks would be affected by the ban was probably not a surprise. See *The TRADE* article from 2017 titled "Nine-in-ten FTSE 100 stocks to hit dark cap in January".

[35] In untabulated results, we include further control variables (and their interaction with the suspension dummy). We use the mean of log market capitalization, trading volume, several liquidity and price efficiency measures, market shares of the different venue types, and tick constraints over the estimation window. Results are unchanged.

Figure 3.4: DVC Ban Announcement Returns
This figure shows the Cumulative Abnormal Returns one day prior and six days after 8 March 2018, for suspended and not suspended stocks. Day 2 marks the day of the actual implementation of the ban. Expected returns are calibrated using a Carhart (1997) 4-factor-model with country-specific factors from Andrea Frazzini's data library with an estimation period from 3 January to 2 March 2018.

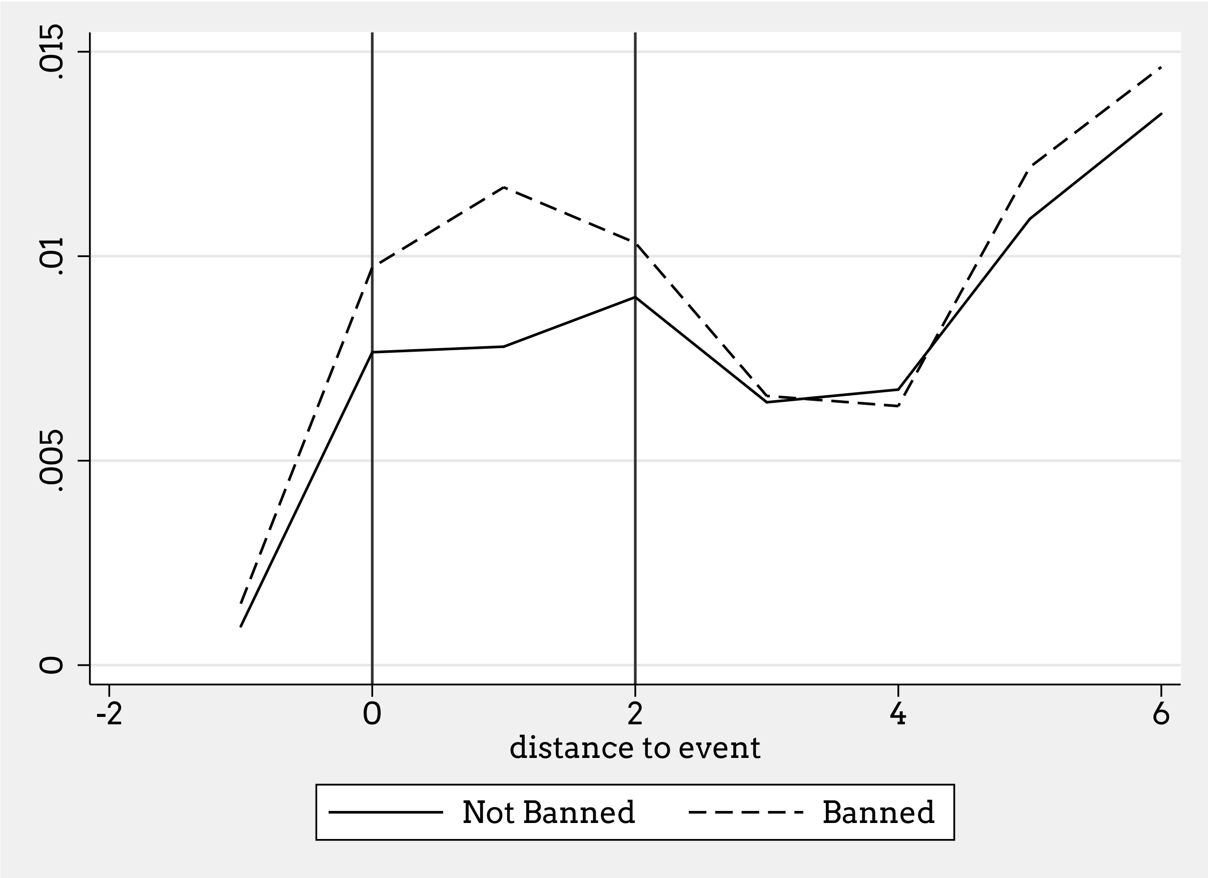


Table 3.16 shows the results. We confirm the above findings by showing that β is positive and economically significant with about 54 and 21 basis points higher daily returns for suspended stocks in the $(-1;+1)$ and $(0;0)$ window, respectively. With the actual implementation of the ban, however, CARs for suspended stocks decrease and are insignificantly different from those of non suspended stocks for the $(-1;6)$ window. Controlling for the absolute distance between the waiver percentage and 8%, these findings are confirmed. The interaction term, while insignificant, supports the argument that stocks closer to the 8% thresholds exhibit a stronger announcement effect.

In summary, we find evidence, consistent with Hypothesis 6A, of a positive announcement effect for suspended stocks.[36] With the actual implementation of the ban this effect is reversed, consistent with investors learning that the positive effect on liquidity did not materialize.

[36]In untabulated results, we observe that the Placebo stocks behave similar to non-suspended stocks around March 8, but like suspended stocks around the second ESMA DVC report's publication on 11 April 2018.

Table 3.16: Ban Returns

This table provides crosssectional OLS regression results of Cumulative Abnormal Returns on a suspension dummy as specified in Equation 3.3 around the publication of the March report on March 8, 2018 for the main sample. *Suspended* is a dummy that equals one for suspended and zero for non suspended stocks. *Abs. Distance* is the absolute difference between a stock's waiver percentage and 8%. Day 2 marks the day of the actual implementation of the ban. Expected returns are calibrated using a Carhart (1997) 4-factor-model with country-specific factors from Andrea Frazzini's data library with an estimation period from 3 January to 2 March 2018. t-statistics are shown in parentheses. N is the number of observations. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively. All regressions use heteroskedasticity robust standard errors.

	CAR(0;0)	CAR(-1;1)	CAR(-1;2)	CAR(-1;3)	CAR(-1;4)	CAR(-1;5)	CAR(-1;6)
Suspended	0.00214**	0.00541***	0.00417**	0.00646***	0.00532**	0.00453*	0.00270
	(2.03)	(3.31)	(2.22)	(3.10)	(2.33)	(1.82)	(0.99)
Constant	0.00662***	0.00745***	0.0107***	0.00500***	0.00734***	0.00958***	0.0119***
	(8.11)	(6.03)	(7.44)	(3.14)	(4.17)	(4.98)	(5.69)
N	1082	1082	1082	1082	1082	1082	1082
adj. R^2	0.00	0.01	0.00	0.01	0.00	0.00	0.00

	CAR(0;0)	CAR(-1;1)	CAR(-1;2)	CAR(-1;3)	CAR(-1;4)	CAR(-1;5)	CAR(-1;6)
Suspended	0.00282*	0.00702***	0.00663**	0.00961***	0.00845**	0.00737*	0.00657
	(1.72)	(2.86)	(2.35)	(3.13)	(2.48)	(1.94)	(1.56)
Abs. Distance	-0.000451	-0.000180	0.000142	0.000524	0.000712	0.000930	0.00110
	(-1.29)	(-0.31)	(0.23)	(0.79)	(0.98)	(1.13)	(1.29)
Suspended * Abs. Distance	-0.000103	-0.000393	-0.000673	-0.000924	-0.000949	-0.000909	-0.00121
	(-0.26)	(-0.61)	(-0.94)	(-1.21)	(-1.14)	(-0.93)	(-1.14)
Constant	0.00803***	0.00801***	0.0102***	0.00336	0.00511*	0.00666**	0.00846***
	(5.99)	(4.01)	(4.49)	(1.37)	(1.89)	(2.28)	(2.69)
N	1082	1082	1082	1082	1082	1082	1082
adj. R^2	0.01	0.01	0.00	0.01	0.00	0.00	0.00

3.8 Conclusion

We use the MiFID II regulation in the EU to evaluate the causal impact of banning non-block trading in midpoint dark pools on market outcomes. The setting of our quasi-natural experiment is unique in that it is characterized by competition between fully transparent, lit venues and several shades of dark venues that offer either partial or no transparency. Most modern equity markets, especially in the developed world, have evolved into such as structure.

We observe that the ban leads to an increase in trading activity across not just continuous lit markets but also across internalization platforms, periodic auctions and block trading venues. In fact, the shift in trading towards (quasi-)dark markets is almost three times as large as the shift towards continuous markets. Contrary to regulators' and markets' expectations, but in line with the minor increase in the market share of lit venues, we observe no effect on liquidity but a deterioration in short-term price efficiency for firms affected by the restrictions. This suggests that a regulatory intervention in one trading mechanism leads to complex changes in the composition of order flow across multiple alternative trading venues which can potentially destroy welfare.

Our results also highlight the necessity for a better understanding of competition between dark pool, public markets, and quasi-dark markets. From a policy-making perspective, our results point to a need for caution in designing and implementing such restrictions. Specifically, regulators should carefully consider the impact of market regulation on equilibrium strategies of investors and profit-maximizing venue operators.

Appendix to Chapter 3

A Data Documentation

Matching Fidessa Fragulator and Thomson Reuters Eikon

Fidessa Fragulator provides weekly Turnover, Volume and Trade Count for five trading mechanisms: Auctions (AUC), Lit Markets (LIT), systematic internalizers (SI), over-the-counter (OTC), and dark venues (DARK). This data must be manually accessed for each firm. Fidessa Fragulator relies on a firm's Reuters Instrument Code (RIC) to provide the trading activity data, whereas the ESMA reports identify firms by their ISIN. While ISINs uniquely identify an instrument, RICs identify instrument-venue combinations.[37] We obtain the above data for each firm in our sample period using the following steps:

- From the ESMA reports, we obtain the firm's ISINs.
- For each ISIN, we obtain the RIC from Thomson Reuters Eikon.
- We use the RIC to download the trading activity data from Fidessa Fragulator. This is done by entering the RIC into the "Stock Selector" window and then selecting "All exchanges/currencies" in the "Listing filter" field, which ensures that all RICs of the same instrument lead to the same results.
- For some firms, RICs are either missing in Eikon or lead to no/incorrect results in Fragulator. In such cases, we identify the correct RIC by entering the firm's ISIN or firm name obtained from Eikon in Fidessa's "Stock Selector" window. Upon entering this information, Fidessa provides a list of relevant RICs for the firm. Before using the RIC we ensure that the different RICs suggested by Fidessa lead to the same output.

Using this stepwise procedure, we are able to establish a one-to-one match between ISINs and RICs for all our sample firms. We confirm the correctness of our matches by comparing prices from Eikon with implied prices from Fragulator.[38] One issue with the Fragulator database is that firms are dropped once they are delisted. To avoid a survivorship bias, we download data from Fragulator right after the end of our sample period on May 11, 2018.

Matching Fidessa Fragulator and Fidessa Block Trading Data

Dark market volumes reported in the Fidessa Fragulator include trades under the LIS and reference price waivers. For our analyses, it is crucial to disentangle trading under the two waivers. For this purpose, we use Fidessa's "Top of the Blocks" database, which provides the number and Turnover (in Euros and exchange currency) of all trades above the LIS threshold from the following venues: Cboe BXE and CXE Dark Order Books, Cboe Large in Scale Service, Euronext Block, Turquoise Plato, Instinet BlockMatch, Liquidnet, Posit, and UBS MTF. This

[37] Each RIC contains a prefix and suffix separated by a period. For example, the Commerzbank RIC (CBKG.DE) contains the firm name (CBKG) in the prefix and Deutsche Börse (DE) in the suffix.

[38] Prices in Eikon and Fragulator for the same instrument are not necessarily denominated in the same currency. We convert all numbers into Euros using exchange rates from Eikon.

list excludes the Nordic dark pools (Copenhagen, Helsinki and Stockholm) and Goldman Sachs' Sigma-X. We obtain block trades executed in the Nordic dark pools from TRTH and aggregate them to a weekly frequency to coincide with the Fidessa's Top of the Blocks database. Sigma-X does not use the LIS waiver.[39] Hence, we allocate the entire Sigma-X volume reported in Fidessa Fragulator to trading under the reference price waiver.

Matching block trading to Fragulator data, we cannot rely on the ISIN to RIC mapping obtained in Section A as the RICs in the block database, specifically the suffix, correspond to the block trading venue. In some cases, even the RIC prefix for the same instrument is different. Finally, some RICs are entirely missing in the block database. Thus, we proceed as follows: We first generate a list of all firms in the block trading dataset and find the ISIN for every firm:

1. For firms that have a corresponding RIC in the block database:
    - We enter the RIC into Fragulator's "Stock Selector"-field and note the corresponding ISIN and instrument name. This process provides results for more than 90% of the stocks in our sample.
    - If we do not obtain any output in Fragulator for the full RIC, we use the RIC prefix to identify the ISIN.
2. For firms that do not have a corresponding RIC in the block database, we use the firm name in Fragulator to identify the ISIN.

Testing the matching quality is non-trivial as we only observe trading turnover and not trading volume and thus cannot calculate implied prices. Instead, we employ the following steps:

- We manually compare firm names from the block database to those from Fragulator and Eikon.
- We test whether the exchange rate implied by the block database is identical to the exchange rate from Fragulator and Eikon.
- Two of the above listed venues, Cboe Large-in-Scale Service and Euronext Block, exclusively use the LIS waiver. For those venues, we ensure that the turnovers from Fragulator and the block database perfectly match.

Disentangling LIS and REF Trading Activity

We merge the Fragulator database and the block database (generated in Subsections A and A) based on ISIN, week and venue. If both datasets were perfect, one would simply need to substract the block volume from the total dark volume to obtain the volume traded under the reference price waiver. However, we face several obstacles:

- Exchange rates used in the block database are sometimes scaled by powers of 10.[40]

[39] See Sigma-X Manual.

[40] These errors in exchange rates do not exhibit any obvious pattern and seem arbitrary.

- Trading volumes from both sources do not always perfectly match due to implied prices being measured at different points in time during the week.
- Potential rounding errors.

We resolve these issues as follows:

- We calculate the implied exchange rates from the block database by dividing the Euro turnover by the exchange currency-turnover. We then compare these implied exchange rates with those used to convert data from Eikon and Fragulator.[41] We expect some rounding errors as prices are measured at different points in time and we use the exchange rate from Eikon on Monday as the point of comparison. Thus, we accept the implied exchange rates as correct if:

$$\left|\frac{\text{implied exchange rate}_{Block,i,j,t}}{\text{exchange rate}_{x,i,j,t}} - 1\right| < 0.05$$

  for instrument i on venue j in week t and $x \in$ (Eikon,Fragulator).

- If the above test fails, we rescale the exchange rate in the block database by choosing a value for $y \in [-10; 10]$ that ensures:

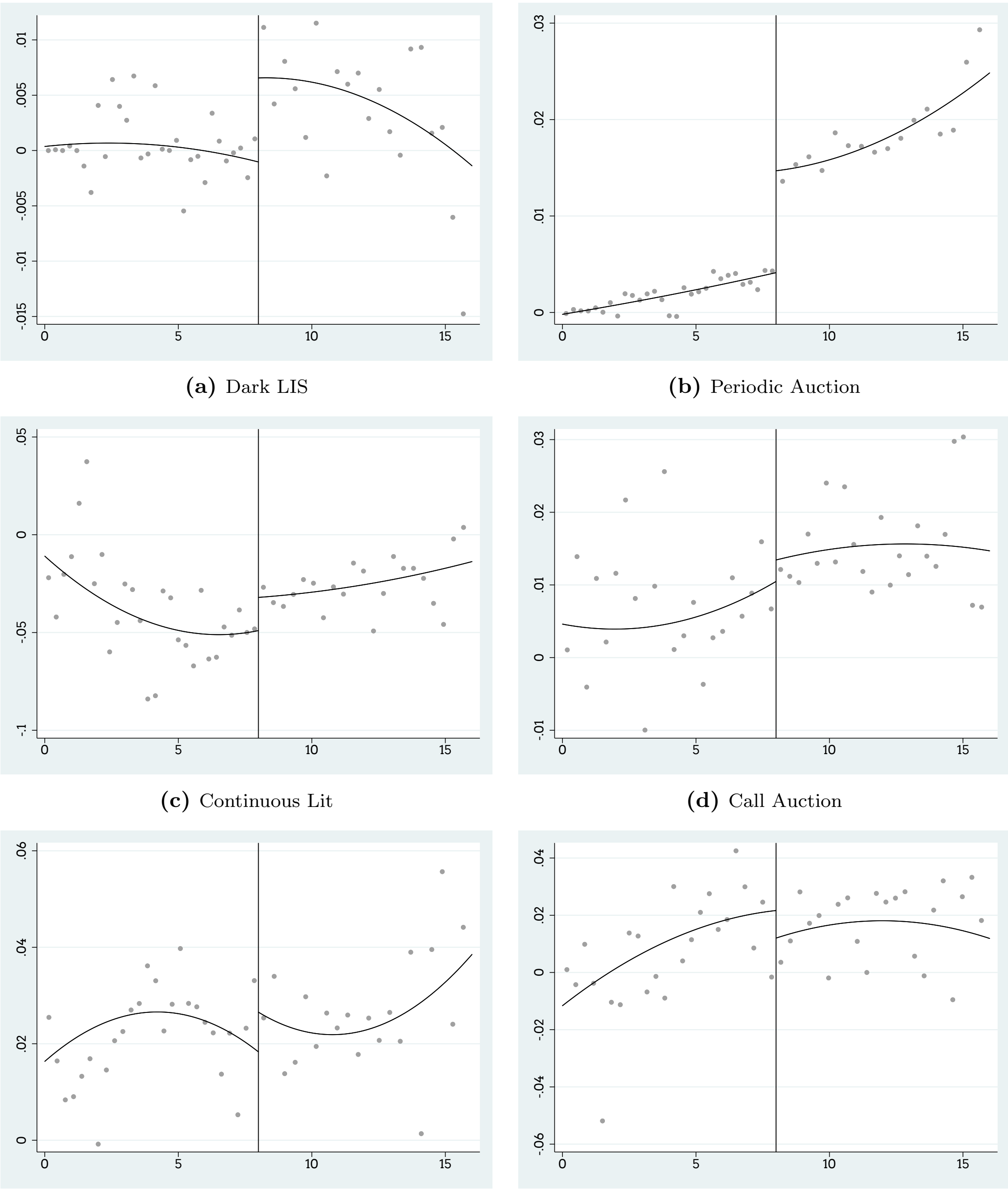
$$\left|\frac{\text{implied exchange rate}_{Block,i,j,t} \cdot 10^{y}}{\text{exchange rate}_{x,i,j,t}} - 1\right| < 0.05$$

- Finally, we calculate $Turnover_{REF,i,j,t} = Turnover_{Fragulator,i,j,t} - Turnover_{Block,i,j,t}$ and set it equal to 0 if $\frac{Turnover_{REF,i,j,t}}{Turnover_{Fragulator,i,j,t}} < 0.05$. Furthermore, in less than 0.1% of the observations we observe that $Turnover_{REF,i,j,t} < 0$. We manually inspect these instances and set $Turnover_{REF,i,j,t} = 0$ and $Turnover_{LIS,i,j,t} = Turnover_{Fragulator,i,j,t}$.

[41] Remember that Eikon and Fragulator do not necessarily report the instrument in the same currency.

B RDD Plots

Figure A3.1: RDD Results: Market Shares
This figure provides data-driven RDD plots of the difference in market shares around the event date, 12 March 2018. A quadratic kernel is employed while estimating the local linear regression.



(a) Dark LIS

(b) Periodic Auction

(c) Continuous Lit

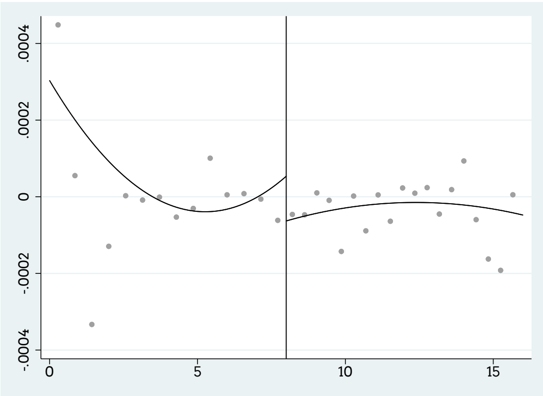
(d) Call Auction

(e) SI

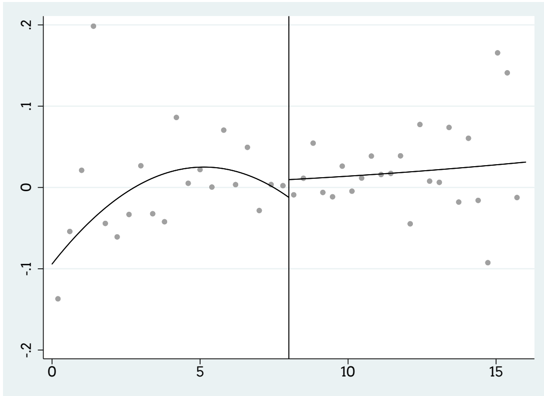
(f) OTC

Figure A3.2: RDD Results: Liquidity

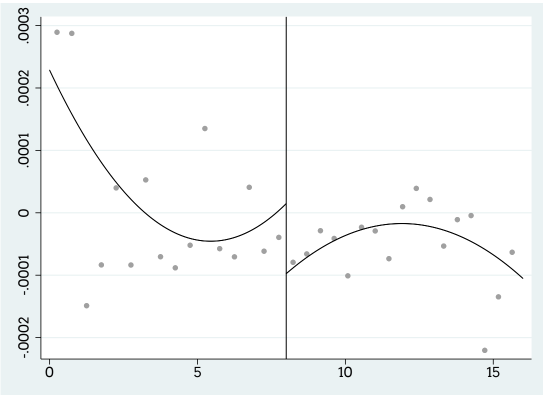
This figure provides data-driven RDD plots of the difference in primary market liquidity around the event date, 12 March 2018. A quadratic kernel is employed while estimating the local linear regression.



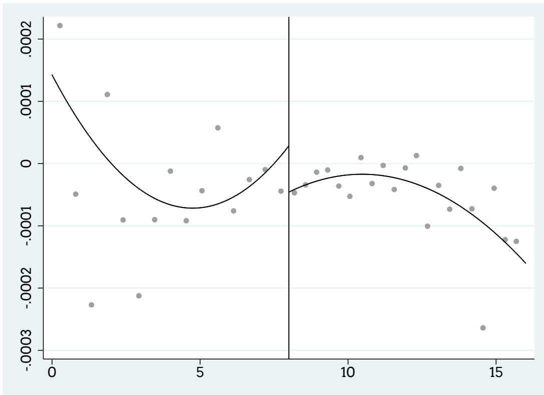
(a) Quoted Spread



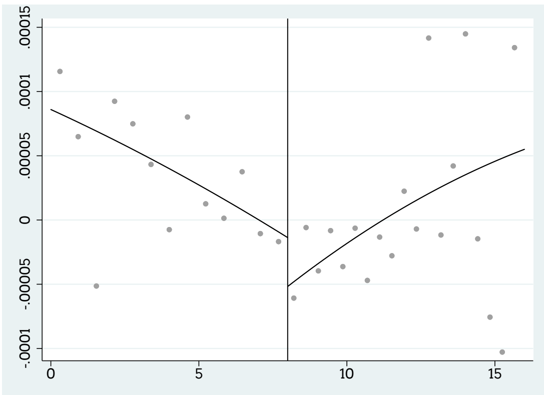
(b) Log Depth



(c) Effective Spread



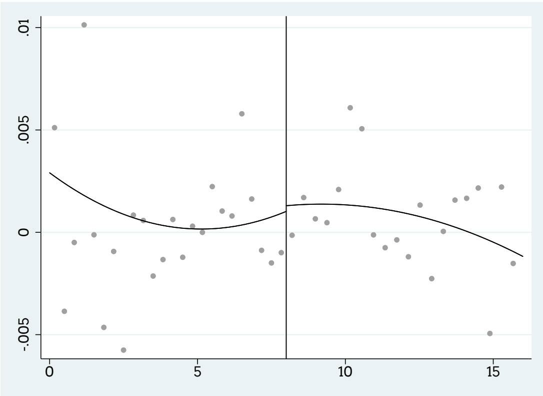
(d) Realized Spread 10s



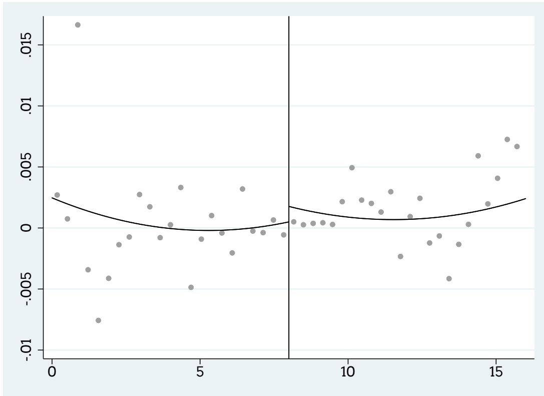
(e) Price Impact 10s

Figure A3.3: RDD Results: Price Efficiency

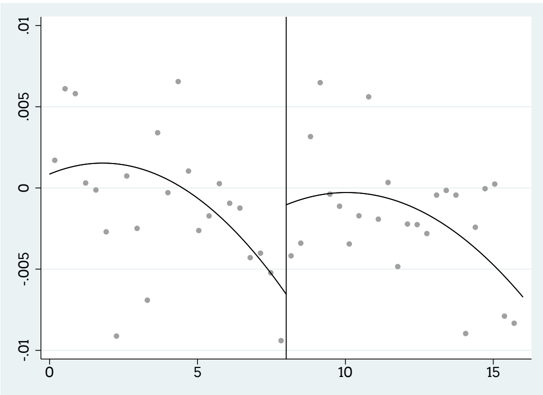
This figure provides data-driven RDD plots of the difference in primary market price efficiency around the event date, 12 March 2018. A quadratic kernel is employed while estimating the local linear regression.



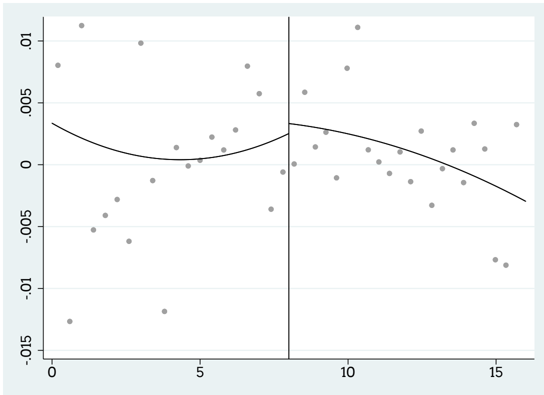
(a) Autocorrelation 10s



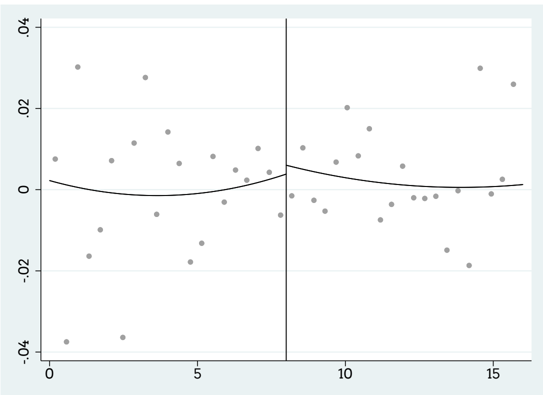
(b) Autocorrelation 30s



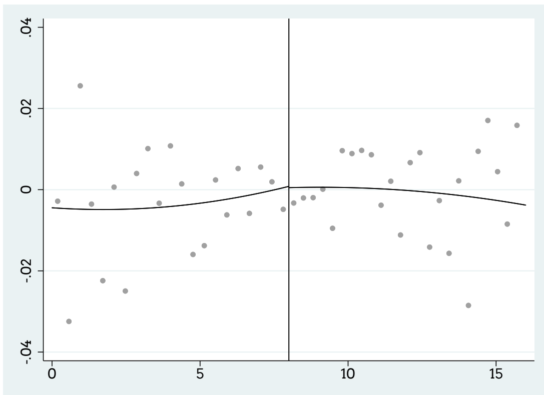
(c) Autocorrelation 300s



(d) Variance Ratio 10s/30s



(e) Variance Ratio 10s/300s



(f) Variance Ratio 30s/300s

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Eidesstattliche Erklärung

Hiermit erkläre ich an Eides statt, dass ich die Dissertation selbständig angefertigt und mich anderer als der in ihr angegebenen Hilfsmittel nicht bedient habe, insbesondere, dass aus anderen Schriften Entlehnungen, soweit sie in der Dissertation nicht ausdrücklich als solche gekennzeichnet und mit Quellenangaben versehen sind, nicht stattgefunden haben. Ebenso versichere ich, dass ich nicht die Hilfe einer kommerziellen Promotionsvermittlung oder -beratung in Anspruch genommen habe.

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