Trading in European Equity Markets: Fragmentation and Market Quality

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Abstract

Since the beginning of the 21st century, we have witnessed substantial changes in secondary European equity markets. Exchanges and trading is becoming increasingly automated and regulations have shaken up the trading landscape in which European exchanges, such as the London Stock Exchange (LSE) and Deutsche Boerse, have enjoyed a national quasi-monopoly in trading. The European Markets in Financial Instruments Directive (MiFID), adopted in 2007, changed the status quo by allowing alternative trading venues to compete with traditional exchanges. This thesis studies how MiFID impacted European equity trading and develops a number of new insights.

In my work I focus on so-called multilateral trading facilities (MTF). On these alternative trading venues users can trade securities as on traditional exchanges. However, compared to established exchanges, MTFs are often considered to offer superior trading speed, lower transaction costs, and more innovative services. Yet while investors may benefit from the greater choice of trading venues and from stronger competition for order flow, multiple platforms also cause fragmentation of trading volume and liquidity. An important question is thus whether this fragmentation caused markets to be less transparent and trading to be more costly.

This thesis provides an empirical analysis of trading in UK-listed blue-chip stocks for two observation periods, the first in 2009 and the second in 2010. My findings suggest that MTFs contribute significantly to overall liquidity and price discovery. In addition, my analysis shows that investors profit from being able to trade on multiple platforms as they trade when and where it is least expensive to do so. I show that the LSE and MTFs provide a liquid market and find no evidence that market fragmentation has harmed market quality. To better understand the implicit, competition driven coordination of markets, I further analyze whether fragmentation leads to increased violations of the law of one price and occurrence of suboptimal executions. Neither situation would be consistent with an efficient market. The evidence suggests that exploitable arbitrage opportunities are resolved quickly when they arise. Further, investors most often trade at the best available price across all markets. Consequently, I conclude that competition for order flow forces disconnected trading venues to quote integrated prices.

Altogether, the findings of this thesis suggest that under MiFID the positive effects of increased competition for order flow outweigh the possible negative side-effects of market fragmentation.

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List of Abbreviations

AMEX	American Stock Exchange
ATS	Alternative Trading System
BaFin	Bundesanstalt für Finanzdienstleistungsaufsicht
CBOE	Chicago Board Options Exchange
CESR	Committee of European Securities Regulators
CIRF	Cumulative Impulse Response Function
CQS	Composite Quotation System
CSE	Cincinnati Stock Exchange
CTA	Consolidated Tape Association
EBB	European Best Bid
EBBO	European Best Bid and Offer
EBO	European Best Offer
EBS	Electronic Broking System
ECN	Electronic Communication Network
ESC	European Securities Committee
ESMA	European Securities and Markets Authority
ETF	Exchange-Traded Fund
FESE	Federation of European Stock Exchanges
FSA	Financial Services Authority
FSAP	Financial Services Action Plan
FTSE 100	Financial Times Stock Exchange 100 index
HFT	High-Frequency Trading
IDB	Inter-Dealer Broker
ISD	Investment Services Directive
ISE	International Securities Exchange
ITS	Intermarket Trading System
LSE	London Stock Exchange
MiFID	Markets in Financial Instruments Directive
MTF	Multilateral Trading Facility
Nasdaq	National Association of Securities Dealers Automated Quotations
NBB	National Best Bid
NBBO	National Best Bid and Offer
NBO	National Best Offer
NMS	National Market System

NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
OTC	Over-The-Counter
PCX	Pacific Exchange
PHLX	Philadelphia Stock Exchange
RegNMS	Regulation National Market System
RIC	Reuters Instrument Code
SEAQ	Stock Exchange Automated Quotation system
SEC	Securities and Exchange Commission
SETS	Stock Exchange Electronic Trading Service
SI	Systematic Internalizer
SIRCA	Securities Industry Research Centre of Asia-Pacific
SRO	Self-Regulatory Organization
UTP	Unlisted Trading Privileges
VAR	Vector Autoregression
VMA	Vector Moving Average
Xetra	Exchange Electronic Trading

Chapter 1

Introduction

1.1 Motivation

The recent automation of exchanges and new regulations has significantly altered the trading landscape. Trading no longer only takes place on a trading floor where brokers meet face to face, it mostly takes place in the server rooms of large financial institutions. Technology has changed how trading venues compete. Most importantly, improvements in information and communication technology have facilitated the creation of electronic trading platforms that compete for business with established exchanges and thereby reducing the end costs for investors.

Prior to 2007, traditional exchanges in Europe (regulated markets under MiFID), such as the London Stock Exchange (LSE) and Deutsche Boerse, enjoyed a quasi-monopoly in trading. To keep pace with technological development and to foster competition in the provision of services to investors and between trading venues, the European Union (EU) adopted the Markets in Financial Instruments Directive (MiFID) that became effective in all EU member states in November of 2007.[1] The new set of rules opened traditional markets to competition from new types of trading venues, most importantly multilateral trading facilities (MTF) such as Chi-X and BATS. Today, the majority of trades is executed on regulated markets and MTFs that successfully captured a significant fraction of trading volume from traditional exchanges. For example, the LSE share in exchange traded volume in UK blue-chip stocks decreased from nearly 100.0% in 2007 to less than 60.0% at the beginning of 2011.[2] Chi-X is the largest MTF,

[1]MiFID was implemented in all 27 EU member states and in Iceland, Norway, and Switzerland.

[2]See, for example, http://fragmentation.fidessa.com/ for statistics on market fragmentation of

accounting for about 25.0% of daily UK blue-chip trading volume. Similar developments can be observed across Europe. For example, the market share of Deutsche Boerse in German blue-chip stocks fell to about 70.0% in the first quarter of 2011 with Euronext (Paris) falling to a market share of roughly 65.0% in French blue-chip stocks over the same period.

MiFID represents a significant overhaul of existing regulation, relying on three different key pillars: market access, transparency, and best execution. First, MiFID abolished the option of a so-called 'concentration rule', meaning that retail orders had to be executed on a national traditional exchange. Today, regulated markets (i.e. traditional exchanges), MTFs, and investment firms can offer their services across borders. Second, transparency obligations require regulated markets and MTFs to publish order book information and executions on a timely basis. Third, under MiFID best execution relies on different factors such as cost, speed, likelihood of execution and settlement, and order size. Intermediaries (e.g. investment firms and brokers) that execute orders on behalf of their clients have to establish a best execution policy and the associated rules have to be reviewed at least annually.

There is currently a debate about the advantages of increased competition in equity markets. One consequence of competition between trading venues is that order flow and liquidity, i.e. the ability to trade shares, is fragmented across platforms. Therefore, investors may not always receive the best available price as MiFID does not enforce price-time priority across markets. In addition, less integrated markets may diminish the price discovery process and generally increase the costs of trading such as search and connectivity costs. Proponents of MiFID, however, argue that intermarket competition has put downward pressure on explicit transaction costs, for instance, exchange fees and brokerage commissions, and has provided trading venues with incentives to innovate on their services (European Commission, 2010). Furthermore, increasing use of technology may mitigate some of the potential negative side effects of market fragmentation. For instance, algorithmic and high-frequency traders may link platforms by consolidating order flow.

The introduction of more nimble trading venues is not per se a new phenomenon. Electronic communication networks (ECN) that compete for order flow in U.S. equity markets emerged on a widescale basis in the late 1990s. New U.S. regulations

European equity markets.

enabled this development. Currently, U.S. equity trading is regulated under the Regulation National Market System (RegNMS). Both MiFID and RegNMS share the goals of enhancing competition between trading venues, ensuring best execution, and guaranteeing fair and orderly trading. A key differentiating factor of both regulations is the lack of formal integration in Europe where markets are not formally linked through networks and price-priority is not enforced across platforms. In addition, European regulation does not establish a single data consolidator to provide comprehensive consolidated market information to investors.

The literature has intensively studied competition between ECNs and traditional markets in the U.S., especially in Nasdaq-listed stocks. The evidence supports the view that ECNs are competitive on liquidity (e.g. Barclay et al., 1999; Weston, 2000) and contribute to price discovery (e.g. Huang, 2002; Barclay et al., 2003). However, the market and regulatory structure is decidedly different in Europe. Therefore, the research on trading venue competition in U.S. markets can only be partially transferred to the European case. Despite the growing body of literature analyzing market fragmentation under MiFID, MiFID's impact on market quality is still not clear. Four years after MiFID considerably altered European equity trading, the time has come for a thorough analysis. This thesis aims to determine the contribution of MTFs to overall liquidity and price discovery in high volume stocks. In addition, it sheds light on the question whether platforms quote closely linked prices without a formal linkage.

1.2 Research Outline

This thesis aims to explore the impact of market fragmentation on market quality under MiFID.[3] Liquidity and price discovery are two of the most important dimensions

[3] Chapter 5 is based on a joint working paper with Ryan Riordan and Andreas Storkenmaier (Riordan et al., 2011). A previous version of the paper was circulated under the title "Fragmentation, Competition and Market Quality: A Post-MiFID Analysis" and presented at the 2nd Center for Financial Studies International Conference: The Industrial Organisation of Securities Markets: Competition, Liquidity and Network Externalities, at the 2010 European Financial Management Association Meeting, at the Doctoral Symposium of the 3rd Erasmus Liquidity Conference, at the 17th Annual Meeting of the German Finance Association (DGF), and at the 2011 Campus for Finance Research Conference. Chapter 6 relies on a working paper with my co-author Andreas Storkenmaier (Storkenmaier and Wagener, 2011). An early version was presented at the 2010 Boerse Stuttgart Research Colloquium. A much more detailed version was presented at the 2011 European Financial Management Association Meeting and accepted for presentation at the 28th International Confer-

of market quality as they determine the level of market efficiency that is a prerequisite for the optimal allocation of capital. In general, the quality of a market is driven by a set of rules and the behavior of market participants. Since investors and regulators may define market quality differently depending on different types of transactions and strategies, the concept cannot be assessed by a single measure. The literature has summarized a number of measures that are commonly used in empirical market microstructure studies to evaluate and compare different trading venues. I apply these measures to examine market quality in UK blue-chip stocks on different platforms, the LSE and MTFs, and from an overall market perspective.

This thesis uses trade and quote data to empirically examine the dimensions of market quality on the most important trading venues in terms of UK trading volume, namely the LSE, Chi-X, BATS, and Turquoise. Competition for order flow may be beneficial when trading venues offering more liquidity attract a substantial fraction of investors. Therefore, this thesis analyzes liquidity on each platform and the variables investors use to condition their order routing decisions. The decision to route an order to one platform or another may also affect the contribution of each trading venue to price discovery. I examine the price discovery process using trades as in Hasbrouck (1991a,b) and quotes as in Hasbrouck (1995). In addition, to better understand the impact of increased fragmentation on market quality, a comparison between a period where fragmentation is considerably lower to a benchmark period is presented. Chapter 5 specifically addresses the following research question:

RQ: Do MTFs contribute to liquidity and price discovery?

In contrast to U.S. equity market regulation, MiFID neither establishes a formal linkage between trading venues nor enforces price-priority across platforms. There is also no official European consolidated tape that allows investors to observe the best available price across markets. This essentially creates a situation where the barriers to competition have fallen and competition forces are left to solve integration. Chapter 6 therefore explores market coordination by analyzing arbitrage opportunities and suboptimal executions. Neither situation seems consistent with an economically efficient market: arbitrage opportunities violate the law of one price and suboptimal executions

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indicate that an investor could have received a better price. The following research question arises:

RQ: Does competition force competing but disconnected trading platforms to quote prices as if they were formally linked?

Methodologically, this chapter is related to Battalio et al. (2004) who study quote and execution quality in U.S. equity options in the absence of a formal linkage. This part of the thesis further aims to reveal under which market conditions arbitrage opportunities and suboptimal execution predominantly arise. Altogether, Chapter 5 and Chapter 6 provide an in-depth analysis of different market quality dimensions (liquidity, price discovery, and market coordination) in the fragmented UK trading environment.

1.3 Structure of the Thesis

The remainder of this thesis is organized as follows. Chapter 2 discusses European equity trading regulation, highlighting the key pillars of MiFID and drawing parallels to U.S. regulation. It additionally provides details on competing platforms in UK equity trading, the main market under research in this thesis. Chapter 3 reviews the related literature. First, theoretical and empirical studies of intermarket competition and its impact on trading behavior, liquidity, and price discovery are summarized. The discussion focuses on U.S. and European markets. Second, effects of recent technological innovations in financial markets, such as algorithmic and high-frequency trading, are reviewed to evaluate their impact on fragmented markets. Chapter 4 provides data characteristics and important details on trading intensity, liquidity, and price discovery measures as well as logistic regressions used in the following chapters. Chapter 5 analyzes competition between the LSE and MTFs in UK blue-chip stocks and discusses whether MTFs contribute to market quality. Chapter 6 aims to examine whether competition between disconnected trading venues forces them to quote prices as if they were formally linked. Finally, Chapter 7 summarizes the key contributions and briefly outlines promising avenues for future research in related topics.

Chapter 2

European Equity Market Structure

This chapter provides a solid background of the European equity market structure to further empirical analyses. Section 2.1 summarizes the key pillars of European equity trading regulation describing its main objectives and drawing parallels to the regulation in the U.S. Section 2.2 provides details on the UK equity market, the market under research in my thesis, and highlights important market developments over the last decade.

2.1 Markets in Financial Instruments Directive

The organizational structure of a financial market is determined by its regulatory framework and by the interaction between market participants. In this context, market microstructure theory studies in detail "the process and outcomes of exchanging assets under a specific set of rules" (O'Hara, 1995, p. 1). To both the suppliers and demanders of liquidity as well as regulators, it is important to understand how specific rules influence trading behavior, market quality, or the way public and private information is incorporated into prices. Market microstructure literature has shown that details in the trading process, reflecting order-handling costs, transparency, exchange infrastructure, and asymmetric information, can have a profound impact on the functioning of a market.[1] In contrast to technological improvements or limited regulatory changes on single exchanges, the introduction of the Markets in Financial Instruments Directive (MiFID) significantly altered the entire secondary trading landscape across Europe.

[1]See Biais et al. (2005) for a detailed review on market microstructure literature.

MiFID is a major part of the European Union's Financial Services Action Plan (FSAP) and came into effect in all 27 member states on November 1, 2007.[2] The overall objective of MiFID is to foster competition in the provision of services to investors and between trading venues. The set of rules is "intended to contribute to deeper, more integrated and liquid financial markets, to drive down the cost of capital for issuers, to deliver better and cheaper services for investors, and thus to contribute to economic growth and job creation" (European Commission, 2010).

I. MiFID: Details and political process

MiFID consists of a framework Directive (Directive 2004/39/EC), an Implementing Directive (Directive 2006/73/EC), and an Implementing Regulation (Regulation No 1287/2006), replacing the Investment Services Directive (ISD, Council Directive 93/22/EEC) which was implemented in July 1995. MiFID broadens the scope of ISD and further harmonizes the rules in the European Union (EU). ISD specifies minimum standards under which investment firms can provide services or establish branches in member states on the basis of home country authorization and supervision. According to Herbst (2003), there are mainly two reasons why a new regulatory framework was necessary. First, investors became more active in financial markets and the range of products offered grew considerably and second, ISD may have not been able to level the playing field across the whole EU.

Table 2.1 highlights important steps towards the MiFID approval by European authorities. In June 1998, the Cardiff European Council invited the European Commission to prepare a 'framework for action' to complete the market for financial services within the European Union, notably with the introduction of the euro in January 1999. The initial FSAP program was published in May 1999 (COM(1999) 232) and outlines specific measures to be taken in order to create a single market for all financial services among EU members. It does not merely focus on one sector such as banking or insurance but rather consists of a set of 42 measures intended to fill gaps and eliminate remaining cross-border barriers. Specifically, FSAP aims to create a single wholesale market, an open and secure retail financial services market, and state-of-the-art prudential rules and supervision.[3]

[2] Iceland, Norway, and Switzerland have also implemented MiFID.

[3] Philipp et al. (2003) provide a well-structured overview over European political initiatives to create a

Table 2.1: **Timeline of MiFID approval**. The table highlights important steps in the political and regulatory process from the ISD adoption to MiFID.

Date	Event
May 10, 1993	Adoption of the ISD (Council Directive 93/22/EEC)
July 1, 1995	ISD came into force
June 15-16, 1998	Cardiff European Council invited European Commission to prepare a 'framework for action' for financial services
May 11, 1999	European Commission published FSAP
March 23-24, 2000	Political agreement on FSAP by Lisbon European Council
November 19, 2002	European Commission completed draft on the revision of the ISD (subsequently MiFID)
September 25, 2003	First reading by European Parliament
October 16-17, 2003	Brussels European Council endorsed MiFID
April 21, 2004	European Parliament approved MiFID framework Directive (Directive 2004/39/EC)
2004-2005	Technical advice by CESR and consultation process on implementing measures
August 10, 2006	European Commission passed the Implementing Directive (Directive 2006/73/EC) and the Implementing Regulation (Regulation No 1287/2006)
November 1, 2007	MiFID came into full effect in all member states of the EU

Legislative process. MiFID is a major part of FSAP and encompasses investment firms and financial instruments. Its introduction followed a four-level legislative process proposed by the Committee of Wise Men on the Regulation of European Securities Markets chaired by Alexandre Lamfalussy (Committee of Wise Men, 2001).[4] Level 1 consists of the framework Directive proposed by the European Commission and was jointly adopted by the European Council and the European Parliament. These rules are adopted to national law by each member state. Level 2 consists of the Implementing Directive and the Implementing Regulation set by the European Commission under assistance of the European Securities Committee (ESC). The Implementing Directive defines organizational requirements and operating conditions for investment firms

single market discussing FSAP in detail.

[4]The Committee of Wise Men was appointed by the European Council in July 2000 and recommended changes to accelerate the passage of necessary legislation. Visscher de et al. (2008) analyze the arrangements of the process and state that "the speed of the process has increased overall and that there are fewer bottlenecks than before in the different steps leading to the adoption of legislation".

and the Implementing Regulation specifies record-keeping obligations for investment firms, transaction reporting, market transparency, admission of financial instruments to trading, and further definitions. While the latter is directly applicable in the member states without transposition, the Implementing Directive needs to be adopted to national law. At Level 3, the Committee of European Securities Regulators (CESR)[5] has to ensure a consistent implementation of Level 1 and Level 2 across member states. It also gives technical advice at Level 2. Level 4 refers to more effective implementation and enforcement of EU laws. The Implementing Directive and Implementing Regulation were finally passed in August 2006 and MiFID came into full effect in all 27 member states of the EU on November 1, 2007.

Categories of trading venues. With MiFID the European authorities "establish a comprehensive regulatory regime [...] to ensure a high quality of execution of investor transactions and to uphold the integrity and overall efficiency of the financial system" (Directive 2004/39/EC, Preamble). It applies to investment firms and regulated markets alike. An 'investment firm' is defined as "any legal person whose regular occupation or business is the provision of one or more investment services to third parties and/or the performance of one or more investment activities on a professional basis" (Directive 2004/39/EC, Article 4(1)) and a 'regulated market' is specified as "a multilateral system operated and/or managed by a market operator, which brings together [...] multiple third-party buying and selling interests in financial instruments [...] in a way that results in a contract [...]" (Directive 2004/39/EC, Article 4(14)). Operators of regulated markets have to fulfill transparent and non-discretionary rules and procedures that provide fair and orderly trading.

The Directive further specifies the following three categories of trading venues: regulated markets, multilateral trading facilities (MTF), and systematic internalizer (SI).[6] While an MTF is defined in a similar fashion than a regulated market (Directive 2004/39/EC, Article 4(15)), a SI is an "investment firm which, on an organised, frequent and systematic basis, deals on own account by executing client orders outside

[5]To further integrate European supervision, the European Securities and Markets Authority (ESMA) replaced CESR in January 2011 (Implementing Regulation No 1095/2010). ESMA assumes all tasks and competences of CESR and has new powers, for instance, the implementation of technical binding standards and additional responsibilities for customer protection.

[6]As of November 10, 2011, there are 93 regulated markets, 144 MTFs, and 14 SIs operating in the EU. See http://mifiddatabase.esma.europa.eu/ for a complete list of all trading venues in each category.

a regulated market or an MTF" (Directive 2004/39/EC, Article 4(7)). Hence, the concept of SIs takes into account the possibility of large investment firms to internalize clients orders. My thesis focuses on competition between regulated markets and MTFs as both trading venue categories are the most important in terms of trading volume. Further discussions are therefore limited to these two categories.[7] In April 2011, Chi-X is the largest MTF in Europe accounting for roughly 26.0% of daily trading volume in FTSE 100 stocks and 18.0% in continental European equity trading, well in front of BATS and Turquoise.[8]

Key pillars of MiFID. MiFID establishes a regulatory regime for each category of trading venue that relies on three different key pillars, namely market access, transparency, and best execution.[9] The next paragraphs discuss each of these factors in detail:

- *Market access*: MiFID abolishes the option for a so-called 'concentration rule' or tax provisions given by ISD (Council Directive 93/22/EEC, Article 14(3)), meaning that retail orders had to be executed on a regulated market. As a consequence, domestic exchanges enjoyed a quasi-monopoly in nearly all member states - especially in Spain, Italy, and France (Davies et al., 2005). Under MiFID, investors' orders can either be executed on a regulated market, an MTF, or a SI. Currently, MTFs offer trading in nearly all European blue-chip stocks and have successfully captured market shares from regulated markets. Their business models are tailored to the needs of speed-sensitive traders offering low-latency trading infrastructure, new fee schedules, and innovative order types. Consistent with ISD, MiFID also allows investment firms to provide services and activities in any other member state (Directive 2004/39/EC, Article 31) or to establish a branch under authorization and supervision of the home state (Directive 2004/39/EC, Article 32).

- *Transparency*: The Directive includes pre- and post-trade transparency requirements for equity trading on regulated markets and MTFs (Directive 2004/39/EC, Articles 29-30 and 44-45). As the number of trading venues

[7] Gomber and Pierron (2010) provide further insights into SI and OTC trading.
[8] See http://www.ft.com/intl/trading-room/.
[9] Davies (2008) and Degryse (2009) also provide a well-structured overview over MiFID.

increases, order book information becomes more fragmented. To ensure a high level of market quality and an integrated price discovery process, MiFID requires regulated markets and MTFs to publish best bid and ask prices along with the number of shares quoted at these prices on a continuous basis. Post-trade requirements include the time of execution, the execution price, and the associated trading volume.

- *Best execution*: The best execution obligation under MiFID applies when investment firms and brokers execute orders on behalf of clients. Article 21 of Directive 2004/39/EC requires intermediaries to "take all reasonable steps to obtain [...] the best possible result for their clients taking into account price, costs, speed, likelihood of execution and settlement, size, nature or any other consideration relevant to the execution of the order". Thus, it applies to the overall characteristics of a possible trade and it is not just based on the best available price across trading venues. According to MiFID, investment firms have to establish an order routing policy that they review on a regular basis.[10] This is in contrast to the standard guidelines prior to the introduction of MiFID. For example, the British Financial Service Authority (FSA) only used LSE quotes to define best execution (Davies, 2008).

Impact of MiFID. When evaluating the impact of MiFID on European equity trading, it is important to keep in mind further developments that may had an impact on exchange operators and investors. First, high market volatility and defaults of major counterparties during the financial crisis influenced financial markets and second, technological improvements in both exchange and trading infrastructure created new trading possibilities. CESR launched a number of reports and consultation papers to evaluate the developments post MiFID (CESR, 2008, 2009, 2010). According to the European Commission (2010), there is evidence that

- the European market for financial services is more integrated under MiFID than before (i.e. investment firms and regulated markets offer products on

[10] In some cases these rules are very simple. Deutsche Bank, for example, outlines that it executes clients' orders in German stocks on Xetra, the electronic order book of Deutsche Boerse, assuming that the largest platform in terms of trading volume also guarantees best prices.

a European scale),

- competition between regulated markets and MTFs has put downward pressure on explicit transaction costs, bid-ask spreads, and trading times, and

- investor protection has been considerably strengthened.

In December 2010, the European Commission started a consultation process intended to get feedback from market participants, investors, national governments, national competent authorities, and academics for the ongoing improvement of MiFID (European Commission, 2010). In this context Internal Market and Services Commissioner Michel Barnier stated that "[...] in many ways, it [MiFID] has been a success. But the world has changed. And we all know the current framework needs improvement. My objective is to ensure that the revision of MiFID will lead to a stronger regulatory framework, adapted to the new trends and players on financial markets [...]".[11] This thesis contributes to the ongoing debate about MiFID by providing empirical evidence on market quality, price discovery, and market coordination on regulated markets and MTFs (Chapter 5 and Chapter 6).

II. Equity trading regulation in the U.S.

It is important to put European equity trading regulation into perspective by comparing MiFID to U.S. regulation. MiFID comes as a set of rules influencing trading and investor behavior on different levels at the same time. Therefore, it is difficult to isolate effects of specific rules outlined in MiFID. Table 2.2 compares objectives and regulatory key pillars of MiFID and the Regulation National Market System (RegNMS), introduced in August 2005 by the U.S. Securities and Exchange Commission (SEC). RegNMS is a further adaption of the Securities Exchange Act of 1934 and includes "new substantive rules that are designed to modernize and strengthen the regulatory structure of the U.S. equity markets" (RegNMS, Summary). It builds upon the National Market System (NMS) established by the U.S. Congress in 1975.

Major regulatory changes in the last century. The 1975 amendments to the Exchange Act of 1934 had a profound impact on the way equities were traded in the U.S. First, the new rules deregulated fixed commissions, such as brokerage rates, and second,

[11] See IP/10/1677, http://europa.eu/rapid/pressReleasesAction.do?reference=IP/10/1677.

Table 2.2: **Comparison of MiFID and RegNMS**. The table provides details to the European regulatory framework on equity markets, MiFID, and the U.S. counterpart regulation, RegNMS.

Category	MiFID	RegNMS
Regulatory framework	• Directive 2004/39/EC • Implementing Directive, Directive 2006/73/EC • Implementing Regulation, Regulation No 1287/2006	Securities Exchange Act Release No. 34-51808
Came into full effect	November 1, 2007	Implementation dates ranging from August 2005 to October 2007
Regulatory authorities	European Commission, ESC, CESR/ ESMA, national authorities (FSA, BaFin,...)	SEC, state authorities, SROs
Objectives	• Foster competition among trading venues by creating a single market for investment services and activities on the basis of a level playing field • Promote innovation, contribute to deeper, more integrated and liquid markets, and protect investors	• Modernize the regulatory structure of the U.S. equity markets • Strengthen an integrated national market
Main measures	• Market access: Removal of concentration rule, passporting • Transpareny: Pre- and post-trade • Best execution: Investor protection, order handling	• Order Protection Rule • Access Rule • Sub-Penny Rule • Market Data Rules
Trading venue classifications	• Regulated markets • Multilateral trading facilities (MTF) • Systematic internalizer (SI)	• Fast markets (automated quotes) • Slow markets (manual quotes)

they mandated the SEC with the establishment of an integrated National Market System (NMS). The NMS links individual trading venues by technology to achieve a fair and orderly market. The SEC has taken many actions to pursuant to its mandate, one of most important ones approved the Intermarket Trading System (ITS) in 1978. ITS is a facility which allows to display best quotes and orders to be routed between participating trading venues. On the basis of best quotes a variety of trading venues compete for orders in a unified system including national exchanges such as the New York Stock Exchange (NYSE) or the National Association of Securities Dealers Automated Quotations (Nasdaq) and regional exchanges. The key requirement is that an exchange is not allowed to trade-through a better price currently offered for an instrument by a competing trading venue. In the case, when another trading venue offers a better price, the order must be sent to this market via ITS.[12] In general, ITS trade-through rules were in place for NYSE-listed stocks unless an exception applied. For instance, small 100-share quotations and large 10,000 share or block transactions were not protected. Trade-throughs were not prohibited in Nasdaq-listed stocks.[13]

The SEC also approved joint industry plans that define standards for quote dissemination to provide a comprehensive source of market information. For NYSE-listed stocks consolidated trade data is distributed by the Consolidated Tape Association (CTA) and quote data is disseminated via the Composite Quotation System (CQS). The Nasdaq Unlisted Trading Privileges (UTP) plan provides consolidated trade and quote information for Nasdaq-listed stocks. Trade reporting includes stock symbol, time, price, and volume. Consolidated quote information comprises the Best Bid and Offer (BBO) price, the corresponding volume, and the trading venue. Quotes are available per trading venue and consolidated across platforms displaying the National Best Bid and Offer (NBBO).

In the 1990s, Electronic Communication Networks (ECN), such as Instinet, increased their market shares, especially in Nasdaq-listed stocks. ECNs are alternative trading systems (ATS) and defined as "electronic trading systems that automatically match buy and sell orders at specific prices" by the SEC.[14] Initially, these trading systems were outside the reach of private investors, mainly used by broker-dealers and institutional investors. This created a two-tiered trading environment resulting in high dealer rents and less competition. For instance, Christie and Schultz (1994) document that Nasdaq market makers avoided odd-eight quotes and Huang and Stoll (1996), among others, find evidence for higher trading costs on Nasdaq compared to the NYSE. In January 1997, new SEC regulations increased competitive pressure on Nasdaq market makers. Most importantly, the new order handling rules required that best quotes offered by Nasdaq market makers on ECNs have to be included in the

[12] Jarrell (1984) gives an overview over the Securities Acts Amendments of 1975 and provides evidence that the deregulation of NYSE brokerage rates broke down the broker cartel and triggered a dramatic growth in institutional trading. Lee (1993) analyzes execution quality on the NYSE, Nasdaq, regional exchanges, and Instinet in 1988/1989 and finds significant price differences between locations. His results raise concerns about the adequacy of ITS.

[13] Despite the absence of a trade-through rule for Nasdaq-listed stocks, Nasdaq's best execution obligation forces broker-dealers to execute orders at the best available price. However, this rule was not strictly enforced on an order-by-order level.

[14] See http://www.sec.gov/answers/ecn.htm.

Nasdaq BBO. In addition, public limit orders must be allowed to compete for order flow, meaning that market makers have to display customers' limit orders if they are better priced than their own quotes.[15] Facing an increase in trading volume on ECNs, the SEC adopted Regulation ATS. This new regulation became effective in April 1999. It required so-called proprietary trading systems, broker-dealer trading systems, and ECNs with 5.0% or more of trading volume in a covered security in four of the last six months to publicly disseminate their best-priced orders in that instrument. In addition, the alternative trading system had to join ITS.

Since 2001, the SEC has required that trading venues publish on a monthly basis, predefined execution quality reports, so-called 'Dash-5 statistics' (Reg NMS, Rule 605). In addition, Rule 606 requires intermediaries to make public on a quarterly basis, trading venues where they route investors' orders. Investors, brokers, and regulators can use these reports to evaluate the efficiency of order routing decisions. Boehmer et al. (2007) provide evidence that brokers condition their order routing decision on Dash-5 statistics. Trading venues tend to lose order flow if their reported execution quality worsens considerably relative to competitors.

RegNMS. New technologies, new types of trading venues, and the decimalization significantly changed the U.S. trading landscape. Following a number of reviews, discussions, and consultations, the SEC adopted RegNMS on June 9, 2005. It aims to reduce the number of trade-troughs and to realign the relationship between various trading venues. The four main rules are described below. While the Sub-Penny Rule came into effect in January 2006, the Order Protection and the Access Rule were implemented for different instruments between July and October 2007. The implementation date of the Market Data Rules was in April 2007.

- *Order Protection Rule (Rule 611)*: This rule requires trading centers to "[...] establish, maintain, and enforce written policies and procedures that are reasonably designed to prevent trade-throughs on that trading center of protected quotations [...]" (RegNMS, Rule 611(a)). A trade-through happens if an order is executed worse than the best available price across trading venues that is represented by immediately for automatic execution accessible quotes. Thus, this rule does not protect hidden orders or manual quotes

[15] A detailed description of the new regulation and its impact on market quality is offered by Barclay et al. (1999).

and only takes outstanding limit orders at the top of the order book into account.[16] It also covers small and large share quotations which were not covered under ITS. Most importantly, there is a uniform regulation for all exchange-listed stocks, no matter whether listed on the NYSE or Nasdaq.

- *Access Rule (Rule 610)*: This rule changed existing regulation significantly. First, it enables fair and efficient access to quotes of any trading center allowing for the use of private linkages by different connectivity providers. Second, it limits the fee for a trading center to access protected quotations. Finally, trading venues are required to prevent their members to post quotes that lock or cross protected quotations on any other trading venue.

- *Sub-Penny Rule (Rule 612)*: This rule specifies that any kind of exchange platform is not allowed to "[...] display, rank, or accept from any person a bid or offer, an order, or an indication of interest in any NMS stock priced in an increment smaller than $0.01 if that bid or offer, order, or indication of interest is priced equal to or greater than $1.00 per share" (RegNMS, Rule 612(a)). Flickering quotes and loss of execution priority by a nominal amount can distort price formation. The SEC therefore sets a minimum threshold of price variation.

- *Market Data Rules (Rule 601 and 603)*: These rules establish a new regime for the functioning of the single market data consolidator. Revenues generated from market data fees are allocated on the basis of a trading venue's contribution to best quotes.

The U.S. equity trading landscape was always more fragmented than its European counterpart. However, price-priority across trading venues is enforced and trading venues are virtually integrated via ITS, private linkages, and consolidated quotation and trade reporting systems. ECNs captured a significant market share in Nasdaq and NYSE-listed stocks. They are organized as electronic open limit order book markets and compete for order flow on the basis of low trading costs, trader anonymity, and

[16]Manual quotes are quotes entered on a 'slow' trading venue that does not offer automatic execution, for example, a trading floor.

fast executions. Chapter 3 discusses the literature on market fragmentation and ECNs in detail.

Conclusion. Both, MiFID and RegNMS have the purpose to foster competition and to enhance investor protection. However, a closer look reveals substantial differences: First, MiFID does not establish formal linkages between trading centers. Investment firms have to decide whether they connect to different trading venues or use intermediary connectivity. Smaller investment firms may decide to avoid high connectivity costs and only connect to the most important markets. U.S. equity exchanges are electronically linked to facilitate an integrated national market. Second, under MiFID the investment firm is obliged to define and implement a best execution policy. Under RegNMS, trading venues are required to establish, maintain, and enforce best execution. Third, MiFID defines best execution on the basis of multiple factors such as execution price, explicit trading costs, speed, and probability of execution. RegNMS specifies that price alone matters and any order must be forwarded to the trading venue with the best available quote for execution. Fourth, European regulation does not establish a single data consolidator. There is no public consolidated tape integrating order book information from various trading venues.[17] MiFID only requires market operators to publish certain pre- and post-trade information as discussed above.

There is an onging debate among practitioners and academics about the impact of differences in MiFID and RegNMS on market quality. Petrella (2010) argues that "[...] the consolidation of market data and the disclosure of execution quality information appear to be more effective [...] in strengthening competition for order flow among trading venues" under RegNMS. Stoll (2001), however, points out that a formal linkage may impede innovation and causes high infrastructure costs. Both studies rely on well-founded arguments but the authors do not assess empirically the question if market efficiency can be ensured without a formal linkage. This question is elaborated in Chapter 6.

[17] There are, however, commercial products available. For example, Thomson Reuters offers a consolidated data stream, see http://thomsonreuters.com/products_services/financial/financial_products/equities_derivatives/.

2.2 Details on the UK Equity Market

This section provides a brief description of the history of the LSE and highlights important market developments in the UK after the introduction of MiFID in November 2007. As discussed in the previous section, MTFs, such as Chi-X, BATS, and Turquoise, became serious competitors of traditional European exchanges during the last years. The UK equity market is particularly suitable for an analysis of the impact of MiFID on competition and market quality for at least two reasons. First, it is the most fragmented equity market in Europe and second, the UK, especially London, has a long tradition as a market place and 20.0% of the European equity trading volume was still centered at the LSE in 2010.[18] The Financial Times Stock Exchange index 100 (FTSE 100) is a well-known blue-chip stock market index. It is an arithmetic average, value-weighted index of the top 100 stocks in terms of market capitalization, listed at the LSE. To assess changes in the UK equity market structure and trading practices, the following subsections describe the market structure on the LSE over time, report trading volume and market share statistics in FTSE 100 constituents, and explore institutional details of the LSE, Chi-X, BATS, and Turquoise.

I. Reforms and technological changes on the LSE

Table 2.3 depicts the most important developments in the history of UK equity trading. Regulated trading on the LSE started on March 3, 1801. It has a long tradition as floor-based broker-dealer market. The following details are based on Clemons and Weber's (1995) article that offers a well-organized description of trading at the LSE. Similar to the specialist system of the NYSE, 'jobbers' were responsible for making the market. They hold inventory for their own accounts, selling to brokers whose customers wanted to buy and buying from brokers with sell orders. The so-called single capacity system prevented firms to perform both jobber and broker functions at the same time. Specifically, jobbers acted as intermediaries between brokers.

Deregulation and introduction of SEAQ. In October 1986, the LSE switched to an open, electronic screen-based quotation system, called the Stock Exchange Automated Quotation system (SEAQ). Simultaneously, numerous changes occurred, including the

[18] See Equity Market Report 2010 of the Federation of European Exchanges (FESE), http://www.fese.eu/.

liberalization of broker-dealer commissions, the replacement of the single with a dual capacity system, and the opening of dealer-ships to banks and other financial institutions (Clemons and Weber, 1995). Dual capacity means that an investment firm can act on SEAQ as an agent for its customers (broker) and be a jobber (dealer) transacting its own business. These market reforms are known under the term 'Big Bang' and had the purpose to encourage competition and to reduce execution costs. The market structure under SEAQ resembles the Nasdaq market. On SEAQ, competing market makers were obliged to enter two-way quotes for no less than the minimum quantity in stocks for which they were registered. This minimum size was determined on the basis of the trading volume over the previous year per stock. In the case where a market maker displayed a larger quantity of shares than the minimum quantity, her quotes were firm in the sense that incoming orders have to be executed against the displayed quantity. Market markers were eligible for relief from the stamp duty, allowed to short sell, and could use the Inter-Dealer Broker (IDB) system. Stamp duty is a form of tax charged for each share transaction in the UK. While quote display systems were automated through SEAQ, order execution was arranged over the phone. Trades were finally reported on SEAQ.[19]

Introduction of SETS. The second central market reform at the LSE was the introduction of the Stock Exchange Trading System (SETS), an electronic open limit order book, which was introduced in October 1997. However, the broker-dealer network was retained in parallel and also today investors can choose to negotiate a trade with a broker-dealer ('off book') or trade in the electronic limit order book. The LSE removed the obligation of broker-dealers to provide two-way quotes on SETS. Liquidity

[19]There are a number of studies analyzing market quality and trading behavior on SEAQ. Abhyankar (1995) provides evidence that equity and futures markets are more integrated after the introduction of SEAQ. He attributes this finding to a higher level of equity market efficiency after the Big Bang relative to the futures market. Jong de et al. (1995) compare French stocks listed on the Paris Bourse, an order-driven market, and traded on the LSE's SEAQ International. The London market provides less favorable execution quality for all except the largest trade size category. Gemmill (1996) analyzes the impact of anonymity for block trades on SEAQ between 1987 and 1992 by different publication rules. Kleidon and Werner (1996) show that prices of UK cross-listed stocks on SEAQ and the NYSE and American Stock Exchange (AMEX) are not integrated. See Abhyankar et al. (1997) for an intraday analysis of quoted spreads, trading volume, and volatility on SEAQ. Reiss and Werner (1998) find that broker-dealers use the IDB system to share inventory risk. Further, Hansch et al. (1998) show that inter broker-dealer trading is driven by inventory changes. It appears that there is a negative relationship between price improvements a dealer offers and trade sizes a broker submits (Bernhardt et al., 2005).

Table 2.3: **UK equity market history**. The table highlights important events that shaped the UK equity trading landscape.

Date	Event
March 3, 1801	Foundation of the LSE
October 10, 1986	Deregulation of the LSE and introduction of SEAQ (known as 'Big Bang')
October 20, 1997	Introduction of SETS on the LSE
June 18, 2007	Introduction of TradElect on the LSE
June 29, 2007	Chi-X started trading in FTSE 100 constituents
November 1, 2007	MiFID came into full effect
August 15, 2008	Turquoise offered trading in FTSE 100 constituents
October 31, 2008	BATS started trading in FTSE 100 constituents
December 21, 2009	Merger between the LSE and Turquoise
February 14, 2011	Introduction of Millenium Exchange on the LSE
February 18, 2011	BATS announced to acquire Chi-X

provision through limit orders is voluntary. Limit orders are sorted by their price and, in case of equality, by the time of their arrival (price-time priority). Initially, SETS was only available for FTSE 100 constituents. In September 1999, FTSE 250 constituents were transferred to SETS, too.

According to Naik and Yadav (1999) and Friederich and Payne (2007), there were three main reasons which led to this market reform: First, it was widely agreed that opacity and trading costs incurred by retail investors were especially high on the LSE. Second, UK regulatory authorities removed certain quoting restrictions for broker-dealers on domestic alternative electronic trading networks opening the market for more competition. Third, many European exchanges moved to fully electronic limit order trading and increased the competitive pressure on the LSE.[20] To date nearly all exchanges operate fully automated electronic limit order books. There are several benefits associated with this kind of market structure. First, investors can decide to buy or sell at specific prices (limit order) or to trade at the best available price (market order). Limit orders give control over the execution price but execution is not certain (execution risk). Market orders provide immediacy but the execution price may vary from

[20] Various European exchanges introduced fully electronic trading systems in the 1990s. For example, Euronext started trading on the Nouveau Système de Cotation (NSC) in 1988 and Deutsche Boerse on the Integrierte Börsenhandels- und Informations-System (IBIS) in 1991. See Jain (2005) for a list of electronic and floor-based trading systems at international exchanges.

the last observable price (price risk). Second, investors are able to observe the entire order book on a timely basis, evaluating trading interests of buyers and sellers. Third, order execution costs are expected to be lower due to electronic order execution.[21]

Further developments. In June 2007, the LSE introduced its new trading and information platform called TradElect to further enhance trading speed and infrastructure efficiency.[22] To strengthen its competitive position and to "[...] capture a healthy slice of the market's growth potential"[23], the LSE aggreed to merge its dark pool unit Baikal with Turquoise on December 21, 2009. The aquisition was completed in February 2010 leaving the LSE with 60.0% of the new company. The existing shareholders, international investment banks, still own 40.0% of the new company. In February 2011, the LSE switched trading from TradElect to Millennium Exchange to enhance trading speed and infrastructure reliability. This step may attract algorithmic order flow which is considered to be predominantly executed on MTFs.

II. Competition between the LSE and MTFs

FTSE 100 constituents are listed on the LSE. Trading is also possible on various MTFs that differ in technology, trading costs, and execution speed. The most successful MTFs in terms of market share in FTSE 100 constituents are Chi-X, BATS, and Turquoise. Under MiFID, the LSE and the three MTFs are regulated through the British Financial Service Authority (FSA). MTFs aim to attract order flow from algorithmic and high-frequency traders. To do so they offer fast trading platforms with high throughput rates and low trading fees. The throughput rate is defined as the average number of messages a trading system can process during a period. It is especially important for automated trading strategies which rely on fast order submissions and cancellations.

[21]There are different studies after the introduction of SETS in 1997. Naik and Yadav (1999) analyze spread measures of FTSE 100 and FTSE 250 constituents in 1998 and for two control periods in 1994 and 1996. They find that trading costs for retail investors decreased under SETS. Overall, their results suggest that allowing limit orders to compete for order flow reduces the market power of broker-dealers (see Barclay et al. (1999) for similar results on Nasdaq). Ellul et al. (2002) study trading through SETS and broker-dealers at the open and close of a trading day. They argue that broker-dealers provide useful additional liquidity. Intraday patterns of quoted spreads, trading volume, and volatility for SETS and SEAQ instruments are examined by Cai et al. (2004). Lai (2007) examines the impact of SETS on trading quality in FTSE 250 constituents. Friederich and Payne (2007) provide evidence that investors' choice of trading on SETS or with broker-dealers depends on order characteristics and market liquidity.

[22]The LSE still uses the acronym 'SETS' for its electronic order book.

[23]See http://www.tradeturquoise.com/press/4-TQ%20completion%20release-2.pdf.

Market entry of MTFs. Chi-X, the largest MTF, started trading in German and Dutch blue-chip stocks about six months ahead of MiFID on March 30, 2007. Eleven FTSE 100 constituents became available on Chi-X at the end of June 2007 and the full list of FTSE 100 constituents in August 2007. BATS began trading of ten FTSE 100 constituents by the end of October 2008. All FTSE 100 constituents were available for trading one week later. BATS is operated by BATS Europe, a subsidiary of the U.S. company BATS Global Markets. In February 2011, BATS agreed to combine with Chi-X Europe.[24] Previously, Chi-X Europe was owned by Instinet, a subsidiary of Nomura Holdings, and a number a major investment banks and broker houses. Turquoise started trading in five FTSE 100 constituents on August 15, 2008. The roll-out of the entire universe of FTSE 100 constituents was completed by the end of the month. The ownership structure of MTFs is an important detail. Investment firms may predominately submit orders to trading venues where they are shareholder.

MTF market shares. Figure 2.1 and Figure 2.2 depict the development of trading volume in FTSE 100 constituents on the LSE, Chi-X, BATS, and Turquoise and the corresponding market shares between July 2007, the month Chi-X started trading in UK instruments, and December 2010.[25] These four trading venues account for roughly 95.0% of trading volume generated on regulated markets and MTFs during the observation period. Figure 2.1 shows that the LSE lost a significant fraction of trading volume in FTSE 100 constituents between 2007 and 2010. There are mainly two reasons for this development. First, trading volume has not yet recovered to the level before the financial crisis and second, Chi-X, BATS, and Turquoise captured a considerable fraction of trading in FTSE 100 constituents. To assess the level of competition, Figure 2.2 presents market shares for Chi-X, BATS, and Turquoise. The LSE market share is by construction one minus the sum of market shares across all MTFs. Chi-X was able to capture a significant fraction of trading over the last three years, reaching about 25.0% market share in FTSE 100 constituents in the first quarter of 2010, an all-time high. BATS steadily increased its market share to almost 10.0% in December 2010. Turquoise reports a lower market share than BATS since October 2009. Its average monthly market share fluctuated between 5.0% and 6.0%.

[24] See http://www.batstrading.co.uk/resources/press_releases/BATS_Chi-X_SPA_FINAL.pdf.

[25] Daily closing prices and number of shares traded are obtained from the Securities Industry Research Centre of Asia-Pacific (SIRCA). I thank SIRCA for providing access to the Thomson Reuters DataScope Tick History archive, http://www.sirca.org.au/.

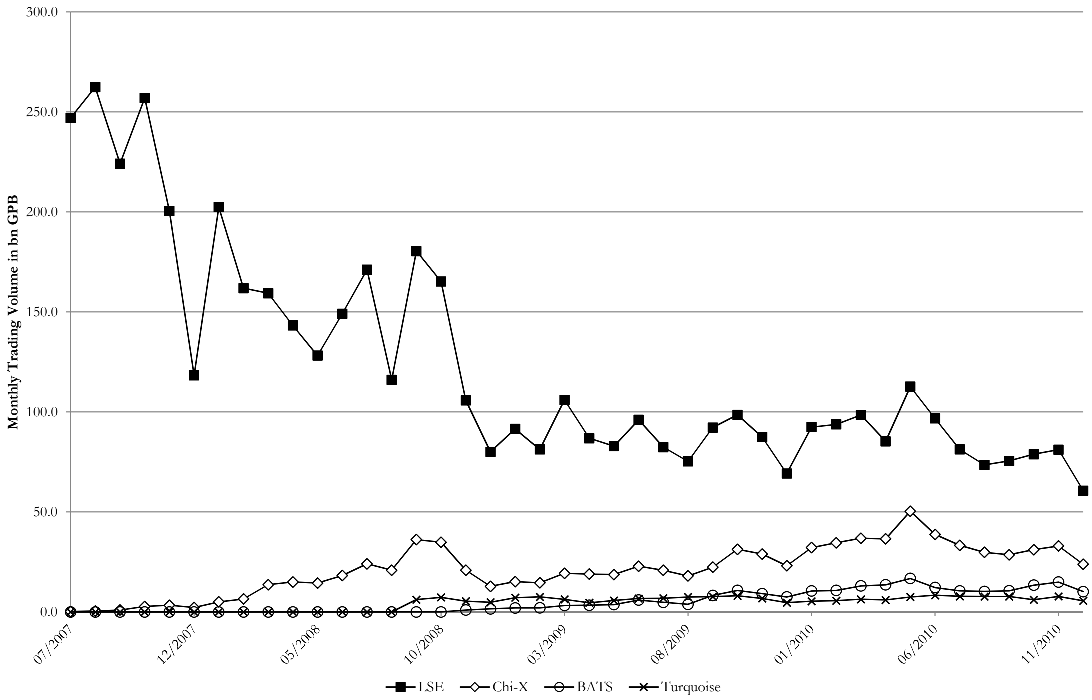

Figure 2.1: **FTSE 100 trading volume on the LSE, Chi-X, BATS, and Turquoise**. The figure shows average monthly trading volume of FTSE 100 constituents on the LSE, Chi-X, BATS, and Turquoise from July 2007 to December 2010. First, daily market shares are obtained by multiplying the daily closing price of an instrument on each trading venue with the corresponding number of shares traded. Second, daily trading volume is averaged across instruments on a monthly basis.

III. Institutional details

In the following three paragraphs, I outline important market features and developments that are relevant for the two observation periods in 2009 and 2010 used throughout my thesis (see Chapter 4.1). In general, a competitive UK trading environment resulted in regular trading infrastructure upgrades on all platforms and frequently changing fee schedules.

Trading mechanism. While regulated markets and MTFs compete primarily on technology and trading costs, the LSE, Chi-X, BATS, and Turquoise provide the same basic market model. They all operate an electronic, fully integrated limit order book which combines both visible and hidden liquidity.[26] Iceberg orders that only display a portion of their total volume are available on all four trading venues. Fully hidden limit orders are not visible to any investor and have to meet the large in scale considerations

[26]See Biais et al. (1995) for a description of a generic limit order book design.

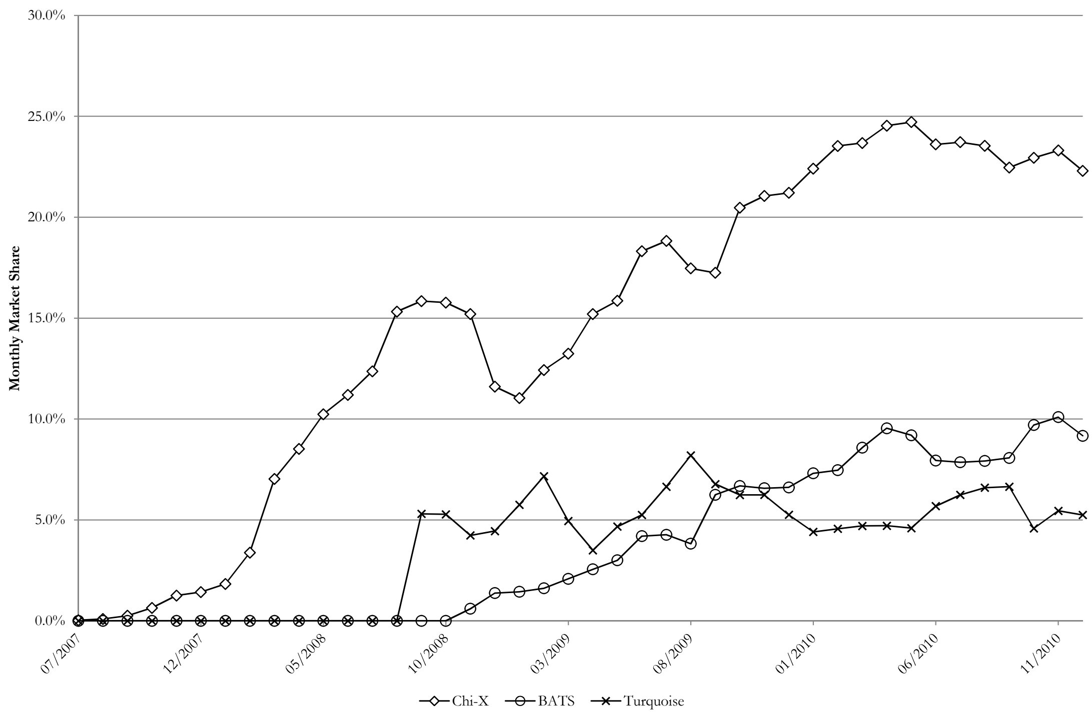

Figure 2.2: **FTSE 100 market share of Chi-X, BATS, and Turquoise**. The figure shows average monthly market shares of FTSE 100 constituents on Chi-X, BATS, and Turquoise from July 2007 to December 2010. First, daily market shares are obtained by multiplying the daily closing price of an instrument on each trading venue with the corresponding number of shares traded. Second, daily market shares are averaged across instruments on a monthly basis.

of MiFID.[27] In general, orders are executed according to 'price-visibility-time priority', i.e. displayed orders have priority over non-displayed fractions of iceberg orders and fully hidden orders with the same price. The LSE introduced fully hidden limit orders on December 14, 2009.

As discussed above, the LSE trades FTSE 100 constituents on SETS. In addition, broker-dealers may provide liquidity off book.[28] Continuous trading starts at 8:00 a.m. GMT on all four trading venues and lasts until 4:30 p.m. GMT. In addition to limit orders, market orders, iceberg orders, and fully hidden orders, Chi-X, BATS,

[27] MiFID requires all regulated markets and MTFs to be pre-trade transparent. An exception are orders that are large in scale compared with normal market size (Directive 2004/39/EC, Article 22(2)). Normal market size is provided by ESMA and reviewed on a yearly basis, see http://mifiddatabase.esma.europa.eu/.

[28] According to the LSE, the majority of trades is executed 'on book', for example, in April 2011, 98.0% of the total number of exchange-reported trades and 82.0% of total exchange-reported trading volume (information obtained from the LSE per e-mail).

and Turquoise offer pegged orders. The execution price for this type of order is determined based on a reference price such as the European Best Bid and Offer (EBBO). Executions on the three MTFs are subject to a price check. Possible trades are not executed if the execution price is in a certain range above or below the EBBO.

Trading Speed. MTFs offer potential benefits to speed-sensitive investors such as algorithmic and high-frequency traders. A delay in the time it takes to process a trade may result in missed trading opportunities, misplaced liquidity, and higher risk exposure. Technically, MTFs offer on average eight to ten times higher trading speed than the LSE during the observation periods. For example, in May 2010, BATS reports an average order latency of 200 microseconds.[29] In October 2010, following its migration to a new trading system, Turquoise claimed to be the world's fastest trading platform with an average order latency of 126 microseconds.[30]

Fee schemes. Algorithmic and high-frequency traders are very sensitive to explicit trading costs. The LSE, Chi-X, BATS, and Turquoise feature a maker/taker pricing scheme, i.e. investors are charged for aggressive orders that take liquidity from the order book and rebated for passive orders that supply liquidity. In April/May 2009, investors pay between 0.45 bps and 0.75 bps for an aggressive order on the LSE and receive a rebate up to 0.40 bps. Chi-X and BATS charge an aggressive order with 0.28 bps and rebate a passive order with 0.20 bps. On Turquoise investors pay 0.28 bps for an aggressive order and receive a rebate of 0.20 to 0.24 bps for a passive order depending on their trading volume during the previous month.

The LSE switched back to a traditional fee schedule on September 1, 2009. Investors are charged between 0.20 bps and 0.45 bps for both aggressive and passive orders. On May 4, 2010, the LSE introduced two additional rates for high-volume traders that run in parallel with the LSE's existing fee schedule. The first new rate waives trading fees of passive orders for firms providing a large amount of liquidity. The second new rate charges 0.29 bps for an aggressive order. Investors have to apply to be included in the new rate groups and have to meet specific criteria such as a high prior trading volume. Over the second observation period in 2010, BATS charges an aggressive order with 0.28 bps and rebates a passive order with 0.18 bps. Maker/taker fees on Chi-X and Turquoise are the same as in the first observation period.

[29]See http://www.batstrading.co.uk/resources/participant_resources/BATSEuro_Latency.pdf.
[30]See http://www.tradeturquoise.com/press/TQ_Latency_Press_Release.pdf.

Chapter 3

Related Work

Market microstructure literature offers a broad range of topics. For the purpose of this thesis, I focus on theoretical and empirical studies on competition between trading venues. Section 3.1 summarizes the findings on costs and benefits of fragmentation and explores parallels between ECNs in the U.S. and MTFs in Europe. Section 3.2 looks at the impact of recent innovations in information and communication technologies on the way trading presently takes place in a fragmented trading environment. The literature on exchange infrastructure as well as algorithmic trading provides important implications on competition and market quality.

3.1 Intermarket Competition

A. Theoretical Literature

From a theoretical perspective, Mendelson (1987) analyzes the effect of fragmentation on various platforms. He finds that there may be a detrimental effect of market fragmentation on market and trading characteristics resulting from the proliferation of alternative trading venues. Comparing a consolidated 'clearing house' and fragmented 'clearing houses', his model demonstrates that fragmentation reduces the expected trading volume, increases price variance, and reduces expected gains from trade.[1]

The literature also describes the effect of network externalities on liquidity. Intuitively, if two markets are combined into one, trading volume concentrates on the single market resulting in a higher probability that investors meet and that bid-ask spreads

[1]In the context of the paper, a 'clearing house' is modeled as a periodic call auction market.

narrow. For the two market case, Pagano (1989b) shows that if trading costs are equal in both markets, trade concentrates on one trading venue resulting in higher liquidity. If trading costs are different between markets or the alternative is to search for a transaction partner at cost, there are multiple equilibria. For both cases, the findings suggest that investors cluster according to the quantities that they wish to trade on each trading venue. In addition, concentration of trade is pareto-improving. However, if concentration of trade involves some search, the model predicts that concentration of trading may be inefficient. Pagano (1989a) further examines the impact of market depth on asset price volatility. His model shows that an increase in depth as a result of the market entry of investors may create a positive network externality.

Chowdhry and Nanda (1991) analyze multi-market trading of informed large investors and uniformed small liquidity traders. They show that small liquidity traders concentrate in the equilibrium in the most liquid market. This market, in turn, also attracts informed trading. Thus, their central result is consistent with Pagano (1989b), trading should concentrate on one trading venue. Admati and Pfleiderer (1988) explain the fact that trading should not only concentrate geographically as discussed before but also intertemporally. If investors have discretion over the timing of their orders, trading tends to concentrate at particular times of the day, since at this point in time liquidity is highest. Studying trading at the LSE, Abhyankar et al. (1997), for instance, find some support for Admati and Pfleiderer's (1988) hypothesis.

Although the theoretical literature emphasizes the importance of network externalities, recently several new trading venues emerged. Madhavan (1995) argues that trading volume would not fragment if trade disclosure was mandatory. In his model, dealers benefit from fragmentation facing reduced price competition and large traders also benefit by being able to hide their orders. Hendershott and Mendelson (2000) discuss the impact of the introduction of crossing networks on an existing dealer market. They find that cost advantages and trading volume are crucial factors for the competitiveness of crossing networks. As described before, a higher level of available liquidity on crossing networks attracts more investors, enforcing the liquidity externality. However, as the level of low-liquidity preference orders exceeds a certain threshold, they may crowd out higher-liquidity preference orders. As a consequence, increasing the order flow on a crossing network can reduce overall welfare. Liquidity effects on the existing dealer market are ambiguous. On the one hand, bid-ask spreads may increase if investors use the dealer market as a 'market of last resort' and on the other hand, adverse selection may decrease on the existing dealer market if informed traders resort to crossing networks.

Summary. Early in the literature, the presence of strong network externalities was recognized. Mendelson (1987), Pagano (1989a), and Chowdhry and Nanda (1991) argue in favor of consolidation on one trading venue. Admati and Pfleiderer (1988) show that there is a strong tendency to concentrate trading intertemporally. Madhavan (1995) and Hendershott and Mendelson (2000) discuss causes that may lead to fragmentation.

B. Empirical Literature

Trading venues compete along other dimensions than just price. Alternative trading venues offer unique trading opportunities to their clienteles, for example, fast exchange infrastructure. In addition, most of the presented theoretical models are developed under the assumption that liquidity suppliers are competitive. However, strategic behavior of liquidity suppliers may lead to market fragmentation (Biais et al., 2005). The following section summarizes empirical evidence on competition between trading venues and its impact on market quality. Table 3.1 gives an overview over the discussed literature.

I. Competition and market structures

Many studies compare market quality and efficiency across different market structures. This section reviews the literature on intermarket competition between the NYSE, Nasdaq, and regional exchanges highlighting important implications for the purpose of this thesis.

Competition between the NYSE and regional exchanges. Hamilton (1979) is one of the first authors who empirically addresses the trade-off between benefits of competition and costs of a more fragmented trading environment.[2] His research is based on a sample of 315 NYSE-listed stocks from the first quarter of 1975. These stocks are also traded on various other third market trading venues. Increased competition from regional exchanges, brokers, and dealers "[...] might stimulate the exchange [NYSE] to supply

[2]Other early studies are Demsetz (1968) and Tinic (1972). They suggest that increased competition for order flow leads to smaller quoted spreads.

Table 3.1: **Intermarket competition: Overview over the empirical literature.**

Article	Trading Venues	Firms	Period	Fragmentation
I. Competition and market structures				
Competition between the NYSE and regional exchanges				
Hamilton (1979)	NYSE, third-market	315 NYSE-listed stocks	01-03/1975	+
Lee (1993)	NYSE, third-market	500 NYSE-listed stocks	01/1988-12/1989	–
Hasbrouck (1995)	NYSE, third-market	Dow Jones 30	08-10/1993	~
Easley et al. (1996)	NYSE, CSE	30 NYSE-listed stocks	10-12/1990	–
Competition between the NYSE and Nasdaq				
Huang and Stoll (1996)	NYSE, Nasdaq	175 NYSE/Nasdaq-listed stocks	01-12/1991	+
Bennett and Wei (2006)	NYSE, Nasdaq	39 voluntary listing switches from Nasdaq to the NYSE	01/2002-03/2003	–
O'Hara and Ye (2011)	Exchanges (including NYSE, Nasdaq), ECNs, ATS	262 Nasdaq/NYSE-listed stocks	01-06/2008	+
Entry of a new competitor				
Boehmer and Boehmer (2003)	Exchanges (including NYSE, Nasdaq), ECNs	30 ETFs	07-08/2001, 03-05/2002	+
Battalio et al. (1997)	NYSE, third-market	327 NYSE-listed stocks	01/1988-12/1990	+
Fontnouvelle de et al. (2003)	AMEX, CBOE, PCX, PHLX, ISE	28 equity options classes	08-09/1999, 07-08/2000	+
Battalio et al. (2004)	AMEX, CBOE, PCX, PHLX, ISE	30 equity option classes	06/2000, 01/2002	+
II. Competition between Nasdaq market makers and ECNs				
Liquidity measures				
Barclay et al. (1999)	Nasdaq, ECNs	100 Nasdaq-listed stocks	11/1996-02/1997	+
Weston (2000)	NYSE, Nasdaq, ECNs	88 NYSE and Nasdaq-listed stocks	09/1996-06/1997	+
Simaan et al. (2003)	Nasdaq, ECNs	87 Nasdaq-listed stocks	09/1997	+
Fink et al. (2006)	Nasdaq, ECNs	2,500 Nasdaq-listed stocks	01/1996-12/2002	+
Execution costs				
Conrad et al. (2003)	Crossing networks, ECNs, broker	Institutional investor trading data	01/1996-03/1998	+
Price discovery				
Huang (2002)	Nasdaq, ECNs	30 Nasdaq-listed stocks	07/1998, 11/1999	+
Barclay et al. (2003)	Nasdaq, ECNs	150 Nasdaq-listed stocks	06/2000	+
Goldstein et al. (2008)	Nasdaq, ECNs	100 Nasdaq-listed stocks	04-06/2003	+
Level of competition				
Biais et al. (2010)	Nasdaq, Island	74 Nasdaq-listed stocks	11/2000, 06/2001	~
III. Competition between regulated markets and MTFs				
Hengelbrock and Theissen (2009)	Regulated markets, Turquoise	260 stocks	05-07/2008, 11/2008-01/2009	+
Hoffmann (2010)	Euronext, Xetra, Chi-X	67 stocks	04-05/2008	–
Degryse et al. (2011)	Euronext, other exchanges, MTFs	52 stocks	01/2006-12/2009	+
Storkenmaier et al. (2010)	LSE, Chi-X	88 stocks	01-12/2009	+

better or cheaper transactions". However, "off-board trading reduces exchange trading volume, which would reduce exchange efficiency, if centralization has economies of scale" (Hamilton, 1979). The picture emerges that both effects are small but the competition effect compensates costs of fragmentation as quoted spreads and daily stock price variances decrease in a more competitive setting. Lee (1993) examines the cost of trading in 500 high volume NYSE-listed stocks on the NYSE and seven other trading venues (regional exchanges, Nasdaq, and Instinet) in 1988 and 1989. Controlling for trade characteristics, costs of trading vary considerably across trading venues and are often lower on the NYSE compared to the third market. Importantly, most differences result from trades which are executed better than the currently available NBBO. This situation suggests that the NBBO does not always reflect available intermarket liquidity. As a consequence, the market for NYSE-listed stocks is less integrated than regulation suggests (NYSE-listed stocks are part of the ITS, see Section 2.1). He concludes that his findings "[...] raise questions about the adequacy of the existing intermarket quote system (ITS), the broker's fiduciary responsibility for 'best execution,' and the propriety of order flow inducements" (Lee, 1993).

Hasbrouck (1995) analyzes price discovery of 30 stocks in the Dow Jones Industrial Average (Dow Jones) from August through October 1993. During the observation period, Dow Jones constituents are predominately traded on the NYSE but also on regional exchanges. The author develops an approach to determine the trading venue's contribution to price discovery which became a standard measure in the market microstructure literature. The information share of a trading venue is defined as the proportion of a market's contribution to the variance in the random walk process of a stock price.[3] Price discovery seems to be concentrated on the NYSE with an average quote based information share of 91.3%. The information content of order flow can be analyzed using prevailing quotes as in Hasbrouck (1995) or trades as in Easley et al. (1996). The latter documents 'cream-skimming' of uninformed liquidity orders for the Cincinnati Stock Exchange (CSE) and the NYSE. During their observation period in 1990, it is widely documented that local brokers and specialists agree to 'purchase' uninformed retail order flow. An adverse selection problem arises leaving the NYSE with the more informed order flow and higher adverse selection risk. This, in turn, means that NYSE specialists may widen their spreads to recover from loses to

[3]Section 4.3 discusses the methodology in more detail.

informed traders. If order purchasers promise to match the NBBO that is mainly set by the NYSE, investors globally receive worse prices.

Competition between the NYSE and Nasdaq. There is an ongoing debate about the merits of dealer and auction markets. While Nasdaq is historically organized as a dealer market, the NYSE is an auction market. A host of studies examines market quality on one of the two competing markets and others compare transaction costs and price efficiency for stocks trading in both markets. Huang and Stoll (1996) are among the first authors who provide an in-depth analysis of differences between Nasdaq and the NYSE.[4] Their data cover all trades in 175 high volume Nasdaq and NYSE-listed stocks in 1991. To allow for a clean analysis of market quality, they match one Nasdaq stock to one NYSE stock on the basis of different criteria such as price and market capitalization. The evidence suggests that quoted and effective spreads are more than twice as large for Nasdaq stocks relative to their NYSE pairs. Huang and Stoll (1996) conclude that "[...] important explanations are the internalization and preferencing of order flow and the presence of alternative interdealer trading systems, factors that limit dealers' incentives to narrow spreads on NASDAQ".

Bennett and Wei (2006) show for a more recent observation period that fragmentation can result in less liquid and less efficient markets. Because of Nasdaq's organization as a dealer market, order flow becomes more consolidated when stocks switch listings from Nasdaq to the NYSE. The authors look at 39 voluntary exchange switchings during January 2002 to March 2003 and find lower quoted, effective, and realized spreads as well as reduced short-term volatility when trading on the NYSE. The improvement in market quality is on average stronger for smaller stocks. The evidence strengthens the view that order flow consolidation encourages price competition between investors and enhances market quality. O'Hara and Ye (2011) argue that these

[4]See Biais et al. (2005) for a well-structured overview over theoretical models on dealer and auction markets. Empirically, Bessembinder and Kaufman (1997a) confirm the results of Huang and Stoll (1996) for a data sample of Nasdaq and NYSE-listed stocks in 1994. Boehmer (2005) shows that significant differences in transaction costs between both trading venues still persist between 2001 and 2003. The international evidence is mixed. Results of Jong de et al. (1995) imply that trading costs on the Paris Bourse, an electronic limit order book, are on average lower than on SEAQ International, LSE's dealer market system. Venkataraman (2001) find that execution costs on the Paris Bourse are higher compared to the NYSE. For an observation period in 2001, Gajewski and Gresse (2007) compare transaction costs on Euronext (Paris), the successor of Paris Bourse, to those on the LSE. Their results suggest that market quality is higher on Euronext. Kasch-Haroutounian and Theissen (2009) show that trading costs on Xetra are lower than on Euronext (Paris). Their observation period spans May to July 2002.

results may rather be driven by stock characteristics and different trading rules or corporate governance requirements on Nasdaq and the NYSE than by competition effects. They analyze market quality in 262 Nasdaq and NYSE-listed stocks between January and June 2008. Their data show that U.S. equity markets feature substantial fragmentation that seems to lower effective spreads and to increase execution speed. Especially, smaller and less liquid stocks benefit from market fragmentation suggesting that fragmentation increases competition for order flow. O'Hara and Ye (2011) emphasize that U.S. market participants benefit from "the development of sophisticated order routing combined with the existence of a consolidated tape and the trade-through rule [which] have resulted in a single virtual market with many points of entry". In their opinion, it is an open question to which extent investors benefit from competition in Europe or Canada where the lack of a consolidated tape and trade-through protection may harm overall market quality.

Entry of a new competitor. Boehmer and Boehmer (2003) document large improvements in liquidity after the NYSE started trading 30 ETFs. Before the market entry which took place in two phases in 2001 and 2002, the ETFs were already traded in parallel on AMEX, Nasdaq, ECNs, and regional exchanges. However, the NYSE gained about 15.0% share in trading volume during the month of entry. Increased competition lowers quoted and effective spreads significantly and increases depth for the entire market and on each individual trading venue. Lower realized spreads indicate smaller profits of liquidity suppliers. The authors conclude that "[...] competition for order flow among market centers is beneficial for overall liquidity and does not seem to adversely affect price discovery" (Boehmer and Boehmer, 2003). Battalio et al. (1997) examine the effect of increased competition after the entry of a third market broker dealer, Bernhard L. Madoff Investment Securities (Madoff), on the NYSE.[5] In January 1988, Madoff started to selectively purchase and execute order of high volume NYSE listed stocks. Applying an event study methodology, Battalio et al. (1997) show that quoted and effective spreads in those stocks decrease. The evidence also implies that the potential adverse selection problem may be economically insignificant and Madoff rather competes on the basis of lower transaction costs than on information advantages.

Fontnouvelle de et al. (2003) and Battalio et al. (2004) find that cross-listing of equity

[5]These results are consistent with other studies on market maker competition on the Nasdaq (Wahal, 1997; Klock and McCormick, 1999).

options improves market quality.[6] In August 1999, several U.S. option exchanges began to trade previously exclusively listed options. One month later, 37.0% of all equity option volume shifted from single to multiple exchange trading. Fontnouvelle de et al. (2003) find that this event is associated with a decrease in quoted (effective) spreads in the post event period by more than 50.0% (35.0%). The findings suggest that the improvement in spreads is higher for low volume series of options. There is little evidence that the changes result from economies of scale in market making. The authors reach the conclusion that "[...] *intra*-exchange competition is not a good substitute for *inter*-exchange competition, evidence that fragmented order flow across competing markets may offer important benefits to investors" (Fontnouvelle de et al., 2003). In late 2002, the SEC imposed a formal linkage and more stringent quoting and disclosure rules on U.S. option markets. Battalio et al. (2004) look at two periods prior to the new rules, June 2000 and January 2002, where the second period was under the threat of the SEC's formal linkage plan. It appears that quoted and effective spreads decline between both observation periods and also in comparison to Fontnouvelle de et al. (2003). They find that locked and crossed market quotes and the number of trade-throughs decrease over time. The average time an option is locked (crossed) decreases from 15.5 minutes (93.6 seconds) per day in June 2000 to 8.8 minutes (14.4 seconds) in January 2002. The daily trade-through rate falls from 11.1% to 3.7% between the first and second observation period. Their results lead them to conclude that competition between trading venues, improved technology, and the threat of increased regulation can integrate platforms without a formal linkage.

Summary. Studies of market quality on Nasdaq and NYSE provide evidence that the market structure of a trading venue affects the level of competition between liquidity suppliers (e.g. Huang and Stoll, 1996). The presented literature demonstrates that there are substantial benefits from increasing competition due to lower quoted and effective spreads (Boehmer and Boehmer, 2003; Fontnouvelle de et al., 2003; Battalio et al., 2004). However, Easley et al. (1996) show that informed trading may increase adverse selection costs asymmetrically, i.e. leaving investors on one market with a higher adverse selection risk than on another market.

[6] Similar results for cross-listed options are found by Mayhew (2002).

II. Competition between Nasdaq market makers and ECNs

Increasing market share of ECNs is primarily a result of regulatory changes. In January 1997, the SEC began to introduce new order handling rules. The set of rules was designed to foster competition for order flow, specifically targeted Nasdaq (see Section 2.1). Previously, trading on Nasdaq suffered from imperfect competition (e.g. Christie and Schultz, 1994; Huang and Stoll, 1996). The new rules were adopted in several phases. The first group of 50 stocks switched to the new regime on January 20, 1997 and a second group of 50 stocks switched on February 10, 1997. By October 13, 1997 all Nasdaq stocks fell under the new regulation. The literature discusses several possible advantages of ECNs, such as low trading costs, improved order exposure, trader anonymity, small tick sizes, or fast executions (e.g. Barclay et al., 2003; Goldstein et al., 2008). Trading with Nasdaq market makers, investors can benefit from long-term internalization agreements and may receive better prices than the NBBO.

Liquidity measures. Barclay et al. (1999) examine the impact of the new order handling rules and thus increased competition on market quality. Their findings support the view that the objectives of the SEC have been met. First, quoted and effective spreads decrease by about 30.0% under the new set of rules and second, depth at the best bid and ask price increases. In addition, competition "[...] significantly narrowed the historical differences in trading costs for Nasdaq and New York Stock Exchange stocks" (Barclay et al., 1999). Weston (2000) confirms these results comparing different matched samples of Nasdaq and NYSE-listed stocks before and after the introduction of the new order handling rules. Testing for changes in order processing, inventory, and adverse selection costs as well as Nasdaq market maker profits, he provides evidence for substantial improvements in market quality on Nasdaq. Still, quoted (effective) spreads on Nasdaq are still about 15.0% (25.0%) larger in comparison to NYSE stocks. Stronger competition among dealers lead to an exit from the market for market making on Nasdaq. However, market maker trading volume is less concentrated under the new rules. Together, both studies suggest that competition between market makers and ECN limit orders increases market quality.

Simaan et al. (2003) look at the quoting behavior of market participants on ECNs and Nasdaq for a ten day period in September 1997. Analyzing the same stocks as those included in Barclay et al. (1999), they find that odd-tick avoidance is less prevalent on ECNs. In addition, odd-tick quotes seem to be generally more competitive than even-tick quotes as they are available for a much shorter period of time. It appears that ECNs narrow spreads, since they are alone (one or more ECNs) at the best available bid and ask in about 19.0% of time. Their findings lead them to conclude that more opaque platforms, such as ECNs, can reduce market makers' fear of retaliation and thus increase aggressivness in order submission. Fink et al. (2006) study competition between ECNs and traditional market makers on Nasdaq between January 1998 and December 2002. Their main analysis covers 2,500 stocks on a quarterly basis. The picture emerges that an increasing ECN market share is associated with smaller NBBO quoted spreads, decreasing effective spreads, and larger depth at the best bid and ask. Competition forces some traditional market makers, such as wholesale dealers, to leave the market as it may be less profitable to purchase order flow.

Execution costs. Conrad et al. (2003) analyze the choice of institutional investors to route orders to day and after-hours crossing systems, ECNs, and traditional brokers. Their data span the time period between the first quarter of 1996 and the first quarter of 1998 and cover about 780,000 orders from 59 institutions. Controlling for order characteristics, their results offer insights into the benefits of alternative trading systems on the basis of trading costs. Relative to traditional broker-filled orders, executed orders on day crossing systems are 30 bps cheaper, after-hours crossing systems 20 bps, and ECNs 66 bps. However, the infusion of competition through new order handling rules in 1997 reduced the comparative advantage of trading on ECNs relative to broker trades.

Price discovery. Besides market liquidity, the informativeness of quotes is an important dimension of market quality. Huang (2002) compares the quality of quotes submitted by two ECNs, Instinet and Island, and traditional Nasdaq market makers. His analysis is based on two samples of trade and quote data of 30 high volume Nasdaq-listed stocks in July 1998 and November 1999. The evidence suggests that both ECNs contribute to price discovery. It appears that prices on Instinet and Island tend to 'move first' relative to market maker quotes. The two trading venues also submit quotes more frequently, have a higher fraction of quotes at the best available bid/ask, and smaller quoted spreads than dealers. Overall, the "[...] evidence suggests that the proliferation of alternative trading venues, such as ECNs, may promote quote quality rather than fragmenting markets" (Huang, 2002).

Barclay et al. (2003) offer further insights into the informativeness of ECN and market maker executed trades. They use trade and quote data of June 2000 that identify all ECN and market maker trades for 150 Nasdaq-listed stocks. First, the authors explore market conditions and the level of market activity under which investors rather send their orders to an ECN than to Nasdaq market makers. Trades are more likely to be executed on ECNs when ECNs offer better prices and lagged trading volume as well as stock return volatility is high. Second, Barclay et al. (2003) find that ECN trades explain more than twice the amount of efficient price variation than market maker trades. In addition, the permanent price impact of ECN trades is at least 50.0% larger than the permanent price impact of market maker trades. These findings lead them to conclude that ECNs and Nasdaq market makers attract different types of investors. Overall, ECNs seem to attract more informed traders and significantly contribute to price discovery.

Goldstein et al. (2008) investigate the impact of anonymity and liquidity on price discovery. Their data sample comprises all trades and quotes on Nasdaq montage and three ECNs (Archipelago, Island, and Instinet) for 100 high volume Nasdaq stocks in the second quarter of 2003. In contrast to Barclay et al. (2003), they show that Nasdaq montage tends to contribute more to price discovery than ECNs in less traded stocks while informed investors prefer trading on ECNs for the most liquid stocks. ECNs, especially Archipelago and Instinet, are at the best bid and ask for a similar fraction of time compared to Nasdaq. However, quotes on Nasdaq montage seem to be more stable, i.e. less volatile. Effective spreads are lower on ECNs than on Nasdaq montage but vary substantially between ECNs. Altogether, it appears that investors benefit from market maker supported liquidity on Nasdaq montage in times of high market volatility and in less actively traded stocks.

Level of competition. The empirical study of Biais et al. (2010) relies on the reduction in tick sizes on Nasdaq from a tick of 1/16 to 1/256 in April 2001. At the same time, there was only a modest change on Island. The ECN reduced its pricing grid to 1/1,000 of a dollar. The authors analyze changes in quoted spreads, trading strategies, and rents of liquidity suppliers for a sample of 74 stocks between November 2000 and June 2001. In contrast to their expectations, spreads decrease on both Nasdaq and Island, suggesting that limit order traders on Island earned excess returns prior to the tick size change. In addition, Island limit orders undercut Nasdaq quotes more often than they do with prices set on Island. Overall, the evidence suggests that "[...] perfect competition cannot be taken for granted, even on a transparent open limit order books with a very thin pricing grid" (Biais et al., 2010).

Summary. The literature on ECNs demonstrates that they have a profound impact on U.S. equity trading, offering more choice of trading to investors and reducing overall transaction costs. First, competition between ECNs and Nasdaq market makers significantly reduces quoted and effective spreads (Barclay et al., 1999; Weston, 2000; Fink et al., 2006). Second, ECN quotes are informative and contribute to price discovery (Huang, 2002; Barclay et al., 2003; Goldstein et al., 2008). However, intermarket competition may not be perfect (Biais et al., 2010).

III. Competition between regulated markets and MTFs

There is a growing body of literature analyzing the impact of increased competition on market quality and price discovery in European equities under MiFID. Hengelbrock and Theissen (2009) examine the liquidity effects of Turquoise's market entry in 14 different countries in September 2008. Cross-sectional regressions suggest that Turquoise gained greater market share in stocks with a higher market capitalization, stocks with previously high bid-ask spreads on the regulated home market, and less volatile stocks. Results on a change in liquidity after Turquoise's market entry are ambiguous. There is some evidence that quoted spreads on the regulated home market decline after the entry of Turquoise, although quoted and effective spreads generally tend to be higher on Turquoise. Hengelbrock and Theissen (2009) conclude that the "[...] new entrant serves as a disciplinary device that reduces rents earned by the suppliers of liquidity in the primary market".

Under MiFID, best execution relies on multiple factors such as price, trading costs, execution speed, and probability of execution (see Section 2.1). Hoffmann (2010) analyzes the impact of multi-dimensional best execution on liquidity supply for a sample of 67 French and German high volume stocks traded on Chi-X and Euronext (Paris) and Xetra, respectively. His findings are threefold: First, differences in effective spreads between Chi-X and regulated markets are not significant for the observation period April to May 2008. However, there is a considerable level of quote competition: Chi-X is 26.0% of the time alone at the best available bid or ask, compared to 51.0% for the regulated markets. Second, Hoffmann (2010) documents a high average trade-through rate of about 50.0% across trading venues. Third, the evidence suggests a high adverse selection risk for liquidity suppliers on Chi-X. Overall, his findings lead to the conclusion that a lack of trade-through protection hampers competition under MiFID. Foucault and Menkveld (2008) show that a higher trade-through rate discourages liquidity supply. They look at the market entry of EuroSETS on the Dutch stock market in May 2004. As predicted by their theoretical model, they find that stronger competition among liquidity suppliers leads to an increase in depth of the consolidated order book. In addition, liquidity is negatively related to the trade-through rate.

Degryse et al. (2011) shed light on the effects of liquidity fragmentation in 52 medium and high volume Dutch stocks between 2006 and 2009. They compute a consolidated order book based on individual order books of Euronext (Amsterdam) and six other trading venues, such as Chi-X or BATS. It appears that depth of the consolidated order book increases with the level of market fragmentation. This effect is mainly driven by depth close to the midpoint. On the regulated home market, Euronext, depth close to the midpoint reduces by about 10.0% relative to a completely concentrated market. Their results suggest that investors who only have access to Euronext are worse off under MiFID.

Storkenmaier et al. (2010) study the effects of public information on market fragmentation characteristics. Their analysis is based on trade and quote data of FTSE 100 constituents traded on the LSE and Chi-X over 2009. A proxy for the aggregated daily tone of public information is computed from Thomson Reuters news wire messages. Consistent with Chowdhry and Nanda (1991), they show that informed traders resort to the most liquid market, the LSE, during times with high levels of public information.

Summary. There is a growing body of studies on European equity market quality and intermarket competition after the introduction of MiFID. The evidence suggests that market fragmentation increased significantly over the last couple of years. MTFs attract a considerable fraction of trading volume, especially in high volume stocks (Hengelbrock and Theissen, 2009), although they do not provide smaller average quoted and effective spreads than regulated markets (Hengelbrock and Theissen, 2009; Hoffmann, 2010; Storkenmaier et al., 2010). Degryse et al. (2011) show that depth in the consolidated order book across trading venues increases with the level of fragmentation. Results on price discovery are mixed. While Hoffmann (2010) finds that trades on MTFs are more informed, Storkenmaier et al. (2010) show that informed investors mainly trade on the regulated market. Hoffmann (2010) also documents a high number of trade-throughs.

3.2 Financial Market Innovation

Trading venues became increasingly automated over the last couple of decades. Stock exchanges around the world introduced electronic limit order books, replacing their trading floors on which brokers manually match orders using an open-outcry system. Improvements in information and communication technologies significantly reduced barriers to enter the market. An efficient market design and efficient trading mechanisms are crucial to attracting more trading volume and to winning greater market share. As discussed in the previous section, new competitors, ECNs in the U.S. and MTFs in Europe, have been very successful in capturing market shares from traditional exchanges. In this section, I present the literature from two related perspectives: exchange infrastructure and algorithmic trading.

Exchange infrastructure. Besides stock characteristics and regulation, market quality is also influenced by exchange infrastructure. Jain (2005) studies the adoption of electronic trading venues and the cost of equity for 56 countries around the world between 1969 and 2001. The picture emerges that the automation of trading improved liquidity and information efficiency and thus lowered the cost of equity for listed firms. Boehmer (2005) provides evidence that there is a negative relationship between trading speed[7] and execution costs measured by effective spreads. His data cover a large sample of Nasdaq and NYSE-listed stocks between November 2001 and December 2003. Investors execute large market orders considerably faster on Nasdaq than on the NYSE but also pay higher transaction costs. For small market orders the relationship between the NYSE and Nasdaq reverses, suggesting that institutional differences between trading venues matter.[8] Garvey and Wu (2010) further analyze the relationship between execution speed, trading costs, and geographic locations of traders. They use a proprietary data set of about 3.6 million orders submitted by 2,000 stock traders from

[7]Trading speed or latency is commonly defined as the time required for an order to travel from the investor system, across the network to the exchange central computer, and for confirmation of the order to be sent back to the investor.

[8]Boehmer et al. (2007) find that trading venues receive more order flow when their reported execution speed increases.

different cities in the U.S. throughout October 1999 to August 2003. It appears that traders located closest to the market's central computer experience faster executions, pay lower transaction costs, and engage in more speed-sensitive trading strategies. For example, arbitrage strategies may become more attractive with trading speed as price and execution risk decrease.

Hendershott and Moulton (2011) analyze the introduction of the NYSE's Hybrid Market at the end of 2006. The new trading system significantly increased automation and execution speed for NYSE market orders from ten to less than one second. Using an event study approach, the authors document that this reduction in latency increases quoted spreads but improves efficiency of prices. Riordan and Storkenmaier (2011) study the impact of a speed-enhancing system upgrade on Xetra, the electronic stock trading system of Deutsche Börse, in April 2007.[9] In contrast to Hendershott and Moulton (2011), they find no change in quoted spreads but significantly smaller effective spreads after the system upgrade. In addition, a substantial fraction of price discovery shifts from trades to quotes.

Algorithmic trading. To date, a steadily increasing fraction of orders is submitted by computer algorithms without human intervention. Hendershott et al. (2011) define algorithmic trading as the "[...] use of computer algorithms to automatically make certain trading decisions, submit orders, and manage those orders after submission". Algorithmic traders have been shown to have positive effects on liquidity supply and the price discovery process and therefore the integration of fragmented equity markets (Hendershott and Riordan, 2009; Hendershott et al., 2011) and foreign exchange markets (Chaboud et al., 2009).[10] Hendershott and Riordan (2009) study algorithmic trading in high volume stocks on Xetra in the first three weeks of January 2008. Their findings suggest that algorithmic traders submit smaller orders than other market participants and continuously monitor the market, consuming liquidity when it is cheap and supplying liquidity when it is expensive. This pattern may level liquidity differences over time. In addition, algorithmic traders have a larger price impact than human

[9] Wagener et al. (2010) analyze the effect of the Xetra upgrade on the pricing gap between stock and futures markets. Pricing discrepancies between futures prices and their theoretical values become smaller in the post event period, suggesting that the system upgrade improves price efficiency on the stock market.

[10] Due to a lack of trading venue data that clearly identify algorithmic traders, some studies use broker data, see Engle et al. (2008) and Brogaard (2010).

traders and also contribute more to quote based price discovery. In contrast to anecdotal evidence, they find no relationship between algorithmic trading activity and market volatility.[11]

Hendershott et al. (2011) are not able to directly identify algorithmic traders in their data but use message traffic as a proxy. Message traffic is defined as the number of order submissions, order cancellations, and trades. Studying the introduction of autoquoting at the NYSE in 2003, their results provide evidence that algorithmic trading causes an improvement in market quality, lowering quoted and effective spreads. In addition, they show that algorithmic trading reduces the informativeness of trades by enhancing quote based price discovery. Hasbrouck and Saar (2011) identify distinct patterns in the millisecond environment to proxy for low-latency trading activity in Nasdaq-listed stocks. Their results suggest a positive relationship between high-frequency trading and market quality, measured by short-term volatility, spreads, and depth in the order book. Chaboud et al. (2009) analyze algorithmic trading in the foreign exchange market on the electronic broking system (EBS) over the years 2006 and 2007. In line with Hendershott and Riordan (2009), they do not find any strong causal relationship between algorithmic trading activity and volatility.

Jovanovic and Menkveld (2010) directly address automated trading in a fragmented trading environment. They look at 14 high volume Dutch stocks on Euronext (Amsterdam) and Chi-X, a high-frequency trader friendly environment. During their observation period, January to April 2008, average liquidity on Euronext is higher than on Chi-X. However, investors benefit from trading in both markets as the consolidated quoted spread is about 20.0% smaller than on Euronext. To determine the impact of high-frequency trading, they analyze a second time period in 2007 (trading is concentrated on Euronext) and use Belgian stocks to control for market-wide changes over time (Chi-X started trading Belgian stocks after the main observation period). Their data sets allow to identify one large high-frequency trader that participates in trading on Euronext and Chi-X in 2008. She is more often on the passive side of an execution and present in roughly every third trade on Chi-X and in every twelfth trade on Euronext. The evidence suggests that she acts as intermediary ('middlemen'). Overall, she has a positive impact on liquidity in the consolidated order book but a detrimental effect on trading volume. There is a sharp decrease in liquidity for the control sample

[11]See, for example, www.ft.com/cms/s/0/3f57311e-c246-11dd-a350-000077b07658.html.

of Belgian stocks but quoted spreads do not change for Dutch stocks. However, trading volume of Dutch stocks declines by 13.0%. Menkveld (2011) uses the same data set and provides further evidence that "[...] the success of a new market, Chi-X, critically depended on the participation of a large HFT who acts as a modern market-maker".

A changing market environment. Only few papers study implications of highly automated and fragmented markets for trading strategies. For example, Shkilko et al. (2008) discuss reasons why non-positive NBBO spreads may naturally arise in a fragmented trading environment. They look at 100 Nasdaq-listed and 100 NYSE-listed firms and find that non-positive NBBO spreads emerge on average about 10.0% of the trading day on Nasdaq and 4.0% on the NYSE during the last quarter of 2003. These market situations occur frequently but they are resolved within seconds. The authors argue that it may be reasonable for investors to ignore outstanding limit orders and to lock or cross stale quotes of slower trading venues or quotes with small associated volume. Overall, they summarize that "[...] although non-positive NBBO periods often disrupt electronic executions and irritate market makers and SEC regulators, they should be viewed as natural phenomena in fast-moving segmented markets" (Shkilko et al., 2008).

Hasbrouck and Saar (2009) analyze 100 Nasdaq stocks traded on INET, an ECN, in October 2004. Limit orders are canceled very quickly and the picture emerges that they do not conform to the classical definition of patient liquidity supply. As a consequence, the fill rate of limit orders that are canceled within 2 seconds, so-called 'fleeting orders', is less than than 8.0%. Their empirical analyses confirm the following three hypotheses: First, traders cancel and resubmit an order if the market moves away from the original price of the limit order. They pursuit an aggressive strategy to obtain price-priority ('chase hypothesis'). Second, limit orders are converted to market orders as the cost of immediacy drops ('cost-of-immediacy hypothesis'). Third, submitted limit orders search for hidden liquidity in the order book. If an order is not executed immediately, it is canceled ('search hypothesis). According to Hasbrouck and Saar (2009), fleeting orders are a relatively new phenomenon. Factors such as automated trading, new active trading practices, coordination in a fragmented trading landscape, and hidden liquidity promote the trend towards fleeting orders.

Summary. Recent technological innovations revolutionized the way assets are traded. Trading speed became an important component of market quality (Garvey and Wu, 2010; Riordan and Storkenmaier, 2011). To date, algorithmic traders generate more than half of the trading volume in blue-chip stocks, submitting smaller orders at a higher frequency than human traders. The literature suggests that algorithmic traders lower spreads (Hendershott et al., 2011), increase depth (Hasbrouck and Saar, 2011), enhance the quote based price discovery (Hendershott and Riordan, 2009), and may integrate fragmented markets (Menkveld, 2011). Altogether, interrelated effects, such as automation of exchange infrastructure, algorithmic trading, and market fragmentation changed the market environment, resulting in new dynamic order submission strategies (Shkilko et al., 2008; Hasbrouck and Saar, 2009).

Chapter 4

Data and Methodology

This chapter is organized as follows. Section 4.1 discusses data characteristics and categories of filters applied to the data sets. Section 4.2 presents trading intensity and liquidity measures. Section 4.3 provides details on the computation of price discovery measures and Section 4.4 discusses logistical regressions.

4.1 Data Selection

To study trading in fragmented markets after the introduction of MiFID, I analyze FTSE 100 constituents traded on the primary market, the LSE, and other alternative trading venues. FTSE 100 constituents are the most fragmented stocks in Europe (see Section 2.2), making them especially suitable to evaluate the presented research questions. In my empirical analyses, I focus on the regulated market, the LSE, and the three largest MTFs, namely Chi-X, BATS, and Turquoise. Since the introduction of MiFID, systematically less than 5.0% of daily trading volume in non-OTC trades is not executed on one of these four trading venues.[1]

Observation periods. Empirical analyses are based on the following two observation periods: April 20 to May 29, 2009 and April 19 to May 28, 2010. The first observation period is determined by the availability of a stable market structure. There are no market microstructure, fee, or trading system changes on any of the four trading venues. I choose the second time period in April/May 2010 to study effects of competition and regulation on quote and execution quality over time. In addition, this choice

[1]Due to a lack of data, I do not include trades executed by SIs or OTC.

reduces seasonal effects that may distort results. Markets are closed on UK bank holidays, May 4 and May 25, 2009 and May 3, 2010. I further exclude May 1, 2009 due to a considerably smaller UK trading volume.[2] The final sample covers 27 trading days in 2009 and 29 trading days in 2010.[3]

Data characteristics. My empirical analysis of the British stock market relies on trade and quote data retrieved from the Thomson Reuters DataScope Tick History archive through SIRCA.[4] I obtain order book information for each trading venue, the LSE, Chi-X, BATS, and Turquoise. FTSE 100 constituents are identified using Thomson Reuters Instrument Codes (RIC), a unique instrument identifier. Specifically, I retrieve trade prices, volumes, best bid and ask including associated volumes, and order book information up to three levels behind best prices for both observation periods. Specific data qualifiers are further used to delete cross-reported trades on the LSE. Trades and quotes are reported in British pence and they are time-stamped to the millisecond. Appendix A presents both a raw data sample of trade and quote data and a raw depth data sample for the LSE. Data formats do not differ for Chi-X, BATS, and Turquoise. However, specific entries can change. For example, Chi-X data comprise different trade and quote data qualifiers than the LSE.

Filter criteria. The sample selection criteria apply on both the trade and quote data and the FTSE 100 constituents finally included into my data sets:

Tick data level: (1): To avoid biases associated with the market opening and closing procedures and to accommodate lagged variables, analyses are restricted to continuous trading, meaning that the first and last fifteen minutes of a trading day are excluded. As a result, my data span the period between 8:15 a.m. and 4:15 p.m. GMT. (2): A single market order trading against more than one limit order produces multiple data entries in the raw data. Thus, I combine all buys (sells) that are recorded in the same millisecond in a FTSE 100 constituent on one trading venue. (3): Prior to the introduction of hidden orders on the LSE in December 2009, trades on the LSE are either executed at the best bid and ask or at multiple prices in the order book. In cases where the raw data records inside the spread executions, I assume technical irregularities and eliminate the

[2]Most European countries celebrate May Day and the markets are closed.

[3]A previous version of Chapter 5 is based on 19 trading days in May 2009. The results do not differ and are therefore not presented.

[4]I thank SIRCA for providing access to the Thomson Reuters DataScope Tick History archive, http://www.sirca.org.au/.

trade from the data set. Such trades account for only 0.9% of all LSE trades and for 1.4% of LSE trading volume over April/May 2009.

Firm level: I apply the following three filters on FTSE 100 constituents in both sample periods. (1): I require all stocks to have more than ten trades per trading day on the LSE, Chi-X, BATS, and Turquoise throughout the observation period. (2): Stocks with missing trade and quote data are excluded.[5] (3): I eliminate firms with corporate actions (e.g. stock splits) during the observation period.[6]

These filters result in 74 stocks for the observation period in April/May 2009 and I obtain 98 stocks for April/May 2010. Table 4.1 reports the FTSE 100 constituents affected by the above presented firm level filter criteria. To highlight developments over time, I also analyze a subsample of 70 firms which are traded in both observation periods.[7] In the observation period in 2009, a considerably higher amount of stocks is affected by the 'ten trade rule', since some stocks are infrequently traded on BATS and Turquoise. Appendix A reports the final sample firms including exchange ticker symbols, average daily trading volume, and average daily market capitalization.[8] In the 2009 observation period, HSBC HOLDINGS is traded most, with an average daily trading volume of 290,973 million GBP. The company with the lowest daily trading volume is STANDARD LIFE with 9,349 million GBP. For the 2010 observation period, the most and least traded stock is BP (477,807 million GBP) and CABLE & WIRELESS (6,740 million GBP), respectively.

To analyze price discovery and the level of market integration, it is necessary to merge individual order books of each trading venue into one consolidated order book per stock. I use single order book information of the LSE, Chi-X, BATS, and Turquoise, the four most important trading venues in terms of trading volume and quote activity. Based on RICs and timestamps, I compute the European Best Bid (EBB), the highest bid across all trading venues, and the lowest ask price, the European Best Offer (EBO). In addition, the associated quoted volume across trading venues is identified (see Figure 4.1 for an example). Thomson Reuters also delivers a consolidated FTSE 100 data feed including the best bid and ask published on all order book driven trading venues. However, the data do not reveal the trading venues that quote the

[5] BATS trade and quote data is missing on SIRCA for stocks affected by this filter.
[6] Corporate actions are obtained through Thomson Reuters.
[7] See Section 5.5 for a more detailed description of this subsample.
[8] Daily market capitalization is retrieved from Bloomberg.

Order Book LSE	
Price	**Size**
125.40	600
125.35	300
125.25	500
125.20	100

Order Book Chi-X	
Price	**Size**
125.40	150
125.35	100
125.20	150
125.15	200

Consolidated Order Book	
Price	**Size**
125.40	1,050
125.35	400
125.30	50
125.25	1,000

Order Book BATS	
Price	**Size**
125.45	50
125.40	300
125.30	50
125.25	400

Order Book TQ	
Price	**Size**
125.50	50
125.45	50
125.25	100
125.15	150

Figure 4.1: **Consolidated order book**. The figure shows an example of how individual order books of the LSE, Chi-X, BATS, and Turquoise are merged into one consolidated order book.

best available prices. To properly assess trading venue differences, I therefore need to compute my own consolidated order book.[9]

4.2 Trading Intensity and Liquidity Measures

In this section, I provide details on the computation of trading intensity and liquidity measures. All variables are computed for each price and volume update on the LSE, Chi-X, BATS, and Turquoise. Obtained values are equally weighted and aggregated per day and per stock for each trading venue. This approach captures intraday dynamics but avoids some of the noise associated with a higher sampling frequency. Trading intensity measures are trading venue market share, corresponding daily trading volume

[9]As a robustness check, I compare my consolidated order book including the LSE, Chi-X, BATS, and Turquoise with the Thomson Reuters consolidated European data feed using the *xbo*-RIC (see http://thomsonreuters.com/products_services/financial/financial_products/a-z/regulatory_compliance_mifid/ for a brief discussion of the data characteristics). First, I compute prevailing midpoint differences on a tick-by-tick basis between both data streams. Then, daily average values per instrument are obtained. The data show a small average midpoint difference of 0.001 pence (0.001 pence) between both data streams for the 2009 (2010) observation period. In light of an average tick size of 0.508 pence (0.559 pence) over the observation period April/May 2009 (2010), my robustness check is evidence for the high quality of my consolidated order book (the presented numbers are obtained for a subsample of 70 stocks, see Section 5.5 for a more detailed description of the data set).

in British Pounds, daily number of trades, average trade size in British Pounds, and price changes in the order book per minute.

The market microstructure literature offers several proxies for liquidity. The most common measure is the quoted spread. The wider the quoted spread, the less liquid is an instrument. However, this variable only captures liquidity for relatively small order sizes. Quoted spreads are calculated as a proxy of trading costs for each trading venue on a individual order book level and for the consolidated order book. Let $a_{i,t}$ be the ask price for an instrument i at time t and $b_{i,t}$ the respective bid price. $m_{i,t}$ denotes the mid quote, then the relative quoted half spread ($qspread_{i,t}$) in basis points is calculated as follows:

$$qspread_{i,t} = (a_{i,t} - b_{i,t})/(m_{i,t} \times 2) \times 10,000 \tag{4.1}$$

This measure is based on a quote-to-quote process that is characterized by each price and volume update and each trade during the trading day. Then, quoted spreads are aggregated on daily per stock basis and averaged per trading venue. To avoid some of the noise of tick-by-tick data, all liquidity measures are winsorized at the 1.0% level and the 99.0% level. Another liquidity measure, quoted spread at trades, captures liquidity represented through the best bid and ask at the time of trade execution.

The effective spread is the spread that is actually paid when an incoming market order trades against a limit order. I use the standard Lee and Ready (1991) algorithm to estimate trade direction as proposed by Bessembinder (2003). Using the variables from above and let $p_{i,t}$ be the execution price, then the effective half spread ($espread_{i,t}$) in basis points is defined as:

$$espread_{i,t} = D_{i,t} \times ((p_{i,t} - m_{i,t})/m_{i,t}) \times 10,000 \tag{4.2}$$

where $D_{i,t}$ denotes the trade direction with -1 for market sell and $+1$ for market buy orders. Effective spreads also capture institutional features of trading venues such as hidden liquidity and market depth. For example, iceberg orders that only display a fraction of total trading volume and completely hidden limit orders are available on the LSE, Chi-X, BATS, and Turquoise. Effective spreads are usually equal to or larger than the second liquidity measure, quoted spreads at trades. However, they may be smaller if trading venues feature hidden liquidity and there is thus a reasonable number of trades executed inside the spread.

I further decompose the spread along its different components (Glosten, 1987). A smaller effective spread may mean less revenue for liquidity providers (realized spread), smaller gross losses due to informed liquidity demanders (price impact), or both. The relationship between the effective spread, the realized spread, and the price impact (adverse selection component) can be formalized for instrument i at time t as follows:

$$espread_{i,t} = rspread_{i,t} + pimpact_{i,t} \tag{4.3}$$

To capture liquidity provider revenues, I compute 5 and 15-minute realized spreads and assume that liquidity providers are able to close their position at the quote mid-point 5 and 15 minutes after the trade, respectively. Let $m_{i,t+x}$ denote the mid quote with $x = \{5, 15\}$ minutes, then the realized half spread ($rspread_{x,i,t}$) in basis points is defined as follows:

$$rspread_{x,i,t} = D_{i,t} \times ((p_{i,t} - m_{i,t+x})/m_{i,t}) \times 10{,}000 \tag{4.4}$$

The price impact captures costs for liquidity demanders that arise in the presence of asymmetric information. A trader with superior information about an instrument may try to buy or sell a large quantity to realize a profit. To compensate for this loss, liquidity suppliers charge a fee on every transaction. Using the same variables, 5 and 15-minute adverse selection components of the spread ($pimpact_{x,i,t}$) in basis points are calculated analogously as follows:

$$pimpact_{x,i,t} = D_{i,t} \times ((m_{i,t+x} - m_{i,t})/m_{i,t}) \times 10{,}000 \tag{4.5}$$

There are more robust measures to capture the information content of a trade that do not dependent on the spread decomposition. These measures are introduced in the next section.

Finally, depth data is used to compute the quoted volume at different order book levels in both individual order books and the consolidated book. The quoted half depth ($depth_{x,i,t}$) in British Pounds is computed as follows:

$$depth_{x,i,t} = \sum_{x=1}^{X} (B_{x,i,t} + A_{x,i,t})/(2 \times 100) \tag{4.6}$$

where $B_{i,t}$ is the corresponding volume at the bid and $A_{i,t}$ at the ask. $X = \{1,3\}$ characterizes different order book levels. $depth_{1,i,t}$ is the average half quoted volume at the best bid and ask and $depth_{3,i,t}$ incorporates the depth up to three ticks behind best prices.

4.3 Price Discovery

In this section, I present measures to determine where the price discovery takes place in a fragmented market. Price discovery can be measured using trades or quotes. First, I introduce Hasbrouck (1995) information shares as one measure to analyze each trading venue's contribution to quote based price discovery. Following Hasbrouck (1991a) and Hasbrouck (1991b), I further separate changes in the efficient price into quote and trade correlated components. Presented equations are tailored to my data sets.

A. Information Shares

Information shares are a relative measure to allocate price discovery across markets (Hasbrouck, 1995). The model attempts to determine which trading venue 'moves first' in revealing information through quote updates. Huang (2002) emphasizes this dimension of market quality, "[...] price leadership, or price discovery, which is accomplished by timely submission of informative quotes". Price leadership of a market may signal an efficient price discovery process through the interaction of buyers and sellers on this platform. This measure has been used in a number of studies with the same interpretation (Goldstein et al., 2008; Hendershott and Riordan, 2009).

The approach relies on co-integration. Although prices p_t are individually nonstationary, a linear combination of prices for the same underlying instrument traded on multiple trading venues may be stationary. If all prices follow a random walk, they are integrated of order one and Δp_t is a stationary process. Prevailing midpoints of the consolidated order book m_t are used to characterize this implicit efficient price. I define the following price vector $p_t = [p_t^{LSE}, p_t^{ChiX}, p_t^{BATS}, p_t^{TQ}]'$ where each p_t^j refers to the same instrument:

$$p_t = m_t + [\epsilon_t^{LSE}, \epsilon_t^{ChiX}, \epsilon_t^{BATS}, \epsilon_t^{TQ}]'$$

and m_t is supposed to follow a random walk:

$$m_t = m_{t-1} + u_t, \tag{4.7}$$

where u_t follows a white noise process with $E(u_t) = 0$, $E(u_t^2) = \sigma_u^2$, and $E(u_t u_s) = 0$ for $t \neq s$. The moving average representation for the price vector Δp_t may be written using a vector moving average (VMA) model:

$$\Delta p_t = \epsilon_t + \sum_i \psi_i \epsilon_{t-i} \tag{4.8}$$

$\epsilon_t = [\epsilon_t^{LSE}, \epsilon_t^{ChiX}, \epsilon_t^{BATS}, \epsilon_t^{TQ}]'$ is a (4 × 1) vector innovation process with $E(\epsilon_t) = 0$ and a variance matrix $Var(\epsilon_t) = \Omega$. The ϵ_t components reflect the new information incorporated into the corresponding market and the ϵ_{t-i} are (4 × 4) matrices. The ϵ_t has the interpretation that its (i, j)-element measures an one-unit increase in this component upon Δp_t.

As shown, the observed prices can be decomposed into a random walk and a covariance-stationary error. The variance of the random walk component is then:

$$\sigma_u^2 = \Psi \Omega \Psi' \tag{4.9}$$

where Ω is the (n × n) covariance matrix of the innovations and Ψ is a polynomial in the lag operator. Then, the random walk variance reflects contributions from all four markets as follows:

$$\sigma_u^2 = A \begin{bmatrix} \sigma_{LSE}^2 & \sigma_{LSE,ChiX} & \sigma_{LSE,BATS} & \sigma_{LSE,TQ} \\ \sigma_{ChiX,LSE} & \sigma_{ChiX}^2 & \sigma_{ChiX,BATS} & \sigma_{ChiX,TQ} \\ \sigma_{BATS,LSE} & \sigma_{BATS,ChiX} & \sigma_{BATS}^2 & \sigma_{BATS,TQ} \\ \sigma_{TQ,LSE} & \sigma_{TQ,ChiX} & \sigma_{TQ,BATS} & \sigma_{TQ}^2 \end{bmatrix} A' \tag{4.10}$$

where $A = [\Psi^{LSE}, \Psi^{ChiX}, \Psi^{BATS}, \Psi^{TQ}]$. If the covariance matrix is diagonal (that is, when $\sigma_{i,j}^2 = 0$) for $i = j$ the contribution of each trading venue to the price discovery process can be clearly identified. The relative size of these contributions indicates the importance of the markets. Hasbrouck (1995) defines the information share (*infoShare*$_j$) of the jth market as:

$$infoShare_j := \frac{\Psi_j^2 \Omega_{jj}}{\Psi \Omega \Psi'} \tag{4.11}$$

where $j \in \{LSE, ChiX, BATS, Turquoise\}$. $\Psi_j^2 \Omega_{jj}$ represents the contribution of market j to price discovery and $\Psi\Omega\Psi'$ is the variance of the random-walk component of stock prices representing the total price discovery. As the contemporaneous midpoint of the different trading venues can be equal, there may be correlation between the midpoints. In consequence, Ω is not diagonal. I follow Hasbrouck (1995) to determine upper and lower bounds that minimize or maximize the contribution of each market in the price discovery process. Information shares are calculated for each trading venue per day and per stock. To determine the contribution of each trading venue, the mean of the upper and lower bounds is computed and compared across the LSE, Chi-X, BATS, and Turquoise. Information shares sum up to 100.0% by construction.

B. Trade and Quote Correlated Information

Following Hasbrouck (1991a,b), I separate changes in the efficient price into quote and trade correlated components differentiating between trades executed on $j \in \{LSE, ChiX, BATS, Turquoise\}$. This results in a five-way vector autoregressive (VAR) model. Let x_{t-i}^j be the trade direction (-1 sell, 1 buy) for trades on LSE, Chi-X, BATS, or Turquoise, respectively, and 0 if the trade is not executed on the specific trading venue. r_{t-i} denotes the quote midpoint changes in the consolidated order book. The full model is as follows:

$$\begin{aligned}
r_t &= \sum_{i=1}^{10} \alpha_{t-i}^{r} r_{t-i} + \sum_{i=0}^{10} \alpha_i^{LSE} x_{t-i}^{LSE} + \sum_{i=0}^{10} \alpha_i^{ChiX} x_{t-i}^{ChiX} + \sum_{i=0}^{10} \alpha_i^{BATS} x_{t-i}^{BATS} + \sum_{i=0}^{10} \alpha_i^{TQ} x_{t-i}^{TQ} + u_{1,t} \\
x_t^{LSE} &= \sum_{i=1}^{10} \beta_i^{r} r_{t-i} + \sum_{i=1}^{10} \beta_i^{LSE} x_{t-i}^{LSE} + \sum_{i=1}^{10} \beta_i^{ChiX} x_{t-i}^{ChiX} + \sum_{i=1}^{10} \beta_i^{BATS} x_{t-i}^{BATS} + \sum_{i=1}^{10} \beta_i^{TQ} x_{t-i}^{TQ} + u_{2,t} \\
x_t^{ChiX} &= \sum_{i=1}^{10} \gamma_i^{r} r_{t-i} + \sum_{i=1}^{10} \gamma_i^{LSE} x_{t-i}^{LSE} + \sum_{i=1}^{10} \gamma_i^{ChiX} x_{t-i}^{ChiX} + \sum_{i=1}^{10} \gamma_i^{BATS} x_{t-i}^{BATS} + \sum_{i=1}^{10} \gamma_i^{TQ} x_{t-i}^{TQ} + u_{3,t} \\
x_t^{BATS} &= \sum_{i=1}^{10} \delta_i^{r} r_{t-i} + \sum_{i=1}^{10} \delta_i^{LSE} x_{t-i}^{LSE} + \sum_{i=1}^{10} \delta_i^{ChiX} x_{t-i}^{ChiX} + \sum_{i=1}^{10} \delta_i^{BATS} x_{t-i}^{BATS} + \sum_{i=1}^{10} \delta_i^{TQ} x_{t-i}^{TQ} + u_{4,t} \\
x_t^{TQ} &= \sum_{i=1}^{10} \epsilon_i^{r} r_{t-i} + \sum_{i=1}^{10} \epsilon_i^{LSE} x_{t-i}^{LSE} + \sum_{i=1}^{10} \epsilon_i^{ChiX} x_{t-i}^{ChiX} + \sum_{i=1}^{10} \epsilon_i^{BATS} x_{t-i}^{BATS} + \sum_{i=1}^{10} \epsilon_i^{TQ} x_{t-i}^{TQ} + u_{5,t}
\end{aligned}$$

The estimation is restarted for each trading day and stock in the sample. Then, I invert the above VAR model to get the VMA representation:

$$\begin{pmatrix} r_t \\ x_t^{LSE} \\ x_t^{ChiX} \\ x_t^{BATS} \\ x_t^{TQ} \end{pmatrix} = \begin{pmatrix} a^r(L)\, a^{LSE}(L)\, a^{ChiX}(L)\, a^{BATS}(L)\, a^{TQ}(L) \\ b^r(L)\, b^{LSE}(L)\, b^{ChiX}(L)\, b^{BATS}(L)\, b^{TQ}(L) \\ c^r(L)\, c^{LSE}(L)\, c^{ChiX}(L)\, c^{BATS}(L)\, c^{TQ}(L) \\ d^r(L)\, d^{LSE}(L)\, d^{ChiX}(L)\, d^{BATS}(L)\, d^{TQ}(L) \\ e^r(L)\, e^{LSE}(L)\, e^{ChiX}(L)\, e^{BATS}(L)\, e^{TQ}(L) \end{pmatrix} \begin{pmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \\ u_{4,t} \\ u_{5,t} \end{pmatrix} \tag{4.12}$$

where L are polynomial lag operators. Following Hasbrouck (1991b) the sums of $\sum_{t=0}^{\infty} a^{LSE}$, $\sum_{t=0}^{\infty} a^{ChiX}$, $\sum_{t=0}^{\infty} a^{BATS}$, and $\sum_{t=0}^{\infty} a^{TQ}$ are used to obtain the cumulative impulse response functions (CIRF) for each of the four trading venues. The CIRF is the permanent price impact of a trade and is generally interpreted as the private information content of a trade. It represents the unexpected part of a trade, the trade innovation, and has been used in a number of other studies with the same interpretation (Barclay and Hendershott, 2003; Madhavan, 2000).

Using the VMA representation from above, information can be decomposed into a trade correlated part for each trading venue and quote correlated portions (Hasbrouck, 1991b). The variance decomposition is as follows:

$$\begin{aligned} \sigma_v^2 = {} & \left(\sum_{i=0}^{\infty} a_i^r\right)^2 \sigma_r^2 + \left(\sum_{i=0}^{\infty} a_i^{LSE}\right)^2 \sigma_{x^{LSE}}^2 + \left(\sum_{i=0}^{\infty} a_i^{ChiX}\right)^2 \sigma_{x^{ChiX}}^2 + \\ & \left(\sum_{i=0}^{\infty} a_i^{BATS}\right)^2 \sigma_{x^{BATS}}^2 + \left(\sum_{i=0}^{\infty} a_i^{TQ}\right)^2 \sigma_{x^{TQ}}^2 \end{aligned} \tag{4.13}$$

The first term represents the information content of quotes. The trade correlated portions are represented through the second term for the LSE, through the third for Chi-X, the fourth for BATS, and through the fifth for Turquoise. All lags are summed to get the total trade correlated contribution of each market to price discovery. The results are reported in basis points for the CIRF and in percent for the information content of quotes.

C. Total Contribution to Price Discovery

To assess the total contribution of a trading venue to price discovery, I combine information shares ($infoShare^{j}_{i,d}$) and the fraction of quote based information ($quoteInfo_{i,d}$) to obtain a variable that describes total quote based price discovery relative to trade based price discovery ($tradeInfo^{j}_{i,d}$). The total contribution to price discovery (*total-Info*$^{j}_{i,d}$) of trading venue j for instrument i on day d emerges as follows:

$$totalInfo^{j}_{i,d} = infoShare^{j}_{i,d} \times quoteInfo_{i,d} + tradeInfo^{j}_{i,d} \tag{4.14}$$

4.4 Logistic Regressions

This section briefly presents the concept of logistic regressions that have generally the same objective as ordinary least square regressions (OLS): A dependent variable is modeled in terms of one or more independent variables. In contrast to OLS, logistic regressions describe the relationship between dichotomous variables and continuous or dichotomous explanatory variables. The dependent variable may have two categories ('event'/'non-event') or more than two categories ('event1'/'event2'/'event3'). The former is used in a bivariate logistic regression and the latter in the multinomial case. However, the illustration in this section is limited to the case where the dependent variable has two categories only. Events and non-events are commonly classified by one/zero coding. For example, an event can be the decision of an investor to rather route an order to either Chi-X (event=1) or to the LSE (event=0).

In logistic regressions, the model transforms the dependent variable and uses the natural logarithm of the odds ratio of being in a particular category for each combination of independent variables. For the order routing decision mentioned above, an odds ratio of 2-1 indicates that it is 2 times more likely that an investor routes her order to Chi-X than to the LSE. For the case of one independent variable, the logistic model has the following form:

$$\pi(x) = \frac{e^{\beta_0+\beta_1 x}}{1+e^{\beta_0+\beta_1 x}} \tag{4.15}$$

where π is the probability that an event Y occurs (odds ratio) given certain values of x, $\pi(x) = E(Y|x)$. β_0 is the intercept and β_1 the regression coefficient. The odds ratios describe the increase or decrease in probability that the event occurs for a unit change in the dependent variable. Taking the log of Equation (4.15) yields:

$$g(x) = \ln\left[\frac{\Pr(event\,|\,x)}{\Pr(non\text{-}event\,|\,x)}\right] = \ln\left[\frac{\pi(x)}{1-\pi(x)}\right] = \beta_0 + \beta_1 x \tag{4.16}$$

This step is called logit transformation and makes the logit *g(x)* of a dichotomous dependent variable and the independent variable linear. The estimate of β_1 determines the direction of the relationship between values of x and the logit of an event Y. Values of β_1 greater (smaller) than zero are associated with larger (smaller) logits of Y, meaning that the event is more (less) likely to occur with higher values of x. Within the framework of inferential statistics, the null hypothesis (H0) states that β_1 equals zero. If H0 is rejected there is evidence for a linear relationship between x and the logit of Y. I generally model bivariate logistic regressions in the spirit of Equation (4.16) and estimate the coefficients by the maximum likelihood method that attempts to find the smallest possible deviance between the observed and predicted values.

In order to evaluate my models, I rely on standard test statistics. First, I look at the overall fit of each model by comparing it to an intercept-only model, i.e. likelihood ratio tests are used to evaluate the proposed model over the baseline intercept-only model. Second, estimated coefficients are tested for statistical significance using Wald chi-square statistics. Third, I validate to which degree estimated odds ratios, the predicted probabilities, agree with the observed outcomes in my data sets.

Table 4.1: **Sample selection: Excluded FTSE 100 constituents**. This table reports eliminated sample firms from the universe of FTSE 100 constituents for the observation periods April/May 2009 (Panel A) and April/May 2010 (Panel B). Firms are excluded if they have less than ten trades per trading day either on the LSE, Chi-X, BATS, or Turquoise (Trade-Rule), trade and quote data is not available on SIRCA (Missing Data) not for every trading day, or stocks have a corporate action during the observation period (Corp. Action).

Firm	Ticker	Trade Rule	Missing Data	Corp. Action
Panel A: April/May 2009				
ADMIRAL GROUP	ADM	X		
ALLIANCE TRUST	ATST	X		
AMEC	AMEC	X		
AMLIN	AML	X		
BALFOUR BEATTY	BALF	X		
COBHAM	COB	X		
FOREIGN & COL. INVEST. TRUST	FRCL	X		
FRESNILLO	FRES	X		
FRIENDS PROVIDENT HOLDINGS	FP	X		
G4S	GFS	X		
INTERTEK GROUP	ITRK	X		
LAND SECURITIES GROUP	LAND		X	
LEGAL & GENERAL GROUP	LGEN		X	
LIBERTY INTERNATIONAL	LII	X		
LLOYDS BANKING GROUP	LLOY			X
LONMIN	LMI			X
MARKS AND SPENCER GROUP	MKS		X	
MORRISON (WM) SUPERMARKETS	MRW		X	
NATIONAL GRID	NG		X	
NEXT	NXT		X	
OLD MUTUAL	OML		X	
PEARSON	PSON		X	
PENNON GROUP	PNN	X		
PETROFAC	PFC		X	
PRUDENTIAL	PRU		X	
ROLLS-ROYCE GROUP	RR			X
SCHRODERS	SDR	X		
SCHRODERS N/V	SDRC	X		
Panel B: April/May 2010				
ALLIANCE TRUST	ATST	X		
CAPITAL SHOP. CENTRES GROUP	CSCG			X
NATIONAL GRID	NG			X
SCHRODERS N/V	SDRC	X		

Chapter 5

Liquidity and Price Discovery

5.1 Introduction

The introduction of MiFID opened regulated markets to competition from MTFs such as Chi-X and BATS. The rapid increase in MTFs' shares of trading volume is a testament to their success. For example, the LSE used to trade close to 100.0% of total daily trading volume in UK stocks. Presently, it captures less than 60.0% of total exchange traded volume. Whether or not MTFs contribute to liquidity and the price discovery process is an open question, since an increase in fragmentation may lead to a deterioration in overall market quality. Liquidity and price discovery are two important dimensions of market quality. For instance, liquidity in the form of quoted spreads reflects the costs of immediancy for an investor and impacts her expected returns (Amihud and Mendelson, 1986). Price discovery through the interaction of buy and sell orders is one of the main functions of a market as market efficiency is a prerequisite for the optimal allocation of capital. It is in general interest of all investors that this process works efficiently and asset prices adjust quickly to changes in supply and demand.

This chapter provides new insights into trading venue competition under MiFID and its effects on market quality. It examines liquidity in FTSE 100 constituents traded on the LSE, Chi-X, BATS, and Turquoise in April/May 2010 and the variables investors use to condition trading decisions. In addition, it also quantifies the contribution to price discovery by each trading venue. Finally, to better understand the impact of increased fragmentation, I compare market quality in the sample period to April/May 2009, a period when MTF market share was 38.0% lower and market liquidity was thus less fragmented.

There are a number of studies which examine the competition between ECNs and traditional exchanges. For example, Barclay et al. (2003) and Goldstein et al. (2008) study Nasdaq market makers under U.S. Regulation ATS. The SEC adopted Regulation ATS in 1998 to integrate ECNs into the NMS (see Section 2.1). The new set of rules provided investors with access to the NBBO including prices posted on ECNs that were previously excluded. Prices of ECNs and exchanges are thus formally linked via the NMS. In Europe, the market and regulatory structure is decidedly different. Most importantly, MiFID does not impose a formal linkage and the competition is not between a human market maker market and electronically organized markets but between several centralized limit order markets. In addition, algorithmic and high-frequency traders are considered to be more active today than in previous studies of multi-market trading (Jovanovic and Menkveld, 2010; Hendershott et al., 2011). This development may mitigate problems associated with the lack of formal linkages. Using these trading technologies traders may intermediate in markets informally, thereby integrating price processes and increasing liquidity.

In a first step I analyze liquidity measures. In 2010, quoted spreads are significantly lower on Chi-X than on any other platform. However, quoted spreads only measure liquidity costs for small trades. Effective spreads proxy for the transaction costs that are actually paid by liquidity demanders. On average effective spreads are tightest on Turquoise, even after controlling for market conditions at the time of trade. However, this finding may be attributed to orders that are executed against stale limit orders on Turquoise. Supposing that liquidity providers on Turquoise react slower to price movements than traders on other platforms, favorable prices for liquidity demanders arise. Regressions further show that trades are more likely to occur on MTFs when their spreads are tighter and their order books are deeper relative to the LSE. The evidence suggests that investors monitor multiple platforms and trade when and where it is relatively inexpensive.

To analyze the contribution of each trading venue to price discovery, I decompose the stock price variance into its trade and quote correlated components (Hasbrouck, 1991a). Trading on the LSE explains roughly 40.0% of trade based price discovery, on Chi-X 35.0%, on BATS 14.0%, and on Turquoise 11.0%. The permanent price impact of trades (Hasbrouck, 1991b) is larger on the LSE than on any other trading venue. Hasbrouck (1995) information shares indicate that more quote based information is impounded into prices on Chi-X. Compared to the observation period in 2009, it appears that liquidity on each trading venue is higher in 2010, despite a more fragmented market. The results suggest that MTFs, especially Chi-X, contribute significantly to liquidity and price discovery and do not seem to be piggy-backing off of the LSE price discovery process.

The remainder of this chapter is organized as follows. Section 5.2 describes the data and provides some descriptive statistics. Section 5.3 presents results on liquidity measures for the LSE and MTFs and examines investors' order routing decisions. Section 5.4 analyzes the roles played in price discovery by each trading venue. Section 5.5 explores changes in market quality between 2009 and 2010. Section 5.6 summarizes and concludes.

5.2 Sample Selection and Descriptive Statistics

This chapter focuses on FTSE 100 constituents that are traded on the regulated market, the LSE, and the three largest MTFs, Chi-X, BATS, and Turquoise. Filter categories result in 98 stocks included into the final data set that spans 29 trading days from April 19 to May 28, 2010 (see Section 4.1). I analyze both the individual order books of the LSE, Chi-X, BATS, and Turquoise and the consolidated order book of the four trading venues. To obtain the consolidated order book, the four individual order books are merged per millisecond for each stock. The consolidated data consist of roughly 19 million trades for a total of 202 billion British Pounds with an additional 448 million quotes.

Table 5.1 reports descriptive statistics for the consolidated order book and for individual order books of the LSE, Chi-X, BATS, and Turquoise per day and per stock in April/May 2010. Markets are fragmented as seen in the 51.8% market share of trading volume for the LSE. However, LSE market shares are slightly higher in low volume stocks. Chi-X is with 30.8% of trading volume the largest of the MTFs. Trade sizes are largest on the LSE. Quote updates are most frequent on Chi-X and BATS. There are about 22.0 price changes per minute on either MTF compared to 16.3 on the LSE and 13.9 on Turquoise. This result may be evidence of clientele effects that play a role in order routing decisions. For instance, algorithmic traders may prefer to trade on Chi-X and BATS and submit, edit, and delete orders at high frequencies.

Table 5.1: **Descriptive statistics: Trading intensity and liquidity measures**. The sample consists of 98 stocks listed on the London Stock Exchange and in the FTSE 100. The observation period contains all trading days from April 19 to May 28, 2010. Descriptive statistics for the consolidated order book (Cons.) and for individual order books of the LSE, Chi-X, BATS, and Turquoise are reported per day and per stock. Market shares are based on daily trading volume (Volume) in British Pounds (GBP). Trade Count is the average daily number of trades and Trade Size the average order size. Price Change is the average number of bid and ask changes per minute. Spread measures are reported in basis points. The Quoted Spread is calculated on a tick-by-tick basis per stock, the Quoted Spread Trade is calculated trade-by-trade. Realized Spread and Price Impact are reported for both 5 and 15 minute benchmarks relative to the midpoint of the consolidated order book. Depth1 is half the quoted depth at the best bid and ask. Depth3 includes the total quoted volume three ticks behind best prices. Mean differences between the LSE and each MTF are tested for statistical significance using Thompson (2011) standard errors with ‘a’ denoting statistical significance at the 1% level and ‘b’ at the 5% level.

	Cons.	LSE	Chi-X	BATS	TQ
Market Shares	100.00%	51.82%	30.81%[a]	11.59%[a]	5.78%[a]
	(0.00%)	(7.95%)	(5.33%)	(4.09%)	(2.26%)
Volume (1,000 GBP)	70,916	36,634	23,064[a]	7,739[a]	3,479[a]
	(105,556)	(56,185)	(36,651)	(10,373)	(4,377)
Trade Count	6,971	2,766	2,502[a]	1,163[a]	539[a]
	(7,414)	(2,995)	(2,870)	(1,174)	(502)
Trade Size (GBP)	8,238	10,713	7,391[a]	5,567[a]	5,487[a]
	(3,652)	(4,877)	(3,578)	(2,812)	(2,459)
Price Change (#/min)	21.22	16.27	22.95[a]	22.10[a]	13.94[a]
	(32.50)	(28.61)	(37.80)	(30.66)	(18.55)
Quoted Spread	3.874	5.718	4.983[a]	6.059[b]	9.118[a]
	(1.422)	(1.895)	(1.841)	(2.750)	(4.931)
Quoted Spread Trade	2.847	3.860	3.697[a]	4.285[a]	5.804[a]
	(1.058)	(1.280)	(1.300)	(1.754)	(3.214)
Effective Spread	3.108	3.138	3.232[a]	3.103	2.470[a]
	(1.093)	(1.130)	(1.106)	(1.133)	(1.022)
Realized Spread 5	-0.077	-0.229	-0.008[a]	0.280[a]	-0.439[a]
	(0.982)	(1.274)	(1.032)	(1.375)	(1.375)
Realized Spread 15	0.145	0.049	0.211[a]	0.379[a]	-0.127
	(1.462)	(1.953)	(1.570)	(2.303)	(3.195)
Price Impact 5	3.189	3.383	3.243[a]	2.822[a]	2.879[a]
	(1.414)	(1.666)	(1.481)	(1.552)	(2.110)
Price Impact 15	2.968	3.106	3.024	2.722[a]	2.568[a]
	(1.708)	(2.162)	(1.829)	(2.361)	(3.319)
Depth1 (GBP)	74,547	40,300	31,905[a]	21,782[a]	12,342[a]
	(72,525)	(27,720)	(28,256)	(20,204)	(8,625)
Depth3 (GBP)	450,484	211,633	158,213[a]	98,924[a]	44,053[a]
	(419,704)	(174,363)	(133,547)	(88,903)	(39,227)

Quoted spreads are calculated for each price and volume update in the order book and quoted spreads at trade time and effective spreads are computed trade-by-trade. I adapt the Bessembinder and Kaufman (1997b) spread calculation in combination with the Bessembinder (2003) adjustment of the Lee and Ready (1991) standard algorithm to estimate trade direction. Section 4.2 provides more details on the calculation of all reported liquidity measures.

Average daily quoted spreads are narrow in all individual order books, ranging from 4.98 bps on Chi-X to 9.12 bps on Turquoise. Quoted spreads at time of execution are consistently narrower than during periods without trades. This result shows that investors trade only when and where it is relatively inexpensive to do so. There is no single trading venue that always offers the best price and smaller spread measures for the consolidated order book show that investors can benefit from trading on multiple markets. For example, the average daily inside quoted spread of the consolidated order book is 3.87 bps, 32.2% smaller than the quoted spread on the LSE, 22.3% than on Chi-X, 36.1% than on BATS, and 57.5% than on Turquoise.

I use the midpoint of the EBBO to compute effective spreads per day and per stock.[1] The effective spread is the spread that is actually paid by liquidity demanders. It appears that the average effective spread on Turquoise is significantly smaller than on any other platform. However, the large difference between quoted spreads at trade time and effective spreads on Turquoise may be an indication that the results are driven by the small number of trades on Turquoise or overall market conditions at the time of execution. Section 5.3.1 reports effective spreads for different trade size categories and estimation results.

The spread is further decomposed into its individual components (Glosten, 1987). Realized spreads are a measure for liquidity suppliers' revenues and price impacts approximate gross losses due to informed trading. I compute both measures for 5 and 15 minutes. Results on realized spreads are ambiguous. At 5 minutes, they are negative for all trading venues except BATS. At 15 minutes, they are positive for the LSE, Chi-X and BATS, indicating that it may be profitable to supply liquidity on these platforms if one is willing to wait longer than 5 minutes for prices to revert to their equilibrium levels. Adverse selection risk appears to be higher on the LSE and Chi-X than on BATS

[1] Related studies of intermarket competition also use the midpoint of best prices as reference price (e.g. Barclay et al., 2003; Battalio et al., 2004; Goldstein et al., 2008).

and Turquoise.

Depth1 is the available half depth at the best bid and ask and Depth3 captures depth up to three ticks behind best prices. The results on depth show that it is significantly larger on the LSE than on any MTF. However, I likely underestimate depth due to iceberg orders or fully hidden orders. Depth measures in the consolidated order book are considerably smaller than the sum of quoted volume in individual order books. This finding provides some evidence for a competitive environment in which not every trading venue is at the best available price.

5.3 Liquidity

Section 5.3.1 studies whether MTFs are competitive in terms of liquidity. I use effective spreads to proxy for the cost of liquidity and study these costs while controlling for trade sizes, the reference price, and market conditions. Section 5.3.2 reports the results of the impact of liquidity conditions on order routing decisions.

5.3.1 Effective Spreads

Panel A of Table 5.2 reports the daily number of trades per stock and per trading venue for different trade size categories.[2] The statistics show that a significantly higher fraction of trades is executed on the LSE than on MTFs for all trade size categories, except for the two smallest categories, less than 499 shares traded and 500 to 1,999 shares traded, for Chi-X. Overall, the results confirm the tendency towards larger trade sizes on the LSE as reported in Table 5.1.

Descriptive statistics on effective spreads are broken down by trade size categories in Table 5.2, Panel B for each trading venue per day and per stock. The midpoint of the EBBO is used as the reference price to compute these variables. Effective spreads are quite small across trade size categories and trading venues, averaging between 2.09 bps and 4.09 bps. This is evidence of the strong competition between the four trading venues and between participants on each platform. Effective spreads are smallest for trades for less than 500 shares and increase along with trade size categories for all trading venues except Turquoise. Effective spreads on Turquoise are strictly lower for all trade

[2]Trade size categories are based on the SEC classification, see RegNMS, Rule 600.

Table 5.2: **Descriptive statistics: Number of trades and effective spreads by trade size categories.** The sample consists of 98 stocks listed on the London Stock Exchange and in the FTSE 100. The observation period contains all trading days from April 19 to May 28, 2010. The average number of trades (Panel A) and average effective spreads for the LSE, Chi-X, BATS, and Turquoise are reported per day and per stock in basis points. Spreads are calculated for each trading venue separately and for the consolidated order book (Cons.) across trading venues. I use the midpoint of the consolidated order book (Panel B) and midpoints of single order books (Panel C) as the reference price. The standard deviation is given in parentheses. Trade size categories are the SEC trade size classifications. Mean differences between the LSE and each MTF are tested for statistical significance using Thompson (2011) standard errors with 'a' denoting statistical significance at the 1% level and 'b' at the 5% level.

	Cons.	LSE	Chi-X	BATS	TQ
Panel A: Trade Count					
$\leq$ 499	2,790	953	1,014^b	560^a	263^a
	(3,463)	(1,222)	(1,399)	(646)	(275)
500 - 1,999	2,417	940	904	395^a	178^a
	(2,731)	(1,048)	(1,141)	(470)	(183)
2,000 - 4,999	1,004	458	347^a	134^a	64^a
	(1,538)	(632)	(613)	(233)	(104)
5,000 - 9,999	407	210	130^a	47^a	20^a
	(951)	(444)	(345)	(138)	(55)
$\geq$ 10,000	353	204	106^a	28^a	14^a
	(1,505)	(812)	(513)	(132)	(72)
Panel B: Effective Spreads - Consolidated Order Book					
$\leq$ 499	2.939	2.980	3.035^a	2.966	2.423^a
	(1.087)	(1.139)	(1.100)	(1.127)	(1.031)
500 - 1,999	3.164	3.144	3.318^a	3.230^a	2.525^a
	(1.148)	(1.190)	(1.188)	(1.242)	(1.125)
2,000 - 4,999	3.438	3.369	3.728^a	3.387	2.547^a
	(1.319)	(1.322)	(1.496)	(1.728)	(1.607)
5,000 - 9,999	3.709	3.625	4.018^a	3.319	2.335^a
	(1.786)	(1.801)	(2.004)	(2.039)	(1.718)
$\geq$ 10,000	4.086	4.087	4.052	3.461	2.091^a
	(2.397)	(2.440)	(2.271)	(2.344)	(1.921)
Panel C: Effective Spreads - Single Order Books					
$\leq$ 499	2.939	3.686	3.479^a	4.146^a	5.142^a
	(1.087)	(1.259)	(1.274)	(1.797)	(3.032)
500 - 1,999	3.164	3.886	3.736^a	4.427^a	5.210^a
	(1.148)	(1.336)	(1.310)	(1.728)	(2.916)
2,000 - 4,999	3.438	4.170	4.069^b	4.800^a	5.361^a
	(1.319)	(1.490)	(1.539)	(2.355)	(3.528)
5,000 - 9,999	3.709	4.549	4.315	4.906^a	5.220^a
	(1.786)	(1.993)	(1.975)	(2.875)	(4.245)
$\geq$ 10,000	4.086	5.165	4.369^a	5.191^a	5.103
	(2.397)	(2.701)	(2.253)	(3.547)	(4.902)

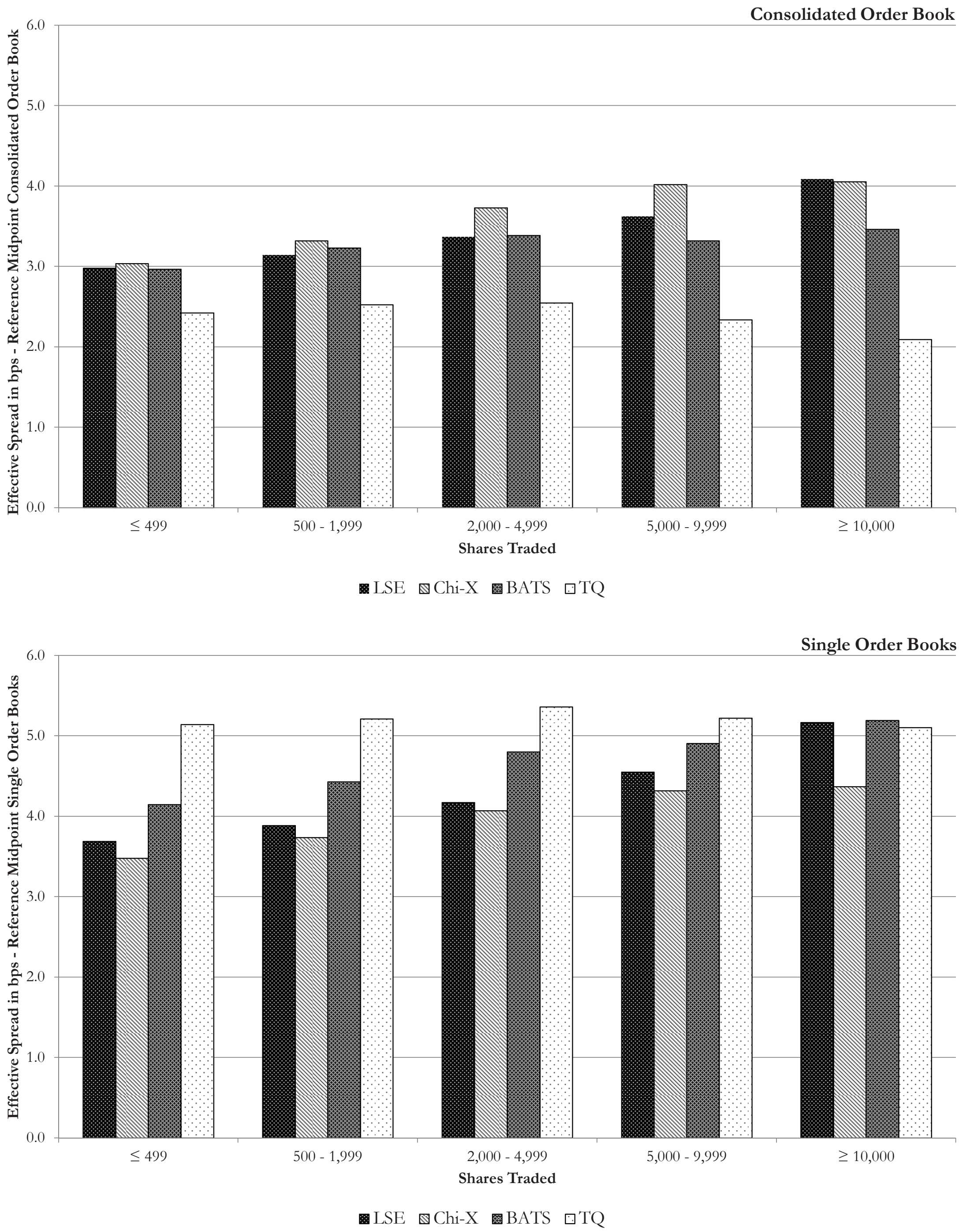

Figure 5.1: **Effective spreads by trade size categories.** The figure shows average daily effective spreads on the LSE, Chi-X, BATS, and Turquoise in FTSE 100 constituents over both observation periods, April/May 2009 and April/May 2010. Effective spreads are the relative difference between the trade price and (1) the midpoint of the consolidated order book across trading venues (upper figure) or (2) midpoints of the single order books of each trading venue (lower figure) per day and per stock.

size categories compared to the LSE, Chi-X, and BATS. One would typically interpret this as evidence that transaction costs are lower on Turquoise than on any of the other three trading venues. However, market shares of Turquoise are very low despite these favorable prices for liquidity demanders. Differences in effective spreads between the LSE, Chi-X, and BATS are economically insignificant for the two smallest trade size categories, ranging between 0.02 bps and 0.17 bps. For larger trade size categories, effective spreads tend to be smaller on BATS compared to the LSE and Chi-X.

Figure 5.1 depicts average effective spreads per day and per stock calculated (1) with the midpoint of the EBBO as in Table 5.2, Panel A (upper figure) and (2) with midpoints of individual order books of the LSE, Chi-X, BATS, and Turquoise as in Table 5.2, Panel B (lower figure). Overall, effective spreads that are based on the midpoint of consolidated order books are considerably smaller than single order book effective spreads, on average 19.7% for the LSE, 9.3% for Chi-X, 30.1% for BATS, and 45.8% for Turquoise. This result reflects the fact that trading venues do not always quote prices at the EBBO. The large difference for Turquoise possibly means that marketable orders are executed at stale prices in the limit order book. This result is in line with the findings of Chapter 6, providing some evidence that liquidity providers on Turquoise react slower to market movements.

To control for market conditions at the time of execution, I estimate pairwise regressions comparing effective spreads on the LSE and Chi-X, BATS, and Turquoise separately as in Barclay et al. (2003). The general model is defined as follows:

$$\begin{aligned} espread_{i,t} = \; & \alpha_i + \sum_{x=1}^{5} \beta_x \, mkt_{i,t} \times size_{i,t,x} + \sum_{x=2}^{5} \gamma_x \, size_{i,t,x} + \delta_1 \, qspread_{i,t} + \\ & \delta_2 \, depth_{i,t} + \delta_3 \, vol15_{i,t} + \delta_4 \, rv15_{i,t} + \epsilon_{i,t} \end{aligned} \tag{5.1}$$

where $espread_{i,t}$ is the effective spread in stock i per trade t. Again, the midpoint of the EBBO is used as reference price. Trade size dummy variables that take the value one for trade sizes between 1 to 499 shares, 500 to 1,999 shares, 2,000 to 4,999 shares, 5,000 to 9,999 shares, and more than 10,000 shares are $size_1$, $size_2$, $size_3$, $size_4$, and $size_5$, respectively. *mkt* takes the value one for a trade on Chi-X, BATS, or Turquoise, respectively and zero for a trade on the LSE. The variables of interest are the trade size dummy variables interacted with the trading venue dummy variables ($mkt \times size_1$ to *mkt* × $size_5$). The coefficients represent the average difference in basis points between similarly sized trades on the LSE and Chi-X, BATS, and Turquoise, respectively. $size_1$ is omitted. Therefore, the coefficients on other size dummy variables measure differences from trade sizes between 1 to 499 shares. Control variables are the quoted spread in the market of execution (*qspread*) and the depth in the order book on the side of the trade (*depth*). *vol15* is the trading volume in British Pounds/10^9 of the previous 15 minutes. The realized volatility *rv15* over all markets is calculated from the average midpoint return of the previous 15 minutes to the 15 minutes before. To control for stock and time period characteristics, I include firm dummy variables and dummy variables for each half-hour during a trading day.

Table 5.3 reports the pairwise regression results for the LSE compared to Chi-X, BATS or Turquoise. Estimation results show a negative sign on all interaction variables (*mkt* × $size_x$) for BATS and Turquoise, meaning that effective spreads are on average smaller on these platforms controlling for market conditions at time of trade. Effective spreads are larger on Chi-X than on the LSE for all trade size categories. While the estimates are mostly economically insignificant for a comparison between the LSE and BATS (-0.11 bps to -0.25 bps), I find remarkable differences between the LSE and Turquoise. Implicit trading costs on Turquoise are 1.25 bps lower for the smallest trade size category and 1.81 bps for the largest. These findings confirm the descriptive statistics. Trading size variables ($size_x$) show the intuitive result that as trade sizes increase so do effective spreads, regardless of the trading venue.

5.3.2 Order Routing Decisions

This section examines the impact that liquidity measures have on the order routing decision. In a perfectly competitive market, traders should prefer to execute at better prices holding other factors, such as available depth, constant. Multinomial logistic regressions are used to predict trading venue choices based on liquidity measures. Section 4.4 provides details on bivariate logistic regressions which are characterized by dependent variables with two categories. The presented model can be modified to handle the case where the dependent variable is nominal with more than two variables. This modification is necessary as investors can choose between the LSE, Chi-X, BATS, and Turquoise, resulting in four different dependent variables (coded 0, 1, 2, and 3).

A suitable approach to model investors' decisions are multinomial logistic regressions that generate n-1 sets of parameter estimates, comparing different categories of the dependent variable to a reference category.[3] To distinguish executions on the regulated market and MTFs, I use the LSE as the reference category.

Results are obtained for the entire sample and for different trading volume categories. The trading volume categories are obtained by ranking the firms in the sample by their total trading volume in April/May 2010. The first category contains the first 33 firms with the highest trading volume (high), the second the next 33 firms (medium), and the third category 32 low volume firms (low). The dependent variable is equal to one for trades on Chi-X, BATS, and Turquoise and zero for trades on the LSE. Therefore, positive coefficients indicate an increase in the likelihood of an MTF trade. The parameters of the model are estimated by maximum likelihood:

$$\begin{aligned}\ln\left[\frac{\pi_j}{\pi_{LSE}}\right] = {} & \beta_1\, qspreadDiff + \beta_2\, rDepth + \\ & \beta_3\, shareVolume + \beta_4\, vol15 + \beta_5\, rv15\end{aligned} \tag{5.2}$$

where π is the modeled response probability and $j \in \{ChiX,\ BATS,\ Turquoise\}$. The first coefficient, *qspreadDiff*, is the most important in terms of market quality. It is defined for a buy order in stock i at time t as follows:

$$qspreadDiff_{i,t} = (EBO_{i,t} - price_{i,t})/m_{i,t} \tag{5.3}$$

where $EBO_{i,t}$ is the best ask across trading venues, $price_{i,t}$ the trade price, and $m_{i,t}$ the midpoint of the consolidated order book. If an order is executed at multiple levels in the order book, the trade price used in the regressions is equivalent to the price of the first order execution level. For a sell order the variable is defined similarly as follows:

$$qspreadDiff_{i,t} = (price_{i,t} - EBB_{i,t})/m_{i,t} \tag{5.4}$$

where $EBB_{i,t}$ is the best bid across trading venues. I estimate separate regressions for the following two depth variables: *rDepth1* is the depth at the bid (ask) for sell (buy)

[3] Hosmer and Lemeshow (2000) provide an in-depth overview of multinomial logistic regressions (p. 31-43).

orders on the platform of execution relative to the average depth across trading venues. *rDepth3* is defined analogously but incorporates depth up to three ticks behind best prices and may better model routing decisions for large institutional orders. The number of shares traded is *shareVolume*. *vol15* and *rv15* are defined as in Equation 5.1. I further include firm dummy variables and intraday dummy variables for each half-hour.

Table 5.4 presents the regression estimates for the entire sample and trading volume categories. The sign on *qspreadDiff* is negative for all estimations, except for the entire sample and the high volume category of Chi-X. This result indicates, as one would expect, that platforms are less likely to attract an order as the difference between posted prices and the EBB (EBO) increases.[4] All coefficients for Chi-X are small and capture the fact that Chi-X prices are very competitive and *qspreadDiff* is often close to zero. In fact, for the entire sample, the odds of a trade on an MTF increase by a multiple of 1.02 for Chi-X, 1.04 for BATS, and 1.12 for Turquoise relative to the LSE when *qspreadDiff* increases by 1 bps, holding all other variables constant. Positive coefficients on *rDepth1* and *rDepth3* reveal that trading venues offering more liquidity relative to other trading venues are more likely to attract an order. It appears that investors condition their trading decision not only on prices but also on available depth. In particular, for the entire sample estimation the picture emerges that an 1.0% increase in *rDepth1* on the platform of execution compared to the LSE increases the likelihood of a trade on Chi-X by 1.02, on BATS by 1.05 and on Turquoise by 1.07. Mostly negative coefficients on *vol15* show that the likelihood of an MTF trade decreases when past volume is high. Results on *rv15* show distinct patterns. While there is a tendency that investors resort to the LSE in times of high volatility for high volume stocks, the opposite is true for medium and low volume stocks.

[4]The results are confirmed for different variable specifications. A dummy variable, indicating whether a platform posts the EBB (EBO) alone, and absolute depth variables also suggest that MTFs offering more liquidity are more likely to attract an order.

Table 5.3: **Regressions of effective spreads**. The sample consists of 98 stocks listed on the London Stock Exchange and in the FTSE 100. The observation period contains all trading days from April 19 to May 28, 2010. I regress effective spreads on dummy variables that capture trading venue, trade size, and market conditions at the time of trade. The midpoint of the consolidated order book is used as reference price to calculate effective spreads. Trade size dummy variables take the value one for trade sizes between 1 to 499 shares, 500 to 1,999 shares, 2,000 to 4,999 shares, 5,000 to 9,999 shares, and more than 10,000 shares are $size_1$, $size_2$, $size_3$, $size_4$, and $size_5$, respectively. I interact trade size dummy variables with trading venue dummy variables ($mkt \times size_1$ to $mkt \times size_5$). *qspread* is the quoted spread and *depth* the quoted depth in the direction of the trade. *vol15* is the trading volume in GBP/10^9 over the previous 15 minutes. The realized volatility *rv15* over all markets is calculated from the average midpoint return from time *t* to time *t*-15 minutes. Firm dummy variables and dummy variables for each half-hour are not reported. I use Newey and West (1987) robust standard errors. 'a' denotes significance at the 1% level and 'b' at the 5% level.

	LSE vs. Chi-X		LSE vs. BATS		LSE vs. TQ	
	Estimate	t-stat.	Estimate	t-stat.	Estimate	t-stat.
Observations	14,225,679		10,611,072		8,926,552	
R^2	53.88%		46.56%		32.42%	
mkt × $size_1$	0.227	178.97[a]	-0.161	-85.09[a]	-1.254	-283.65[a]
mkt × $size_2$	0.272	190.44[a]	-0.113	-50.26[a]	-1.272	-253.28[a]
mkt × $size_3$	0.370	168.14[a]	-0.105	-27.66[a]	-1.353	-164.80[a]
mkt × $size_4$	0.421	115.32[a]	-0.159	-21.98[a]	-1.495	-87.16[a]
mkt × $size_5$	0.481	104.06[a]	-0.253	-23.73[a]	-1.810	-59.03[a]
$size_2$	0.049	36.25[a]	0.039	27.25[a]	0.059	38.88[a]
$size_3$	0.090	47.86[a]	0.073	36.16[a]	0.103	46.84[a]
$size_4$	0.124	45.39[a]	0.107	36.99[a]	0.141	44.20[a]
$size_5$	0.171	50.68[a]	0.180	48.92[a]	0.223	52.39[a]
qspread	0.741	1,128.88[a]	0.680	528.21[a]	0.548	287.51[a]
depth/10^6	0.000	41.37[a]	0.000	72.51[a]	0.000	76.76[a]
vol15/10^9	-0.004	-6.41[a]	-0.009	-11.36[a]	0.009	8.10[a]
rv15	0.029	1.27	0.147	4.85[a]	0.797	20.40[a]

Table 5.4: **Logistic regressions: Order routing decisions**. The sample consists of 98 stocks listed on the London Stock Exchange and in the FTSE 100. The observation period contains all trading days from April 19 to May 28, 2010. The table presents multinominal logistic regressions for the choice of trading venue. The LSE is used as reference category. The dependent variable is equal to zero for LSE trades and one for trades on Chi-X, BATS, and Turquoise. Chi-Square statistics are reported in parentheses below the estimated log odds ratios. The trading volume categories are obtained by ranking the firms in the sample by their total trading volume in April/May 2010. The first category contains 33 firms with the highest trading volume (high), the next 33 firms (medium), and the remaining 32 low volume firms (low). *qspreadDiff* is the difference between the EBB (EBO) for a sell (buy) order and the trade price relative to the midpoint of the consolidated order book. *rDepth1* is the depth at the bid (ask) for sell (buy) orders on the platform of execution relative to the average depth across trading venues and *rDepth3* includes depth three ticks behind the best price. The number of shares traded is *shareVolume*. The trading volume in British Pounds over all markets during the previous 15 minutes is *vol15*. The realized volatility *rv15* is the squared midpoint return from time t to time t-15 minutes. Firm fixed effects and dummy variables for each half-hour time period are not reported. 'a' denotes significance at the 1% level and 'b' at the 5% level.

Variable	MKT	Entire Sample		High		Medium		Low	
qspreadDiff	Chi-X	0.008^{a}	0.007^{a}	0.021^{a}	0.019^{a}	-0.009^{a}	-0.009^{a}	-0.013^{a}	-0.019^{a}
		(348)	(278)	(1,168)	(955)	(136)	(128)	(169)	(342)
	BATS	-0.033^{a}	-0.044^{a}	-0.024^{a}	-0.038^{a}	-0.041^{a}	-0.053^{a}	-0.051^{a}	-0.069^{a}
		(3,805)	(5,217)	(896)	(1,933)	(1,754)	(2,284)	(1,802)	(2,318)
	TQ	-0.105^{a}	-0.132^{a}	-0.108^{a}	-0.139^{a}	-0.106^{a}	-0.136^{a}	-0.102^{a}	-0.141^{a}
		(36,726)	(28,162)	(17,095)	(16,694)	(10,640)	(7,452)	(7,424)	(6,356)
rDepth1	Chi-X	2.143^{a}		1.708^{a}		2.780^{a}		3.230^{a}	
		(603,584)		(261,095)		(202,892)		(147,544)	
	BATS	5.576^{a}		5.450^{a}		5.538^{a}		6.131^{a}	
		(1,288,829)		(789,370)		(302,197)		(179,711)	
	TQ	6.823^{a}		6.991^{a}		7.088 ^{a}		6.019^{a}	
		(849,446)		(524,365)		(207,941)		(110,601)	

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Variable	MKT	Entire Sample		High		Medium		Low	
rDepth3	Chi-X		4.802[a]		3.517[a]		6.859[a]		8.055[a]
			(1,154,274)		(470,252)		(419,262)		(292,183)
	BATS		17.586[a]		15.598[a]		19.895[a]		20.944[a]
			(3,162,277)		(1,834,804)		(823,252)		(480,048)
	TQ		36.827[a]		31.264[a]		49.850[a]		40.670[a]
			(2,694,998)		(1,549,810)		(654,365)		(420,794)
$shareVolume/10^3$	Chi-X	0.016[a]	0.019[a]	0.015[a]	0.017[a]	0.038[a]	0.054[a]	0.058[a]	0.086[a]
		(22,621)	(28,171)	(18,773)	(22,232)	(6,716)	(12,062)	(4,100)	(8,105)
	BATS	0.042[a]	0.037[a]	0.038[a]	0.035[a]	0.072[a]	0.073[a]	0.104[a]	0.115[a]
		(33,277)	(23,600)	(25,408)	(19,056)	(7,892)	(7,058)	(4,650)	(4,844)
	TQ	0.034[a]	0.004[a]	0.031[a]	0.009[a]	0.056[a]	-0.005[a]	0.055[a]	-0.006[a]
		(14,986)	(206)	(9,444)	(857)	(2,879)	(113)	(1,123)	(48)
$vol15/10^9$	Chi-X	-0.052[a]	-0.141[a]	-0.041[a]	-0.102[a]	-0.429[a]	-1.414[a]	-0.801[a]	-2.502[a]
		(4,468)	(28,229)	(2,617)	(14,631)	(1,864)	(17,531)	(693)	(5,603)
	BATS	-0.041[a]	-0.224[a]	-0.035[a]	-0.187[a]	-0.667[a]	-2.767[a]	-1.607[a]	-4.246[a]
		(1,540)	(34,223)	(1,069)	(23,784)	(3,014)	(34,219)	(1,794)	(8,237)
	TQ	0.022[a]	-0.270[a]	0.018[a]	-0.222[a]	0.165[a]	-3.712[a]	-0.346[a]	-4.689[a]
		(211)	(23,019)	(129)	(15,891)	(98)	(22,018)	(48)	(4,986)
rv15	Chi-X	-0.203[a]	-0.416[a]	-0.106[a]	-0.282[a]	0.003	0.906[a]	0.456[a]	1.388[a]
		(166)	(632)	(32)	(213)	(0)	(522)	(67)	(501)
	BATS	-0.083[a]	-0.456[a]	0.041	-0.502	0.345[a]	2.411[a]	1.164[a]	3.170[a]
		(15)	(341)	(2)	(294)	(49)	(1,695)	(242)	(1,232)
	TQ	0.557[a]	-0.241[a]	0.719[a]	-0.332[a]	-0.298[a]	3.014[a]	1.790[a]	4.718[a]
		(317)	(42)	(359)	(58)	(23)	(1,118)	(213)	(1,097)
Observations		18,853,790	18,853,790	11,984,060	11,984,060	4,362,334	4,362,334	2,507,396	2,507,396

Studying competition in Nasdaq-listed stocks, Barclay et al. (2003) provide evidence that investors are more likely to route orders to ECNs when these platforms offer better prices than Nasdaq market makers. I find similar results for MTFs, although there is no official European consolidated tape that allows investors to observe prices across platforms. It appears that investors use technology such as smart order routing (SOR) systems. SOR systems are designed to automate the selection process of an execution venue and thus may help to execute orders optimally in the fragmented European trading landscape (Foucault and Menkveld, 2008).

5.4 Price Discovery

An important component of market quality is price discovery. To characterize trade based price discovery, I perform analyses presented in Hasbrouck (1991a) and Hasbrouck (1991b) and extend the typically used vector autoregressions (VAR) to differentiate between different trading venues as in Barclay et al. (2003) and in Hendershott and Jones (2005). In the estimation I separate trades executed on the LSE, Chi-X, BATS, and Turquoise and thus their individual impact on the consolidated midpoint process across trading venues. The results of the VAR analysis are the average cumulative response functions for different trading venues over 10 trades estimated separately per day and per stock. The permanent price impact of a trade, the trade innovation, is typically interpreted as representing the private information of investors (Hasbrouck, 1991a). To measure the contribution to quote based price discovery of each trading venue, I follow Hasbrouck (1995) who suggests that the contribution to price discovery of a market can be measured as the proportional contribution of trading venue innovations to innovations in the common efficient price. Section 4.3 provides an in-depth explanation of the methodology that I use in this section.

Table 5.5 presents the results on different dimensions of price discovery per day and per stock. LSE trades impound 22.4% of the total information into stock prices (% Trade Based) in April/May 2010. Trade based information on Chi-X is with 19.6% marginally lower than on the LSE. On both BATS and Turquiose the relative contribution is statistically and economically significantly lower at 7.7% and 6.1%, respectively.[5]

[5]I also test differences between the LSE and each MTF for all stocks separately. Trade based information is higher at the 5.0% signifiance level for 42 stocks out of 98 stocks on the LSE compared to

Table 5.5: **Trade and quoted based price discovery**. The sample consists of 98 stocks listed on the London Stock Exchange and in the FTSE 100. The observation period contains all trading days from April 19 to May 28, 2010. I present trade based measures, average daily information content of trades Hasbrouck (1991b) and daily permanent price impacts Hasbrouck (1991a). Average daily information content of quotes Hasbrouck (1991b) and information shares Hasbrouck (1995) are reported as quote based measures. Information shares are the mean of lower and upper bounds. I sum information shares and trade correlated and quote correlated information to arrive at total price discovery. Standard deviations are given in parentheses below the daily means. Mean differences between the LSE and each MTF are tested for statistical significance using Thompson (2011) standard errors with 'a' denoting statistical significance at the 1% level and 'b' at the 5% level.

	Overall Value	LSE	Chi-X	BATS	TQ
Trade Based Price Discovery					
% Trade Based		22.42%	19.57%^{a}	7.74%^{a}	6.08%^{a}
		(6.12%)	(6.04%)	(4.30%)	(4.34%)
Trade Innovation		1.254	1.144^a	0.718^a	0.641^a
		(0.598)	(0.515)	(0.404)	(0.417)
Quote Based Price Discovery					
% Quote Based	44.18%				
	(10.08%)				
Inform. Shares		27.63%	56.77%^{a}	11.66%^{a}	3.94%^{a}
		(10.50%)	(12.57%)	(7.54%)	(4.78%)
Total Contribution to Price Discovery					
Fraction of PD		34.63%	44.62%^{a}	12.91%^{a}	7.84%^{a}
		(8.07%)	(9.19%)	(4.95%)	(4.56)

The permanent price impact of a trade on the LSE is on average 1.25 bps, 1.14 bps on Chi-X, 0.72 bps on BATS, and 0.64 bps on Turquoise.[6]

Quote based contribution to price discovery averages 44.2% using the Hasbrouck (1991b) variance decomposition technique. In contrast to the trade based measures, I find that Chi-X contributes considerably more to quote based price discovery. Information shares of the LSE are 27.6%, of Chi-X 56.8%, of BATS 11,7%, and of Turquoise 3.9%.[7]

Chi-X. The opposite relationship is found for 12 stocks. For all stocks significantly more information is impounded into prices on the LSE relative to BATS and Turquoise.

[6]Trades in 41 stocks on the LSE contain on average more information than on Chi-X. The opposite is true for 12 stocks. Trade innovation is higher for 97 (98) stocks on the LSE relative to BATS (Turquoise).

[7]Mean information shares are significantly higher at the 5.0% level for 96 out of 98 stocks on Chi-X compared to the LSE. This is true for 83 (98) stocks for a comparison between the LSE and BATS (Turquoise).

To assess the total contribution of a trading venue to price discovery, I combine information shares and the fraction of quote based information to obtain a variable that describes total quote based price discovery relative to trade based price discovery as shown in Equation (4.14). The results are reported in the last row of Table 5.5, labeled 'Fraction of PD'. I find that the LSE contributes 34.6% to total price discovery in April/May 2010. Surprisingly, Chi-X contributes 10.0% more to price discovery (44.6%) than the LSE. This result is in contrast to the common concern that MTFs may piggy-back on the prices determined in regulated markets. Most importantly, the prices posted on Chi-X are more efficient, in that they 'move first', compared to any other market. BATS and Turquoise participate significantly less in total price discovery than the LSE and Chi-X, 12.9% and 7.8% and may in fact be simply piggy-backing off of prices determined elsewhere. The results also indicate that a higher fraction of price discovery is not simply generated by higher trading activity. For example, the LSE's market share is about 17.0% higher than its contribution to total price discovery. The divergence between total trading volume and information shares is also documented by Barclay et al. (2003) and in Hendershott and Jones (2005). In the cross-section, LSE's total contribution to price discovery increases from an average of 30.3% for high volume stocks to 38.8% for low volume stocks.[8]

Some regulators and practitioners are concerned that MTFs free-ride off price discovery delivered by regulated markets. The results presented in this section indicate that MTFs, especially Chi-X, contribute considerably to price discovery. However, it is important to emphasize that these results are characteristic of a 'normal' trading environment, i.e. the regulated market is fully operational. MTFs may not be able to provide a similar level of overall market quality when the regulated market has to stop trading as documented for the LSE outage on November 9 and November 26, 2009.[9]

The literature studies in detail competition between Nasdaq market makers and ECNs and shows that the latter significantly contribute to price discovery. Huang (2002) and Barclay et al. (2003) find that informed traders prefer to trade on anonymous ECNs instead with Nasdaq market makers. In this context, Goldstein et al. (2008) study the trade-off between anonymity and liquidity. It appears that informed

[8]Trading volume categories are obtained as described in Section 5.3.2.

[9]See http://www.ft.com/cms/s/0/49b9fc9e-ea6e-11de-a9f5-00144feab49a.html#axzz1LbS299Yr/ for an overview of LSE outages.

trading gravitates towards the most liquid platform in order to ensure fast executions. This chapter differs to the extent that both the LSE and MTFs are organized as electronic limit order books, i.e. they are anonymous. My results suggest that the highest fraction of informed trading takes place on the most liquid trading venues, the LSE and Chi-X.

5.5 Changes Over Time

Since their introduction in 2007, MTFs have gained considerably in market share (see Section 2.2), raising the question whether an increase in MTF total market share and therefore an increase in fragmentation, corresponds to a higher contribution of MTFs to market quality. This section therefore presents results of a comparison between the period analyzed in the previous sections, April 19 to May 28, 2010, and April 20 to May 29, 2009. I select these two periods because they leave enough time for developments and mitigate seasonal effects that may affect the analysis.

Equivalent to the first observation period in April/May 2010 (see Section 4.1), I retrieve trade and quote data for the LSE, Chi-X, BATS, and Turquoise from Thomson Reuters DataScope Tick History for April/May 2009. I apply the same filters on FTSE 100 constituents as for the first observation period and obtain 74 stocks. To assure a clean comparison, I restrict the analysis to 70 stock pairs contained in both samples.[10] Compared to the data set consisting of 98 sample firms used in the previous sections, the 70 selected stocks are more actively traded and are generally more liquid. However, results on liquidity and price discovery are very similar, i.e. Chi-X is the most liquid trading venue and contributes significantly more to price discovery than any other platform. The selected sample also confirms the widely observed tendency that trading was more concentrated on the LSE in April/May 2009 with a market share of 70.2% compared to only 51.8% in April/May 2010.[11]

Figure 5.2 and Figure 5.3 present the development of average daily effective spreads and total contribution to price discovery of the LSE, Chi-X, BATS, and Turquoise

[10] CABLE & WIRELESS (CW), CADBURY (CBRY), DRAX GROUP (DRX), and THOMSON REUTERS (TRIL) are removed from the April/May 2009 data set containing 74 sample firms (see Appendix B).

[11] In Chapter 6 the 70 stock pairs are analyzed from a different perspective, see Table 6.1 for details on descriptive statistics in April/May 2009 and April/May 2010.

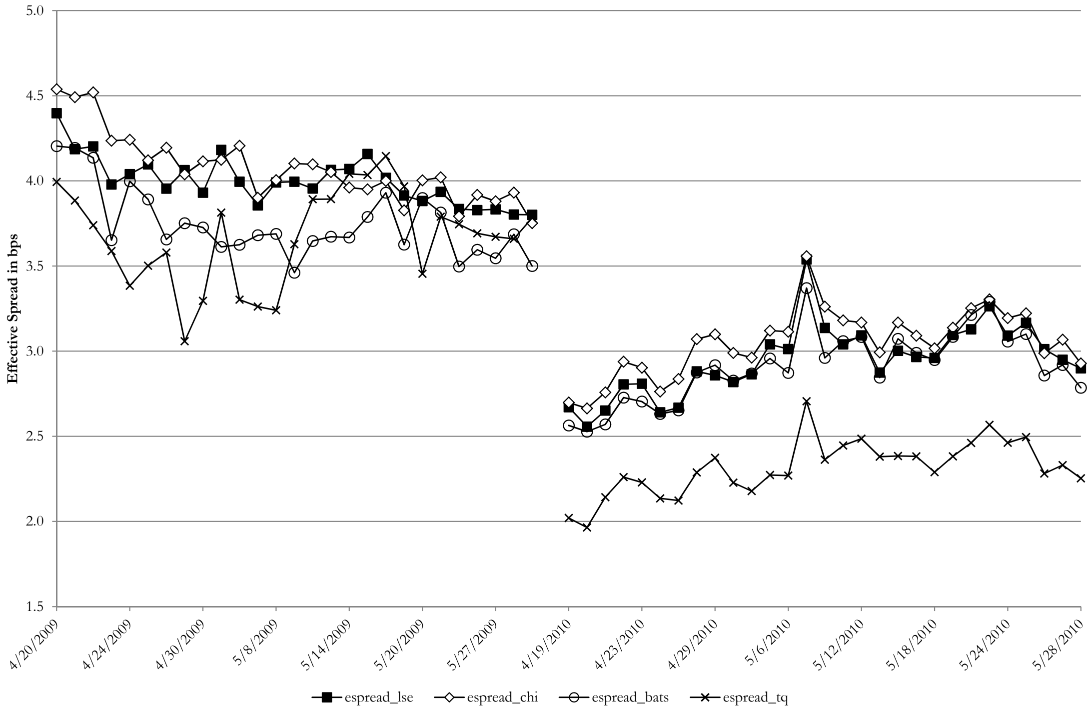

Figure 5.2: **Effective spreads over time**. The figure shows average daily effective spreads on the LSE, Chi-X, BATS, and Turquoise in FTSE 100 constituents over both observation periods, April/May 2009 and April/May 2010. Effective spreads are the relative difference between the trade price and the midpoint of the consolidated order book across trading venues per day and per stock.

for both observation periods. Average effective spreads are substantially lower in April/May 2010 compared to April/May 2009. In addition, differences between the LSE, Chi-X, and BATS seem to be smaller in the second observation period. Effective spreads are clearly lower on Turquoise than on any other trading venue, especially in 2010. Figure 5.3 depicts that Chi-X takes the leadership in total price discovery from the LSE for April/May 2010. BATS also increases its contribution to the price discovery process relative to the observation period in 2009.

To control for differences in market conditions between both observation periods, I use a regression model similar to Hendershott and Moulton (2011):

$$measure_{i,t} = \alpha_i + \beta_{i,t}\, year_{i,t} + \gamma_{i,t} \sum controls_{i,t} + \epsilon_{i,t} \tag{5.5}$$

where the dependent variables are various trading intensity, liquidity, and price discovery measures as defined in the previous sections. The main variable of interest,

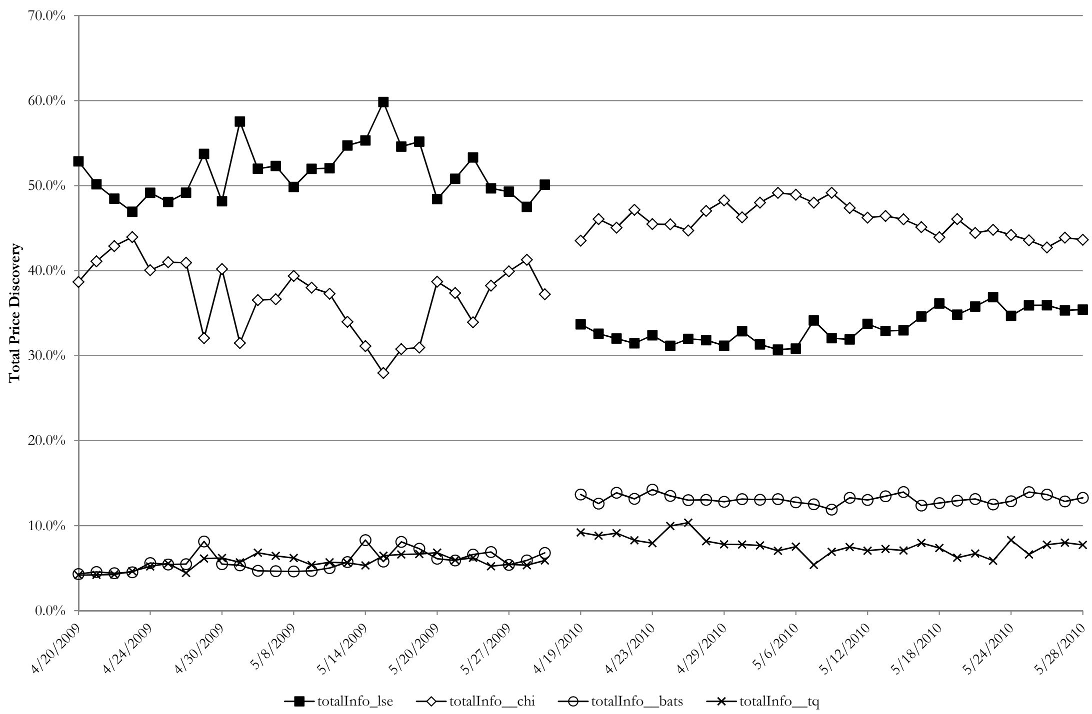

Figure 5.3: **Total price discovery over time**. The figure shows the average daily contribution to total price discovery of the LSE, Chi-X, BATS, and Turquoise in FTSE 100 constituents over both observation periods, April/May 2009 and April/May 2010. To arrive at total price discovery, I sum information shares and trade correlated and quote correlated information per day and per stock as defined in Equation 4.14.

$year_{i,t}$, captures the differences between the observation period in April/May 2009 and April/May 2010. It takes the value one for a trading day in the 2010 observation period and is zero otherwise. I further include the logarithm of daily market capitalization, the average daily realized volatility, the logarithm of average trade prices across trading venues, and firm dummy variables. Robust Thompson (2011) clustered standard errors are reported. In Table 5.6, the first columns for each trading venue (2010-2009) reports coefficients on $year_{i,t}$, the difference in dependent variables between April/May 2009 and April/May 2010. The second columns, with the exception of the LSE, report the difference to the LSE (Venue-LSE) and reveals whether or not a platform is improving over time relative to the LSE.

Table 5.6: **Trading intensity, liquidity, and price discovery measures between 2009 and 2010**. I compare stocks listed on the London Stock Exchange's and in the FTSE 100 in two observation periods. The first period contains trading days between April 20 to May 29, 2009 and the second between April 19 to May 28, 2010. The final sample contains 70 stock pairs. The following regression model is used to test for differences (1) between the observation periods (2010-2009) and (2) for trading venue differences relative to the LSE (Venue-LSE) per day t and per stock i: $measure_{i,t} = \alpha_{i,t} + \beta_{i,t}\, year_{i,t} + \gamma_{i,t} \sum controls_{i,t} + \epsilon_{i,t}$. Control variables are the average daily realized volatility, the log of daily stock prices across trading venues, and the log of the market capitalization. The $year_{i,t}$ dummy variable, reported below, captures differences between the two periods. It is zero for 2009 and one for 2010. Dependent variables ($measure_{i,t}$) are the same as defined in the previous tables. I use Thompson (2011) clustered standard errors. t-statistics are presented below the regression estimates in italic letters. 'a' denotes significance at the 1% level and 'b' at the 5% level.

	LSE	Chi-X		BATS		TQ	
	2010-2009	2010-2009	ChiX-LSE	2010-2009	BATS-LSE	2010-2009	TQ-LSE
Panel A: Trading Intensity and Liquidity							
Market Shares	-16.74%[a]	9.37%[a]	26.11%[a]	7.81%[a]	24.54%[a]	-0.44%	16.30%[a]
	-14.93	*13.34*	*15.31*	*12.74*	*15.24*	*-1.01*	*12.03*
Volume (1,000 GBP)	4,320	12,935[a]	8,615[a]	6,672[a]	2,352	371	-3,948
	0.92	*3.39*	*2.85*	*4.86*	*0.59*	*0.94*	*-0.88*
Trade Count	282	1,191[a]	909[a]	926[a]	644[a]	72	-210
	0.99	*4.00*	*6.34*	*6.07*	*3.38*	*1.43*	*-0.84*
Trade Size (GBP)	288	1,120[a]	832[a]	791[a]	503	105	-183
	0.79	*3.59*	*3.03*	*2.60*	*1.68*	*0.43*	*-0.58*
Price Changes (#/min)	9.17[a]	12.86[a]	3.69[b]	12.32[a]	3.16[b]	4.90[b]	-4.27[a]
	3.27	*3.25*	*2.03*	*3.49*	*2.00*	*2.27*	*-2.74*
Quoted Spread	-0.445	-1.396[a]	-0.951[a]	-1.303[a]	-0.858[a]	-2.160	-1.715
	-1.50	*-4.64*	*-7.52*	*-3.56*	*-3.51*	*-1.32*	*-1.10*
Quoted Spread Trade	-0.905[a]	-1.291[a]	-0.386[a]	-1.324[a]	-0.419[a]	-1.534	-0.629
	-4.24	*-5.50*	*-4.84*	*-4.90*	*-2.59*	*-1.74*	*-0.74*
Effective Spread	-0.882[a]	-0.857[a]	0.025	-0.658[a]	0.224[a]	-1.242[a]	-0.361[a]
	-4.82	*-4.57*	*0.58*	*-3.91*	*3.26*	*-7.24*	*-4.06*

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	Overall	LSE	Chi-X		BATS		TQ	
	2010-2009	2010-2009	2010-2009	ChiX-LSE	2010-2009	BATS-LSE	2010-2009	TQ-LSE
Realized Spread 5		0.487[a]	0.584[a]	0.097	0.638[a]	0.152	0.053	-0.434[b]
		2.82	*3.93*	*0.87*	*4.23*	*0.96*	*0.22*	*-2.44*
Realized Spread 15		0.150	0.346	0.196	0.376	0.226	-0.334	-0.485
		0.75	*1.81*	*1.37*	*1.71*	*1.12*	*-0.73*	*-1.19*
Price Impact 5		-1.369[a]	-1.441[a]	-0.073	-1.298[a]	0.071	-1.308[a]	0.060
		-5.27	*-5.97*	*-0.71*	*-5.83*	*0.41*	*-5.07*	*0.34*
Price Impact 15		-1.036[a]	-1.201[a]	-0.165	-1.027[a]	0.009	-0.922[b]	0.114
		-4.05	*-4.88*	*-1.11*	*-4.00*	*0.04*	*-1.99*	*0.28*
Depth1 (GBP)		-351	-2,361	-2,010	-3,338	-2,987	2,660[b]	3,011
		-0.08	*-0.42*	*-0.58*	*-0.83*	*-1.02*	*2.27*	*0.76*
Depth3 (GBP)		69,410[a]	-3,666	-72,217[a]	2,238	-66,506[a]	14,648[b]	-54,160[b]
		2.82	*-0.14*	*-3.59*	*0.14*	*-3.72*	*2.48*	*-2.44*
Panel B: Price Discovery								
% Trade Based		-11.39%[a]	4.32%[a]	15.71%[a]	4.65%[a]	16.04%[a]	1.74%[a]	13.12%[a]
		-14.59	*7.56*	*16.51*	*9.36*	*16.61*	*4.00*	*15.69*
Trade Innovation		-1.163[a]	-0.464[a]	0.699[a]	-0.008	1.155[a]	-0.162[a]	1.001[a]
		-9.70	*-5.43*	*11.55*	*-0.13*	*12.22*	*-3.06*	*10.14*
% Quote Based	0.67%							
	0.49							
Inform. Shares		-12.96%[a]	8.85%[a]	21.81%[a]	5.50%[a]	18.46%[a]	-1.38%[b]	11.58%[a]
		-5.28	*3.59*	*4.60*	*4.37*	*6.00*	*-2.47*	*4.67*
Fraction of PD		-16.64%[a]	8.45%[a]	25.09%[a]	7.09%[a]	23.73%[a]	1.10%[b]	17.74%[a]
		-11.84	*5.95*	*9.35*	*10.92*	*13.49*	*2.16*	*11.76*

The market activity results in Table 5.6, Panel A show that trading volume and the number of trades significantly increase between April/May 2009 and April/May 2010 for Chi-X and BATS whereas they do not change for the LSE and Turquoise. A higher number of price updates suggests that order submission strategies are more responsive to market conditions on these trading venues. An important question is whether or not liquidity is also increasing with activity. I find the expected negative coefficients on the dummy variable $year_{i,t}$ for quoted spreads, quote spreads at trade time, and effective spreads, indicating that liquidity has improved over time despite increased fragmentation. The latter falls over time by -0.88 bps on the LSE, -0.86 bps on Chi-X, -0.66 bps on BATS, and -1.24 bps on Turquoise (see Figure 5.2). I also find that for Chi-X and BATS that quoted spreads and quoted spreads at trade time fall significantly compared to the LSE spreads.

Panel B of Table 5.6 reports regression results for price discovery variables. These results show a clear increase in the relative contributions to price discovery of MTFs over time and compared to the LSE. While trade based information falls on the LSE by -11.4% between April/May 2009 and April/May 2010, it increases by 4.3% on Chi-X, 4.7% on BATS, and 1.7% on Turquoise. Overall trades become less informed but trade innovation increases significantly on all MTFs relative to the LSE. The contribution to quote based price discovery of the LSE and Turquoise falls between both oberservation periods by -13.0% and -1.4%, respectivley, whereas information shares raise by 8.9% for Chi-X and by 5.5% for BATS. In 2009, the LSE contributes on average more to total price discovery than any MTF, about 52.0%. The regression results provide empirical support for a sharp increase in total contribution to price discovery of Chi-X and BATS (see Figure 5.3). Chi-X leads total price discovery in the 2010 observation period as discussed in the previous section.

The data do not allow for direct tests of the impact of different competitive actions such as trading fee changes, exchange system updates, and the impact of algorithmic and high-frequency traders. However, the picture emerges that market quality on MTFs as "high-frequency trader friendly environment" (Menkveld, 2011) improves between April/May 2009 and April/May 2010 relative to the LSE. In addition, the data do not support the claim that fragmentation harms overall market quality. It appears that both the LSE and MTFs become more liquid in terms of quoted and effective spreads.

5.6 Conclusion

MiFID ended the quasi-monopoly of national exchanges across Europe and new alternative trading platforms have emerged. These competitive market dynamics in combination with recent technological improvements, such as low-latency trading infrastructure or algorithmic and high-frequency trading, significantly transformed European equities trading. The question arises whether MTFs are competitive on liquidity and contribute to overall market quality in a fragmented trading landscape.

There is currently a debate about the impact of market fragmentation. Some authors argue in favor of order flow consolidation on one single platform (e.g. Easley et al., 1996; Bennett and Wei, 2006). Other studies emphasize that competition for order flow may improve overall market quality (e.g. Barclay et al., 2003; Goldstein et al., 2008, O'Hara and Ye, 2011). There is a growing body of literature that analyzes European equities trading post MiFID (e.g. Degryse et al., 2011; Menkveld, 2011), under a set of rules which differs considerably from U.S. regulation. This chapter contributions to this line of literature, offering new insights on liquidity, investors' order routing decisions, and price discovery.

It appears that Chi-X, an MTF, is the most liquid platform for FTSE 100 constituents in terms of quoted spreads during the observation period, April/May 2010. Effective spreads are significantly smaller on Turquoise than on the LSE, Chi-X, and BATS. However, this finding may be driven by executions against stale limit orders in the order book of Turquoise. The time a trading venue spend at the European Best Bid and Offer (EBBO) varies and investors can profit, in terms of better transaction prices, from trading on multiple platforms. Logistic regression results imply that investors condition their trading decisions on general liquidity factors, i.e. orders are more likely to be routed to MTFs when these platforms offer better prices relative to the LSE.

The evidence suggests that the most liquid trading venues Chi-X and the LSE lead in trade and quote based price discovery. In April/May 2010, on Chi-X 44.6% of total information is impounded into prices compared to 34.6% on the LSE, 12.9% on BATS, and 7.8% on Turquoise. I further compare trading intensity, liquidity, and price discovery measures between April/May 2010 and April/May 2009. Market quality improves on each trading venue over time in the level of market fragmentation and price discovery shifts towards MTFs.

There is a widespread concern among regulators, practitioners, and academics that MiFID, in contrast to U.S. RegNMS, may fail to integrate the various trading venues. O'Hara and Ye (2011), for instance, argue that "it is hard to see how a single virtual market can emerge in Europe" without consolidated trade and quote information and a lack of trade-through protection. For high volume stocks, this chapter provides some evidence that competitive forces within the MiFID framework ensure a high level of market quality and that MTFs, despite the concerns, contribute significantly to equity market quality. To further examine the level of market coordination, the next chapter analyzes apparent arbitrage opportunities and suboptimal executions.

Chapter 6

Arbitrage and Suboptimal Executions

6.1 Introduction

The automation of exchanges and newly introduced regulations have significantly altered the trading landscape during the last decade. These changes have facilitated new trading venues and allowed their entry into the market for exchange business. One consequence of competition between trading venues is that liquidity, i.e. the ability to trade a certain number of shares at a given price, is fragmented across different trading venues. This fragmentation imposes increased search costs on investors. In the U.S., different trading venues are linked by the NMS so that investors can observe the best available price. In Europe, there is no such link. Since it is in the investors interest to trade at best prices, it is an open question whether competition ensures an integrated market in the absence of a formal linkage.

Comparing European equity trading regulation under MiFID and its U.S. counterpart, RegNMS, reveals substantial differences (see Section 2.1). In Europe, there is no trade-through protection or consolidated trade and quote information. RegNMS requires trading venues to establish, maintain, and enforce procedures to prevent trade-throughs (Rule 611), i.e. orders that are executed at worse prices than the best available price across trading venues. For this purpose trading venues are electronically linked via the ITS and private linkages. In the U.S., comprehensive consolidated market information is available to provide price information to the public. The data comprise the NBBO for a stock, the corresponding volume, and the trading venue. European regulation does not establish a single data consolidator. However, firms, such as Thomson Reuters and Dow Jones, offer consolidated data streams on a commercial basis to investors.

There is an ongoing debate among practitioners and academics about the impact of differences in MiFID and RegNMS on market quality. MiFID allows the market entry of new platforms but it does not impose formal linkage requirements. For instance, O'Hara and Ye (2011) highlight that European equity markets lack consolidated trade and quote information and trade-through protections. In their opinion, it is therefore unlikely that one virtual market can emerge. Stoll (2001), however, points out that a formal linkage may impede innovation and cause high infrastructure costs. Battalio et al. (2004) study the U.S. option market in the absence of a formal linkage and conclude that the costs of a formal linkage may be avoided in the case of fierce intermarket competition, sophisticated investor technology, and the threat of increased regulation.

Following Battalio et al. (2004), this chapter uses different order book scenarios to evaluate the coordination of quotes across trading venues as depicted in Figure 6.1. Scenario 1 characterizes a 'normal' trading environment with a positive inside spread (EBB<EBO). Quotes are locked if the best posted bid across trading venues (EBB) equals the best ask (EBO, Scenario 2) and crossed if the best bid exceeds the best posted ask (EBB>EBO, Scenario 3). Crossed quotes represent apparent arbitrage opportunities and thus are inconsistent with the law of one price. In addition, this chapter characterizes suboptimal executions, i.e. trades which are executed worse than the best available price across trading venues (Scenario 4).

This chapter studies FTSE 100 constituents traded on the LSE and the three largest MTFs, namely Chi-X, BATS, and Turquoise. The analysis is based on two observation periods: April/May 2009 and April/May 2010. Initially, I examine spread and quote measures as a proxy for competition. While the LSE posts on average the smallest quoted spreads and is most often at the best available price in the consolidated order book over the observation period in 2009, Chi-X is more liquid in 2010. Locks and crosses offer insights into market coordination. In April/May 2009, I find that markets are locked (crossed) for 24.5 minutes (16.0 minutes) of each trading day per stock. Over the observation period in 2010, the average time of locks (crosses) decreases to 6.4 minutes (19.8 seconds), representing an 74.0% (97.6%) decline. Quotes of Turquoise are considerably more often locked and crossed than quotes of any other trading venue. Potential revenues from arbitrage activities during crossed market periods are particularly interesting. I identify overall revenues of 614,217 GBP before transaction costs

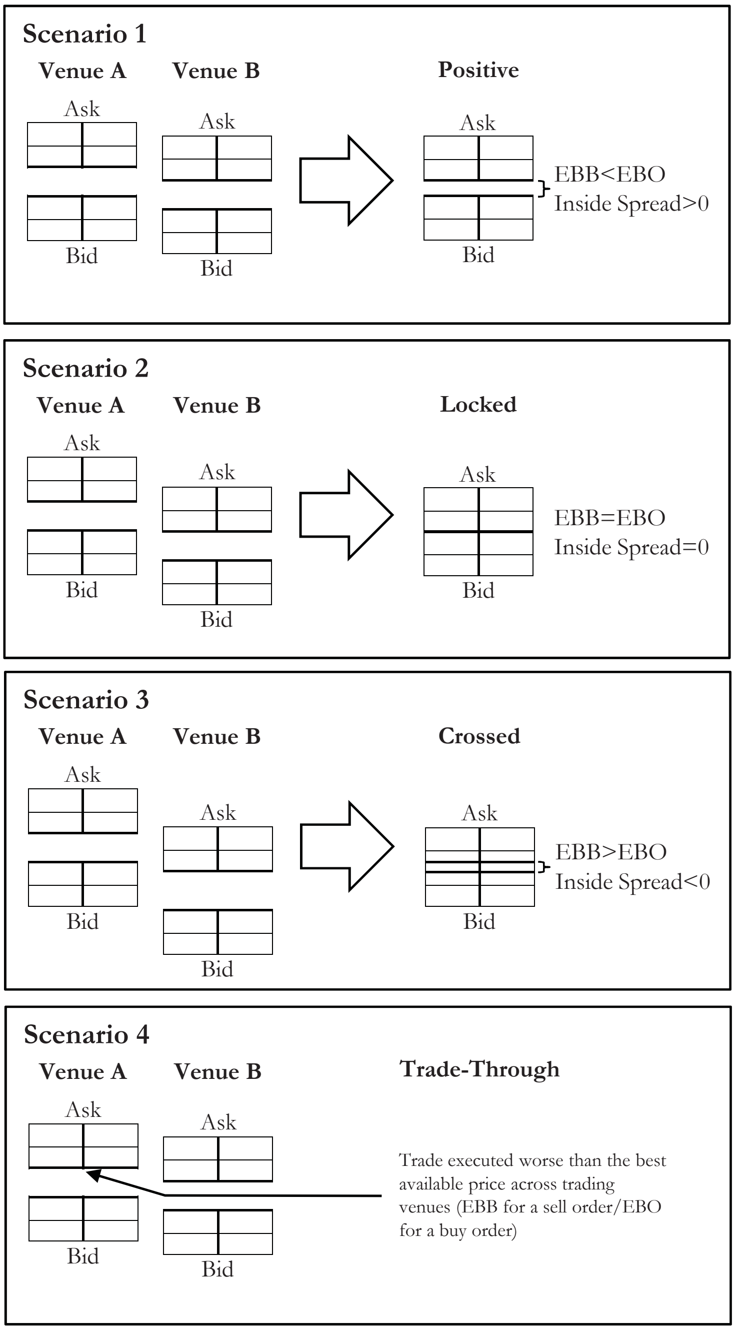

Figure 6.1: **Order book scenarios: Locks, crosses, and trade-troughs**. The figure illustrates four order book scenarios used to examine market conditions. In Scenario 1, trading venue A posts the inside bid and trading venue B is at the inside ask (EBB<EBO). In Scenario 2, trading venue A's bid equals trading venue B's ask and the market is locked (EBB=EBO). In Scenario 3, the market is crossed (EBB>EBO) and trading venue A's bid is higher than trading venue B's ask. Scenario 4 illustrates a buy at trading venue A's ask which is higher than trading venue B's ask, i.e. the best available price across trading venues is traded-through.

across stocks over the 2009 observation period and 404,700 GBP in 2010, representing a 34,1% decline. However, not every arbitrage opportunity is exploitable after transaction costs.

Trade-through rates are a common statistic to evaluate price-priority violations. The fraction of trade-throughs as a percentage of the total number of trades per day and per stock ranges from 5.2% to 8.7% across trading venues in the 2009 observation period and from 4.7% to 6.9% in 2010. Taking the available depth at the EBBO into account, investors strictly executing at the best available price can realize potential savings of 2,095 GBP per day and per stock in April/May 2009 and 1,569 GBP in April/May 2010. Economic intuition suggests that investors may evaluate execution speed over best prices in times of high intermarket activity. To proxy for intermarket activity, I use inside quoted spreads. Smaller spreads may be accociated with a higher demand of speedy executions. The regression results confirm my expectations, the likelihood of trade-throughs increases in the demand of speedy executions. This pattern implies that investors trade off liquidity and search costs. Overall, my results suggest that disconnected trading venues behave as if they were formally linked, indicating a high level of market integration in FTSE 100 constituents.

The remainder of this chapter is structured as follows. Section 6.2 describes the sample selection and presents descriptive statistics. Section 6.3 examines the quote process, discussing apparent arbitrage opportunities in detail. Section 6.4 analyzes trade executions across trading venues. Section 6.5 summarizes and concludes.

6.2 Sample Selection and Descriptive Statistics

The empirical analyses in this chapter are based on FTSE 100 constituents during the following two observation periods: April 20 to May 29, 2009 and April 19 to May 28, 2010. The first observation period was selected because of the lack of structural market changes. There are no market microstructure, fee, or trading system changes on the LSE, Chi-X, BATS, and Turquoise. I choose the second time period in April/May 2010 to study effects of competition on quote and execution quality over time. In addition, this choice reduces seasonal effects that can distort results. The final sample covers 27 trading days in 2009 and 29 trading days in 2010.

The filter criteria as presented in Section 4.1 result in 74 stocks for the first observa-

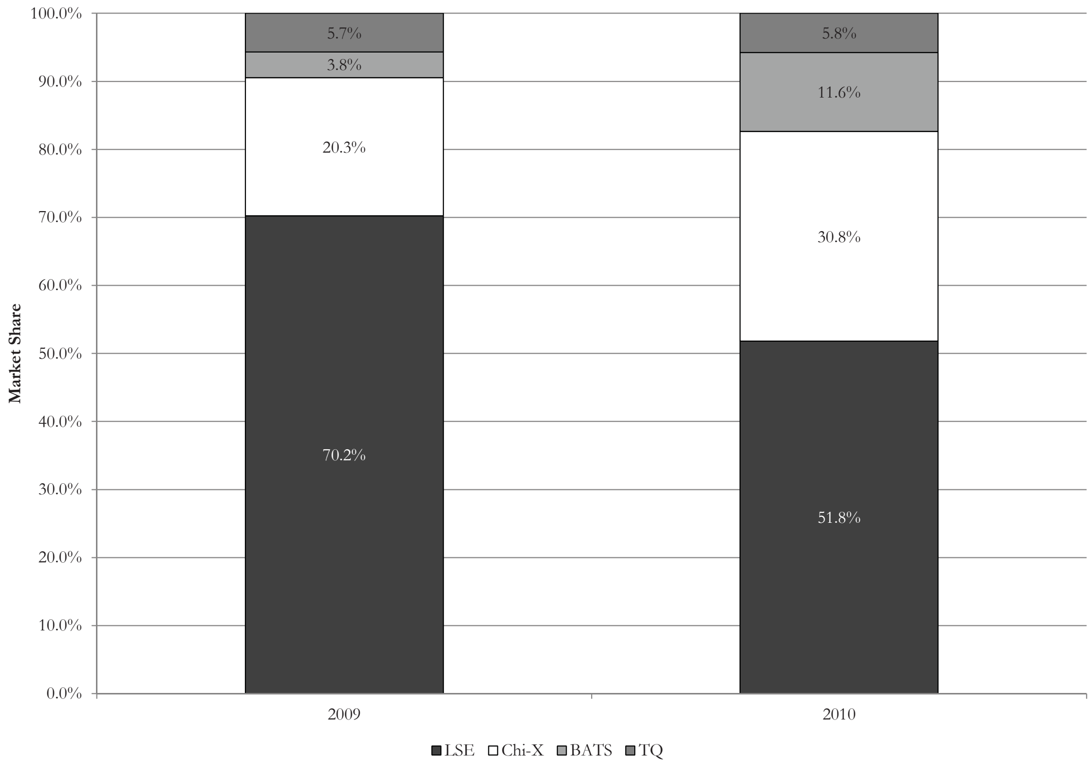

Figure 6.2: **Market shares of the LSE, Chi-X, BATS, and Turquoise**. The figure shows market shares for FTSE 100 constituents traded on the LSE, Chi-X, BATS, and Turquoise. The sample consists of 70 stocks pairs traded during both observation periods: April 20 to May 29, 2009 and April 19 to May 28, 2010. Market shares are based on trading volume in British Pounds per day and per stock.

tion period, April/May 2009, and in 98 stocks for April/May 2010. To analyze differences over time, I restrict the sample to 70 firms which are traded in both observation periods. To analyze the level of market integration, it is necessary to merge single order books from each trading venue into one consolidated order book per stock. Based on RICs and timestamps, I compute the EBB, the highest bid, across the LSE, Chi-X, BATS, and Turquoise, and the lowest ask price, the EBO. The data set is also used in Section 5.5 which studies trading intensity, liquidity, and price discovery over time.

Figure 6.2 illustrates the average daily share in trading volume of the LSE, Chi-X, BATS, and Turquoise for the observation periods in 2009 and 2010. Over the 2009 observation period the LSE attracts on average 70.2% of daily trading volume. As expected, I find a significantly smaller LSE market share of 51.8% in 2010. Chi-X, the largest MTF, attracts about 20.3% of daily trading volume over the 2009 observation period and 30.8% in April/May 2010. BATS more than triples its market share between both observation periods to 11.6% in 2010. The market share of Turquoise reaches 6.0% of daily trading volume over both observation periods. Hence, the descriptive statistics show that trading in FTSE 100 constituents became more fragmented whereas liquidity is still to be analyzed.

Table 6.1 reports trading activity and liquidity measures for both observation periods computed per day and per stock. In line with expectations, the data show a significantly higher daily trading volume for all trading venues over the 2010 observation period than in 2009.[1] Interestingly, the average trade size increases across all trading venues. In both sample periods average trade sizes on the LSE are statistically and economically significantly larger than on any MTF.

Quoted spreads are calculated for each price and volume update in the order book whereas quoted spreads at trades and effective spreads are computed trade-by-trade. Spreads are calculated as described in Section 4.2, meaning that I adapt the Bessembinder and Kaufman (1997b) spread calculation in combination with the Bessembinder (2003) adjustment of the standard Lee and Ready (1991) algorithm to estimate the trade direction. In April/May 2009, the average daily quoted spread ranges from 6.27 bps for the LSE to 14.00 bps for Turquoise. All trading venues have smaller quoted spreads at trades than during periods without trades. This result is evidence that investors actively monitor multiple order books and trade when it is relatively inexpensive to do so. Effective spreads are calculated on an individual order book level and are not considerably different from quoted spreads at trades, indicating that most trades are executed at the inside bid or ask. These findings also suggest that a considerable number of trades are executed against hidden orders on Turquoise, since the average effective spread is considerably smaller than the quoted spread at trades.[2] Order book depth is another dimension of liquidity and is significantly larger on the LSE and Chi-X than on BATS and Turquoise over the observation period in 2009.

[1] According to the European Equity Market Report of the Federation of European Securities Exchanges (FESE), average daily trading volume on the LSE, Chi-X, BATS, and Turquoise increases by about 54.0% between the first half of 2009 and 2010, see http://www.fese.eu/.

[2] A high number of inside the spread executions on Turquoise supports this result. In April/May 2009, on average about 0.1% of all trades on Chi-X and BATS and 3.0% on Turquoise are executed inside the individual order book's bid-ask spread. The corresponding values are 0.8% for the LSE in April/May 2010, 1.9% for Chi-X, 2.3% for BATS, and 10.9% for Turquoise.

Table 6.1: **Descriptive statistics: Trading intensity and liquidity measures**. The sample consists of 70 stocks listed on the London Stock Exchange and in the FTSE 100. The selected stocks are traded in both observation periods: April 20 to May 29, 2009 and April 19 to May 28, 2010. Descriptive statistics are reported for individual order books of the LSE, Chi-X, BATS, and Turquoise per day and per stock. Volume gives the trading volume in thousand British Pounds, Trade Count the corresponding number of executed trades, and Trade Size the average order size in British Pounds. Spread measures are reported relative to the midpoint of individual order books in basis points. The Quoted Spread is calculated on a tick-by-tick basis per stock, the Quoted Spread Trade is calculated trade-by-trade. Depth1 is half the quoted depth at the best bid and ask. Depth3 includes the total quoted volume three ticks behind best prices. Mean differences between the two observation periods are tested for statistical significance using Thompson (2011) clustered standard errors with 'a' denoting statistical significance at the 1% level and 'b' at the 5% level.

	April/May 2009				April/May 2010			
	LSE	Chi-X	BATS	TQ	LSE	Chi-X	BATS	TQ
Volume (1,000 GBP)	36,754	11,282	2,136	3,232	43,981[b]	28,301[a]	9,250[a]	4,082[a]
	(45,893)	(14,031)	(2,902)	(4,572)	(62,799)	(41,325)	(11,459)	(4,755)
Trade Count	2,949	1,460	352	493	3,105	2,874[a]	1,318[a]	606[a]
	(2,139)	(1,098)	(307)	(488)	(3,192)	(3,141)	(1,264)	(532)
Trade Size (GBP)	9,982	6,044	4,723	5,306	11,624[a]	8,118[a]	6,048[a]	5,867[a]
	(4,883)	(3,223)	(2,519)	(2,328)	(4,953)	(3,690)	(2,899)	(2,488)
Quoted Spread	6.266	6.632	8.075	14.003	5.373[a]	4.612[a]	5.561[a]	8.037[a]
	(2.336)	(2.651)	(6.455)	(16.128)	(1.873)	(1.745)	(2.346)	(3.739)
Quoted Spread Trade	4.714	5.019	5.852	8.852	3.644[a]	3.459[a]	3.975[a]	5.131[a]
	(1.727)	(1.899)	(2.439)	(8.726)	(1.290)	(1.278)	(1.570)	(2.197)
Effective Spread	4.792	5.115	6.067	8.711	3.662[a]	3.430[a]	3.998[a]	4.570[a]
	(1.757)	(1.933)	(2.518)	(8.721)	(1.289)	(1.239)	(1.556)	(1.900)
Depth1 (GBP)	36,334	30,342	21,623	8,917	43,696[b]	35,540	23,988	13,377[a]
	(29,335)	(33,416)	(23,191)	(5,738)	(28,845)	(30,450)	(21,648)	(9,161)
Depth3 (GPB)	129,579	141,376	83,333	28,445	231,022[a]	174,592	108,224[b]	48,911[a]
	(111,706)	(160,010)	(91,600)	(28,060)	(185,854)	(145,087)	(95,801)	(43,028)

In 2010, the average daily number of trades is 3,105 per stock on the LSE and 2,874 on Chi-X. However, the average trading volume is still considerably higher on the LSE. The average LSE trade size is roughly 3,500 GBP larger than on Chi-X. This result is consistent with Goldstein et al. (2008) who find smaller trade sizes on ECNs compared to Nasdaq montage. Quoted spreads on the LSE decrease between the 2009 observation period and 2010 by 0.89 bps, on Chi-X by 2.02 bps, on BATS by 2.51 bps, and on Turquoise by 6.00 bps. The descriptive statistics provide first evidence of strong competition for liquidity supply and additionally for a market where overall liquidity increases over time.[3]

6.3 Quote Quality

This section focuses on quote quality. Quotes are determined by traders who submit limit orders. It is possible that traders systematically ignore competing quotes on other platforms, so that arbitrage opportunities arise. Section 6.3.1 describes how long each market is at the inside spread in the sense that it quotes the highest bid (EBB) and the lowest ask across trading venues (EBO). Section 6.3.2 investigates the prevalence of locked (EBB=EBO) and crossed markets (EBB>EBO). Section 6.3.3 provides details on determinants of non-positive spread initiations and terminations per platform.

6.3.1 Quote Competition

Transaction costs comprise explicit and implicit trading costs. Explicit costs include, for instance, transaction fees and taxes, implicit costs are associated with costs for immediacy, market risk, and market impact. Assuming equal explicit costs and sufficient market depth across trading venues, investors can realize best execution by selling (buying) in the market with the highest bid (lowest ask). As a consequence, the attractiveness of a trading venue to liquidity takers may be characterized by the platform's participation rate in the inside spread. I provide four measures of quote competitiveness (Goldstein et al., 2008): (1): presence at the EBBO (inside bid and/or ask) (2): presence at the EBB and EBO (3): alone at the EBBO (inside bid and/or ask) (4): alone at the EBB and EBO.

[3] In general, the results are in line with the evidence found in Section 5.5.

Table 6.2: **Quote based competition: Trading venue participation in the EBBO**. The sample consists of 70 stocks listed on the London Stock Exchange and in the FTSE 100. The selected stocks are traded in both observation periods: April 20 to May 29, 2009 and April 19 to May 28, 2010. A trading venue is at the European Best Bid and/or Offer (EBBO) if it quotes the highest bid and/or the lowest ask. If it participates alone in the EBBO, it provides the best price alone across the four trading venues. For both categories the table further presents statistics if a trading venue forms the entire EBBO. A trading venue has time priority if it is alone at the EBBO or posted the best price earlier than all other trading venues. Mean differences between the two observation periods are tested for statistical significance using Thompson (2011) clustered standard errors with 'a' denoting statistical significance at the 1% level and 'b' at the 5% level.

	April/May 2009				April/May 2010			
	LSE	Chi-X	BATS	TQ	LSE	Chi-X	BATS	TQ
Panel A: Time-weighted averages, % of trading day								
At EBBO	85.00%	76.85%	60.59%	52.87%	78.16%[a]	87.24%[a]	68.20%[a]	53.14%
(bid and/or ask)	(12.14%)	(11.16%)	(15.78%)	(17.80%)	(12.05%)	(5.51%)	(17.16%)	(21.70%)
At both inside	73.49%	59.47%	36.96%	30.10%	62.66%[a]	75.82%[a]	48.54%[a]	32.55%
(bid and ask)	(16.97%)	(15.57%)	(17.42%)	(17.86%)	(18.06%)	(9.60%)	(22.03%)	(24.17%)
Alone at EBBO	11.98%	1.97%	2.08%	4.05%	6.99%[a]	5.03%[a]	1.49%[a]	1.65%[a]
(bid and/or ask)	(5.60%)	(2.36%)	(2.59%)	(5.23%)	(3.79%)	(4.06%)	(0.86%)	(1.04%)
Alone at both inside	1.30%	0.26%	0.04%	0.09%	0.37%[a]	1.33%[a]	0.04%	0.03%[a]
(bid and ask)	(1.91%)	(1.45%)	(0.15%)	(0.26%)	(0.61%)	(2.25%)	(0.09%)	(0.08%)
Panel B: Trade-weighted averages, % of trades								
At EBBO	76.82%	55.18%	44.15%	41.00%	66.96%[a]	60.71%[a]	50.98%[a]	41.36%
(bid or ask)	(8.54%)	(9.47%)	(12.33%)	(12.97%)	(7.19%)	(6.44%)	(12.34%)	(14.34%)
At both inside	57.48%	40.58%	24.76%	19.28%	48.04%[a]	50.34%[a]	34.10%[a]	21.14%
(bid and ask)	(12.90%)	(11.70%)	(13.23%)	(12.46%)	(13.38%)	(8.51%)	(15.87%)	(16.38%)
Alone at EBBO	22.87%	5.88%	3.76%	5.72%	16.82%[a]	11.11%[a]	5.33%[a]	4.83%
(bid or ask)	(7.01%)	(3.03%)	(2.22%)	(5.19%)	(5.49%)	(4.86%)	(1.83%)	(1.67%)
Alone at both inside	1.28%	0.22%	0.04%	0.05%	0.58%[a]	1.08%[a]	0.09%	0.02%
(bid and ask)	(1.97%)	(0.95%)	(0.07%)	(0.14%)	(0.87%)	(1.60%)	(0.10%)	(0.04%)
Panel C: Time priority, % of trading day								
Time priority	44.48%	29.91%	9.68%	15.04%	38.78%[a]	37.70%[a]	12.17%[a]	11.05%[a]
	(7.88%)	(7.32%)	(4.03%)	(7.38%)	(6.60%)	(6.91%)	(3.84%)	(4.14%)

Table 6.2 reports results on each measure as a percentage of the total trading day (Panel A) and as percentage of daily executed trades (Panel B) per stock during the observation periods. Over the 2009 observation period, the LSE quotes either the EBB or EBO or both for 85.0% of the trading day, Chi-X for 76.9%, BATS for 60.6%, and Turquoise for 52.9%. The participation rate of BATS and Turquoise is statistically and economically significantly lower than that of the LSE and Chi-X. The contribution of all trading venues to quote competition falls significantly when analyzing presence at both sides of the inside spread. This measure ranges between 73.5% for the LSE and 30.1% for Turquoise. The LSE quotes the EBBO alone for 12.0% of the trading day. The patterns are confirmed by the fraction of trade executions on the different trading venues (Table 6.2, Panel B). There is a high number of trades when one trading venue posts the EBBO alone. This suggests that investors actively monitor multiple markets seeking best execution.

Over the observation period in 2010, Chi-X is the most active quoting platform for FTSE 100 constituents, i.e. it is the highest fraction of time at the EBBO (Table 6.2, Panel B). The LSE is at the EBBO only in 78.2% of the trading day compared to 87.2% for Chi-X. Quote contribution is lower on BATS and Turquoise. The LSE still provides competitive quotes, however, Chi-X and also BATS significantly increase their quote quality between 2009 and 2010.

Figure 6.3 provides insight into the fraction of the trading day that a trading venue is not at the EBBO (ticks away>0). In this case, all trading venues provide quotes close to the EBBO for both observation periods. In April/May 2009, prevalence at the EBBO, one tick away, or two ticks away averages about 94.0% of time and 96.0% in April/May 2010. In line with the results on quoted spreads, Turquoise seems to be a significantly higher fraction of time further away from the EBBO than any other market. Overall, my findings are in line with Goldstein et al. (2008) who find similar results for quote competition between Nasdaq's Super Montage and three ECNs, Archipelago, Island, and Instinet. Their findings show that the largest trading venue, Nasdaq's Super Montage, contributes more to the inside spread than the three ECNs.

I further analyze time priority of best quotes (Table 6.2, Panel C). A quote is considered to have time priority either if it is at the best bid or ask alone or if it is at the best bid or ask and additionally has been submitted earlier than quotes at the same price (Goldstein et al., 2008). Time priority is averaged for the bid and ask side of the order

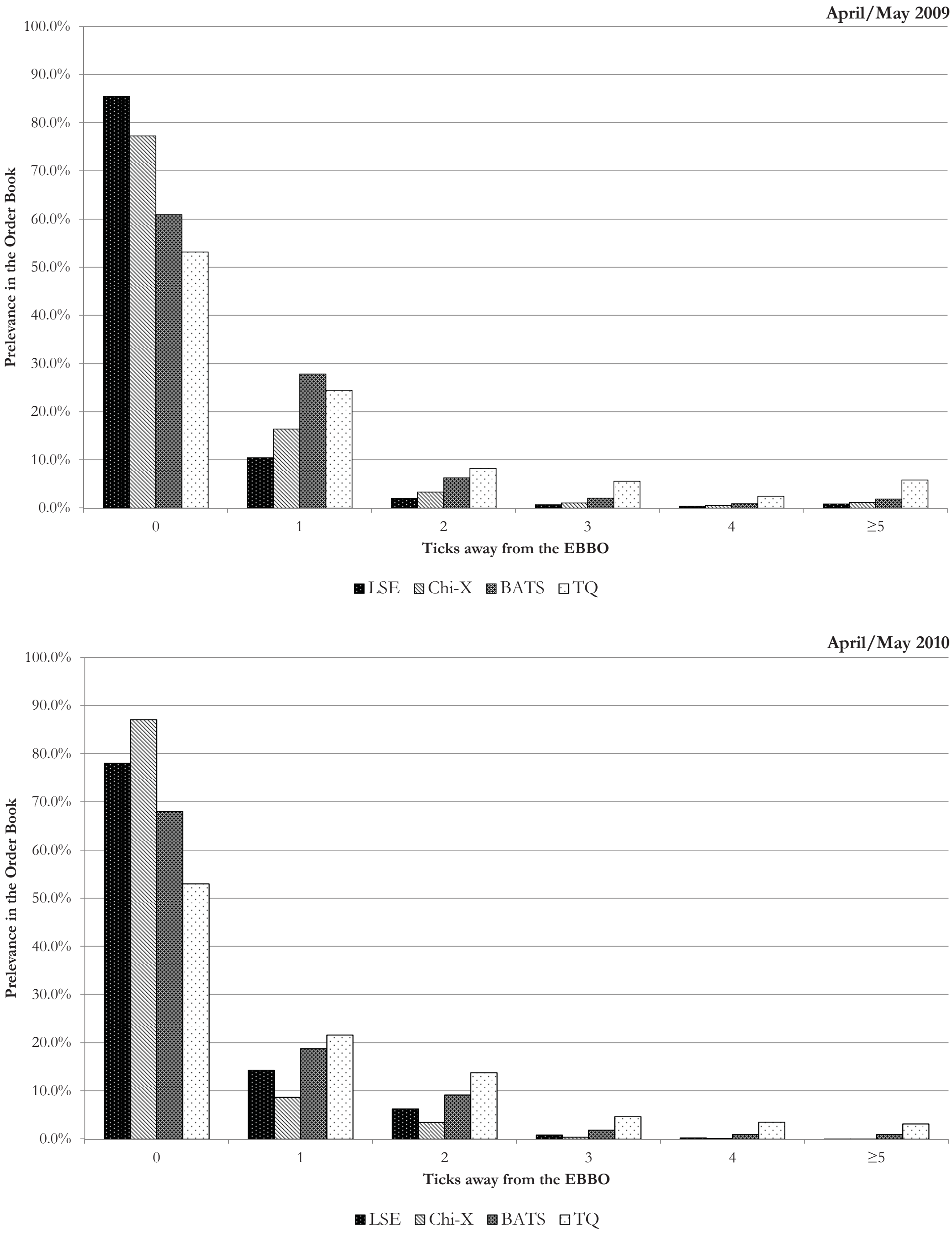

Figure 6.3: **Quotations relative to the EBBO**. The figures depict the fraction of a trading day a trading venue spends at the EBBO (ticks away=0) and at different levels away from the EBBO per day and per stock. Results for the observation period April/May 2009 are presented in the upper figure and for April/May 2010 in the lower figure.

book per day and per stock. This measure varies between 29.9% for Chi-X, 9.7% for BATS, and 15.0% for Turquoise over the observation period in 2009. LSE quotes have time priority in 44.5% in 2009 and in 38.8% in 2010. However, Chi-X increases time priority of its quotes by 7.8% between the two observation periods. In comparison to the LSE and Chi-X, time priority of BATS and Turquoise is smaller indicating more frequent quote changes. This phenomenon may cause some regulatory concerns, since flickering quotes may reduce transparency, discourage liquidity provision, and complicate best execution.

6.3.2 Locked and Crossed Markets

This section follows Battalio et al. (2004) and identifies locks and crosses in the consolidated order book. A stock is considered locked if the best bid equals the best ask on another trading venue (EBB=EBO, inside spread is zero) and it is crossed if the highest bid across trading venues is greater than the lowest ask across trading venues (EBB>EBO, inside spread is negative). Battalio et al. (2004) argue that "locked and crossed quotes represent foregone trading opportunities" and are not in the investor's best interest, assuming that investors want to trade instead of quoting. Under RegNMS, the SEC requires trading venues to establish, maintain, and enforce rules which prevent traders to lock or cross protected quotations (Rule 610), assuming that non-positive spreads are inconsistent with fair and orderly markets. MiFID does not address this concern. Further important details of RegNMS and MiFID are discussed in Section 2.1.

Table 6.3 reports locks and crosses as percentage of quotes, as percentage of the trading day, and as percentage of trades. By construction, the percentage of positive inside spreads, locks, and crosses sum to 100.0%. In April/May 2009, the consolidated order book across trading venues has a non-positive spread in 8.5% (5.1% + 3.4%) of the trading day compared to 1.4% (1.3% + 0.1%) in 2010. On average, the percentage of quotes forming locked (crossed) quotes decreases from 11.1% (3.9%) to 5.5% (0.7%). Further the average duration of a lock (cross) decreases from 2.51 sec (10.83 sec) to 0.86 sec (0.41 sec). This trend represents a 65.8% (96.2%) reduction. These findings support the view that competition for order flow may force participants on all trading venues to quote closely linked prices.

Table 6.3: **Locked and crossed market statistics**. The sample consists of 70 stocks listed on the London Stock Exchange and in the FTSE 100. The selected stocks are traded in both observation periods: April 20 to May 29, 2009 and April 19 to May 28, 2010. The table presents statistics on locks and crosses per day and per stock. A positive inside spread characterizes a 'normal' market regime with a positive inside spread (EBB<EBO). A stock is locked if the best posted bid across all trading venues equals the best ask (EBB=EBO). If markets are crossed, a trading venue's inside bid is greater than another markets ask (EBB>EBO). Mean differences between the two observation periods are tested for statistical significance using Thompson (2011) clustered standard errors with with 'a' denoting statistical significance at the 1% level and 'b' at the 5% level.

	April/May 2009			April/May 2010		
	Positive	Locked	Crossed	Positive	Locked	Crossed
% of quotes	84.99%	11.12%	3.89%	93.80%[a]	5.50%[a]	0.65%[a]
	(9.22%)	(4.23%)	(6.96%)	(2.75%)	(2.57%)	(0.60%)
% of trading day	91.53%	5.11%	3.35%	98.60%[a]	1.33%[a]	0.08%[a]
	(10.92%)	(3.40%)	(6.57%)	(1.07%)	(0.94%)	(0.11%)
% of trades	74.57%	20.11%	5.30%	84.78%[a]	13.69%[a]	1.52%[a]
	(9.34%)	(5.02%)	(7.28%)	(3.57%)	(3.54%)	(1.32%)
Time of trading day, min	439.35	24.49	15.99	473.23[a]	6.36[a]	0.33[a]
	(52.42)	(16.33)	(31.53)	(5.13)	(4.49)	(0.54)
Average duration, sec	48.00	2.51	10.83	72.59[a]	0.86[a]	0.41[a]
	(31.86)	(3.22)	(24.94)	(61.23)	(1.25)	(6.13)

Table 6.4: **Detailed analysis of crossed market quotes**. The sample consists of 70 stocks listed on the London Stock Exchange and in the FTSE 100. The selected stocks are traded in both observation periods: April 20 to May 29, 2009 and April 19 to May 28, 2010. The table presents statistics for crossed market regimes per day and per stock. A stock is crossed, if a trading venue's inside bid is greater than another markets ask (EBB>EBO). The average number of crosses, the percentage of crosses with one or more trades reported during the cross, the average tick size, the average difference of the best bid and ask in pence, and potential arbitrage revenues in British Pounds are presented for different duration of crosses per day and per stock. Mean differences between the two observation periods are tested for statistical significance using Thompson (2011) clustered standard errors with 'a' denoting statistical significance at the 1% level and 'b' at the 5% level.

	April/May 2009					April/May 2010				
Duration of cross, ms	No. of crosses	With trades	Tick size	Value of cross	Arbitrage	No. of crosses	With trades	Tick size	Value of cross	Arbitrage
0	15.17					28.68[b]				
	(20.33)					(71.27)				
1 to 9	12.17	63.90%	0.504	0.539	41.10	38.49[a]	79.63%[a]	0.538	0.536	75.38[a]
	(17.37)	(25.92%)	(0.342)	(0.425)	(65.00)	(97.55)	(18.80%)	(0.641)	(0.646)	(147.28)
10 to 19	11.01	73.15%	0.506	0.546	44.12	16.87	87.52%[a]	0.517	0.521	39.63
	(14.44)	(23.90%)	(0.344)	(0.399)	(68.98)	(39.00)	(16.92%)	(0.601)	(0.647)	(70.17)
20 to 49	17.51	77.20%	0.507	0.559	75.66	17.53	90.84%[a]	0.504	0.523	43.25[a]
	(22.10)	(19.39%)	(0.340)	(0.464)	(123.67)	(37.93)	(14.82%)	(0.553)	(0.585)	(71.34)
50 to 99	7.99	78.79%	0.504	0.569	42.01	5.44[b]	89.65%[a]	0.420[b]	0.449[a]	16.25[a]
	(9.92)	(24.87%)	(0.341)	(0.457)	(73.69)	(14.24)	(20.86%)	(0.496)	(0.546)	(29.98)
100 to 999	9.62	75.37%	0.503	0.542	30.07	7.25	82.74%[a]	0.408[a]	0.428[a]	15.27[a]
	(11.60)	(23.86%)	(0.342)	(0.404)	(39.29)	(19.52)	(25.89%)	(0.439)	(0.484)	(31.27)
1,000 to 4,999	6.01	77.40%	0.502	0.575	22.64	1.64[a]	85.09%[a]	0.349[a]	0.399[a]	4.56[a]
	(8.27)	(26.06%)	(0.341)	(0.472)	(31.24)	(3.94)	(27.08%)	(0.456)	(0.596)	(7.69)
$\geq$ 5,000	10.31	88.26%	0.503	0.939	69.38	0.33[a]	87.23%	0.356[a]	0.494[a]	5.01[a]
	(17.26)	(19.79%)	(0.339)	(2.005)	(113.13)	(0.83)	(30.47%)	(0.512)	(0.749)	(14.61)
Total	89.79	76.30%	0.506	0.587	322.54	116.24	86.10%[a]	0.553	0.562	208.99[a]
	(97.23)	(23.40%)	(0.340)	(0.429)	(417.79)	(279.09)	(22.12%)	(0.650)	(0.669)	(403.01)

Crossed quotes provide potential arbitrage opportunities and thus are particularly interesting. Assuming that one trading venue quotes a higher bid than the lowest ask across the other platforms (EBB>EBO), an arbitrageur may buy shares and immediately sell them to realize a profit. To explore arbitrage activity, I look at the duration of crosses along with trading activity when a stock is crossed. I establish seven duration of cross categories: 1 to 9 milliseconds, 10 to 19 milliseconds, 20 to 49 milliseconds, 50 to 99 milliseconds, 100 to 999 milliseconds, 1,000 to 4,999 milliseconds, and equal to or greater than 5 seconds. Table 6.4 reports the number of crosses, the percentage of crosses with at least one trade, the tick size, and the value of a cross per category on a daily stock basis. Overall, differences in the number of crosses do not differ significantly between both observation periods. However, I find a strong tendency towards a shorter average duration of crosses. For example, the average number of daily crosses that lasts more than 5 seconds decreases from roughly 10 over the 2009 observation period to less than 1 in 2010. The average tick size and the value of a cross reveals that a high number of crosses are initiated by a difference of one tick between the EBB and the EBO. Trading activity may be one proxy for arbitrage activity. While there is at least one trade for crossed market periods that last less than 10 milliseconds in 63.9% of time in April/May 2009, the corresponding faction is 79.6% in April/May 2010. The data show that trading activity increases along with duration of cross categories. For example, the trading activity is considerably higher for crosses with a duration of more than 5 seconds compared to all other duration of cross categories. In this category I find at least one trade in 88.3% of time in 2009 and in 87.2% in 2010.[4]

The data allow to estimate revenues from apparent arbitrage opportunities. I obtain the number of outstanding shares a trader can arbitrage for each cross and use the value of a cross to calculate associated revenues. Supposing that a high-frequency trader is able to submit a pair of orders to arbitrage crossed quotes within 1 millisecond, such a trader can earn on average 323 GBP per day and per stock in 2009 and 209 GBP in 2010 (see Table 6.4), representing a 35,3% decline. Altogether, total potential revenues are 614,217 GBP for 70 FTSE 100 constituents during 27 trading days in April/May 2009

[4]Table 6.1 shows a significant increase in daily number of trades between the observation period in 2009 and 2010. As a consequence, trades during crosses may become more likely by construction. However, I argue that arbitrageurs actively take advantage of price differences. This assumption seems reasonable, since, for example, BATS reports an average order latency of 200 microseconds in May 2010 (see http://www.batstrading.co.uk/resources/participant_resources/BATSEuro_Latency.pdf).

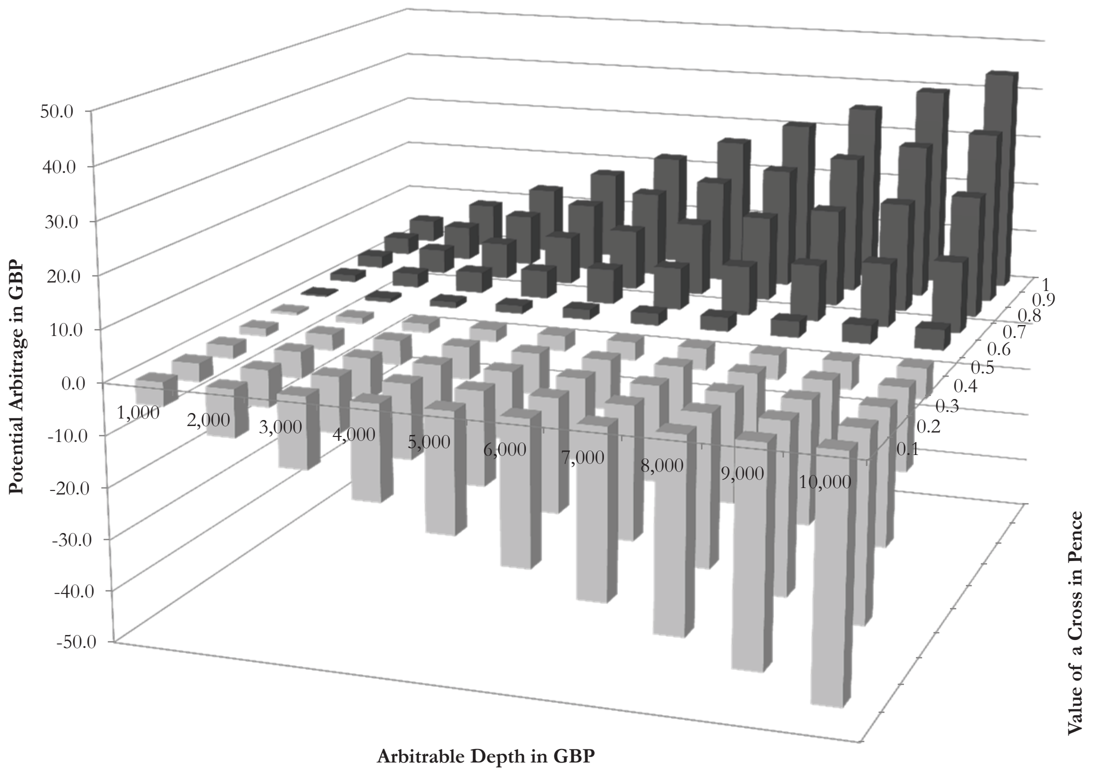

Figure 6.4: **Potential arbitrage revenues after transaction costs**. The figure depicts potential arbitrage revenues by arbitrable depth in British Pounds and the value of a cross in pence. To resolve a crossed market, the transaction costs for a pair of active trades are assumed to be two times 0.28 bps of arbitrable depth, the minimum threshold across markets.

and 404,700 GBP during 29 trading days in April/May 2010.

Transaction costs may be one reason why these arbitrage opportunities exist. The data show an average arbitrable depth of 5,093 GBP during a cross in 2009 and 5,956 GBP in 2010, significantly smaller than the average daily depth across all trading venues (see Table 6.1). Minimum transaction costs are 0.28 bps of trading value for active orders (see Section 2.2). The associated transaction costs therefore average 1,103 GBP in 2009 and 1,477 GBP in 2010 per day and per stock and thus are considerably larger than potential arbitrage revenues. Figure 6.4 depicts potential arbitrage revenues as a function of arbitrable depth and the value of a cross. It appears that - given the minimum transaction costs from above - crossed quotes are economically not exploitable under 0.56 pence as a value of a cross. This number roughly equals the average value of a cross, 0.59 pence in April/May 2009 and 0.56 pence in April/May 2010, I find on average in the data (see Table 6.1). Hence, the data support the view that not all arbitrage opportunities are economically exploitable.

6.3.3 Determinants of Locked and Crossed Markets

This section examines initiations and terminations of locks and crosses for each trading venue separately. While I analyze the aggregated market in the previous sections, I now aim to identify differences in initiations and terminations of locks and crosses between platforms. Logistic regressions further test for several factors that potentially affect investors decisions to submit locking or crossing quotes.

Table 6.5 provides descriptive statistics on active, passive, and simultaneous locks and crosses for the LSE, Chi-X, BATS, and Turquoise per day and per stock. According to Shkilko et al. (2008), active initiations of locks (crosses) are characterized by an outstanding quote which is actively locked (crossed) and which stands in the order book for a minimum duration before being locked (crossed), here 250 milliseconds.[5] Active terminations of locks and crosses are defined accordingly. A simultaneous lock (cross) happens if an investor submits a limit order that locks (crosses) a quote which was posted less than 250 milliseconds before. Passive locks occur when a trading venue comes out of a cross. Assuming a crossed market, an investor may send an order to a trading venue which potentially locks a quote. Then, if the cross is resolved, the passive quote becomes active and locks the stock. By construction, the percentages of active, simultaneous, and passive locks sum to 100.0%. I average bid and ask-initiated and terminated locks and crosses and report the main statistics of interest, active locks and crosses, for each trading venue separately.

In April/May 2009, I find that active locks (crosses) represent on average 78.1% (85.1%) of all initiated locks (crosses), simultaneous locks (crosses) 14.8% (14.9%), and passive locks 7.0% (Table 6.5, Panel A). Traders on Chi-X and the LSE enter significantly more locking quotes than traders on the other two MTFs, 36.0% and 31.2% of all

[5] I also perform the analysis with a time limit of 1 second and find the expected significant increase in simultaneous locks and crosses. Because of faster trading compared to Shkilko et al. (2008), I reduce the time limit for simultaneous initiations and terminations to 250 milliseconds. However, similar patterns of active lock and cross initiations and terminations between trading venues and over time are found for the 1 second case and are not reported for brevity.

Table 6.5: **Initiations and terminations of locks and crosses**. The sample consists of 70 stocks listed on the London Stock Exchange and in the FTSE 100. The selected stocks are traded in both observation periods: April 20 to May 29, 2009 and April 19 to May 28, 2010. The table presents statistics on locks and crosses per day and per stock. A trading venue locks another, if it posts a bid (ask) which equals the outstanding ask (bid) on another venue (locking), trading venues on the passive side of such an initiation are locked. A trading venue crosses another, if it quotes an ask that is greater than the highest bid across all trading venues (crossing). Trading venues with the highest bid are locked. Terminations are unlocking and uncrossing, respectively. Active (simultaneous) initiations and terminations are characterized by an outstanding inside quote on the other side that is posted at least (less than) 250 milliseconds before the lock or cross happens. Passive locks happen, if a trading venue comes out of a cross. First, the table shows shares for actively, passively, and simultaneously initiated locks and crosses. Active initiations and terminations are also reported for each trading venue separately. Fractions of lock- and cross-initiating quotes in the total number of inside quotes are given in the second part of each panel. Mean differences between the two observation periods are tested for statistical significance using Thompson (2011) clustered standard errors with ‘a’ denoting statistical significance at the 1% level and ‘b’ at the 5% level.

	% of inside quotes	Locking	Locked	Unlocking	Crossing	Crossed	Uncrossing
Panel A: April/May 2009							
% of locked and crossed market initiations and terminations							
Active		78.13%	80.03%	62.35%	85.09%	84.81%	57.80%
		(9.00%)	(8.84%)	(10.84%)	(12.28%)	(12.29%)	(19.26%)
LSE	32.00%	31.17%	22.91%	22.06%	44.48%	6.71%	25.79%
	(8.27%)	(8.28%)	(6.76%)	(7.09%)	(16.97%)	(7.25%)	(12.95%)
Chi-X	36.17%	36.01%	15.84%	20.22%	32.69%	9.14%	13.99%
	(5.14%)	(8.94%)	(4.57%)	(6.67%)	(14.17%)	(7.74%)	(9.23%)
BATS	24.05%	9.32%	19.27%	14.29%	4.98%	28.70%	8.56%
	(5.98%)	(5.75%)	(5.48%)	(6.22%)	(5.72%)	(16.99%)	(7.57%)
TQ	7.79%	1.63%	22.01%	5.79%	2.94%	40.26%	9.47%
	(4.81%)	(1.26%)	(7.14%)	(2.86%)	(6.50%)	(21.92%)	(9.76%)
Passive		7.03%	5.76%				
		(6.09%)	(5.30%)				

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	% of inside quotes	Locking	Locked	Unlocking	Crossing	Crossed	Uncrossing
Simultaneous		14.84%	14.21%	37.65%	14.91%	15.19%	42.20%
		(5.90%)	(5.99%)	(10.84%)	(12.28%)	(12.29%)	(19.26%)
Locked and crossed market initiations and terminations as % of inside quotes per venue							
LSE		0.64%	0.74%	0.46%	0.11%	0.03%	0.07%
		(0.24%)	(0.39%)	(0.24%)	(0.12%)	(0.05%)	(0.09%)
Chi-X		0.68%	0.44%	0.39%	0.09%	0.02%	0.04%
		(0.35%)	(0.24%)	(0.26%)	(0.13%)	(0.02%)	(0.06%)
BATS		0.26%	0.89%	0.42%	0.03%	0.14%	0.06%
		(0.26%)	(0.68%)	(0.34%)	(0.05%)	(0.34%)	(0.12%)
TQ		0.17%	5.02%	0.81%	0.03%	1.85%	0.38%
		(0.21%)	(7.08%)	(1.01%)	(0.09%)	(5.09%)	(1.01%)
Panel B: April/May 2010							
% of locked and crossed market initiations and terminations							
Active		72.02%[a]	73.75%[a]	50.05%[a]	71.60%[a]	71.88%[a]	42.73%[a]
		(11.26%)	(11.16%)	(8.78%)	(17.78%)	(17.92%)	(18.58%)
LSE	26.40%[a]	24.47%[a]	17.87%[a]	17.14%[a]	31.37%[a]	6.59%	20.20%[a]
	(6.59%)	(8.11%)	(5.10%)	(5.52%)	(19.75%)	(6.31%)	(15.37%)
Chi-X	41.98%[a]	35.79%	14.46%[a]	18.09%[a]	31.02%	9.45%	13.94%
	(7.27%)	(8.30%)	(4.11%)	(5.79%)	(17.51%)	(10.99%)	(11.36%)
BATS	24.23%[a]	9.48%	19.73%	9.72%[a]	7.81%[a]	22.48%[a]	5.97%[a]
	(6.46%)	(4.84%)	(5.61%)	(4.50%)	(9.49%)	(16.61%)	(8.10%)
TQ	7.39%[a]	2.27%[a]	21.69%	5.10%[a]	1.41%[b]	33.37%[a]	2.62%[a]
	(3.80%)	(1.69%)	(6.07%)	(2.64%)	(3.97%)	(17.31%)	(4.58%)

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% of inside quotes	Locking	Locked	Unlocking	Crossing	Crossed	Uncrossing
Passive	4.38%[a]	3.65%[a]				
	(3.35%)	(2.93%)				
Simultaneous	23.60%[a]	22.60%[a]	49.95%[a]	28.40%[a]	28.12%[a]	57.27%[a]
	(8.70%)	(8.91%)	(8.78%)	(17.78%)	(17.92%)	(18.58%)
Locked and crossed market initiations and terminations as % of inside quotes per venue						
LSE	0.35%[a]	0.42%[a]	0.25%[a]	0.04%[a]	0.02%	0.03%
	(0.17%)	(0.27%)	(0.14%)	(0.04%)	(0.03%)	(0.03%)
Chi-X	0.32%[a]	0.19%[a]	0.16%[a]	0.02%[a]	0.01%	0.01%
	(0.15%)	(0.09%)	(0.10%)	(0.03%)	(0.01%)	(0.01%)
BATS	0.15%[a]	0.48%[a]	0.15%[a]	0.01%	0.04%[a]	0.01%
	(0.10%)	(0.25%)	(0.10%)	(0.02%)	(0.05%)	(0.02%)
TQ	0.12%[a]	2.00%[a]	0.32%[a]	0.01%	0.28%[a]	0.02%[a]
	(0.10%)	(1.17%)	(0.26%)	(0.02%)	(0.39%)	(0.04%)

actively posted locks. 44.5% of all crosses are actively initiated by the LSE, 32.7% by Chi-X, 5.0% by BATS, and 3.0% by Turquoise. Quotes of all four trading venues are quite often locked, the percentage varies between 22.9% for the LSE and 15.8% for Chi-X. BATS and Turquoise are most affected by active crosses with a fraction of 28.7% and 40.3% during the 2009 observation period. The LSE and Chi-X appear to terminate locks and crosses most actively.

The analyses show a significantly higher percentage of simultaneously submitted quotes during the observation period in 2010 compared to 2009, indicating a higher trading speed (Table 6.5, Panel B). As a consequence, percentages of almost every category of active cross and lock initiations and terminations decrease significantly between both observation periods. Chi-X and the LSE still submit the highest fraction of active locks and crosses and BATS and Turquoise are still most often actively crossed. Compared to the observation period in 2009, a similar pattern is found for locked quotes, unlocks, and uncrosses in 2010. This may provide evidence that investors use each trading venue for similar trading strategies during both observation periods.

However, the number of quote updates that each trading venue posts has to be taken into account. As a percentage of the total number of submitted EBBO quotes, Chi-X provides a daily average fraction of 36.2% and 42.0% over the observation periods in 2009 and 2010, respectively. The LSE also enters a considerable number of quotes that form the inside spread, 32.0% and 26.4%. The average daily fraction of BATS remains relatively stable at roughly 24.0% and well ahead of Turqouise with less than 8.0%. Comparable to Shkilko et al. (2008), I further examine active locked and crossed market initiations and terminations as percentages of EBBO updates (Table 6.5, Panel A & B). Overall, I do not find significant differences for lock and cross initiations across trading venues ranging from 0.03% to 0.70% of all posted quotes per market over the observation period in 2009. All corresponding statistics are significantly smaller over the 2010 observation period. The results do not provide evidence that one trading venue causes a substantially higher fraction of locks and crosses relative to its number of EBBO updates. A different pattern can be seen for inside quotes being locked and crossed. Turquoise quotes are significantly more often locked and crossed over both observation periods. However, Turquoise also shows the highest number of unlocks and uncrosses. Chapter 5 analyzes the contribution of the LSE, Chi-X, BATS, and Turquoise to price formation in FTSE 100 constituents in April/May 2009 and April/May 2010. It appears that Turquoise contributes significantly less to quote based price discovery than the three other trading venues. Taken together, the evidence suggests that Turquoise is more often locked and crossed as a result of stale quotes.

There are several reasons why locks and crosses can arise. Investors may want to avoid trading against an outdated quote or against a limit order with a small associated volume. To directly test these arguments, I estimate bivariate logistic regressions for each of the observation periods. Logistic regressions allow the estimation of the impact of changes in different explanatory variables on the probability of locks and crosses (see Section 4.4). Separate regressions for bid-initiated (ask-initiated) locks and crosses are presented.[6] The general model is defined as follows:

$$\ln\left[\frac{\pi_j}{\pi_{Quote}}\right] = \beta_1\, InsideSpreadLag + \beta_2\, TimeLSE + \beta_3\, TimeChiX + \beta_4\, TimeBATS + \beta_5\, TimeTQ + \beta_6\, vol1 + \beta_7\, rv1 \tag{6.1}$$

where the dependent variable equals one for bid-initiated (ask-initiated) non-positive inside spreads with $j \in \{Lock, Cross\}$ and is zero otherwise. π is the modeled response probability, *InsideSpreadLag* the inside quoted spread before a lock or cross is initiated, and *TimeLSE*, *TimeChiX*, *TimeBATS* and *TimeTQ* represent the outstanding quote time on each of the four trading venues in seconds. The variables *vol1* and *rv1* are control variables representing lagged one minute trading volume in British Pounds/10^6 and lagged one minute realized volatility in basis points preceding a price change.[7] I further include firm dummy variables and intraday dummy variables for each half-hour of the trading day.

Times of high trading activity may be an indication that traders disagree on public information or have different private information. The resulting demand for speedy executions can increase the probability of locks and crosses. According to Shkilko et al. (2008), I expect locks and crosses to become more likely when inside spreads are narrow. In line with these expectations, I obtain significantly negative coefficients on

[6] I exclude quote updates that do not change the EBB (EBO) from the regressions.

[7] Given the average duration of positive inside spreads (about 48 sec over the 2009 observation period and 73 sec in 2010, see Table 6.3), lagged one minute variables seem to be a reasonable choice. However, I rerun all regressions with lagged three minute control variables. The results do not change and are therefore not reported.

InsideSpreadLag for all regression models (see Table 6.6). In fact, the odds of locking (crossing) decrease by a multiple of 0.95 (0.89) in April/May 2009 and by 0.80 (0.66) in April/May 2010 when the inside spread increases by 1 bps, holding all other variables constant. To validate the predicted probabilities, two measures are presented, Somers's D statistic and the c statistic. Somers's D indicates that between 16.0% and 26.0% in 2009 and between 41.0% to 64.0% in 2010 fewer errors would be made in predicting locks and crosses by using the proposed model than by chance alone. The c statistics confirm this pattern. The model correctly assigned higher probabilities to between 58.0% and 62.0% of locks and crosses in 2009 and to between 70.0% and 82.0% in 2010 than to non-event outcomes.

In their study of locks and crosses in Nasdaq and NYSE-listed stocks, Shkilko et al. (2008) find a positive coefficient on outstanding quote time, indicating that some exchanges are often slow with quote updates. Over the observation period in 2009, the data only indicate that the outstanding quote time increases the likelihood of a lock on the LSE. BATS and Turquoise show a significant positive coefficient on *TimeBATS* and *TimeTQ* over the 2010 observation period. However, the effect seems to be small. Lagged volatility and trading volume may also indicate a period of high liquidity and varying trading interests. Although, I would expect locks and crosses to become more likely with an increasing value of *rv1* and *vol1*, I only find significant positive coefficients for the more recent observation period in 2010.

MiFID's main objective is to create greater competition for order flow across Europe and to contribute to more integrated financial markets. The evidence on quote competition suggests that inside quotes change frequently. In addition, the results supports the view that cross and lock initiations and terminations are not caused by one specific trading venue. Due to interrelated effects of intermarket competition, such as lower explicit trading fees, faster exchange infrastructure (Riordan and Storkenmaier, 2011), an increasing use of co-location services (Garvey and Wu, 2010), and more sophisticated high-frequency trading strategies (Menkveld, 2011), traders may be able to quickly resolve arbitrage opportunities. My results suggest that locks and crosses are more likely in fast-moving market periods and are correlated with investor's demand for speedy executions.

Table 6.6: **Logistic regressions: Determinants of lock and cross initiations**. The sample consists of 70 stocks listed on the London Stock Exchange and in the FTSE 100. The selected stocks are traded in both observation periods: April 20 to May 29, 2009 and April 19 to May 28, 2010. I run bivariate logistical regressions on locks and crosses for both observation periods separately. The dependent variable equals one for bid-initiated (ask-initiated) non-positive inside spread initiations and is zero otherwise. The last inside spread in basis points is *InsideSpreadLag* and *TimeLSE*, *TimeChiX*, *TimeBATS*, and *TimeTQ* represent the outstanding quote time in seconds on each of the four trading venues before a quote change. *vol1* and *rv1* are control variables, representing the lagged trading volume in British Pounds/10^6 and the realized volatility in basis points over the one minute interval proceeding the quote change. Chi-Square statistics are reported in parentheses below the regression estimates. 'a' denotes significance at the 1% level and 'b' at the 5% level. Firm dummy variables and intraday dummy variables for each half hour are not reported.

	April/May 2009				April/May 2010			
	Locking		Crossing		Locking		Crossing	
	Bid-Initiated	Ask-Initiated	Bid-Initiated	Ask-Initiated	Bid-Initiated	Ask-Initiated	Bid-Initiated	Ask-Initiated
InsideSpreadLag	-0.0516[a]	-0.0554[a]	-0.1110[a]	-0.1140[a]	-0.2142[a]	-0.2200[a]	-0.4107[a]	-0.4107[a]
	(31,297)	(38,486)	(46,870)	(50,804)	(76,390)	(81,669)	(71,569)	(71,762)
TimeLSE	0.0018[a]	0.0018[a]	-0.0081[a]	-0.0113[a]	-0.0006[a]	-0.0003[a]	-0.0140[a]	-0.0161[a]
	(3,787)	(3,427)	(575)	(974)	(228)	(43)	(917)	(1,266)
TimeChiX	-0.0028[a]	-0.0037[a]	-0.0295[a]	-0.0361[a]	-0.0047[a]	-0.0054[a]	-0.0453[a]	-0.0540[a]
	(1,922)	(3,120)	(2,600)	(3,254)	(3,145)	(3,806)	(1,678)	(1,910)
TimeBATS	-0.0008[a]	-0.0007[a]	-0.0022[a]	-0.0026[a]	0.0004[a]	0.0003[a]	0.0013[a]	0.0003[b]
	(1,305)	(1,003)	(1,996)	(1,439)	(92)	(46)	(82)	(4)
TimeTQ	-0.0004[a]	-0.0006[a]	-0.0012[a]	-0.0015[a]	0.0010[a]	0.0009[a]	0.0010[a]	0.0014[a]
	(653)	(1,298)	(1,016)	(1,332)	(1,031)	(786)	(139)	(295)
vol1	-0.2773[a]	-0.2255[a]	-2.8594[a]	-4.2109[a]	0.0176[a]	0.0207[a]	0.0477[a]	0.0440[a]
	(341)	(219)	(502)	(669)	(31)	(49)	(72)	(49)
rv1	-1.3447[a]	-1.1901[a]	-3.6891[a]	-3.5326[a]	0.0491[a]	0.0533[a]	0.2527[a]	0.2745[a]
	(9,972)	(8,474)	(9,113)	(8,626)	(9)	(10)	(119)	(153)
# Obs.	19,544,959	21,144,046	19,544,959	21,144,046	39,787,992	40,574,964	39,787,992	40,574,964
Somers's D	0.235	0.258	0.160	0.160	0.405	0.414	0.639	0.639
c statistic	0.617	0.629	0.580	0.580	0.702	0.707	0.820	0.820

6.4 Trade-Throughs

In the fragmented UK trading environment, investors sometimes execute worse than the best available price, i.e. the best available price is traded-through. Trade-throughs represent a violation of price-priority and "[...] are indicative of economically inefficient trades because investors should receive better prices" (Battalio et al., 2004). Section 6.4.1 examines the question whether investors do execute at the best available price and Section 6.4.2 analyzes determinants of trade-throughs using logistic regressions.

6.4.1 Trade-Through Statistics

Table 6.7 reports trade-through rates as percentages of the daily number of trades (Panel A) and as percentage of daily trading volume (Panel B) per stock over both observation periods.[8] I further differentiate between five trade sizes categories measured by shares traded: 0-499 shares, 500-1,999 shares, 2,000-4,999 shares, 5,000-9,999 shares, and trades with 10,000 shares or more.[9] The data show a decrease in the percentage of trade-throughs for the LSE and Chi-X and the expected negative sign for the other two MTFs between the observation periods in 2009 and 2010. The fraction varies across trading venues between 5.2% and 8.7% for the 2009 observation period and between 4.7% and 6.9% for 2010.[10] Overall, Turquoise attracts over both periods the lowest number of trade-throughs. The fraction of trade-throughs does not differ considerably between the LSE, Chi-X, and BATS. In addition, an increasing trade-through rate in trade-sizes provides some evidence that investors trade off best prices and available depth. Large orders may execute against multiple limit orders at different levels in the order book. A higher trade-through rate for large orders may therefore indicate that investors rather optimize the average volume-weighted trade price than executing simply at the best price. Furthermore, it appears that trade-throughs are much more prevalent in volume terms (Table 6.7, Panel B).

So far, the presented statistics on trade-throughs do not incorporate the available

[8]Orders may execute against hidden orders in the order book that are not visible to any investor. To allow a clean analysis of trade-through determinants, I do not include those types of trades.

[9]Trade size categories are the SEC trade size classifications, see RegNMS, Rule 600.

[10]In their May 2010 report, Equiduct Trading provides an average trade-through rate of 8.6% for FTSE 100 constituents traded on the LSE, Chi-X, BATS, and Turquoise that is slightly higher than the fraction I find in my data sets, see http://www.equiduct.com/.

depth at the EBBO. However, this dimension is seemingly important, since there may not always be sufficient depth available to execute the entire order strictly at the best price. Table 6.7, Panel C therefore presents the fraction of trade-throughs which can be filled entirely at the EBBO for different trade size categories. It is important to recognize that the underlying order routing strategy may, in the case that more than one trading venue is at the EBBO, involve order splitting across platforms. In line with economic intuition, the variable decreases in trade size categories for all trading venues, i.e. large trade-throughs are less likely to be filled entirely at the EBBO. In April/May 2009, on average 42.0% of trade-throughs on the LSE, 55.7% on Chi-X, 60.7% on BATS, and 68.8% on Turquoise may entirely be executed at a strictly better price. The percentages differ by 3.7% for the LSE, 0.3% for Chi-X, -2.2% for BATS and 4.9% for Turquoise in April/May 2010 compared to the first observation period.

Figure 6.5 depicts the fraction of trades for different order execution levels relative to the EBBO. On average, about 92.3% of all trades across platforms are executed at the EBBO (order execution level=0) in 2009 and 94.0% in 2010. It appears that a high fraction of trade-throughs is executed one (order execution level=1) or two ticks (order execution level=2) away from the EBBO during both observation periods. This finding impacts potential savings of avoiding trade-throughs that the data allow to estimate, since the benefits of searching for better prices are likely to increase in the number of ticks away from the EBBO. As discussed above, it is, however, important to emphasize that there is not always sufficient depth available at the EBBO to execute the entire order strictly at the best price. Under the assumption that a trade-through executes at the available EBBO volume, investors would have been able to save on average 1,451 GBP per day and stock on the LSE, 474 GBP on Chi-X, 84 GBP on BATS, and 87 GBP on Turquoise in 2009. In 2010, the corresponding statistics are 761 GBP for the LSE, 530 GBP for Chi-X, 210 GBP for BATS, and 68 GBP for Turquoise. The increase in potential savings on Chi-X and BATS between both observation periods is driven by a higher absolute number of trade-throughs. Altogether, I obtain potential savings of roughly 4,0 million GBP for the sample of 70 FTSE 100 constituents during 27 trading days in April/May 2009 and 3,2 million GBP during 29 trading days in April/May 2010.[11]

[11]If I assume that sufficient depth at the EBBO for each order size is available, I obtain total potential savings of roughly 15,4 million GBP in 2009 and 14,2 million GBP in 2010.

Table 6.7: **Trade-through statistics**. The sample consists of 70 stocks listed on the London Stock Exchange and in the FTSE 100. The selected stocks are traded in both observation periods: April 20 to May 29, 2009 and April 19 to May 28, 2010. The table presents trade-through rates as a percentage of daily number of trades (Panel A) and as a percentage of daily trading volume (Panel B) per stock. Trade-throughs occur when a trade is executed worse than the EBB (EBO). Panel C reports the percentage of trade-throughs whose entire volume may be executed at the EBBO. Trade size categories are the SEC trade size classifications. Mean differences between the two observation periods are tested for statistical significance using Thompson (2011) clustered standard errors with 'a' denoting statistical significance at the 1% level and 'b' at the 5% level.

	April/May 2009				April/May 2010			
	LSE	Chi-X	BATS	TQ	LSE	Chi-X	BATS	TQ
Panel A: Trade-weighted averages, % of daily number of trades								
≤499	7.04%	7.55%	7.08%	4.69%	4.80%[a]	4.51%[a]	5.39%[b]	3.63%[a]
	(6.95%)	(6.89%)	(7.78%)	(5.24%)	(3.32%)	(2.97%)	(3.37%)	(2.81%)
500 to 1,999	8.89%	9.33%	8.98%	5.49%	6.49%[a]	6.72%[a]	8.48%	5.59%
	(7.36%)	(7.44%)	(8.80%)	(5.64%)	(4.06%)	(4.14%)	(5.76%)	(5.01%)
2,000 to 4,999	10.87%	11.68%	10.35%	5.55%	8.77%[b]	9.23%[a]	10.39%	7.21%[b]
	(9.18%)	(11.38%)	(15.54%)	(11.28%)	(5.67%)	(7.21%)	(10.28%)	(12.44%)
5,000 to 9,999	12.91%	13.78%	10.80%	5.30%	11.89%	12.78%	13.38%[b]	8.49%[a]
	(13.11%)	(18.04%)	(18.90%)	(12.47%)	(11.01%)	(15.15%)	(18.49%)	(18.43%)
≥10,000	21.14%	14.61%	12.11%	5.68%	18.20%[b]	15.71%	14.46%	11.88%[a]
	(23.96%)	(23.51%)	(21.64%)	(14.29%)	(19.24%)	(22.46%)	(23.06%)	(24.06%)
Total	8.71%	8.68%	8.20%	5.22%	6.51%[a]	6.00%[a]	6.93%	4.69%
	(7.04%)	(6.69%)	(7.10%)	(4.58%)	(3.79%)	(3.31%)	(3.94%)	(3.24%)
Panel B: Trade-weighted averages, % of daily trading volume								
≤499	7.33%	7.87%	7.62%	5.08%	5.12%[a]	4.99%[a]	6.28%	4.19%
	(7.20%)	(7.11%)	(8.21%)	(6.01%)	(3.56%)	(3.43%)	(4.25%)	(5.77%)
500 to 1,999	9.12%	9.59%	9.08%	5.38%	6.73%[a]	6.94%[a]	8.80%	5.75%
	(7.44%)	(7.63%)	(8.91%)	(5.48%)	(4.14%)	(4.30%)	(5.95%)	(5.45%)

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	April/May 2009				April/May 2010			
	LSE	Chi-X	BATS	TQ	LSE	Chi-X	BATS	TQ
2,000 to 4,999	11.03%	11.88%	10.54%	5.56%	8.99%[b]	9.45%[a]	10.53%	7.37%[b]
	(9.32%)	(11.46%)	(15.74%)	(11.36%)	(5.83%)	(7.31%)	(10.41%)	(12.70%)
5,000 to 9,999	13.01%	14.01%	10.88%	5.32%	12.14%	12.95%	13.50%[b]	8.53%[a]
	(13.25%)	(18.37%)	(19.04%)	(12.58%)	(11.40%)	(15.34%)	(18.63%)	(18.55%)
≥10,000	26.07%	14.95%	12.43%	5.70%	22.86%[b]	15.82%	14.76%	12.10%[a]
	(27.07%)	(23.72%)	(21.86%)	(14.39%)	(24.05%)	(22.44%)	(23.38%)	(25.15%)
Total	12.08%	10.36%	9.55%	5.50%	10.26%[b]	7.97%[a]	9.12%	5.96%
	(8.32%)	(6.87%)	(7.42%)	(4.98%)	(6.55%)	(3.98%)	(5.14%)	(4.90%)
Panel C: Trade-weighted averages, % of daily number of trade-throughs								
≤499	71.20%	73.12%	75.36%	85.49%	74.38%[a]	74.29%	74.01%	88.79%[a]
	(18.38%)	(18.03%)	(25.34%)	(20.66%)	(15.82%)	(14.51%)	(16.77%)	(17.61%)
500 to 1,999	44.86%	50.74%	54.97%	62.16%	47.03%	54.05%[b]	51.75%[b]	67.33%[a]
	(22.26%)	(22.93%)	(30.31%)	(32.96%)	(21.41%)	(18.69%)	(21.77%)	(29.13%)
2,000 to 4,999	22.51%	32.66%	40.27%	46.06%	24.13%	35.83%	32.17%[a]	48.70%
	(21.07%)	(26.15%)	(36.40%)	(39.05%)	(22.29%)	(24.32%)	(27.28%)	(37.54%)
5,000 to 9,999	12.11%	27.41%	36.60%	42.19%	13.80%	26.98%	25.56%[a]	43.98%
	(18.76%)	(30.51%)	(38.79%)	(39.62%)	(20.92%)	(27.65%)	(30.65%)	(40.30%)
≥10,000	5.70%	26.86%	39.25%	42.87%	4.93%	20.92%[b]	19.25%[a]	33.91%
	(12.98%)	(31.23%)	(39.61%)	(37.45%)	(11.69%)	(28.35%)	(25.81%)	(36.44%)
Total	41.99%	55.74%	60.73%	68.75%	45.74%[a]	56.03%	58.52%	73.69%[a]
	(18.38%)	(12.98%)	(20.87%)	(22.98%)	(15.82%)	(11.00%)	(13.15%)	(18.91%)

Overall, this chapter reports a dramatically lower trade-through rate than Foucault and Menkveld (2008) who study competition on the Dutch stock market after the market entry of EuroSETS in May 2004. They find an average trade-through rate of over 73.0%. Since 2004, computer algorithms advanced and smart order routing (SOR) systems that split large orders seeking best execution for investors became more sophisticated. The smaller trade-through ratio may provide some evidence that on the one hand trading venues post more aligned quotes and that on the other hand liquidity takers make more use of SOR systems.

6.4.2 Determinants of Trade-Throughs

To better understand the factors that lead to a trade-through, I estimate bivariate logistic regressions on trade-throughs for each of the two observation periods. The dependent variable takes the value one for a trade-through and is zero otherwise. The general model is defined as follows:

$$\begin{aligned} \ln\left[\frac{\pi_{TradeThrough}}{\pi_{Trade}}\right] &= \beta_1\, \mathit{InsideSpread} + \beta_2\, \mathit{AvgDepth1} + \\ &\quad \beta_3\, \mathit{ShareVolume} + \beta_4\, \mathit{vol1} + \beta_5\, \mathit{rv1} \end{aligned} \tag{6.2}$$

where π is the modeled response probability, *InsideSpread* the inside spread in basis points at trade time, and *AvgDepth1* the average quoted volume of the individual order books. *ShareVolume* is the number of shares traded divided by 1,000. The variables *vol1* and *rv1* are control variables and defined as in Equation (6.1).[12] I further include firm dummy variables and intraday dummy variables for each half-hour during the trading day. Table 6.8 provides the regression estimates for all trading venues combined and each trading venue separately over both observation periods.

[12]Changing the lag length to three minutes does not affect the results.

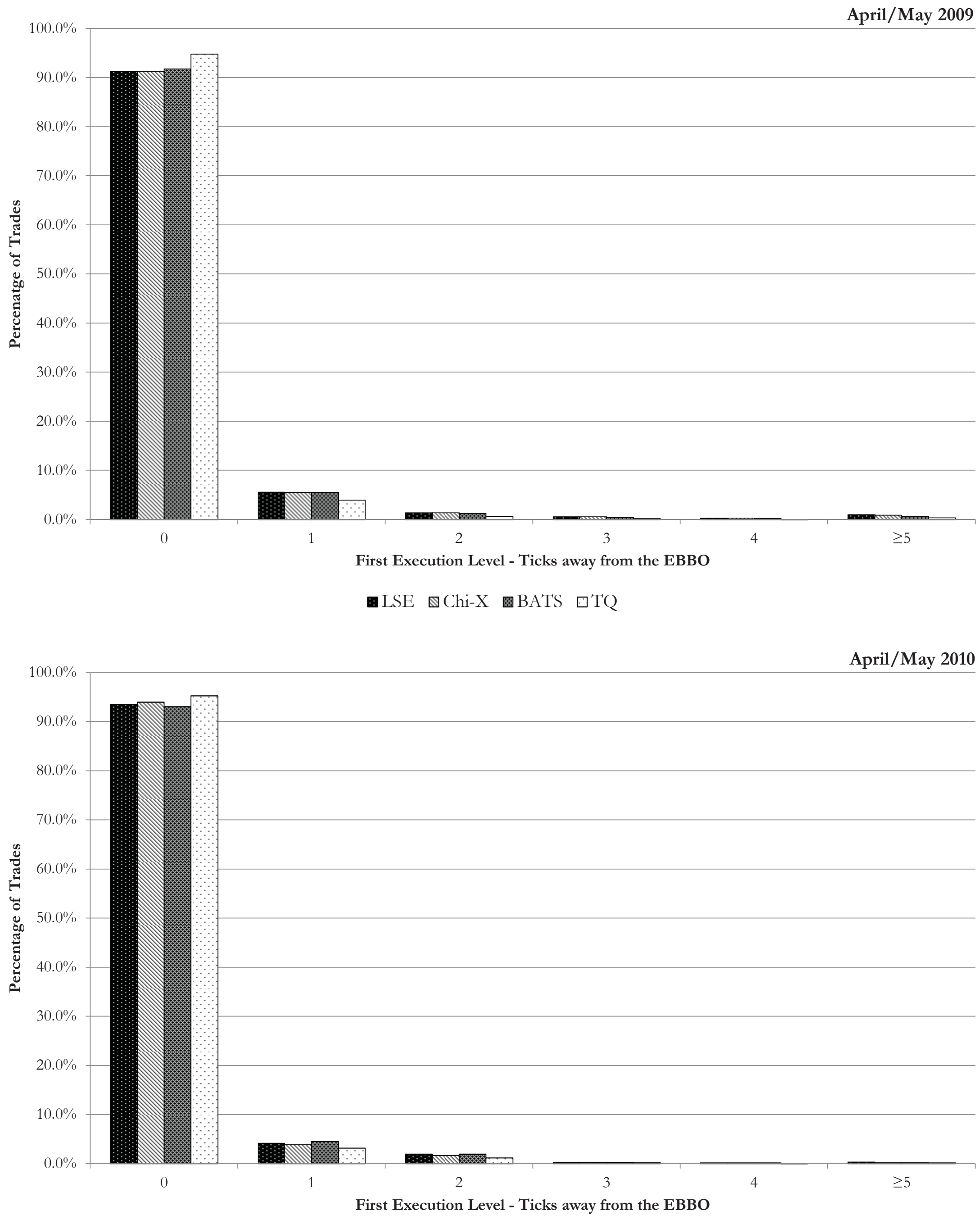

Figure 6.5: **Order execution levels relative to the EBBO**. The figures depict the fraction of trades as a percentage of the total number of trades for different order execution levels relative to the EBBO per day and per stock. Trades executed at the best available price are zero ticks away from the EBBO. Results for the observation period April/May 2009 are presented in the upper figure and for April/May 2010 in the lower figure.

Table 6.8: **Logistic regressions: Determinants of trade-throughs**. The sample consists of 70 stocks listed on the London Stock Exchange and in the FTSE 100. The selected stocks are traded in both observation periods: April 20 to May 29, 2009 and April 19 to May 28, 2010. I run bivariate logistical regressions on trade-throughs for both observation periods separately. The dependent variable equals one for a trade ignoring the best available price across trading venues and is zero otherwise. *InsideSpread* is the inside spread at time of execution. *AvgDepth1* is the average depth at best best prices in the consolidated order book in British Pounds/10^6. *ShareVolume* is the number of shares traded. *vol1* and *rv1* are control variables representing the lagged trading volume in British Pounds/10^6 and the realized volatility in basis points over the one minute interval preceding a trade. Chi-Square statistics are reported in parentheses below the regression estimates. 'a' denotes significance at the 1% level. Firm dummy variables and intraday dummy variables for each half hour are not reported.

	April/May 2009					April/May 2010				
	All	LSE	Chi-X	BATS	TQ	All	LSE	Chi-X	BATS	TQ
InsideSpread	-0.171^a	-0.152^a	-0.206^a	-0.230^a	-0.157^a	-0.259^a	-0.105^a	-0.461^a	-0.367^a	0.011^a
	(222,857)	(113,803)	(82,125)	(19,480)	(9,357)	(169,374)	(11,370)	(155,659)	(60,483)	(18)
AvgDepth1	-3.862^a	-4.303^a	-3.113^a	-2.491^a	-3.484^a	-4.111^a	-4.906^a	-3.208^a	-2.578^a	-10.750^a
	(2,040)	(1,465)	(357)	(53)	(141)	(3,108)	(1,846)	(617)	(225)	(1,193)
ShareVolume	0.011^a	0.009^a	0.024^a	0.030^a	0.005^a	0.009^a	0.006^a	0.021^a	0.025^a	0.025^a
	(6,319)	(4,269)	(3,224)	(656)	(8)	(5,589)	(2,448)	(4,361)	(1,782)	(546)
vol1	0.216^a	0.164^a	0.277^a	0.279^a	0.275^a	0.070^a	0.048^a	0.081^a	0.085^a	0.108^a
	(8,235)	(2,569)	(3,992)	(974)	(1,255)	(8,688)	(1,856)	(3,867)	(2,121)	(1,007)
rv1	0.245^a	0.242^a	0.225^a	0.178^a	0.360^a	1.158^a	1.091^a	1.294^a	1.179^a	0.531^a
	(501)	(288)	(119)	(14)	(74)	(4,474)	(1,924)	(1,682)	(681)	(62)
# Obs.	9,193,651	5,090,696	2,624,776	625,402	852,777	14,879,290	5,882,072	5,416,966	2,510,581	1,069,671
Somers's D	0.517	0.500	0.581	0.546	0.411	0.357	0.296	0.460	0.436	0.301
c statistic	0.759	0.750	0.790	0.773	0.706	0.678	0.648	0.730	0.718	0.651

In line with the results on locks and crosses, I expect trades-throughs to become more likely with smaller inside spreads. Narrow spreads may be a sign of high trading activity and the demand for speedy executions (Shkilko et al., 2008). In addition, when spreads are narrow the benefits to search for better terms of trade are likely to fall. The results confirm my expectations. The coefficients on *InsideSpread* are negative and highly significant for all regressions, except for Turquoise over the 2010 observation period. The corresponding odds ratios indicate that the likelihood of a trade-through falls for an 1 bps increase in *InsideSpread* by a value of 0.84 for the entire sample in April/May 2009, 0.86 for the LSE, 0.81 for Chi-X, 0.80 for BATS, and 0.86 for Turquoise, holding all other factors constant. In April/May 2010, I obtain the following odds ratios: 0.77 for the entire sample, 0.90 for the LSE, 0.63 for Chi-X, 0.69 for BATS, and 1.01 for Turquoise. Somers's D and the c statistic are generally high for all estimations, indicating that high (low) predicted probabilities are indeed associated with an event (non-event).

The average quoted depth across trading venues can be an additional explanatory variable for investors' order routing decisions. The coefficients on *AvgDepth1* are significantly negative, indicating that trade-throughs become less likely with an increasing average depth at best prices in the consolidated order book. The results are confirmed when I replace *AvgDepth1* with average depth up to three ticks behind best prices. This result may be evidence that depth as a decision factor becomes less important for investors along with a high level of consolidated depth. Investors are rather concerned to trade at the best available price across trading venues. These findings are mirrored in the results on *ShareVolume*, which has a positive coefficient in all regressions and confirms the descriptive statistics (Table 6.7), i.e. the probability of a trade-through increases in trade size. Increasing lagged trading volume (*vol1*) and lagged volatility (*rv1*) have a significantly positive effect on trade-throughs across all trading venues. In times of high market activity, liquidity in the order books should be high. Investors may want to trade promptly and trade off searching costs, liquidity, and speed of execution. In summary, the regression models indicate that investors condition their decision to trade-through the best available price on different market variables such as bid-ask spreads and available depth.

Best execution under MiFID relies on multiple factors. MiFID explicitly allows financial service providers to include multiple factors such as price, trading costs, speed, probability of execution, or probability of settlement in their best execution policy. In contrast, RegNMS requires to link fragmented trading venues by technology and enforces price-priority across platforms. Prior to the linkage of U.S. equity option markets, Battalio et al. (2004) find an average trade-through rate of 11.1% in June 2000 and 3.7% in January 2002. Compared to their second observation period, my data reveal on average a higher trade-through rate for FTSE 100 constituents. However, the evidence suggests that investors base their trading decisions on best prices and other variables such as available depth.

6.5 Conclusion

One of the main objectives of MiFID is to promote competition among trading venues. Since its introduction in November 2007, established exchanges have been challenged by MTFs that gained significant market share in nearly all European equity markets. In contrast to U.S. equity market's regulation, RegNMS, MiFID neither imposes a formal linkage between trading venues nor does it establish a single data consolidator for pre and post-trade information. Further, intermediaries, such as investment firms or brokers, acting on behalf of their clients have to ensure best execution and trading venues are required to publish quote and trade information. In this chapter, I study whether competition for order flow of disconnected platforms forces a single virtual market to emerge.

I use order book data of FTSE 100 constituents traded on the LSE and the three largest MTFs, namely Chi-X, BATS, and Turquoise. The analysis is based on two observation periods in April/May 2009 and April/May 2010. Between both observation periods, the LSE market share in FTSE 100 constituents decreases from 70.2% to 51.8%. While the LSE posts on average the narrowest quoted spread over the first observation period, Chi-X is the most liquid platform in April/May 2010. To examine market coordination, I analyze arbitrage opportunities and suboptimal executions. Quotes are locked if the best bid across trading venues equals the best ask (EBB=EBO) and crossed if the best bid exceeds the best posted ask (EBB>EBO). Neither situation seems consistent with an efficient market: Locked quotes suggest that traders who could trade on a consolidated market do not and crossed quotes are arbitrage opportunities in the simple form as they violate the law of one price. The picture emerges that markets are locked (crossed) in 24.5 minutes (16.0 minutes) of a trading day during the 2009 observation period. In April/May 2010, I find locks (crosses) in 6.4 minutes (19.8 seconds) per trading day. This result represents a 83.5% decline in non-positive spreads. In addition, potential arbitrage revenues before transaction costs seemingly fall by 35,3% between both observation periods per day and per stock. Hence, it appears that competition for order flow forces disconnected trading venues to quote closely aligned prices.

Best execution under MiFID is multi-dimensional on factors such as price, trading costs, speed, size, probability of execution, and other factors. This policy is in contrast to U.S. regulation which enforces price-priority across trading venues. I examine trade-throughs, i.e. trades that are executed worse than the best available price across platforms. The data show that the average trade-through rate decreases from 7.7% over the first observation period to 6.0% in April/May 2010. The findings support the view that an increasing number of investors use SOR systems. Regressions show that trade-throughs become more likely in times of narrow inside spreads, suggesting that investors trade off liquidity and search costs during fast-moving market periods.

Regulatory authorities, practitioners, and academics are concerned that MiFID results in a fragmented European trading landscape, but leaves it to the market to solve integration. This chapter provides some evidence that competitive forces may be able to integrate disconnected platforms and that infrastructure costs of a formal linkage can be avoided.

Chapter 7

Conclusion

7.1 Summary

The structure of European equity markets has significantly changed over the past decade. Most importantly, the introduction of MiFID in November 2007 ended the quasi-monopoly of traditional exchanges and opened regulated markets for competition from alternative trading systems, in particular multilateral trading facilities (MTF). On the one hand, investors may benefit from a greater choice of execution venues and from competition for order flow that put downward pressure on transaction fees. On the other hand, increased fragmentation of trading volume and liquidity may finally lead to less transparent financial markets and more costly trading. The results of this thesis suggest that the positive effects of increased competition for order flow under MiFID outweigh the negative side-effects.

To better understand the impact of a highly competitive trading environment on market quality and its dynamics over time, this thesis focuses on UK blue-chip stocks that are analyzed for two observation periods, one in 2009 and a second in 2010. The market for these stocks is the most fragmented in Europe and therefore well-suited to examine the impact of fragmentation on market quality. Chapter 5 studies whether MTFs are competitive on liquidity and price discovery. It appears that MTFs compete successfully for order flow, especially in high volume stocks, with an increasing share in trading volume over time. The evidence suggests that Chi-X and the LSE are the most liquid trading venues in terms of quoted spreads during both observation periods. While quoted spreads on the LSE are slightly smaller than on Chi-X in 2009, the inverse relationship is true in 2010. Transaction costs measured by effective spreads are the lowest on Turquoise during both observation periods, even after controlling for trade characteristics. However, these favorable prices to liquidity demanders possibly arise due to stale quotes on Turquoise. Regressions further reveal that investors tend to submit orders to MTFs when liquidity is higher on them relative to the LSE. This result suggests that investors actively monitor multiple platforms and trade when and where it is relatively cheap to do so.

Price discovery is an important dimension of market quality. Chapter 5 provides evidence that trade and quote based price discovery mainly takes place on the most liquid trading venues, the LSE and Chi-X. In 2010, 44.6% of total information is impounded into prices on Chi-X compared to 34.6% on the LSE, 12.9% on BATS, and 7.8% on Turquoise. This result is mainly due to the fact that a high fraction of quote based price discovery takes place on Chi-X, on average 56.8%. Comparing 2009 and 2010, total contribution to price discovery tends to shift towards Chi-X and BATS in the second observation period. Altogether, the results of Chapter 5 show that MTFs significantly contribute to overall liquidity and that Chi-X and BATS do not seem to be piggy-backing off of the LSE price discovery process.

From a regulatory perspective, it is important to ask the question whether competition for order flow forces trading venues to quote closely linked prices. Alternatively, an European National Market System (NMS) comparable to U.S. regulation may ensure that a virtual single market emerges. Chapter 6 elaborates on this question by studying arbitrage opportunities. Crossed market periods (EBB>EBO) that represent arbitrage opportunities fall from 16.0 minutes per day and per stock in 2009 to 19.8 seconds in 2010, a 97.6% decline. Further analyses imply that few arbitrage opportunities are profitable after transaction costs in both observation periods. In a second step, trade-through rates are used to evaluate suboptimal executions, i.e. an investor does not receive the best available price across markets. The fraction of trade-throughs is relatively small for both observation periods and decreases from on average 7.7% across platforms in 2009 to 6.0% in 2010. Other estimations show that investors prefer to optimize the volume-weighted average trade price rather than to execute at the EBBO. Overall, the results, presented in Chapter 6, provide evidence for a high level of market integration under MiFID and therefore imply that the costs for a formal linkage as in the U.S. (e.g. infrastructure, maintenance, latency) can be avoided.

This thesis contributes to the growing body of literature that examines intermarket competition and order flow fragmentation post MiFID. Specifically, it offers an in-depth analysis of market quality, i.e. liquidity, price discovery, and market coordination, in high volume stocks. To understand the underlying dynamics of market quality is of general importance, since the quality of a market has been shown to impact transaction costs for investors and the cost of capital for issuers alike. Highlighting recent trends in European equity trading, two different observation periods are analyzed that leave enough time for developments. However, this approach does not allow me to distinguish between increasing fragmentation over time and other changes, for example, faster exchange infrastructure and a higher fraction of algorithmic trading, which may also impact market quality.

It is further important to address the fact that this work is based on specific data sets. First of all, the presented analysis focuses on UK high volume stocks. Although, this market segment was chosen for well-founded arguments (e.g. the high level of UK market fragmentation) and there is no reason to assume that trading strategies in these stocks differ considerably from other European high volume stocks, there may be still unknown differences. In addition, the results are based on frequently traded stocks for which algorithmic and high-frequency traders are considered to be more active than for less frequently traded stocks. Therefore, the results may differ for low volume stocks. Finally, it is important to emphasize that this thesis examines market quality from an overall perspective, i.e. it does neither incorporate unique transaction fees that retail investors face trading through their broker nor individual investor trading data.

7.2 Outlook

While important questions on the impact of MiFID on European equity trading have been addressed in this thesis, there are still open questions that may provide future research directions. The following briefly discusses the most promising avenues.

Liquidity and price discovery in different European markets

This thesis offers important implications and a guideline to study market quality in further European markets post MiFID. Studying different markets seem to be important, since the level of intermarket competition and the characteristics of market participants possibly impact market quality. In this context, two promising approaches arise. First, future research may consider to study countries where trading volume is more concentrated on the regulated market, such as Italy and Spain, and second, less actively traded stocks may be analyzed. It seems particularly interesting to examine the relationship between MTFs market share and their contribution to price discovery. Studies of additional countries and market segments may therefore offer broader insights into the nature of market quality across Europe.

The market environment and intraday dynamics

Studying regulated markets and MTFs in different market environments may offer further insights into trading venue competition under MiFID. For example, a platform's contribution to market quality may differ between 'normal' and 'uncertain' market conditions. Therefore, investors may use one platform as a 'market of last resort'. Most likely associated changes in investor behavior vary for different time periods over the trading day. Further studies may therefore also examine the intraday dynamics of trading intensity, liquidity, and price discovery measures.

An optimal level of market fragmentation

Research that would be interesting for regulators and practitioners alike may tend to determine whether overall market quality is maximized for a specific level of market fragmentation. The associated level may combine benefits of intermarket competition and order flow consolidation on a single platform. To evaluate associated research questions, a theoretical approach seems to be more suitable than empirical research. The model may incorporate varying levels of arbitrage activity and SOR system use by investors.

The role of algorithmic and high-frequency traders

It is generally believed that algorithmic and high-frequency traders submit between

40.0-60.0% of trading volume in European high volume stocks.[1] Due to a lack of trading venue data that clearly identify these types of traders, their role in a fragmented European trading landscape has not yet been studied in detail. Broker level data would further allow to research the role of algorithmic and high-frequency traders in market-making and cross-market arbitrage.

[1]See, for example, http://hft.thomsonreuters.com/.

Appendix A

Sample Data

Table A.1: **Raw TAQ data - LSE.** This table presents raw TAQ data from the LSE retrieved from Thomson Reuters Tick History archive. TAQ data is available on most exchanges in a similar format. In this sample the firm is 'Vodafone' (VOD.L).

#RIC	Date[G]	Time[G]	GMT Offset	Type	Price	Volume	Bid Price	Bid Size	Ask Price	Ask Size	Qualifiers
VOD.L	19-APR-2010	09:11:20.717	+1	Quote			150.05	71698	150.15	43516	
VOD.L	19-APR-2010	09:11:20.717	+1	Quote			150.05	71698	150.15	30726	
VOD.L	19-APR-2010	09:11:20.717	+1	Quote			150.05	71698	150.15	49971	
VOD.L	19-APR-2010	09:11:20.717	+1	Quote			150.05	71698	150.15	63142	
VOD.L	19-APR-2010	09:11:20.717	+1	Quote			150.05	71698	150.15	68557	
VOD.L	19-APR-2010	09:11:20.814	+1	Quote			150.05	71698	150.15	67508	
VOD.L	19-APR-2010	09:11:20.914	+1	Quote			150.05	87956	150.15	67508	
VOD.L	19-APR-2010	09:11:20.989	+1	Quote			150.05	87956	150.1	1049	
VOD.L	19-APR-2010	09:11:20.989	+1	Quote			150.05	87956	150.1	6583	
VOD.L	19-APR-2010	09:11:21.107	+1	Trade	150.1	907					A[ACT_FLAG1];A[CONDCODE_1]; [...]
VOD.L	19-APR-2010	09:11:21.107	+1	Quote			150.05	87956	150.1	5676	
VOD.L	19-APR-2010	09:11:21.353	+1	Trade	150.05	11178					N[ACT_FLAG1];N[CONDCODE_1]; [...]
VOD.L	19-APR-2010	09:11:21.430	+1	Quote			150.05	87956	150.1	15099	
VOD.L	19-APR-2010	09:11:21.587	+1	Quote			150.05	87956	150.1	19445	
VOD.L	19-APR-2010	09:11:21.712	+1	Trade	150.05	8786					N[ACT_FLAG1];N[CONDCODE_1]; [...]
VOD.L	19-APR-2010	09:11:23.152	+1	Quote			150.05	84556	150.1	19445	
VOD.L	19-APR-2010	09:11:23.163	+1	Quote			150.05	81156	150.1	19445	
VOD.L	19-APR-2010	09:11:23.186	+1	Quote			150.05	78406	150.1	19445	
VOD.L	19-APR-2010	09:11:23.216	+1	Quote			150.05	77911	150.1	19445	
VOD.L	19-APR-2010	09:11:23.339	+1	Quote			150.05	70556	150.1	19445	
VOD.L	19-APR-2010	09:11:23.401	+1	Quote			150.05	70331	150.1	19445	
VOD.L	19-APR-2010	09:11:23.423	+1	Quote			150.05	70556	150.1	19445	
VOD.L	19-APR-2010	09:11:23.911	+1	Quote			150.05	70301	150.1	19445	
VOD.L	19-APR-2010	09:11:24.481	+1	Quote			150.05	70301	150.1	22945	
VOD.L	19-APR-2010	09:11:24.981	+1	Quote			150.05	102120	150.1	22945	
VOD.L	19-APR-2010	09:11:26.034	+1	Quote			150.05	102120	150.1	19445	
VOD.L	19-APR-2010	09:11:26.518	+1	Quote			150.05	102120	150.1	22945	
VOD.L	19-APR-2010	09:11:28.376	+1	Quote			150.05	102120	150.1	24240	

Table A.2: **Raw depth data - LSE.** This table presents raw depth data from the LSE at three levels into the order book retrieved from Thomson Reuters Tick History archive. Depth data is available on most exchanges. In this sample the firm is 'Vodafone' (VOD.L).

#RIC	Date[G]	Time[G]	GMT Offset	Type	L1 Bid Price	L1 Bid Size	L1 Ask Price	L1 Ask Size	L2 Bid Price	L2 Bid Size	L2 Ask Price	L2 Ask Size	L2 Bid Price	L2 Bid Size	L2 Ask Price	L2 Ask Size
VOD.L	19-APR-2010	09:00:17.237	+1	Market Depth	150.25	75463	150.3	10814	150.2	122100	150.35	93927	150.15	119853	150.4	216138
VOD.L	19-APR-2010	09:00:17.337	+1	Market Depth	150.25	75463	150.3	10814	150.2	122100	150.35	93927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.374	+1	Market Depth	150.25	62773	150.3	10814	150.2	122100	150.35	93927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.374	+1	Market Depth	150.25	62773	150.3	10814	150.2	122100	150.35	93927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.381	+1	Market Depth	150.25	62773	150.3	10814	150.2	122100	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.381	+1	Market Depth	150.25	62773	150.3	18814	150.2	122100	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.460	+1	Market Depth	150.25	62773	150.3	18814	150.2	118600	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.460	+1	Market Depth	150.25	62773	150.3	18814	150.2	118600	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.501	+1	Market Depth	150.25	61673	150.3	18814	150.2	118600	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.501	+1	Market Depth	150.25	59798	150.3	18814	150.2	118600	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.514	+1	Market Depth	150.25	59648	150.3	18814	150.2	118600	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.514	+1	Market Depth	150.25	60898	150.3	18814	150.2	118600	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.568	+1	Market Depth	150.25	60898	150.3	18814	150.2	118600	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.568	+1	Market Depth	150.25	60898	150.3	18814	150.2	122100	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.613	+1	Market Depth	150.25	60898	150.3	18814	150.2	122100	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.613	+1	Market Depth	150.25	64298	150.3	18814	150.2	122100	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.665	+1	Market Depth	150.25	64298	150.3	20523	150.2	122100	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.678	+1	Market Depth	150.25	63048	150.3	20523	150.2	122100	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.823	+1	Market Depth	150.25	59648	150.3	20523	150.2	122100	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.823	+1	Market Depth	150.25	59648	150.3	20523	150.2	122100	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.980	+1	Market Depth	150.25	59648	150.3	20523	150.2	122100	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:17.993	+1	Market Depth	150.25	59648	150.3	20523	150.2	122100	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:19.035	+1	Market Depth	150.25	59648	150.3	20523	150.2	122100	150.35	85927	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:19.036	+1	Market Depth	150.25	59648	150.3	20523	150.2	122100	150.35	101349	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:19.859	+1	Market Depth	150.25	59488	150.3	20523	150.2	122100	150.35	101349	150.15	102703	150.4	216138
VOD.L	19-APR-2010	09:00:19.878	+1	Market Depth	150.25	59473	150.3	20523	150.2	122100	150.35	101349	150.15	102703	150.4	216138

Appendix B

Sample Firms

Table B.1: **Sample firms - April/May 2009.** This table reports sample firms for the observation period April/May 2009 including LSE ticker symbols, average daily market capitalization in million GBP, and average daily trading volume in thousand GBP.

Firm	Ticker	MCAP [mGBP]	Trading Volume [kGBP]
HSBC HOLDINGS	HSBA	89,706	290,973
BP	BP	92,676	219,338
VODAFONE GROUP	VOD	64,226	207,958
BHP BILLITON	BLT	87,152	199,162
RIO TINTO	RIO	41,400	186,825
BARCLAYS	BARC	22,202	178,338
GLAXOSMITHKLINE	GSK	54,092	144,314
ASTRAZENECA	AZN	36,052	136,819
ANGLO AMERICAN	AAL	19,915	134,475
XSTRATA	XTA	18,370	129,580
ROYAL DUTCH SHELL ‘B’	RDSB	98,844	109,885
STANDARD CHARTER	STAN	21,671	96,588
TESCO	TSCO	27,792	90,435
BRITISH AMERICAN TOBACCO	BATS	33,043	86,797
BG GROUP	BG	36,492	82,601
ROYAL DUTCH SHELL ‘A’	RDSA	98,844	75,460
UNILEVER	ULVR	42,930	69,703
DIAGEO	DGE	20,897	64,166
IMPERIAL TOBACCO GROUP	IMT	16,033	60,306
ROYAL BANK OF SCOTLAND GROUP	RBS	22,071	58,912
RECKITT BENCKISER GROUP	RB	19,020	57,225
BAE SYSTEMS	BAES	12,643	55,106
AVIVA	AV	8,467	45,741
SABMILLER	SAB	17,903	42,190
WPP	WPP	5,721	40,251
CENTRICA	CNA	12,203	39,262
COMPASS GROUP	CPG	6,339	36,030
KINGFISHER	KGF	4,234	35,937
VEDANTA RESOURCES	VED	3,459	34,298
REED ELSEVIER	REL	5,677	33,786
BT GROUP	BT	6,962	30,323
KAZAKHMYS	KAZ	3,272	29,323
SCOTTISH AND SOUTHERN ENERGY	SSE	10,303	27,906
ANTOFAGASTA	ANTO	5,732	27,269
CADBURY	CBRY	7,211	26,718
TULLOW OIL	TLW	7,083	25,350
BRITISH SKY BROADCASTING GROUP	BSY	8,069	25,089
CARNIVAL	CCL	14,594	25,021
RANDGOLD RESOURCES	RRS	2,848	24,302
SAINSBURY (J)	SBRY	5,786	24,075
BRITISH LAND COMPANY	BLND	3,554	23,433
MAN GROUP	EMG	4,101	23,009
THOMSON REUTERS	TRIL	15,408	22,525
CABLE & WIRELESS	CW	3,802	21,692
BRITISH AIRWAYS	BAY	1,849	21,316
EXPERIAN	EXPN	4,718	21,085
AUTONOMY CORPORATION	AUTN	3,388	20,115
SHIRE	SHP	4,891	18,632
HOME RETAIL GROUP	HOME	2,190	18,239
SMITH & NEPHEW	SN	4,067	18,195
INTERNATIONAL POWER	IPR	3,971	17,751
INTERCONTINENTAL HOTELS GROUP	IHG	1,859	17,666
EURASIAN NATURAL RESOURCES	ENRC	7,809	16,699
CAIRN ENERGY	CNE	3,153	16,495
CAPITA GROUP	CPI	4,316	15,879

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…continued from Table B.1

Firm	Ticker	MCAP [mGBP]	Trading Volume [kGBP]
RSA INSRANCE GROUP	RSA	4,304	14,379
UNITED UTILITIES GROUP	UU	3,571	13,896
SMITHS GROUP	SMIN	2,848	13,716
WHITBREAD	WTB	1,532	13,120
HAMMERSON	HMSO	2,105	12,645
THOMAS COOK GROUP	TCG	2,177	12,184
ICAP	IAP	2,468	12,025
DRAX GROUP	DRX	1,693	11,885
ASSOCIATED BRITISH FOODS	ABF	5,779	11,547
BUNZL	BNZL	1,691	11,513
JOHNSON MATTHEY	JMAT	2,607	11,330
TUI TRAVEL	TT	2,890	11,234
INVENSYS	ISYS	1,653	11,223
SEVERN TRENT	SVT	2,570	11,158
SAGE GROUP	SGE	2,445	10,261
REXAM	REX	1,942	10,149
SERCO GROUP	SRP	1,848	9,481
INMARSAT	ISA	2,339	9,413
STANDARD LIFE	SL	4,190	9,349

Table B.2: **Sample firms - April/May 2010.** This table reports sample firms for the observation period April/May 2010 including LSE ticker symbols, average daily market capitalization in million GBP, and average daily trading volume in thousand GBP.

Firm	Ticker	MCAP [mGBP]	Trading Volume [kGBP]
BP	BP	105,663	477,807
RIO TINTO	RIO	75,532	434,376
HSBC HOLDINGS	HSBA	114,162	374,792
BHP BILLITON	BLT	121,875	372,968
BARCLAYS	BARC	39,229	313,998
XSTRATA	XTA	30,966	277,829
VODAFONE GROUP	VOD	73,377	254,027
ANGLO AMERICAN	AAL	35,332	239,908
LLOYDS BANKING GROUP	LLOY	40,748	204,118
ROYAL DUTCH SHELL ‘B’	RDSB	116,881	159,076
GLAXOSMITHKLINE	GSK	61,920	152,854
ASTRAZENECA	AZN	41,613	150,532
STANDARD CHARTER	STAN	34,526	146,108
PRUDENTIAL	PRU	13,831	142,791
BG GROUP	BG	35,999	142,052
ROYAL DUTCH SHELL ‘A’	RDSA	112,658	135,342
BRITISH AMERICAN TOBACCO	BATS	41,404	123,491
ROYAL BANK OF SCOTLAND GROUP	RBS	28,860	117,950
TESCO	TSCO	33,738	105,456
IMPERIAL TOBACCO GROUP	IMT	18,854	96,667
UNILEVER	ULVR	57,568	90,810
SABMILLER	SAB	31,389	90,643
DIAGEO	DGE	27,381	87,880
RECKITT BENCKISER GROUP	RB	24,452	81,551
WPP	WPP	8,497	79,128
BT GROUP	BT	9,742	67,048
AVIVA	AV	9,330	65,015
VEDANTA RESOURCES	VED	6,668	62,606
TULLOW OIL	TLW	10,025	61,876
KAZAKHMYS	KAZ	6,871	61,772
CENTRICA	CNA	14,835	60,142
BAE SYSTEMS	BAES	11,851	56,635
ROLLS ROYCE GROUP	RR	10,798	51,907
WOLSELEY	WOS	4,520	51,754
ANTOFAGASTA	ANTO	9,152	51,568
CARNIVAL	CCL	21,912	47,337
BRITISH SKY BROADCASTING GROUP	BSY	10,404	45,879
NEXT	NXT	4,066	43,897
SHIRE	SHP	8,017	42,903
COMPASS GROUP	CPG	9,994	41,641
MARKS AND SPENCER GROUP	MKS	5,580	41,592
PEARSON	PSON	8,031	41,556
KINGFISHER	KGF	5,444	41,352
EURASIAN NATURAL RESOURCES	ENRC	14,069	41,189
SCOTTISH AND SOUTHERN ENERGY	SSE	9,983	40,620
REED ELSEVIER	REL	6,091	40,149
RANDGOLD RESOURCES	RRS	5,071	39,806
CAIRN ENERGY	CNE	5,540	38,037
ARM HOLDINGS	ARM	3,231	37,955
MORRISON (WM) SUPERMARKETS	MRW	7,353	35,160
MAN GROUP	EMG	3,986	33,645
CAPITA GROUP	CPI	4,984	31,724
SMITH & NEPHEW	SN	5,819	31,494
BRITISH AIRWAYS	BAY	2,424	30,740
EXPERIAN	EXPN	6,176	29,040

continued on the next page. . .

. . . continued from Table B.2

Firm	Ticker	MCAP [mGBP]	Trading Volume [kGBP]
LAND SECURITIES GROUP	LAND	4,776	27,702
LEGAL & GENERAL GROUP	LGEN	4,800	27,531
SAINSBURY (J)	SBRY	6,172	25,112
INTERNATIONAL POWER	IPR	4,797	24,906
INTERCONTINENTAL HOTELS GROUP	IHG	3,155	24,848
AUTONOMY CORPORATION	AUTN	4,237	24,377
OLD MUTUAL	OML	6,237	24,135
AGGREKO	AGGK	3,347	23,709
BRITISH LAND COMPANY	BLND	3,941	23,285
HOME RETAIL GROUP	HOME	2,356	23,087
G4S	GFS	3,750	23,079
LONMIN	LMI	3,535	22,921
PETROFAC	PFC	3,849	21,188
BURBERRY GROUP	BRBY	2,953	20,668
REXAM	REX	2,759	20,248
ASSOCIATED BRITISH FOODS	ABF	7,735	20,117
JOHNSON MATTHEY	JMAT	3,560	19,123
RSA INSRANCE GROUP	RSA	4,137	17,927
UNITED UTILITIES GROUP	UU	3,648	17,703
ICAP	IAP	2,468	17,618
SAGE GROUP	SGE	3,172	17,359
AMEC	AMEC	2,727	16,989
SMITHS GROUP	SMIN	4,256	16,722
WHITBREAD	WTB	2,561	15,847
SEVERN TRENT	SVT	2,735	15,097
HAMMERSON	HMSO	2,586	14,472
TUI TRAVEL	TT	2,899	14,470
COBHAM	COB	2,873	14,258
INVENSYS	ISYS	2,502	14,130
THOMAS COOK GROUP	TCG	1,977	13,866
SERCO GROUP	SRP	3,080	13,699
3I GROUP	III	2,661	12,244
INVESTEC	INVP	3,786	11,580
BUNZL	BNZL	2,436	11,267
STANDARD LIFE	SL	4,291	11,174
SEGRO	SGRO	2,166	10,851
INTERTEK GROUP	ITRK	2,293	9,134
INMARSAT	ISA	3,487	9,104
FRESNILLO	FRES	6,007	8,811
ADMIRAL GROUP	ADML	3,464	8,706
SCHRODERS	SDR	3,755	8,403
LONDOND STOCK EXCHANGE	LSE	1,816	7,378
CABLE & WIRELESS	CWP	2,190	6,740

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