The Role of Traditional Exchanges in Fragmented Markets *

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Abstract

The Markets in Financial Instruments Directive (MiFID) considerably changed the nature of European equity markets. Introduced in November 2007, it allowed alternative trading venues to compete for order flow with traditional exchanges. This paper studies the impact of increased fragmentation of order flow on market quality in UK blue chip stocks from two different dimensions. First, we provide evidence that market quality increases along with the level of market fragmentation over 2009. Second, we evaluate intraday patterns of trading intensity and market quality measures. Our results show that the traditional exchange has an important function at market opening and closing, attracting a significantly higher share of trading volume compared to other periods of the trading day. Additionally, we find converging intraday patterns across trading venues over time which indicates a maturing market.

JEL Classification: G10, G14.

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1 Introduction

The introduction of the Markets in Financial Instruments Directive (MiFID) in 2007 has significantly altered European equity markets. National exchanges such as the London Stock Exchange (LSE) or Deutsche Boerse faced increased competition by the proliferation of new trading venues. Enhanced competition for order flow within European equity markets induced by MiFID has also spurred empirical research on fragmented markets in market microstructure literature. Tick-by-tick order book data of the LSE and three alternative trading venues allow us to analyze trading from an interday and intraday perspective. In particular, this paper studies interday changes of trading intensity and market quality measures in fragmented markets over time and it investigates whether spreads, trading volume, market shares, and informed trading concentrate on single platforms during specific periods of the trading day.

MiFID became effective in the European Union (EU) on November 1, 2007.[1] On the one hand, MiFID aims to enhance investor protection by creating transparent European equity markets. On the other hand, MiFID pursuits the improvement of market quality by fostering competition between trading venues. MiFID allows different types of trading venues to compete for order flow in European equity markets. Besides traditional regulated markets such as the LSE, Deutsche Boerse, or other national exchanges, new types of trading venues entered the European market for exchange business. These are so called multilateral trading facilities (MTF), such as Chi-X, BATS, or Turquoise, and systematic internaliser (SI), such as Goldman Sachs International. As a consequence, order flow and liquidity fragmented across platforms.[2] MiFID defines traditional exchanges as regulated markets where a buyer's demand is matched with a seller's supply according to a specific set of trading rules. MTFs are similar to regulated markets in matching buy and sell

[1]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). It was also adopted by Iceland, Liechtenstein, and Norway.

[2]See `http://mifiddatabase.esma.europa.eu/` for a complete list of all MTFs, SIs, and regulated markets operating in the EU.

orders. However, they are liable to different regulatory prerequisites and have no listing process. Therefore, MTFs have a certain cost advantage relative to regulated markets and are able to compete on the basis of low transaction fees.[3]

After the introduction of MiFID, new trading venues complied with heterogeneous desires of their clientele, such as trading speed, anonymity, or fee schedules. As a consequence, order flow and liquidity became fragmented across trading venues. Intuitively, the probability of order execution falls if demand and supply are separated across various platforms. Market microstructure theory also addresses this question. Pagano (1989a), Pagano (1989b), and Chowdhry and Nanda (1991) study the effect of network externalities, i.e. a liquid market attracts even more liquidity. Their findings predict that order flow should concentrate on one single platform. However, increased intermarket competition may reduce the monopoly power of traditional exchanges and thus decrease transaction costs and inspire trading venues to develop new services (European Commission (2010)). Market statistics show that trading has constantly become more fragmented since the introduction of MiFID. UK blue chip stocks are the most fragmented European equities. For example, LSE's market share in FTSE 100 constituents continually decreased from close to 100% in 2007 to just 43% in June 2011.[4]

The debate whether order flow and liquidity should be concentrated geographically is an important question which has been discussed in detail by various authors empirically (e.g. Easley, Kiefer, and O'Hara (1996)) and theoretically (e.g. Hendershott and Mendelson (2000)). Yet, potential negative effects of market fragmentation may today be alleviated by modern information and communication technology where various trading venues can virtually be integrated. Investors may use Smart Order Routing (SOR) technologies which guarantee best execution across trading venues (Foucault and Menkveld (2008)).[5] In our paper, we investigate the influence of market fragmentation on trading

[3]This paper focuses on regulated markets and MTFs. Therefore, we do not discuss SIs in detail.

[4]For detailed statistics on European equity market fragmentation, see `http://fragmentation.fidessa.com`.

[5]In contrast to MiFID, U.S. equity markets are electronically linked by technology via the Intermarket Trading System (ITS) and private low latency communications linkages.

intensity and market quality for UK blue chip stocks from January until December 2009. To evaluate market fragmentation over time, we focus on two periods with distinct levels of market fragmentation, quarter one and four of 2009. We find evidence that market quality improves on all platforms while market fragmentation and competition between the LSE and the three MTFs increase.

However, we are not only interested in the influence of market fragmentation on market quality. For a single trading platform, Admati and Pfleiderer (1988) explain theoretically why trading tends to be concentrated at particular periods within the trading day. Given a fragmented European trading landscape, the interesting question is how order flow and liquidity are connected during the trading day and whether one market dominates others in specific periods of trading. Overall, we observe that intraday patterns of trading volume, market shares, quoted spreads, and price impacts converge from Q1 to Q4 across trading venues, i.e. measures develop with a higher similarity across trading venues over time, which indicates a maturing market. We find that increasing market fragmentation does not significantly change intraday patterns over time, with the exception of quoted spreads on Turquoise. Within the trading day, our data provide evidence that market shares shift away from the regulated market to MTFs after market opening and then back to the LSE before market closing. This suggests that market participants trust more the price formation process on the LSE in times of increased volatility and price uncertainty (e.g. Foster and Viswanathan (1993)). Quoted spreads are predominantly crude reversed J-shaped on all trading venues. For trading volume, we find opposing patterns for the LSE and MTFs. While LSE trading volume follows a U-shape (in line with e.g. Foster and Viswanathan (1993) and Werner and Kleidon (1996)), trading volume at MTFs starts to increase only during the second half of the trading day. On all trading venues we find the inverse relationship between decreasing spreads and growing volume over the trading day, also documented by McInish and Wood (1992) and Cai, Hudson, and Keasey (2004). Price impacts decrease on all platforms during the trading day in both of our observation periods. This result indicates a decreasing information content of trades during the trading day.

The remainder of this paper is structured as follows. Section 2 describes related literature on intermarket competition and intraday patterns. Section 3 gives details on competition in the UK equity market over time. Section 4 describes our data and methodology. Section 5 examines trends between the first and the fourth quarter of 2009 and Section 6 analyzes intraday patterns of the data. Finally, Section 7 summarizes and concludes the paper.

2 Related Work

2.1 Intermarket Competition

The relationship between fragmentation and competition is ambiguous. Intuitively, fragmentation should have a detrimental effect on market quality through scattering order flow and liquidity across various trading venues. Compared to a single market, multiple trading venues induce higher search costs for investors. Mendelson (1987) theoretically addresses the impact of fragmentation on market quality. He shows that market fragmentation reduces expected trading volume, increases price variance, and lowers expected trading profits for investors. Literature also refers to positive effects of network externalities on liquidity. For example, Pagano (1989b) analyzes a two market scenario with equal trading costs at both markets. He argues that investors will predominately trade on one platform and thus increase liquidity on this trading venue relative to the second market. Chowdhry and Nanda (1991) study a multi-market scenario with a few large-scale informed investors and many noise traders. They show that in equilibrium, noise traders tend to choose the most liquid market which reversely attracts more informed trading.

Despite strong network externalities, the proliferation of new trading venues may strengthen competition for order flow. Trading venues may increase their market share by lowering transaction costs, i.e. they can offer lower explicit fees and thus attract more liquidity provision, and by providing better services to their clients, i.e. introducing faster technology. Several studies address the ambiguous effects of fragmentation and competition on market quality. Battalio, Greene, and Jennings (1997) provide evidence that increased competition in NYSE listed stocks leads towards smaller quoted and effective spreads. Biais, Bisire, and Spatt (2010) study the effects of tick-size reductions on market quality for NASDAQ listed stocks and a competing Electronic Communication Network (ECN).[6] They show that smaller tick sizes at the competing ECN are responsible for an overall reduction of quoted spreads on both trading venues.

Foucault and Menkveld (2008) analyze the market entry of the LSE on the Dutch stock market in 2004. They find that competition between the two results in increased liquidity on both platforms. Degryse, Jong de, and Kervel (2011) study the effect of MiFID induced fragmentation on order book depth for a sample of Dutch stocks from 2006 to 2009. They find that overall liquidity increases across trading venues with the level of market fragmentation. However, liquidity on the regulated home market, Euronext Amsterdam, decreases by nearly 10% relative to a completely consolidated market. They conclude that investors who only have access to Euronext Amsterdam may be worse off under MiFID. Riordan, Storkenmaier, and Wagener (2011) compare market quality in FTSE 100 constituents on the LSE and three MTFs over two trading periods in 2009 and 2010. Their results indicate that increasing fragmentation prompts an improvement of market quality on each trading venue. They also find a shift in price discovery away from the LSE towards MTFs in 2010. Overall, they provide evidence that MTFs contribute to market quality.

2.2 Evidence of Intraday Patterns

Theory suggests that trade does not only concentrate on individual trading venues but also during particular times within a trading day. The models of Admati and Pfleiderer (1988) and Brock and Kleidon (1992) provide theoretical explanations for the existence

[6]ECNs are the U.S. counterpart to European MTFs.

of intraday trading patterns on individual trading platforms.

Admati and Pfleiderer (1988) focus on reciprocal strategic decisions of informed traders, discretionary liquidity traders, and non-discretionary liquidity traders. They argue that intraday patterns in volume and price volatility arise due to liquidity traders who choose to trade at discrete periods during the day. Their model shows that these periods attract informed traders who try to conceal their superior information in periods of high trading activity. This leads to a increase of traded volume and price volatility at certain periods. According to the authors opening and the closing of the market may represent such distinctive clustering points.

Brock and Kleidon (1992) extend Merton (1971) who studies portfolio positions in a continuous market. They argue that market participants exhibit an increased and less elastic desire to trade at market opening and closing compared to other periods within the trading day due to portfolio rebalancing. At market opening, portfolios have to be adjusted due to the arrival of new overnight information. Shortly before market closing, investors need to optimize their positions for the overnight period which again triggers increased trading activity. This trading behavior creates U-shaped patterns in traded volume. The authors also argue that spreads and volume are positively correlated. They justify larger spreads at open and close of the market because market makers may price discriminate market participants who need to rebalance their holdings during these periods.

Empirical literature on intraday patterns of trading intensity and market quality find varying results which do not necessarily follow theoretical predictions. Figure 1 summarizes empirical findings on intraday patterns of trading volume, quoted spreads, and informativeness of trading at the NYSE, NASDAQ and the LSE. Intraday trading intensity measures predominantly follow an U-shape for the NYSE and NASDAQ (Jain and Joh (1988), Foster and Viswanathan (1993), and Chan, Christie, and Schultz (1995)). Results are mixed for the LSE. Werner and Kleidon (1996) report an U-shaped pattern while Abhyankar, Ghosh, Levin, and Limmack (1997) and Cai, Hudson, and Keasey (2004) report a two-humped pattern for intraday volume.

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Insert Figure 1 here

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Empirical evidence on intraday quoted spreads is homogeneous across markets with decreasing liquidity over the trading day. For example, McInish and Wood (1992) report a crude reversed J-shaped pattern of quoted spreads which is similar to empirical findings for the LSE. For NASDAQ stocks, Chan, Christie, and Schultz (1995) find decreasing quoted spreads only at the close of the market while liquidity changes little throughout the day. According to the authors, diverging patterns on NYSE and NASDAQ can be explained by structural market differences, i.e. NYSE is organized as a specialist market and NASDAQ as a dealer market. A possible reason for the decrease in quoted spreads on NASDAQ may be dealer inventory controls prior to market closing.

McInish and Wood (1992) and Foster and Viswanathan (1993) find characteristic patterns for informed trading over the trading day. The information content of trades peaks at market opening and decreases until market close. Additionally, McInish and Wood (1992) address the relationship between quoted spreads and information based trading. They define unusual large trade sizes as information based trading and find a direct connection to wider spreads. Foster and Viswanathan (1993) argue that adverse selection costs are high at market opening, fall during the trading day and increase before market closing. They also provide evidence for a direct relationship between high adverse selection costs and trading volume.

3 Details on the UK Equity Market

This section gives a brief overview of the UK equity market structure in our 2009 observation period and outlines the competitive environment between the LSE and the most important MTFs in terms of trading volume. Chi-X started trading the full set of

FTSE 100 constituents in August 2007, while all FTSE 100 constituents were available on Turquoise and BATS in August 2008 and November 2008, respectively. In 2009, the LSE, Chi-X, BATS, and Turquoise account for almost 100% of non-OTC trading volume in FTSE 100 constituents.[7]

Figure 2 depicts the development of weekly market shares of FTSE 100 constituents traded on the LSE, Chi-X, BATS, and Turquoise between January 2 and December 30, 2009.[8] The figure shows a shift in market shares away from the LSE towards the three MTFs during our observation period. While LSE's market share dropped from 74.8% in January 2009 to 57.6% at the end of 2009, Chi-X and BATS increased their share in trading volume. Chi-X, the largest European MTF, almost doubled its market share in FTSE 100 constituents from 14.7% to 27.3% over 2009. BATS's market share more than quadrupled from 2.1% to 9.3%. Turquoise lost market shares to the other two MTFs. Its share in trading volume decreased from 8.5% to 5.7%.

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Regulated markets and MTFs mainly compete for order flow based on trading costs and speed of execution. In general, the LSE and the three MTFs are organized as electronic limit order books. Continuous trading opens at 8:00 and closes at 16:30 GMT on all platforms. On the LSE, FTSE 100 constituents are traded on the Stock Exchange Trading System (SETS). Unlike at MTFs, trading at the LSE starts with a 10-minute opening auction and ends with a 10-minute closing auction prior and post continuous trading hours. MTFs have adjusted their trading mechanism to speed-sensitive investors. Algorithmic and high frequency traders (HFT) have flourished over the past years and with them the need for faster trading technologies.[9] Low latency leads to increased liquidity and

[7]See `http://fragmentation.fidessa.com` for further details.

[8]The FTSE 100 index represents the 100 largest companies listed on the LSE. Our data sample consists of 69 FTSE 100 stocks. See 4.1 for details of our sample selection. Trading volume based market shares per day and per stock are averaged to obtain weekly market shares.

[9]To date, the trading volume of algorithmic and high frequency traders in most European blue chip

thus to better chances for order placement at the right time (Riordan and Storkenmaier (2011)).[10] Compared to their human counterparts, algorithmic and high frequency traders place, cancel, or execute a multitude of orders within milliseconds. Transaction costs may thus increase for algorithmic and high frequency traders that submit a large quantity of orders. Differences in trading fees between the LSE and MTFs may be responsible for the shift away from the regulated market. During our observation period the fee structure of all trading venues is subject to changes, except for Turquoise. At the beginning of 2009, all platforms had installed a "maker-taker" tariff system. "Maker-taker" systems charge investors for aggressive (taker) orders that consume liquidity from the order book, i.e. these orders are executed against outstanding limit orders in the order book. For executed passive (maker) orders that provide liquidity to the order book, investors receive a rebate.

At the beginning of 2009, the LSE charged an investor between 0.45 bps and 0.75 bps of the order volume for aggressive orders. Passive orders received a rebate up to 0.40 bps. On September 1, 2009, the LSE switched back to a traditional fee scheme charging both aggressive and passive orders between 0.20 bps and 0.45 bps depending on the monthly trading volume of an investor. Chi-X and BATS charged investors 0.30 bps for an aggressive and rebate an executed passive order with 0.20 bps during 2009. However, both platforms offered special inverted pricing promotions for investors during the year. Chi-X offered customers under certain volume conditions a rebate of 0.20 bps for aggressive orders in October 2009. BATS subsidized trades by offering customers a 0.40 bps rebate on executed passive orders while charging aggressive orders with 0.20 bps during September 2009. From October 2009, BATS lowered its constant tariff schedule to 0.25 bps for aggressive orders while keeping the rebate for passive. On Turquoise, investors pay 0.28 bps for an aggressive order and receive a rebate between 0.20 bps and

indices adds to more than 50%, see http://hft.thomsonreuters.com/.

[10]For a discussion of the need for higher trading speed, see `http://www.ftmandate.com/news/fullstory.php/aid/2335/The_need_for_speed.html`.

0.24 bps for executed passive orders depending on the traded volume.[11]

4 Data and Methodology

4.1 Sample Selection

Our data comprise FTSE 100 constituents which are traded on the LSE and the three largest MTFs, Chi-X, BATS, and Turquoise during January 2 and December 31, 2009. We obtain trade and quote data for each trading venue from the Thomson Reuters DataScope Tick History archive through the Securities Industry Research Centre of Asia-Pacific (SIRCA).[12] The data contain trade prices, volumes, best bid and ask including associated volumes, and order book information up to three levels behind best prices. All trades and quotes are reported in British pence and time stamped to the millisecond. We focus on continuous trading from 8:00 until 16:30 GMT and use unique qualifiers in our raw data to delete certain reported executions, such as cross-reported trades and call auction trades. Our data sets include multiple data entries if a single marketable order trades against several limit orders in the order book. We treat those kinds of orders as a single trade and therefore combine all buy (sell) orders in a stock on one trading venue if they are reported within the same millisecond.

In order to obtain a clean sample, we filter sample firms according to the following criteria. First, selected stocks have to be included in the FTSE 100 index over the whole observation period. Second, we exclude companies with stock splits or other corporate actions. Third, we delete stocks with missing trade and quote data or missing data on market capitalization.[13] Fourth, each selected stock has to be traded at least 10 times

[11] See http://www.londonstockexchange.com/about-the-exchange/media-relations/press-releases/2009/london-stock-exchange-introduces-new-orderbook-trading.htm, http://www.thetradenews.com/asset-classes/equities/3673, http://www.chi-xeurope.com/trading-notices-pdfs/trading-notice-0183.pdf, http://www.tradeturquoise.com/market_notices/tariff_Schedule.pdf.

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

[13] We obtain daily market capitalizations per stock from Bloomberg.

per day on each trading venue. Finally, we obtain 69 stocks over 245 trading days.[14]

In our study we analyze both individual order books of the LSE, Chi-X, BATS, and Turquoise and the consolidated order book of all four trading venues. In order to create the consolidated order book, we integrate all four individual order books into a single order book on a per stock per millisecond base.

4.2 Trading Intensity and Spread Measures

To measure trading intensity, we focus on market shares, trading volume, trade count, and trade size. All measures are calculated per day and per stock for the individual order books of the LSE, Chi-X, BATS, and Turquoise. Market shares are based on daily trading volume in British Pounds per stock. Trade count is defined as the average number of daily trades per stock for each trading venue. Trade size represents the average amount of GBP per trade.

We measure market quality by calculating quoted spreads, quoted spreads at trade, effective spreads, realized spreads (5 and 15 minutes), price impacts (5 and 15 minutes), and order book depth at best prices and three ticks behind best prices.

The most common measure for liquidity 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 an individual order book level. 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:

$$qspread_{i,t} = (a_{i,t} - b_{i;t})/(m_{i,t} * 2) * 10,000$$

This measure is based on a quote-to-quote process that is characterized by every price or volume update and each trade during the trading day. Then, quoted spreads are

[14] Seven trading days are excluded due to infrequent trading.

aggregated on a daily per instrument 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. Additionally, we calculate quoted spread at trades, which capture liquidity represented through the best bid and ask at the time of execution.

The effective spread is the spread that is actually paid when an incoming market order trades against a limit order. We 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 ($espread_{i,t}$) is defined as:

$$espread_{i,t} = D_{i,t} * ((p_{i,t} - m_{i,t})/m_{i,t}) * 10,000$$

where $D_{i,t}$ denotes the trade direction with -1 for marketable sell and +1 for marketable buy orders. Effective spreads also capture institutional features of trading venues like hidden liquidity or 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.[15] Effective spreads are usually equal to or larger than the second liquidity measure, quoted spreads at trades. However, they might be smaller if trading venues feature hidden liquidity and there are a reasonable number of trades executed inside the spread.

We further investigate the individual components of the quoted spread according to Glosten (1987). In order to capture liquidity provider revenues, we compute realize spreads and assume that liquidity providers are able to close their position at the quote midpoint 5 minutes (15 minutes) after the trade. Let $m_{i,t+x}$ denote the mid quote with $x = \{5, 15\}$ minutes, then the realized half spread ($rspread_{x,i,t}$ is defined as:

$$rspread_{x,i,t} = D_{i,t} * ((p_{i,t} - m_{i,t+x})/m_{i,t}) * 10,000$$

[15]Fully hidden orders are available at the LSE starting from December 14, 2009. We clean our data for inside the spread executions prior to the introduction that represent 7.25% of all LSE trades.

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

$$pimpact_{x,i,t} = D_{i,t} * ((m_{i,t+x} - m_{i,t})/m_{i,t}) * 10,000$$

We use the midpoint of the consolidated order book of the LSE, Chi-X, BATS, and Turquoise to compute effective spreads, realized spreads, and price impacts. These three measures need a reference price that is usually the midpoint of the best quoted bid and ask.[16]

Finally, depth data is used to the compute quoted volume at different order book levels in the individual order books. Let $B_{i,t}$ be the corresponding volume at the bid and $A_{i,t}$ at the ask, then the quoted half depth ($depth_{x,i,t}$) in British Pounds is computed as follows:

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

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

5 Interday Results

5.1 Descriptive Statistics

Table 1 reports descriptive statistics of trading intensity and market quality measures for the first quarter of 2009 (Q1). Markets are fragmented with a LSE market share of

[16] Barclay, Hendershott, and McCormick (2003) also use the midpoint of best prices as reference price.

72.31% of total trading volume. Chi-X captures 16.74% of trading volume, BATS 2.47%, and Turquoise 8.48%. The largest trades are executed on the LSE with an average trade size of 10,304 GBP. Trade sizes are larger on Turquoise with 7,000 GBP compared to Chi-X and BATS with 6,373 GBP and 5,302 GBP, respectively.

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Average daily quoted spreads at the LSE and Chi-X are relatively small with 7.38 bps and 9.80 bps, respectively. BATS and Turquoise show wider average daily quoted spreads with 12.91 bps and 20.21 bps. This indicates less liquidity on these two trading platforms. Interestingly, average daily quoted spreads at trade are considerably smaller than daily quoted spreads on all platforms. This suggests that investors monitor markets and decide to trade when spreads are narrow.

Effective spreads represents the cost that is actually paid by a liquidity demander for a transaction. On the LSE, a liquidity demander has to pay on average 4.90 bps during Q1. Interestingly, effective spreads are smaller on Chi-X with 4.81 bps and Turquoise with 4.18 bps. BATS shows the largest effective spread with 5.16 bps. Smaller effective spreads from the consolidated order book compared to quoted spreads at trade from single order books suggest that investors could economically benefit from trading on all four venues simultaneously. Typically, effective spreads and quoted spreads at trade are relatively close. However, we observe that average daily effective spreads are lowest on Turquoise while this platform also shows the largest discrepancy between effective spreads and quoted spreads at trade among all trading venues. This result is in line with Riordan, Storkenmaier, and Wagener (2011) who provide evidence that Turquoise's small effective spread is considerably influenced by overall market conditions and the small number of trades on Turquoise.

5 and 15-minute realized spreads deliver mixed results across platforms. BATS is the only trading venue where investors benefit from supplying liquidity with 1.35 bps given

that they close their position 5 minutes after the trade. For the 15 minutes interval, all trading venues except Turquoise show positive realized spreads. Informed liquidity demanders seem to be most active on the LSE, as 5-minute price impact are highest on this platform, 5.19 bps, compared to 4.95 bps on Chi-X, 3.84 bps on BATS, and 4.49 bps on Turquoise.

On the LSE, average order book depth at level one is 29,487 GBP and 102,326 GBP for the cumulated depth three ticks behind best prices. Compared to the LSE, depth is slightly higher on Chi-X but significantly lower on BATS and Turquoise. However, our measures do not consider iceberg orders and fully hidden liquidity which influence order book depth.

5.2 Changes over Time

We compare quarter 1 (Q1) and quarter 4 (Q4) of 2009 in order to analyze differences in trading intensity and market quality measures over time and across trading venues along with the level of market fragmentation. Similar to Hendershott and Moulton (2011), we control for market conditions between both observation periods. The general regression model is defined per day t and per stock i as follows:

$$measure_{i,t} = \alpha_i + \beta_{i,t}\ quarter_{i,t} + \gamma_{i,t} \sum controls_{i,t} + \epsilon_{i,t} \tag{1}$$

where our dependent variables $measure_{i,t}$ are different trading intensity and market quality measures as introduced in Section 4.2. The variable of interest, $quarter_{i,t}$, is a dummy variable which takes the value 1 for Q4 and is 0 otherwise. It captures differences between Q1 and Q4 of 2009 which are reported by the coefficient $\beta_{i,t}$. To control for market conditions, we include the logarithm of daily market capitalization, the average daily realized volatility, the logarithm of daily closing prices, and firm dummy variables. We report robust standard errors using Thompson (2011). Table 2 depicts differences between quarters and trading venues relative to the LSE. The first column of each trading venue

(Q4-Q1) shows differences in trading intensity and market quality measures between Q1 and Q4 of 2009. The second column (Venue-LSE) reports changes of each trading venue over time relative to the LSE.

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Insert Table 2 here

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As expected, the regression results confirm that the LSE market share declines significantly by 17.48% between both observation periods. Chi-X and BATS gain significant market shares over time, with 11.99% and 7.57%, respectively. The market share of Turquoise decreases by 2.08% from Q1 to Q4. Trading volume and the number of trades decrease on the LSE and Turquoise between Q1 and Q4, while Chi-X and BATS show an increase in trading activity. Average trade size in terms of GBP per trade increases most significant on the LSE with 932 GBP and slightly on Chi-X with 264 GBP. Trades on BATS and Turquoise become smaller over time with a decrease of -614 GBP and -2,417 GBP, respectively. We assume that this development is connected to clientele effects. MTFs offer economically more beneficial fee schedules to algorithmic and high frequency traders as these investors submit smaller orders at a higher frequency compared to human traders (Hendershott and Riordan (2009)).

For our market quality measures, quoted spreads, quoted spreads at trade, and effective spreads, we find negative coefficients for all trading venues over time, i.e. liquidity improves between Q1 and Q4 on each platform. Quoted spreads decrease between -0.72 bps on the LSE and -5.00 bps on Turquoise. Relative to the LSE, quoted spreads on each MTF improve over 2009. For example, the difference in quoted spreads between the LSE and Chi-X decreases by -2.51 bps. Differences between Q1 and Q4 in effective spreads range between -0.69 bps on Turquoise and -1.29 bps on BATS.

Results on realized spreads are mixed. While realized spreads decrease on the LSE and BATS between Q1 and Q4, they do not change significantly on the LSE and Turquoise. Price impacts for 5 and 15-minute benchmarks decrease significantly on all platforms over time. Relative to the LSE, 5-minute price impacts decrease by -0.26 bps on Chi-X and do not change significantly on BATS and Turquoise. On the LSE, order book depth increases by 11,695 GBP on the best bid and ask and 92,502 GBP three ticks behind best prices from Q1 to Q4. Depth 1 does not change on Chi-X and BATS but falls significantly on Turquoise by -8,717 GBP.

In contrast to theoretical argumentation (e.g. Mendelson (1987)), we find some evidence that increased market fragmentation may have a positive effect on market quality. The regression results show that liquidity measured in terms of quoted spreads increases considerably on the LSE, Chi-X, BATS, and Turquoise between Q1 and Q4 along with the level of market fragmentation. Unfortunately, our data do not allow us to analyze the impact of different types of investors on market quality. For example, algorithmic and high frequency traders may considerably contribute to smaller quoted spreads (Hendershott and Riordan (2009)).

6 Intraday Results

Differences in trading intensity and market quality between trading venues may not only differ over time but may also exhibit intraday variations. By analyzing the latter, we gain insights into the behavior of different investor clienteles on each platform. Specifically, we focus on intraday patterns of trading volume, market shares, quoted spreads, and 5-minute price impacts. Following Abhyankar, Ghosh, Levin, and Limmack (1997) and Cai, Hudson, and Keasey (2004), we use 15-minute intraday averages and obtain 34 intervals across the trading day. 15-minute snapshots are small enough to capture intraday effects but at the same time level volatility of the trading process.

For trading volume, we multiply the traded quantity with the corresponding execution price and obtain the sum for each 15-minute interval per trading venue across stocks. Market shares are the fraction of total trading volume for each platform on a 15-minute basis. Quoted spreads and 5-minute price impacts are calculated as presented in Section 4.2 and averaged for each 15-minute interval.

To analyze intraday patterns of each variable, we rely on two methods. First, we graphically evaluate time variations of each variable for both observation periods, Q1 and Q4. Second, to test for statistical significance of intraday changes, we use the following regression model as in Cai, Hudson, and Keasey (2004):

$$measure_{i,t,j} = \alpha_{i,t} + \sum_{j=1}^{16} \beta_{i,t,j} D_{i,t,j} + \sum_{j=18}^{34} \beta_{i,t,j} D_{i,t,j} + \epsilon_{i,t} \quad (2)$$

where $measure_{i,t,j}$ represents our variables of interest, namely trading volume, market shares, quoted spreads, and 5-minute price impacts. Dummy variables for each 15-minute interval of the trading day take the value 1 for an observation within this interval and 0 otherwise. We omit the midday interval, the 17th interval of the trading day from 12:00 to 12:15. Therefore, all coefficients $\beta_{i,t,j}$ measure the difference relative to this reference interval. We include firm and day dummy variables and use robust Thompson (2011) clustered standard errors.

6.1 Trading Intensity

Trading Volume Figure 3 depicts the average trading volume on the LSE, Chi-X, BATS and Turquoise for each 15-minute interval during Q1 and Q4 of 2009. For all intervals, the largest amount of volume is traded on the LSE. However, trading volume shifts towards the MTFs relative to the LSE between Q1 and Q4, i.e. market fragmentation increases over time.

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Insert Figure 3 here

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In Q1, Chi-X depicts the highest intraday trading volume among MTFs closely followed by Turquoise and BATS. The figure reveals differing intraday patterns for the LSE and the three MTFs. Trading volume on the LSE resembles a crude U-shaped pattern starting with average volumes at nearly 1,800,000 GBP per stock in the first 15-minutes of the trading day. Volume then decreases close to 800,000 GBP until 13:30 and rises to nearly 3,200,000 GBP in the last interval before market closing. Compared to the LSE, trading volume starts on lower levels on the MTFs ranging from 258,000 GBP on Chi-X over 89,000 GBP on Turquoise down to 34,000 GBP on BATS during the first 15-minute interval. In contrast to BATS and Turquoise, which depict flat volume lines across the day, trading volume on Chi-X rises after 13:00 up to 643,000 GBP during the last intraday interval. We attribute the 13:00 co-moving increase in trading volume on the LSE and Chi-X to the U.S. market opening.[17] The interconnectivity of global markets may force investors to adopt their strategies to new information coming from the U.S. market.

In Q4, trading volume on Chi-X and BATS is generally higher compared to Q1 while trading on Turquoise is less active. The LSE still exhibits a crude U-shape in trading volume while MTFs show no major volume changes from market opening until 13:00. All MTFs, particularly Chi-X, depict increasing trading volumes and an approaching co-movement to the LSE after 13:00. This suggests that the market matures and grows closer together over time. Our results depict for all venues, but particularly the LSE and Chi-X, a strong increase in trading volume within the last five intraday intervals in both quarters.

The regression results in Table 3 confirm our graphically observed intraday patterns of trading volume. The reported coefficients show the difference of each 15-minute interval relative to the midday interval (*Intercept*) from 12:00 to 12:15.[18]

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Insert Table 3 here

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For the LSE, our findings of a crude U-shape in trading volume are consistent with

[17] U.S. trading starts at 14:30 GMT, however, new market information is disseminated much earlier, often starting from 13:00 GMT

[18] The regression coefficients slightly differ from the numbers in our figures, since the regression model controls for firm and time specific effects.

the theoretical predictions of Brock and Kleidon (1992) who argue that trading volume is concentrated at market opening and closing. Investors react on new information at the beginning of a trading day and adapt their holdings for an overnight position before market closing. Similar to Abhyankar, Ghosh, Levin, and Limmack (1997) and Cai, Hudson, and Keasey (2004), we find an increase in trading volume before U.S. market opening on the LSE and Chi-X in Q1 and at all venues in Q4. In addition, our findings confirm an increase in trading volume on the LSE and Chi-X in Q1 and on all platforms in Q4 during the last trading hour of a trading day.

Market Shares Figure 4 depicts intraday patterns of market shares for all four trading venues. The LSE is the largest trading venue with highest traded volumes over both quarters. However, the figure also displays a shift in market shares away from the LSE towards the MTFs over time.

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Insert Figure 4 here

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In Q1, the LSE dominates Chi-X, BATS, and Turquoise as the most active platform throughout the trading day. The LSE's market share follows a clear U-shape during the trading day with a peak around 80.0% at market opening and closing. During the trading day, LSE's share in trading volume drops by about 10.0%. In contrast to the LSE, Chi-X and Turquoise depict an inverted U-shape with Turquoise gaining more market share at the beginning and Chi-X at the end of the trading day.

In Q4, the LSE again exhibits an inverted U-shape, however with a slighter increase in trading activity during the second half of the trading day. Chi-X still leads the MTFs as most active trading platform in Q4. Intraday market shares increase on both MTFs, Chi-X and BATS, until 15:00. Afterwards, trading activity slowly shifts back to the LSE. Particularly during the last 15 minutes of the trading day, we observe a strong increase of 4.0% in Q1 on the LSE relative to the three MTFs and 4.1% in Q4. In Q4, Turquoise does not resemble an inverted U-shape any more but loses market shares from an initial high at the beginning of the trading day. Our regression results in Table 4 confirm our graphical findings for both quarters.

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Insert Table 4 here

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The shifts in intraday trading activity between the regulated market and MTFs may indicate that investors put more trust in the price formation process of the LSE during market opening and closing. Foster and Viswanathan (1993) emphasize a positive relationship between higher volatility and price uncertainty at the market opening and closing and a higher adverse selection risk. Intuitively, investors prefer the most liquid and stable market under such circumstances, especially when they have an increased desire to trade in these periods due to portfolio rebalancing (Brock and Kleidon (1992)). Investors even seem to be willing to accept the price premium at the LSE during such market conditions since transaction costs at MTFs are lower. Thus, our findings accentuate the importance of traditional exchanges in the price formation process in an increasingly fragmented European market environment.

6.2 Liquidity

Figure 5 reports intraday patterns of quoted spreads for all four trading venues. In line with our interday analysis, we find that quoted spreads decrease for every 15-minute interval on each platform from Q1 to Q4. We observe that quoted spreads on MTFs approach the LSE level and show a more definite co-movement with the regulated market over time.

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Insert Figure 5 here

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In Q1, the LSE shows the smallest quoted spreads for each 15-minute interval compared to the other platforms. Spreads on Chi-X follow very closely the liquidity patterns on the LSE. BATS and Turquoise exhibit larger and more volatile spreads over the day. On all platforms, spreads are relatively large at market opening and narrow quickly during the first 75 minutes of the trading day. During this period, spreads on the LSE drop by -52.5%, on Chi-X by -65.6%, on BATS by -57.6%, and on Turquoise by -32.7%. In the last half hour of the trading day, quoted spreads increase on all venues. This increase is stronger on MTFs with 3.5% on Chi-X, 4.0% on BATS, and 2,3% on Turquoise, compared to 0.2% on the LSE. On the LSE, Chi-X and BATS quoted spreads thus follow a (crude) reversed J-shaped pattern. Spreads on Turquoise exhibit a differing pattern, which resembles a crude U-shape. They narrow after market opening until 10:00 but then start a slight but steady increase until market closing.

In Q4, quoted spreads on all trading venues are of similar magnitude and exhibit a strong co-movement over the day. Again, liquidity decrease quickly during the first 75 minutes of the trading day. Afterwards, spreads slowly narrow during the remaining trading day, again resembling a reversed J-shape. There is an exception at 13:30 were spreads on all venues widen for one 15-minute interval.[19] We attribute this spread increase to higher uncertainty due to new information arrival from the U.S. market opening. Compared to Q1, spreads on the LSE, Chi-X, and BATS do not widen shortly before market closing. Turquoise is the only platform, which exhibits increasing spreads in the last 30 minutes of the trading day in Q4. Our regression results support our graphical findings, with the exception of the 13:30 spread increase. Regression results only document a highly significant increase on the LSE during this period.

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Insert Table 5 here

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The (crude) reversed J-shaped pattern of quoted spreads which we find on the LSE,

[19] In Q1, we find a similar increase in quoted spreads on the LSE, Chi-X, and BATS.

Chi-X, BATS, and Turquoise in Q4 is also documented by McInish and Wood (1992), Abhyankar, Ghosh, Levin, and Limmack (1997), and Cai, Hudson, and Keasey (2004). The crude U-shape on Turquoise and the slight spread increases at the end of the trading day on the LSE, Chi-X, and BATS in Q1 are in line with theoretical predictions of Brock and Kleidon (1992). Looking at the relationship between trading volume and quoted spreads, our findings document a negative correlation on all MTFs. This indicates that liquidity on MTFs increases over the day along with decreasing spreads. McInish and Wood (1992), Kleidon and Werner (1993), and Cai, Hudson, and Keasey (2004) also document this intuitively expected relationship. On the LSE, we do not find this inverse relationship within the trading day. In contrast to the MTFs, trading volume on the LSE is high while quoted spreads are wide during the first hour of the trading day. This finding again indicates the important function of the regulated market in a fragmented European market environment. Investors seem to accept higher implicit transaction costs on the LSE relative to MTFs in order to profit from price discovery on the traditional exchange during market opening.

6.3 Informed Trading

Figure 5 depicts intraday patterns of 5-minute price impacts on the LSE, Chi-X, BATS and Turquoise. The figure shows that price impacts decrease for each 15-minute interval on all venues from Q1 to Q4. Similar to our findings on intraday quoted spreads, price impacts move more closely and show less variation over time. The highest fraction of informed trades takes place at the LSE in both quarters during most time of the trading day. However, intraday patterns of price impacts are very close across trading venues even in Q1 compared to the previous measures.

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Insert Figure 6 here

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In Q1, price impacts on all platforms decrease throughout the trading day, more quickly during the first hour of trading and then modestly for the rest of time. During the first hour of the trading day price impacts decrease by -31,2% on the LSE, by -25.8% on Chi-X, by -38.0% on BATS, and by -23.3% on Turquoise. As a consequence, trades convey most information during market opening and lose information content over the day. Investors on the LSE and Chi-X seem more informed than on BATS and Turquoise.

In Q4, price impacts on all platforms show a strong co-movement and still a continuing decrease over the trading day. Again, the largest decrease in price impacts can be attributed to the first trading hour. Our regression results confirm the statistical significance of all presented developments.

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Insert Table 6 here

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Similar to McInish and Wood (1992), we find a positive relationship between adverse selection risk and quoted spreads. This contradicts the findings of Foster and Viswanathan (1993) who report increased adverse selection at both, market opening and closing. Several market microstructure models address the relationship of informed trading and liquidity (e.g. Glosten and Milgrom (1985)). Accordingly, quoted spreads widen when the amount of information based trading increases. Our results may indicate that informed traders benefit most from their informational advantage at market opening while the rest of the market is still relatively uninformed. Higher price uncertainty may thus represent a favorable opportunity for informed traders to act in order to conceal their superior knowledge.

7 Conclusion

MTFs have successfully captured a high fraction of European equity trading volume, especially in the UK. The market share of the LSE in blue chips decreased from almost

100.0% in 2007 to less than 60.0% at the end of 2009. We study the influence of increased market fragmentation on trading intensity and market quality under the Markets in Financial Instruments Directive (MiFID) over time and from an intraday perspective. Our sample comprises 69 FTSE 100 stocks traded on the regulated market, the LSE, and the three largest MTFs, Chi-X, BATS, and Turquoise, between January and December 2009.

Over 2009, competition between the LSE and MTFs increases as trading volume becomes more dispersed. Market shares strongly move away from the LSE which loses -17.2% towards MTFs. Despite this increase in order flow fragmentation, we find improving market quality on all trading venues. Quoted and effective spreads decrease on all platforms during our observation period. This result suggests an increase in overall liquidity.

We obtain further insights into investor behavior by analyzing intraday patterns of trading volume, market shares, quoted spreads, and price impacts. To evaluate the impact of increased fragmentation on changes in intraday patterns over time, we focus on the first (Q1) and last quarter (Q4) of 2009. We find that intraday patterns for each analyzed measure converge across platforms from Q1 to Q4. This finding indicates that the market matures and grows closer together.

Intraday patterns of trading volume differ between the LSE and MTFs during both quarters. The LSE resembles a crude U-shape which is in line with theoretical predictions of Brock and Kleidon (1992) and empirical findings of other authors (e.g. Werner and Kleidon (1996)), while MTFs show increasing trading volume only in the second half of the trading day.[20] Trading volume increases in the afternoon at all venues which can be associated to the U.S. market opening. The analysis of intraday market shares reveals the importance of traditional exchanges in a fragmented market environment. Our data suggests that investors prefer to trade on the regulated market at opening and closing, whereas trading switches to MTFs during the trading day. This result may indicate that market participants rely on the price formation process of regulated markets in periods

[20]See Figure 1 for an overview of related empirical findings.

of increased volatility and price uncertainty.

In contrast to theoretical predictions of Admati and Pfleiderer (1988) and Brock and Kleidon (1992), our results for quoted spreads suggest a reversed J-shape which is in line with other empirical studies (e.g. Cai, Hudson, and Keasey (2004)). The underlying market structures may be one explanation for differences in theoretical and empirical evidence. The aforementioned theoretical models are based on quote-driven markets while we analyze order-driven markets. Intraday results for price impacts are in line with theoretical predictions of informed trading and liquidity (e.g. Glosten and Milgrom (1985)). Our data suggest that the information content of trades declines quickly during the first trading hour and then falls continuously for the rest of the trading day, along with quoted spreads.

Appendix

Market	Authors	Trading Intensity	Quoted Spreads	Informed Trading
NYSE	Jain and Joh (1988)	U-shaped	n/a	n/a
	McInish and Wood (1992)	Crude J-shaped	Crude reversed J-shaped	Declining over the day
	Foster and Viswanahtan (1993)	U-shaped	n/a	Crude reversed J-shaped
NASDAQ	Chan, Christie, and Schultz (1995)	U-shaped	Stable through day, but narrow at market closing	n/a
LSE/MTFs	Werner and Kleidon (1996)	U-shaped	Crude reversed J-shaped	n/a
	Abhyankar, Gosh, and Limmack (1997)	2-humped	Reversed J-shaped	n/a
	Cai, Hudson, and Keasey (2004)	2-humped	Reversed J-shaped	n/a
	Spankowski and Wagener (2011)	LSE: U-shaped MTFs: Increasing in the afternoon	LSE & MTFs: Reversed J-shaped	LSE & MTFs: Declining over the day

Figure 1
Overview of Related Intraday Literature

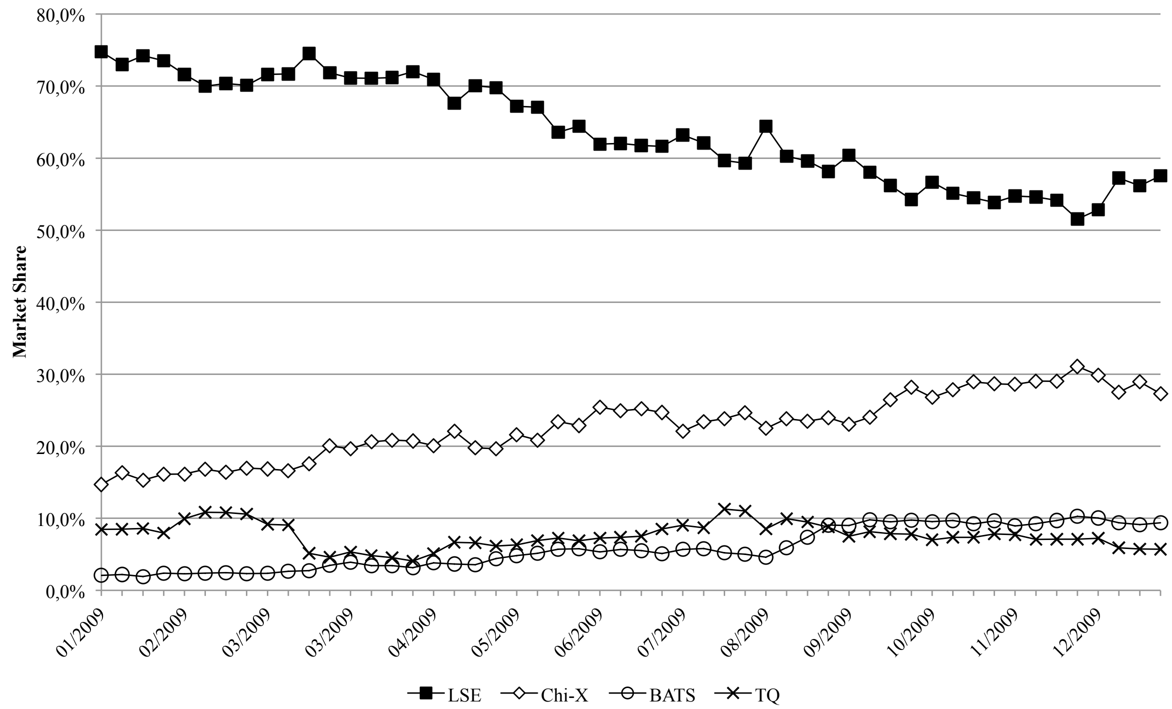

Figure 2

Market Shares of the LSE, Chi-X, BATS, and Turquoise

The sample consists of 69 stocks listed in the London Stock Exchange's FTSE 100 segment. The observation period comprises trading days from January 2 to December 30, 2009. The figure shows average daily shares in trading volume per week for the LSE, Chi-X, BATS, and Turquoise. First, daily market shares are obtained by multiplying the daily closing price per stock and per trading venue with the corresponding number of shares traded. Second, daily market shares are averaged across stocks on a weekly basis.

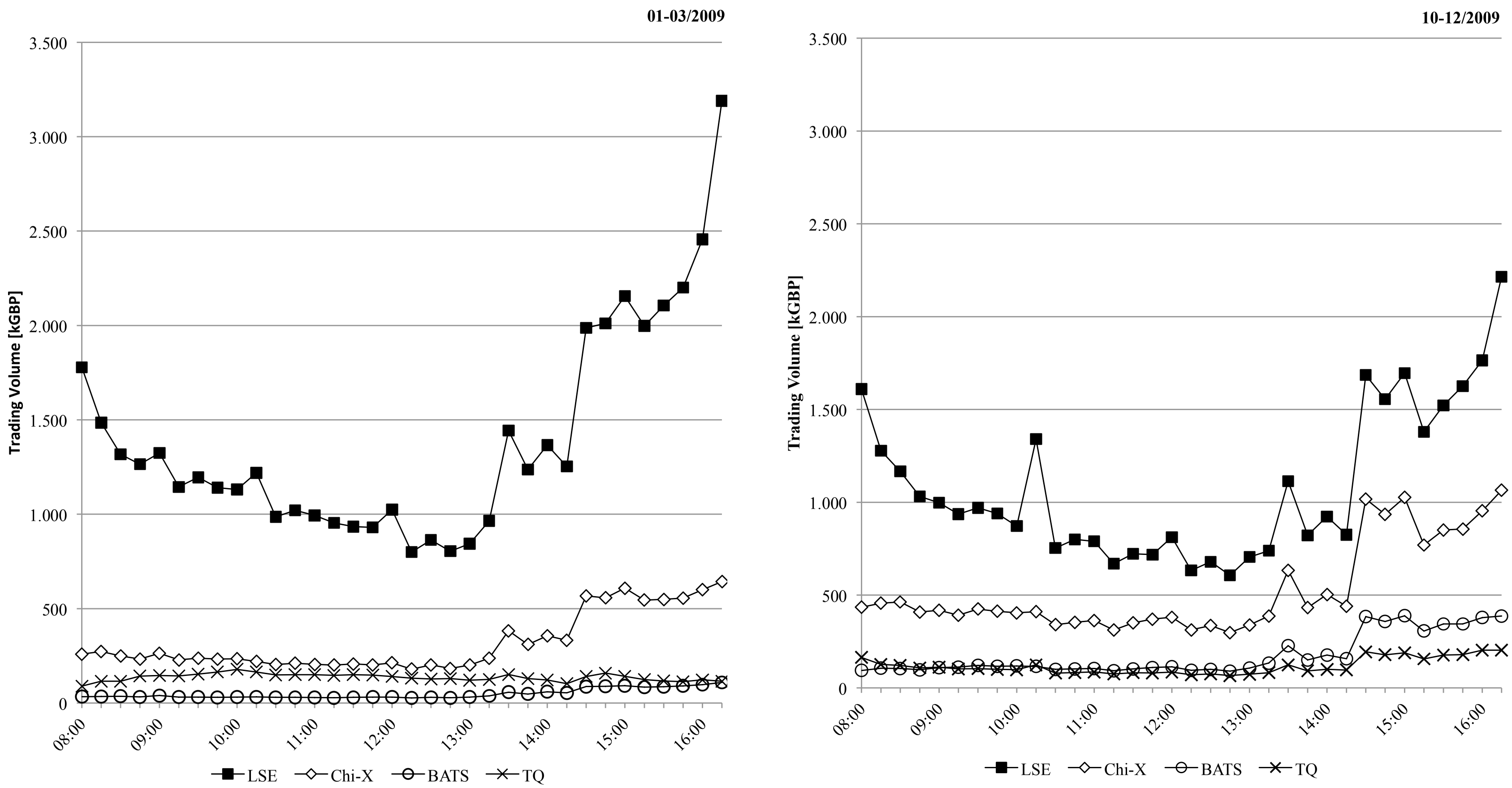

Figure 3

15-minute Snapshots of Intraday Trading Volumes of the LSE, Chi-X, BATS, and Turquoise

The figure shows 15-minute intraday trading volume snapshots of 69 FTSE 100 constituents on the LSE, Chi-X, BATS, and Turquoise for Q1 and Q4 of 2009. We aggregate the trading volume for all executions on a 15-minute interval per day and per stock on each platform. Then we obtain averages per platform over the two quarters.

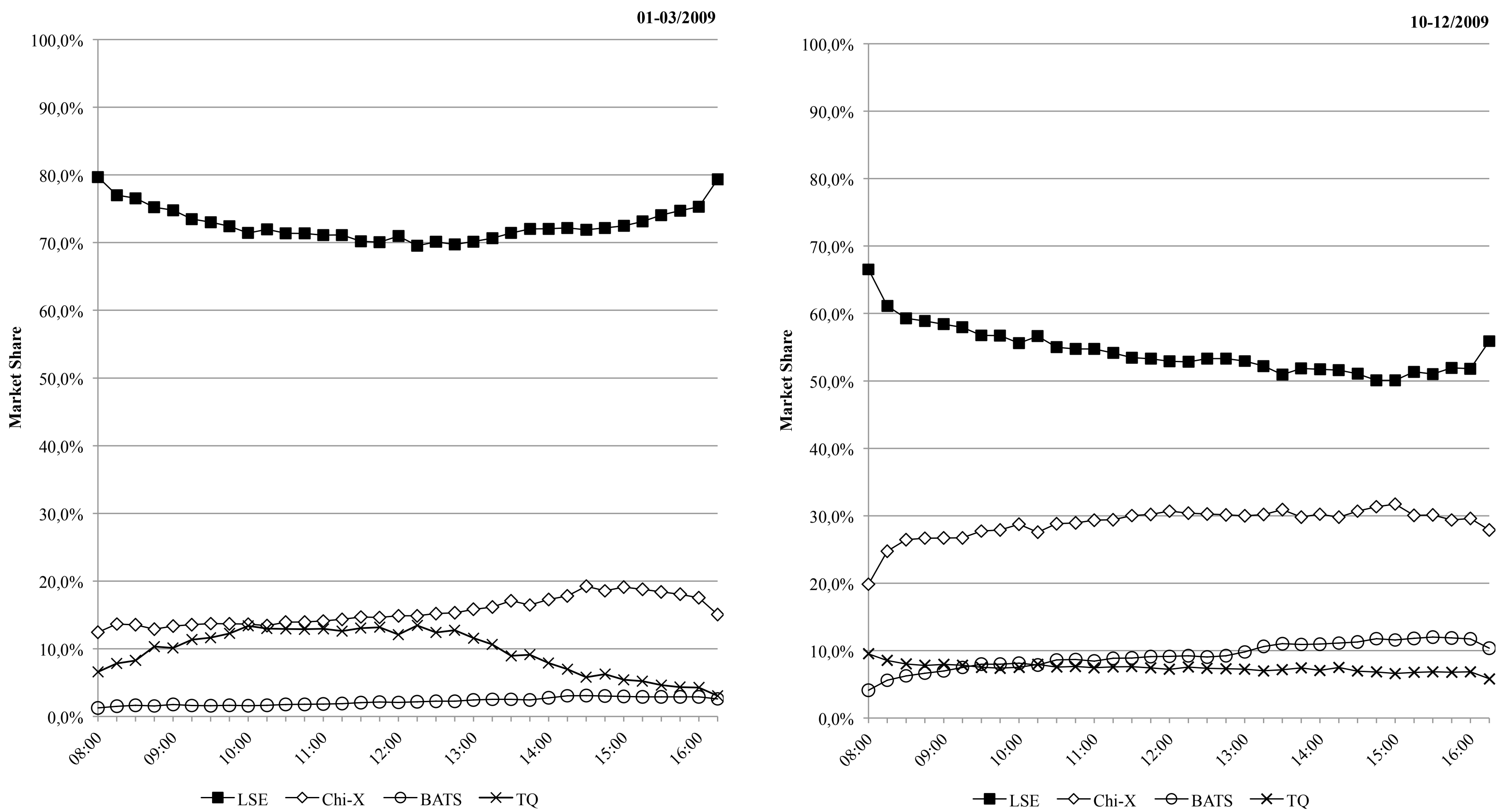

Figure 4

15-minute Snapshots of Intraday Market Shares of the LSE, Chi-X, BATS, and Turquoise

The figure shows 15-minute intraday market share snapshots of 69 FTSE 100 constituents on the LSE Chi-X, BATS, and Turquoise for Q1 and Q4 of 2009. We aggregate the trading volume for all executions on a 15-minute interval per day and per stock on each platform. Market shares represent each platform's fraction of trading volume for every 15-minute interval. Then we obtain averages per platform over the two quarters.

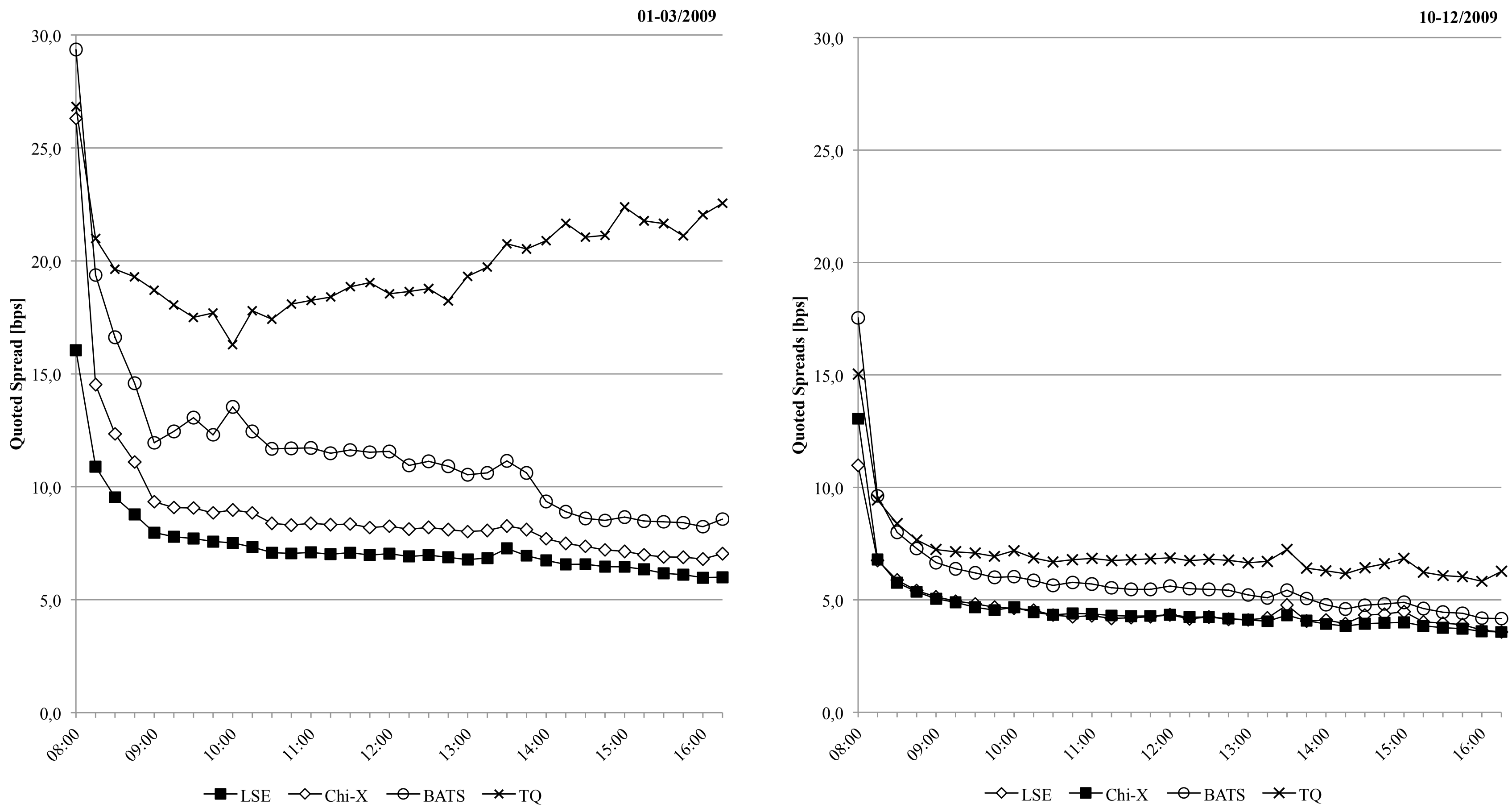

Figure 5

15-minute Snapshots of Intraday Quoted Spreads of the LSE, Chi-X, BATS, and Turquoise

The figure shows average intraday 15-minute quoted spread snapshots of 69 FTSE 100 constituents on the LSE Chi-X, BATS, and Turquoise for Q1 and Q4 of 2009. We calculate average quoted spreads as presented in Section 4.2. We aggregate the trading volume for all executions on a 15-minute interval per day and per stock on each platform. Market shares represent each platform's fraction of trading volume for very 15-minute interval. Then we obtain averages per platform over the two quarters.

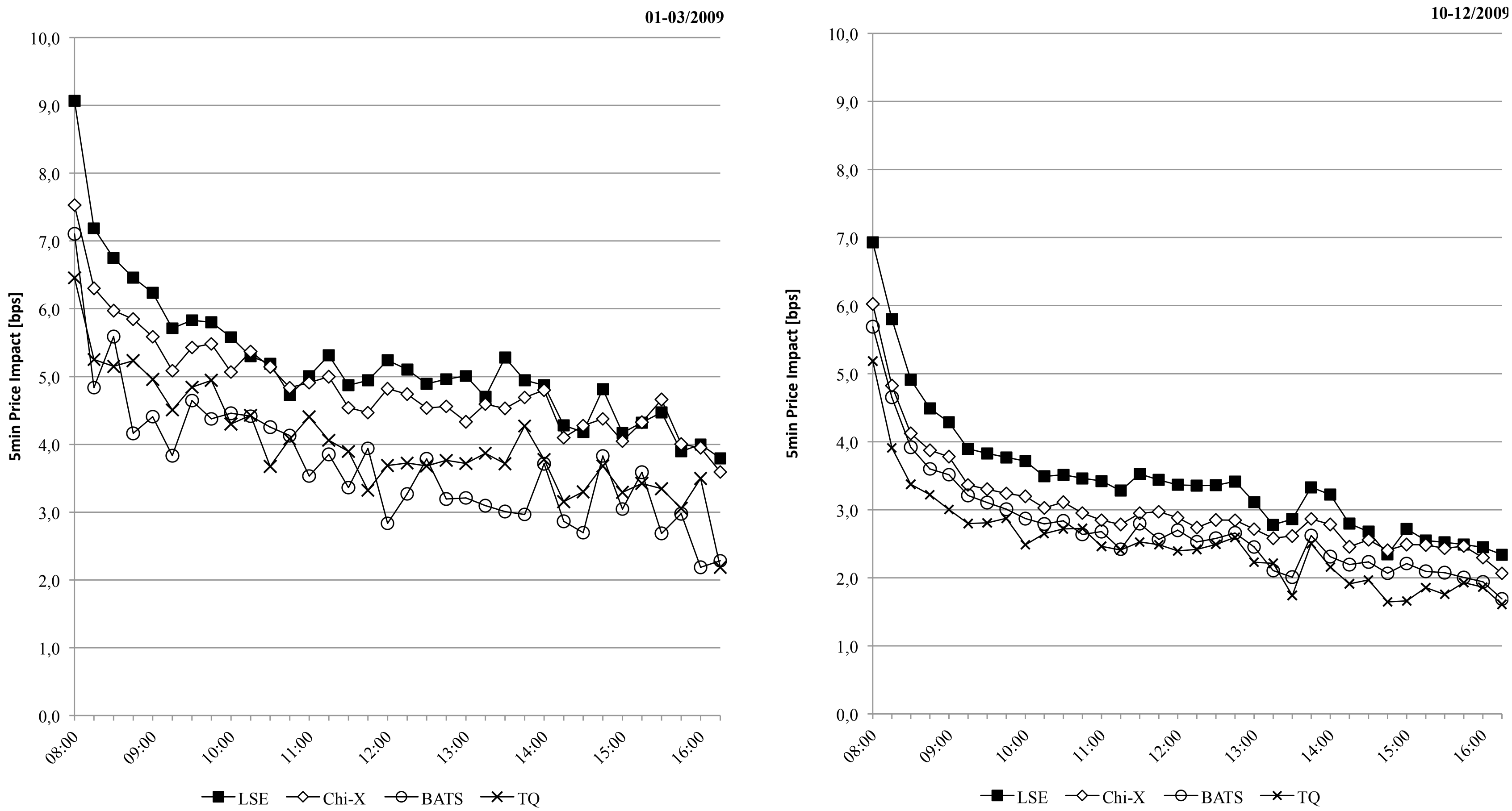

Figure 6

15-minute Snapshots of Intraday Price Impacts of the LSE, Chi-X, BATS, and Turquoise

The figure shows average intraday 15-minute price impact snapshots of 69 FTSE 100 constituents on the LSE Chi-X, BATS, and Turquoise for Q1 and Q4 of 2009. We calculate price impacts as presented in Section 4.2 and obtain averages per day, stock, and 15-minute interval for each platform. Then we average all observations per 15-minute interval and platform over the two quarters.

Table 1

Descriptive Statistics: Trading Intensity and Liquidity Measures

The sample consists of 69 stocks listed on the LSE and in the FTSE 100. The observation period contains trading days from January 5 to March 31, 2009. Descriptive statistics 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). All 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. Standard deviations are reported in parenthesis. 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, and 'c' at the 10% level.

	LSE	Chi-X	BATS	TQ
Market Shares	72.31%	16.74%^{a}	2.47%^{a}	8.48%^{a}
	(7.27%)	(5.32%)	(1.30%)	(4.72%)
Volume (1,000 GBP)	43,536	10,763^a	1,625^a	4,597^a
	(54,029)	(13,988)	(2,260)	(4,971)
Trade Count	3,527	1,362^a	247^a	572^a
	(2,518)	(1,046)	(223)	(404)
Trade Size (GBP)	10,304	6,373^a	5,302^a	7,000^a
	(5,191)	(3,376)	(3,012)	(3,972)
Quoted Spread	7.378	9.804^a	12.913^a	20.217^a
	(4.162)	(9.467)	(24.512)	(89.838)
Quoted Spread Trade	5.625	6.232	7.695^a	10.328^a
	(3.293)	(3.532)	(3.977)	(17.606)
Effective Spread	4.909	4.811^b	5.164^a	4.189^a
	(2.938)	(2.886)	(3.104)	(2.9583)
Realized Spread 5	-0.248	-0.136^c	1.351^a	-0.280
	(1.938)	(2.502)	(4.955)	(4.327)
Realized Spread 15	0.183	0.127	1.044^a	-0.186^c
	(3.140)	(3.924)	(8.952)	(7.042)
Price Impact 5	5.190	4.955^a	3.840^a	4.489^a
	(3.160)	(3.350)	(5.273)	(4.328)
Price Impact 15	4.778	4.700	4.156^a	4.400^b
	(4.034)	(4.611)	(9.285)	(7.066)
Depth1 (GBP)	29,487	29,812	20,300^a	18,269^a
	(30,674)	(30,674)	(21,776)	(15,210)
Depth3 (GBP)	102,326	124,319^b	69,358^a	58,858^a
	(133,551)	(133,551)	(72,050)	(53,398)

Table 2

Interday Results: Trading Intensity and Liquidity Measures over 2009

We compare 69 stocks listed on the LSE and in the FTSE 100. The first period contains trading days between January 5 to March 31, 2009 (1st quarter) and the second between October 1 to December 30, 2009 (4th quarter). The final sample contains 69 stock pairs. We use the following regression model to test for differences (1) between the observation periods (Q4-Q1) and (2) for trading venue differences relative to the LSE (Venue-LSE) per day t and per stock i: $measure_{i,t} = \alpha_i + \beta_{i,t}\ quarter_{i,t} + \gamma_{i,t} \sum controls_{i,t} + \epsilon_{i,t}$. Control variables are the average daily realized volatility, the log of daily stock prices across trading venues, the log of the market capitalization, and firm dummy variables. The $quarter_{i,t}$ dummy variable, reported below, captures differences between the two periods. It is zero for the first quarter and one for the second quarter. Dependent variables ($measure_{i,t}$) are the same as defined in the previous tables. We use Thompson (2011) clustered standard errors. t-statistics are presented below the regression estimates in italic letters. 'a' denotes significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

	LSE	Chi-X		BATS		TQ	
	Q4-Q1	Q4-Q1	ChiX-LSE	Q4-Q1	BATS-LSE	Q4-Q1	TQ-LSE
Market Shares	-17.48%^{a}	11.99%^{a}	29.46%^{a}	7.57%^{a}	25.04%^{a}	-2.08%^{a}	15.40%^{a}
	-33.06	*20.59*	*29.50*	*21.09*	*34.89*	*-4.13*	*19.79*
Volume (1,000 GBP)	-14,107^a	3,732^a	17,840^a	3,853^a	17,961^a	-1,793^a	12,315^a
	-5.78	*3.80*	*7.15*	*7.26*	*6.50*	*-4.15*	*5.76*
Trade Count	-980^a	543^a	1,522^a	614^a	1,594^a	-15	965^a
	-7.46	*6.26*	*10.94*	*10.75*	*10.25*	*-0.36*	*7.65*
Trade Size (GBP)	932^a	264	-669^a	-614^a	-1,546^a	-2,417^a	-3,349^a
	2.73	*1.15*	*-3.21*	*-2.89*	*-6.70*	*-6.08*	*-10.07*
Quoted Spread	-0.719^a	-3.231^a	-2.512^a	-2.337^c	-1.618	-4.990	-4.271
	-3.15	*-4.88*	*-3.87*	*-1.82*	*-1.27*	*-1.27*	*-1.51*
Quoted Spread Trade	-0.674^a	-1.974^a	-1.300^a	-2.895^a	-2.221^a	-0.587	0.087
	-3.09	*-5.44*	*-3.44*	*-8.25*	*-5.83*	*-0.60*	*0.09*
Effective Spread	-0.781^a	-0.706^a	0.075	-1.289^a	-0.508^a	-0.690^a	0.091
	-4.21	*-3.82*	*1.41*	*-6.86*	*-8.31*	*-3.61*	*0.92*

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	LSE	Chi-X		BATS		TQ	
	Q4-Q1	Q4-Q1	ChiX-LSE	Q4-Q1	BATS-LSE	Q4-Q1	TQ-LSE
Realized Spread 5	-0.145	0.182	0.327[a]	-1.140[a]	-0.995[a]	0.073	0.218
	-1.37	*1.50*	*4.77*	*-4.55*	*-3.67*	*0.39*	*1.47*
Realized Spread 15	-0.298[b]	0.102	0.399[a]	-0.617[b]	-0.319	0.326	0.623[a]
	-2,14	*0.73*	*3.93*	*-2.41*	*-0.98*	*1.35*	*3.44*
Price Impact 5	-0.643[a]	-0.903[a]	-0.260[a]	-0.162	0.481[c]	-0.771[a]	-0.129
	-3.88	*-5.49*	*-2.92*	*-0.65*	*1.88*	*-5.73*	*-1.18*
Price Impact 15	-0.488[a]	-0.823[a]	-0.335[a]	-0.685[a]	-0.196	-1.017[a]	-0.529[a]
	-2.70	*-4.47*	*-3.01*	*-2.24*	*-0.63*	*-5.10*	*-3.03*
Depth1 (GBP)	11,695[a]	5,031	-6,664[a]	-2,868	-14,562[a]	-8,717[a]	-20,422[a]
	4.12	*1.19*	*-2.88*	*-1.12*	*-7.77*	*-5.00*	*-7.34*
Depth3 (GBP)	92,502[a]	61,284[a]	-31,218[b]	14,054	-78,448[a]	-23,412[a]	-115,973[a]
	5.78	*2.80*	*-2.34*	*1.34*	*-7.92*	*-3.90*	*-7.49*

Table 3

Intraday Regressions Results: Trading Volume

We compare 69 stocks listed on the LSE and in the FTSE 100 between January 5 to March 31, 2009 (1st quarter) and October 1 to December 30, 2009 (4th quarter). We use the following regression model to test for intraday differences day per day t and per stock i: $measure_{i,t,j} = \alpha_{i,t} + \sum_{j=1}^{16} \beta_{i,t,j}\ \mathrm{D}_{i,t,j} + \sum_{j=18}^{34} \beta_{i,t,j}\ \mathrm{D}_{i,t,j} + \epsilon_{i,t}$, where $measure_{i,t}$ represents trading volume. Dummy variables for each 15-minute interval of the trading day take the value 1 for a corresponding observation and are 0 otherwise. We omit the midday interval from 12:00 to 12:15 p.m. GMT, the *17th* interval of the trading day. Therefore, all coefficients $\beta_{i,t,j}$ measure the difference relative to this reference interval, represented by the coefficient $\alpha_{i,t}$. We report robust standard errors following Thompson (2011), t-statistics are presented in italic letters. 'a' denotes significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

	January to March 2009								October to December 2009							
	LSE	t-stat.	Chi-X	t-stat.	BATS	t-stat.	TQ	t-stat.	LSE	t-stat.	Chi-X	t-stat	BATS	t-stat.	TQ	t-stat.
Intercept	2,525.81	*35.84*[a]	425.01	*25.10*[a]	60.89	*67.30*[a]	157.41	*7.45*[a]	1,909.26	*18.91*[a]	1022.79	*21.43*[a]	270.82	*14.96*[a]	76.64	*8.30*[a]
8:00	756.73	*3.91*[a]	46.86	*2.66*[a]	2.42	*0.84*	-50.72	*-5.97*[a]	796.55	*4.89*[a]	53.12	*1.49*	-20.53	*-2.19*[b]	79.02	*5.70*[a]
8:15	462.87	*4.20*[a]	60.80	*3.07*[a]	3.61	*1.26*	-24.51	*-2.95*[a]	465.41	*3.83*[a]	74.97	*2.04*[b]	-7.88	*-0.80*	40.93	*3.70*[a]
8:30	296.16	*3.89*[a]	36.89	*2.27*[b]	3.91	*1.31*	-25.34	*-3.71*[a]	353.92	*3.55*[a]	81.51	*2.39*[b]	-9.53	*-1.11*	35.26	*3.68*[a]
8:45	242.61	*3.56*[a]	20.96	*1.53*	0.63	*0.32*	1.56	*0.27*	218.41	*2.86*[a]	28.16	*1.05*	-15.24	*-2.02*[b]	23.09	*2.95*[a]
9:00	302.04	*4.54*[a]	51.07	*3.45*[a]	9.03	*2.92*[a]	5.79	*1.03*	184.84	*2.63*[a]	36.44	*1.36*	-5.12	*-0.61*	25.97	*3.63*[a]
9:15	122.81	*2.50*[b]	16.32	*1.45*	0.23	*0.12*	3.17	*0.56*	122.97	*1.90*[c]	10.42	*0.39*	-1.66	*-0.19*	16.93	*2.48*[b]
9:30	173.29	*3.20*[a]	25.55	*2.20*[b]	0.19	*0.09*	13.03	*1.98*[b]	157.22	*2.41*[b]	43.79	*1.53*	6.72	*0.84*	18.55	*2.60*[a]
9:45	119.08	*2.19*[b]	20.89	*1.83*[c]	-0.62	*-0.35*	23.65	*3.42*[a]	126.86	*1.98*[b]	31.66	*1.25*	3.39	*0.43*	14.67	*2.28*[b]
10:00	109.12	*1.89*[c]	21.87	*1.78*[c]	-0.28	*-0.13*	38.02	*4.01*[a]	59.42	*0.99*	23.72	*0.94*	3.65	*0.50*	12.28	*1.86*[c]
10:15	197.94	*1.41*	8.39	*0.72*	0.74	*0.30*	23.94	*3.06*[a]	527.12	*1.87*[c]	29.79	*1.32*	2.11	*0.30*	38.89	*1.32*
10:30	-35.37	*-0.79*	-8.35	*-0.94*	-1.53	*-0.77*	9.07	*1.69*[c]	-58.91	*-1.10*	-41.09	*-1.94*[c]	-14.04	*-2.05*[b]	-6.34	*-1.34*
10:45	-1.61	*-0.02*	-1.87	*-0.13*	-0.73	*-0.25*	9.95	*1.46*	-12.71	*-0.18*	-27.99	*-1.23*	-11.10	*-1.62*	-2.42	*-0.55*
11:00	-28.97	*-0.59*	-7.23	*-0.67*	-2.69	*-1.46*	9.41	*1.40*	-23.27	*-0.45*	-17.91	*-0.79*	-9.24	*-1.38*	0.42	*0.08*
11:15	-68.77	*-1.45*	-11.41	*-1.11*	-2.73	*-1.57*	6.06	*1.07*	-144.05	*-2.59*[a]	-68.93	*-3.07*[a]	-21.15	*-3.04*[a]	-10.05	*-1.97*[b]
11:30	-88.61	*-1.74*[c]	-4.98	*-0.47*	-1.50	*-0.88*	10.05	*1.59*	-89.77	*-1.79*[c]	-31.25	*-1.41*	-11.48	*-1.87*[c]	-3.92	*-0.77*
11:45	-92.61	*-2.55*[b]	-10.06	*-1.50*	-0.44	*-0.30*	7.53	*1.61*	-94.17	*-2.07*[b]	-9.88	*-0.46*	-3.38	*-0.58*	-5.17	*-1.25*
12:15	-224.72	*-4.26*[a]	-33.69	*-3.94*[a]	-4.50	*-3.33*[a]	-9.10	*-1.93*[a]	-179.56	*-3.74*[a]	-68.52	*-3.59*[a]	-18.67	*-3.10*[a]	-15.03	*-3.40*[a]
12:30	-162.69	*-2.91*[a]	-11.18	*-1.13*	-0.78	*-0.41*	-13.83	*-2.77*[a]	-133.02	*-2.16*[a]	-44.74	*-1.58*	-13.56	*-1.54*	-10.61	*-1.67*[c]
12:45	-222.82	*-3.64*[a]	-29.23	*-3.46*[a]	-3.55	*-2.07*[b]	-11.71	*-2.27*[b]	-206.09	*-3.52*[a]	-83.07	*-3.45*[a]	-23.97	*-3.31*[a]	-18.74	*-3.54*[a]
13:00	-183.66	*-3.27*[a]	-12.25	*-1.54*	0.14	*0.06*	-20.38	*-3.68*[a]	-107.08	*-1.77*[c]	-41.57	*-1.79*[c]	-6.49	*-0.88*	-11.71	*-2.18*[b]
13:15	-62.99	*-1.17*	24.11	*2.02*[b]	6.17	*3.07*[a]	-15.08	*-2.32*[b]	-74.17	*-1.18*	6.11	*0.24*	20.53	*2.58*[a]	-3.89	*-0.68*
13:30	414.52	*4.28*[a]	169.29	*4.63*[a]	25.35	*4.99*[a]	9.73	*1.32*	301.37	*2.35*[b]	252.75	*3.68*[a]	113.01	*4.37*[a]	38.80	*3.12*[a]
13:45	206.61	*2.78*[a]	95.87	*3.72*[a]	15.78	*4.24*[a]	-11.11	*-1.54*	10.06	*0.13*	51.27	*1.32*	36.33	*2.59*[a]	5.97	*0.83*
14:00	335.18	*3.80*[a]	141.72	*4.36*[a]	27.43	*4.88*[a]	-19.62	*-2.63*[a]	110.82	*1.31*	121.90	*2.60*[a]	63.52	*3.74*[a]	14.47	*1.75*[c]
14:15	220.64	*3.43*[a]	117.93	*4.51*[a]	22.43	*6.01*[a]	-38.21	*-4.47*[a]	12.60	*0.18*	58.67	*1.82*[c]	43.87	*3.82*[a]	11.07	*1.62*
14:30	951.36	*6.10*[a]	351.77	*5.67*[a]	55.86	*7.40*[a]	-1.16	*-0.16*	872.23	*6.40*[a]	635.61	*6.39*[a]	269.62	*6.57*[a]	109.64	*7.86*[a]
14:45	974.95	*6.93*[a]	341.29	*6.43*[a]	56.64	*7.56*[a]	17.38	*2.37*[b]	741.65	*5.87*[a]	553.04	*6.23*[a]	243.93	*6.50*[a]	92.71	*6.90*[a]
15:00	1,117.31	*6.77*[a]	392.62	*6.38*[a]	59.63	*7.25*[a]	-0.62	*-0.09*	884.10	*6.06*[a]	644.68	*6.36*[a]	274.08	*6.48*[a]	104.03	*6.85*[a]
15:15	956.12	*7.31*[a]	327.71	*6.70*[a]	52.30	*7.40*[a]	-18.28	*-2.17*[b]	567.08	*5.87*[a]	387.52	*6.48*[a]	192.10	*7.13*[a]	71.00	*6.89*[a]
15:30	1,059.27	*7.36*[a]	330.98	*6.94*[a]	54.48	*7.20*[a]	-26.49	*-3.00*[a]	708.68	*5.98*[a]	467.72	*6.42*[a]	229.82	*6.90*[a]	91.76	*7.20*[a]
15:45	1,143.36	*7.70*[a]	334.33	*7.30*[a]	57.72	*7.41*[a]	-30.60	*-3.57*[a]	812.66	*6.17*[a]	472.81	*6.54*[a]	229.77	*7.04*[a]	92.87	*7.44*[a]
16:00	1,385.05	*7.90*[a]	374.32	*7.33*[a]	63.68	*7.69*[a]	-22.32	*-2.38*[b]	947.53	*7.32*[a]	568.72	*7.14*[a]	262.93	*7.48*[a]	117.47	*7.77*[a]
16:15	2,090.52	*8.83*[a]	409.74	*7.56*[a]	74.75	*8.05*[a]	-33.32	*-3.60*[a]	1,377.17	*8.36*[a]	668.49	*8.11*[a]	268.69	*8.81*[a]	115.30	*7.48*[a]
Obs.	141,671		141,671		141,671		141,671		142,534		142,534		142,534		142,534	
R^2	48.37%		55.97%		36.79%		52.10%		36.55%		50.82%		44.42%		36.29%	

Table 4

Intraday Regression Results: Market Shares

We compare 69 stocks listed on the LSE and in the FTSE 100 between January 5 to March 31, 2009 (1st quarter) and October 1 to December 30, 2009 (4th quarter). We use the following regression model to test for intraday differences day per day t and per stock i: $measure_{i,t,j} = \alpha_{i,t} + \sum_{j=1}^{16} \beta_{i,t,j}\ \mathrm{D}_{i,t,j} + \sum_{j=18}^{34} \beta_{i,t,j}\ \mathrm{D}_{i,t,j} + \epsilon_{i,t}$, where $measure_{i,t}$ represents market shares. Dummy variables for each 15-minute interval of the trading day take the value 1 for a corresponding observation and are 0 otherwise. We omit the midday interval from 12:00 to 12:15 p.m. GMT, the *17th* interval of the trading day. Therefore, all coefficients $\beta_{i,t,j}$ measure the difference relative to this reference interval, represented by the coefficient $\alpha_{i,t}$. We report robust standard errors following Thompson (2011), t-statistics are presented in italic letters. 'a' denotes significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

	January to March 2009								October to December 2009							
	LSE	t-stat.	Chi-X	t-stat.	BATS	t-stat.	TQ	t-stat.	LSE	t-stat.	Chi-X	t-stat	BATS	t-stat.	TQ	t-stat.
Intercept	74.00%	*156.36*[a]	17.37%	*82.45*[a]	2.47%	*35.24*[a]	6.16%	*51.25*[a]	56.34%	*79.17*[a]	32.84%	*67.97*[a]	8.47%	*45.68*[a]	2.35%	*22.30*[a]
8:00	8.76%	*11.69*[a]	-2.43%	*-5.20*[a]	-0.82%	*-7.42*[a]	-5.50%	*-10.23*[a]	13.62%	*14.15*[a]	-10.88%	*-16.16*[a]	-5.01%	*-12.70*[a]	2.28%	*5.58*[a]
8:15	6.08%	*9.20*[a]	-1.22%	*-2.97*[a]	-0.60%	*-5.50*[a]	-4.26%	*-8.52*[a]	8.21%	*8.93*[a]	-5.98%	*-8.73*[a]	-3.53%	*-9.44*[a]	1.29%	*3.28*[a]
8:30	5.61%	*9.62*[a]	-1.33%	*-3.27*[a]	-0.44%	*-4.46*[a]	-3.84%	*-8.85*[a]	6.36%	*7.38*[a]	-4.24%	*-7.13*[a]	-2.90%	*-8.89*[a]	0.78%	*2.48*[b]
8:45	4.27%	*7.61*[a]	-1.97%	*-5.22*[a]	-0.53%	*-5.87*[a]	-1.78%	*-4.95*[a]	5.97%	*7.15*[a]	-4.06%	*-6.84*[a]	-2.49%	*-8.25*[a]	0.58%	*2.21*[b]
9:00	3.85%	*6.20*[a]	-1.53%	*-3.89*[a]	-0.33%	*-3.51*[a]	-1.99%	*-6.02*[a]	5.49%	*6.72*[a]	-4.03%	*-7.26*[a]	-2.17%	*-8.03*[a]	0.71%	*2.76*[a]
9:15	2.54%	*4.92*[a]	-1.31%	*-3.76*[a]	-0.46%	*-4.75*[a]	-0.77%	*-2.61*[a]	5.04%	*6.55*[a]	-3.99%	*-8.03*[a]	-1.64%	*-5.90*[a]	0.59%	*2.59*[a]
9:30	2.09%	*3.96*[a]	-1.15%	*-3.44*[a]	-0.49%	*-6.00*[a]	-0.45%	*-1.40*	3.84%	*4.82*[a]	-2.97%	*-5.76*[a]	-1.14%	*-4.04*[a]	0.28%	*1.12*
9:45	1.46%	*3.18*[a]	-1.18%	*-4.11*[a]	-0.44%	*-4.97*[a]	0.16%	*0.53*	3.82%	*4.87*[a]	-2.83%	*-5.62*[a]	-1.15%	*-4.28*[a]	0.16%	*0.71*
10:00	0.45%	*0.80*	-1.21%	*-3.97*[a]	-0.51%	*-4.87*[a]	1.27%	*3.84*[a]	2.68%	*3.71*[a]	-1.98%	*-4.39*[a]	-0.99%	*-3.75*[a]	0.30%	*1.47*
10:15	1.01%	*1.71*[c]	-1.46%	*-3.63*[a]	-0.44%	*-4.38*[a]	0.89%	*3.10*[a]	3.71%	*3.70*[a]	-3.15%	*-5.80*[a]	-1.28%	*-4.87*[a]	0.72%	*0.95*
10:30	0.44%	*0.92*	-0.94%	*-3.22*[a]	-0.31%	*-3.22*[a]	0.82%	*2.73*[a]	2.08%	*4.37*[a]	-1.89%	*-5.28*[a]	-0.53%	*-2.72*[a]	0.33%	*1.76*[c]
10:45	0.40%	*0.88*	-0.92%	*-3.01*[a]	-0.28%	*-3.12*[a]	0.79%	*2.84*[a]	1.82%	*3.47*[a]	-1.79%	*-5.00*[a]	-0.45%	*-2.68*[a]	0.42%	*2.21*[b]
11:00	0.17%	*0.33*	-0.77%	*-2.66*[a]	-0.26%	*-3.07*[a]	0.86%	*2.78*[a]	1.83%	*4.18*[a]	-1.37%	*-4.53*[a]	-0.70%	*-4.23*[a]	0.24%	*1.41*
11:15	0.18%	*0.38*	-0.53%	*-1.86*[c]	-0.19%	*-2.16*[b]	0.54%	*2.07*[b]	1.22%	*2.80*[a]	-1.30%	*-3.42*[a]	-0.29%	*-1.78*[c]	0.36%	*2.69*[a]
11:30	-0.74%	*-1.75*[c]	-0.17%	*-0.69*	-0.04%	*-0.64*	0.96%	*3.54*[a]	0.55%	*1.30*	-0.69%	*-2.15*[b]	-0.25%	*-1.54*	0.39%	*2.27*[b]
11:45	-0.88%	*-2.29*[b]	-0.25%	*-1.25*	0.06%	*0.85*	1.07%	*4.50*[a]	0.33%	*0.90*	-0.51%	*-1.73*[c]	-0.03%	*-0.25*	0.20%	*1.47*
12:15	-1.41%	*-3.81*[a]	-0.01%	*-0.03*	0.06%	*0.96*	1.35%	*5.81*[a]	-0.11%	*-0.24*	-0.31%	*-0.98*	0.11%	*0.59*	0.31%	*1.83*[c]
12:30	-0.83%	*-1.98*[b]	0.34%	*1.23*	0.16%	*2.65*[a]	0.33%	*1.37*	0.38%	*0.74*	-0.43%	*-1.39*	-0.09%	*-0.38*	0.14%	*0.78*
12:45	-1.22%	*-3.18*[a]	0.40%	*1.65*[c]	0.16%	*1.90*[c]	0.65%	*2.57*[b]	0.39%	*0.57*	-0.58%	*-1.40*	0.11%	*0.46*	0.08%	*0.44*
13:00	-0.77%	*-1.84*[c]	0.91%	*3.55*[a]	0.34%	*3.76*[a]	-0.49%	*-2.00*[b]	0.03%	*0.03*	-0.72%	*-1.41*	0.68%	*2.28*[b]	0.02%	*0.10*
13:15	-0.29%	*-0.66*	1.27%	*4.14*[a]	0.45%	*5.17*[a]	-1.44%	*-5.35*[a]	-0.69%	*-0.65*	-0.53%	*-0.78*	1.46%	*4.94*[a]	-0.24%	*-1.01*
13:30	0.47%	*0.99*	2.19%	*6.74*[a]	0.44%	*4.63*[a]	-3.10%	*-9.01*[a]	-1.99%	*-1.78*[c]	0.19%	*0.27*	1.88%	*5.50*[a]	-0.08%	*-0.38*
13:45	1.08%	*2.38*[b]	1.55%	*4.91*[a]	0.35%	*4.46*[a]	-2.97%	*-8.59*[a]	-1.06%	*-0.93*	-0.90%	*-1.22*	1.76%	*4.89*[a]	0.21%	*0.86*
14:00	1.13%	*2.37*[b]	2.38%	*7.00*[a]	0.66%	*7.20*[a]	-4.17%	*-10.94*[a]	-1.19%	*-1.32*	-0.46%	*-0.76*	1.83%	*6.11*[a]	-0.17%	*-0.84*
14:15	1.25%	*2.41*[b]	2.88%	*9.26*[a]	0.97%	*8.94*[a]	-5.10%	*-10.77*[a]	-1.30%	*-1.40*	-0.95%	*-1.55*	1.98%	*5.97*[a]	0.27%	*1.24*
14:30	0.99%	*1.66*[c]	4.30%	*12.00*[a]	1.00%	*8.56*[a]	-6.29%	*-11.86*[a]	-1.86%	*-2.02*[b]	-0.01%	*-0.01*	2.15%	*6.61*[a]	-0.28%	*-1.23*
14:45	1.27%	*2.28*[b]	3.65%	*10.96*[a]	0.93%	*8.16*[a]	-5.84%	*-11.51*[a]	-2.87%	*-3.38*[a]	0.63%	*1.14*	2.64%	*8.28*[a]	-0.40%	*-2.02*[b]
15:00	1.60%	*2.65*[a]	4.19%	*10.96*[a]	0.88%	*7.50*[a]	-6.68%	*-12.11*[a]	-2.88%	*-3.49*[a]	1.05%	*1.92*[c]	2.45%	*7.84*[a]	-0.62%	*-3.31*[a]
15:15	2.26%	*3.83*[a]	3.83%	*9.68*[a]	0.82%	*6.83*[a]	-6.90%	*-12.19*[a]	-1.64%	*-1.93*[c]	-0.62%	*-1.09*	2.69%	*8.36*[a]	-0.43%	*-2.05*[b]
15:30	3.22%	*4.88*[a]	3.47%	*8.42*[a]	0.80%	*6.69*[a]	-7.49%	*-12.33*[a]	-1.99%	*-2.55*[b]	-0.56%	*-1.03*	2.88%	*8.90*[a]	-0.34%	*-1.72*[c]
15:45	3.93%	*5.62*[a]	3.05%	*8.05*[a]	0.81%	*6.21*[a]	-7.80%	*-12.16*[a]	-1.12%	*-1.32*	-1.27%	*-2.28*[b]	2.79%	*8.49*[a]	-0.40%	*-1.90*[c]
16:00	4.55%	*6.35*[a]	2.51%	*6.15*[a]	0.81%	*6.20*[a]	-7.87%	*-12.52*[a]	-1.26%	*-1.77*[c]	-1.04%	*-2.11*[b]	2.65%	*8.82*[a]	-0.34%	*-1.61*
16:15	8.71%	*12.33*[a]	-0.01%	*-0.02*	0.49%	*4.29*[a]	-9.19%	*-13.98*[a]	2.75%	*3.47*[a]	-2.73%	*-4.82*[a]	1.34%	*4.07*[a]	-1.36%	*-5.33*[a]
Obs.	141,668		141,668		141,668		141,668		142,480		142,480		142,480		142,480	
R^2	22.15%		28.30%		13.94%		36.76%		15.89%		12.94%		24.10%		12.42%	

Table 5

Intraday Regression Results: Average Quoted Spreads

We compare 69 stocks listed on the LSE and in the FTSE 100 between January 5 to March 31, 2009 (1st quarter) and October 1 to December 30, 2009 (4th quarter). We use the following regression model to test for intraday differences day per day t and per stock i: $measure_{i,t,j} = \alpha_{i,t} + \sum_{j=1}^{16} \beta_{i,t,j}\ \mathrm{D}_{i,t,j} + \sum_{j=18}^{34} \beta_{i,t,j}\ \mathrm{D}_{i,t,j} + \epsilon_{i,t}$, where $measure_{i,t}$ represents quoted spreads. Dummy variables for each 15-minute interval of the trading day take the value 1 for a corresponding observation and are 0 otherwise. We omit the midday interval from 12:00 to 12:15 p.m. GMT, the *17th* interval of the trading day. Therefore, all coefficients $\beta_{i,t,j}$ measure the difference relative to this reference interval, represented by the coefficient $\alpha_{i,t}$. We report robust standard errors following Thompson (2011), t-statistics are presented in italic letters. 'a' denotes significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

	January to March 2009								October to December 2009							
	LSE	t-stat.	Chi-X	t-stat.	BATS	t-stat.	TQ	t-stat.	LSE	t-stat.	Chi-X	t-stat	BATS	t-stat.	TQ	t-stat.
Intercept	6.096	*63.94*[a]	6.253	*51.31*[a]	10.700	*43.61*[a]	19.375	*46.72*[a]	5.317	*84.59*[a]	5.486	*78.11*[a]	6.619	*23.34*[a]	10.646	*20.08*[a]
8:00	8.997	*11.55*[a]	18.044	*11.99*[a]	17.778	*11.72*[a]	8.276	*2.23*[b]	6.657	*16.85*[a]	8.720	*16.13*[a]	11.926	*15.57*[a]	8.157	*13.67*[a]
8:15	3.845	*9.91*[a]	6.251	*9.49*[a]	7.796	*8.56*[a]	2.429	*0.71*	2.428	*13.72*[a]	2.456	*9.55*[a]	4.003	*8.43*[a]	2.573	*6.67*[a]
8:30	2.491	*8.86*[a]	4.082	*8.98*[a]	5.037	*7.43*[a]	1.080	*0.35*	1.553	*11.82*[a]	1.431	*6.87*[a]	2.388	*6.13*[a]	1.515	*4.27*[a]
8:45	1.725	*8.27*[a]	2.838	*8.57*[a]	3.005	*5.94*[a]	0.744	*0.41*	1.080	*10.17*[a]	1.020	*5.22*[a]	1.670	*4.36*[a]	0.796	*2.33*[b]
9:00	0.922	*6.78*[a]	1.069	*5.90*[a]	0.371	*0.82*	0.160	*0.11*	0.805	*8.45*[a]	0.709	*3.87*[a]	1.048	*2.91*[a]	0.367	*1.11*
9:15	0.745	*6.71*[a]	0.811	*5.20*[a]	0.879	*1.84*[c]	-0.499	*-0.38*	0.619	*6.62*[a]	0.554	*3.14*[a]	0.769	*2.20*[b]	0.261	*0.79*
9:30	0.664	*6.18*[a]	0.795	*4.92*[a]	1.484	*3.06*[a]	-1.051	*-0.64*	0.496	*5.80*[a]	0.336	*2.00*[b]	0.584	*1.71*[c]	0.205	*0.64*
9:45	0.533	*5.66*[a]	0.572	*4.59*[a]	0.722	*1.53*	-0.862	*-0.60*	0.338	*4.17*[a]	0.210	*1.27*	0.385	*1.16*	0.067	*0.20*
10:00	0.467	*5.37*[a]	0.711	*4.79*[a]	1.963	*3.66*[a]	-2.270	*-0.95*	0.297	*3.03*[a]	0.334	*1.81*[c]	0.421	*1.26*	0.322	*0.90*
10:15	0.288	*3.42*[a]	0.581	*3.76*[a]	0.875	*2.06*[b]	-0.756	*-0.86*	0.209	*2.54*[b]	0.116	*0.70*	0.244	*0.73*	-0.013	*-0.04*
10:30	0.038	*0.56*	0.115	*1.15*	0.103	*0.25*	-1.133	*-1.15*	-0.007	*-0.11*	-0.005	*-0.04*	0.027	*0.10*	-0.181	*-0.73*
10:45	0.007	*0.11*	0.039	*0.44*	0.131	*0.30*	-0.446	*-1.18*	-0.078	*-1.53*	0.055	*1.77*[c]	0.167	*2.24*[b]	-0.086	*-0.92*
11:00	0.046	*0.80*	0.125	*1.61*	0.155	*0.72*	-0.288	*-0.68*	-0.033	*-0.70*	0.045	*1.13*	0.089	*1.20*	-0.028	*-0.42*
11:15	-0.030	*-0.52*	0.063	*0.89*	-0.087	*-0.42*	-0.143	*0.54*	-0.157	*-3.00*[a]	-0.033	*-1.16*	-0.069	*-0.78*	-0.117	*-1.66*[c]
11:30	0.044	*0.61*	0.091	*1.12*	0.058	*0.41*	0.310	*1.24*	-0.131	*-2.99*[a]	-0.063	*-2.32*[b]	-0.150	*-1.41*	-0.088	*-1.64*
11:45	-0.066	*-1.43*	-0.063	*-1.32*	-0.038	*-0.21*	0.497	*0.75*	-0.084	*-2.74*[a]	-0.047	*-2.19*[b]	-0.147	*-1.60*	-0.047	*-1.06*
12:15	-0.132	*-3.71*[a]	-0.126	*-3.25*[a]	-0.618	*-1.67*[c]	0.096	*0.27*	-0.168	*-4.20*[a]	-0.109	*-5.27*[a]	-0.116	*-3.35*[a]	-0.134	*-3.07*[a]
12:30	-0.064	*-1.13*	-0.045	*-0.63*	-0.425	*-1.17*	0.215	*0.32*	-0.086	*-1.52*	-0.094	*-2.66*[a]	-0.146	*-2.78*[a]	-0.067	*-1.12*
12:45	-0.161	*-2.92*[a]	-0.142	*-2.26*[b]	-0.642	*-1.71*[c]	-0.327	*-0.96*	-0.190	*-4.20*[a]	-0.173	*-3.42*[a]	-0.184	*-3.57*[a]	-0.113	*-2.18*[b]
13:00	-0.255	*-4.52*[a]	-0.214	*-2.96*[a]	-1.020	*-3.01*[a]	0.745	*1.39*	-0.222	*-4.03*[a]	-0.223	*-3.95*[a]	-0.395	*-4.21*[a]	-0.220	*-3.62*[a]
13:15	-0.183	*-2.62*[a]	-0.165	*-1.43*	-0.927	*-2.39*[b]	1.154	*0.62*	-0.140	*-2.09*[b]	-0.286	*-3.96*[a]	-0.522	*-3.92*[a]	-0.156	*-1.37*
13:30	0.240	*2.30*[b]	0.037	*0.27*	-0.395	*-1.07*	2.172	*3.39*[a]	0.440	*2.95*[a]	-0.017	*-0.18*	-0.186	*-1.25*	0.361	*1.90*[c]
13:45	-0.084	*-1.04*	-0.118	*-0.97*	-0.922	*-2.40*[b]	1.937	*3.28*[a]	-0.276	*-3.15*[a]	-0.265	*-4.87*[a]	-0.550	*-4.23*[a]	-0.463	*-3.10*[a]
14:00	-0.286	*-3.17*[a]	-0.517	*-4.39*[a]	-2.179	*-4.07*[a]	2.334	*4.85*[a]	-0.226	*-2.72*[a]	-0.408	*-2.74*[a]	-0.833	*-2.84*[a]	-0.575	*-2.10*[b]
14:15	-0.458	*-5.67*[a]	-0.724	*-5.26*[a]	-2.634	*-4.45*[a]	3.166	*3.45*[a]	-0.387	*-5.30*[a]	-0.504	*-3.20*[a]	-1.018	*-3.27*[a]	-0.704	*-2.48*[b]
14:30	-0.440	*-4.76*[a]	-0.841	*-5.33*[a]	-2.907	*-4.62*[a]	2.720	*3.67*[a]	-0.011	*-0.18*	-0.391	*-2.47*[b]	-0.846	*-2.69*[a]	-0.431	*-1.52*
14:45	-0.551	*-5.73*[a]	-0.995	*-5.68*[a]	-2.996	*-5.07*[a]	2.878	*3.51*[a]	0.034	*0.50*	-0.348	*-2.31*[b]	-0.771	*-2.58*[a]	-0.238	*-0.87*
15:00	-0.549	*-5.54*[a]	-1.050	*-5.94*[a]	-2.835	*-5.27*[a]	4.189	*2.94*[a]	0.149	*1.51*	-0.322	*-2.14*[b]	-0.688	*-2.34*[b]	0.002	*0.01*
15:15	-0.655	*-6.42*[a]	-1.192	*-7.60*[a]	-2.992	*-4.73*[a]	3.612	*3.42*[a]	-0.309	*-4.40*[a]	-0.461	*-3.36*[a]	-0.936	*-3.43*[a]	-0.579	*-2.22*[b]
15:30	-0.812	*-7.86*[a]	-1.250	*-8.09*[a]	-2.994	*-5.02*[a]	3.563	*4.21*[a]	-0.360	*-4.87*[a]	-0.531	*-4.13*[a]	-1.080	*-4.22*[a]	-0.702	*-2.81*[a]
15:45	-0.850	*-8.40*[a]	-1.233	*-8.07*[a]	-2.988	*-4.87*[a]	3.244	*4.41*[a]	-0.430	*-5.39*[a]	-0.563	*-4.70*[a]	-1.102	*-4.62*[a]	-0.742	*-3.25*[a]
16:00	-0.942	*-8.95*[a]	-1.260	*-8.00*[a]	-3.095	*-4.82*[a]	4.384	*3.34*[a]	-0.673	*-8.55*[a]	-0.663	*-5.77*[a]	-1.303	*-5.63*[a]	-0.919	*-4.21*[a]
16:15	-0.842	*-9.36*[a]	-0.910	*-6.41*[a]	-2.642	*-4.36*[a]	5.603	*7.09*[a]	-0.741	*-9.26*[a]	-0.659	*-5.76*[a]	-1.313	*-5.71*[a]	-0.469	*-1.85*[c]
Obs.	141,671		141,671		141,671		141,671		142,534		142,534		142,534		142,534	
R^2	71.07%		53.81%		16.93%		13.55%		69.80%		67.84%		50.85%		52.38%	

Table 6

Intraday Regression Results: 5-minute Price Impact

We compare 69 stocks listed on the LSE and in the FTSE 100 between January 5 to March 31, 2009 (1st quarter) and October 1 to December 30, 2009 (4th quarter). We use the following regression model to test for intraday differences day per day t and per stock i: $measure_{i,t,j} = \alpha_{i,t} + \sum_{j=1}^{16} \beta_{i,t,j}\, \mathrm{D}_{i,t,j} + \sum_{j=18}^{34} \beta_{i,t,j}\, \mathrm{D}_{i,t,j} + \epsilon_{i,t}$, where $measure_{i,t}$ represents price impacts. Dummy variables for each 15-minute interval of the trading day take the value 1 for a corresponding observation and are 0 otherwise. We omit the midday interval from 12:00 to 12:15 p.m. GMT, the *17th* interval of the trading day. Therefore, all coefficients $\beta_{i,t,j}$ measure the difference relative to this reference interval, represented by the coefficient $\alpha_{i,t}$. We report robust standard errors following Thompson (2011), t-statistics are presented in italic letters. 'a' denotes significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

	January to March 2009								October to December 2009							
	LSE	t-stat.	Chi-X	t-stat.	BATS	t-stat.	TQ	t-stat.	LSE	t-stat.	Chi-X	t-stat	BATS	t-stat.	TQ	t-stat.
Intercept	4.970	*21.74*^{a}	4.359	*16.27*^{a}	2.868	*5.26*^{a}	2.979	*8.48*^{a}	3.199	*22.12*^{a}	3.486	*30.38*^{a}	3.146	*21.86*^{a}	2.815	*16.37*^{a}
8:00	3.951	*8.48*^{a}	2.784	*4.63*^{a}	4.302	*4.16*^{a}	2.872	*5.22*^{a}	3.580	*10.93*^{a}	3.159	*11.27*^{a}	3.015	*8.82*^{a}	2.812	*9.56*^{a}
8:15	1.969	*5.64*^{a}	1.468	*3.40*^{a}	1.965	*2.14*^{b}	1.578	*2.89*^{a}	2.424	*8.61*^{a}	1.934	*9.31*^{a}	1.957	*7.51*^{a}	1.521	*8.00*^{a}
8:30	1.543	*3.64*^{a}	1.177	*2.42*^{b}	2.755	*4.03*^{a}	1.493	*2.59*^{a}	1.529	*6.58*^{a}	1.232	*6.08*^{a}	1.218	*4.43*^{a}	0.978	*4.06*^{a}
8:45	1.206	*3.13*^{a}	1.010	*2.74*^{a}	1.302	*1.83*^{c}	1.545	*2.61*^{a}	1.111	*5.72*^{a}	0.985	*7.46*^{a}	0.901	*4.25*^{a}	0.828	*4.21*^{a}
9:00	0.918	*2.80*^{a}	0.705	*1.81*^{c}	1.512	*3.03*^{a}	1.221	*2.27*^{b}	0.895	*4.35*^{a}	0.885	*4.67*^{a}	0.811	*3.67*^{a}	0.600	*2.34*^{b}
9:15	0.429	*1.36*	0.230	*0.69*	0.958	*1.75*^{c}	0.780	*1.97*^{c}	0.519	*2.91*^{a}	0.479	*3.01*^{a}	0.515	*2.90*^{a}	0.408	*1.80*^{c}
9:30	0.549	*1.94*^{c}	0.568	*1.90*^{c}	1.777	*3.26*^{a}	1.139	*2.81*^{a}	0.446	*2.21*^{b}	0.409	*2.78*^{a}	0.405	*1.86*^{c}	0.410	*1.81*^{c}
9:45	0.526	*1.65*^{c}	0.624	*1.73c*	1.500	*2.50*^{b}	1.236	*3.27*^{a}	0.386	*2.18*^{b}	0.350	*2.29*^{b}	0.306	*1.69*^{c}	0.477	*2.34*^{b}
10:00	0.289	*0.95*	0.178	*0.61*	1.559	*1.95*^{c}	0.581	*1.29*	0.331	*1.42*	0.306	*1.86*^{c}	0.169	*0.70*	0.085	*0.39*
10:15	0.018	*0.07*	0.510	*1.50*	1.524	*2.81*^{a}	0.711	*1.77*^{c}	0.106	*0.63*	0.136	*1.02*	0.094	*0.70*	0.250	*1.19*
10:30	-0.115	*-0.41*	0.260	*0.94*	1.388	*2.28*^{b}	-0.057	*-0.14*	0.133	*0.74*	0.220	*1.40*	0.134	*0.66*	0.317	*1.63*
10:45	-0.561	*-2.03*^{b}	-0.040	*-0.12*	1.242	*1.93*^{c}	0.343	*0.73*	0.093	*0.64*	0.059	*0.52*	-0.068	*-0.44*	0.320	*1.85*^{c}
11:00	-0.239	*-0.81*	0.094	*0.28*	0.712	*1.36*	0.713	*1.55*	0.048	*0.29*	-0.045	*-0.37*	-0.031	*-0.22*	0.057	*0.34*
11:15	0.040	*0.14*	0.153	*0.47*	0.997	*1.59*	0.344	*0.75*	-0.090	*-0.61*	-0.103	*-0.87*	-0.282	*-1.87*^{c}	0.007	*0.04*
11:30	-0.354	*-1.46*	-0.251	*-0.77*	0.557	*0.98*	0.229	*0.50*	0.154	*0.96*	0.057	*0.47*	0.090	*0.50*	0.126	*0.55*
11:45	-0.294	*-1.18*	-0.354	*-1.08*	1.096	*2.13*^{b}	-0.347	*-0.76*	0.063	*0.35*	0.084	*0.56*	-0.141	*-0.83*	0.083	*0.39*
12:15	-0.149	*-0.63*	-0.099	*-0.33*	0.413	*0.78*	0.037	*0.10*	-0.003	*-0.02*	-0.142	*-1.15*	-0.164	*-1.25*	0.029	*0.17*
12:30	-0.387	*-1.51*	-0.326	*-1.02*	0.941	*1.90*^{c}	-0.021	*-0.05*	-0.013	*-0.07*	-0.038	*-0.29*	-0.124	*-0.75*	0.089	*0.44*
12:45	-0.284	*-1.19*	-0.259	*-0.92*	0.373	*0.82*	0.087	*0.24*	0.054	*0.35*	-0.036	*-0.27*	-0.041	*-0.24*	0.199	*0.96*
13:00	-0.254	*-1.19*	-0.499	*-1.60*	0.375	*0.65*	0.026	*0.07*	-0.266	*-1.95*^{c}	-0.181	*-1.65*^{c}	-0.252	*-1.66*^{c}	-0.173	*-1.00*
13:15	-0.580	*-2.18*^{b}	-0.247	*-0.72*	0.258	*0.47*	0.154	*0.29*	-0.614	*-2.39*^{b}	-0.324	*-1.70*^{c}	-0.607	*-3.20*^{a}	-0.198	*-0.74*
13:30	-0.050	*-0.18*	-0.358	*-1.18*	0.155	*0.31*	-0.038	*-0.08*	-0.545	*-2.57*^{b}	-0.296	*-1.51*	-0.714	*-4.27*^{a}	-0.682	*-2.76*^{a}
13:45	-0.343	*-1.09*	-0.179	*-0.48*	0.099	*0.17*	0.541	*1.08*	-0.075	*-0.37*	-0.044	*-0.27*	-0.097	*-0.55*	0.087	*0.36*
14:00	-0.428	*-1.37*	-0.060	*-0.19*	0.852	*1.62*	0.038	*0.09*	-0.183	*-1.04*	-0.126	*-0.88*	-0.403	*-2.45*^{b}	-0.257	*-1.27*
14:15	-1.100	*-4.42*^{a}	-0.816	*-2.90*^{a}	-0.016	*-0.03*	-0.636	*-1.14*	-0.602	*-3.66*^{a}	-0.445	*-3.38*^{a}	-0.515	*-2.82*^{a}	-0.499	*-2.70*^{a}
14:30	-1.220	*-3.48*^{a}	-0.651	*-1.76*^{c}	-0.179	*-0.32*	-0.510	*-1.18*	-0.743	*-4.37*^{a}	-0.364	*-2.48*^{b}	-0.497	*-3.19*^{a}	-0.458	*-2.08*^{b}
14:45	-0.588	*-2.05*^{b}	-0.556	*-1.64*	0.941	*1.71*^{c}	-0.135	*-0.28*	-1.075	*-5.29*^{a}	-0.512	*-3.45*^{a}	-0.660	*-3.76*^{a}	-0.779	*-3.63*^{a}
15:00	-1.224	*-4.55*^{a}	-0.875	*-2.51*^{b}	0.159	*0.31*	-0.513	*-1.16*	-0.699	*-3.96*^{a}	-0.431	*-2.96*^{a}	-0.519	*-3.51*^{a}	-0.767	*-3.61*^{a}
15:15	-1.069	*-4.23*^{a}	-0.596	*-1.88*^{c}	0.704	*1.45*	-0.379	*-1.00*	-0.870	*-4.51*^{a}	-0.434	*-2.70*^{a}	-0.635	*-3.61*^{a}	-0.571	*-2.79*^{a}
15:30	-0.914	*-3.52*^{a}	-0.259	*-0.82*	-0.189	*-0.32*	-0.453	*-0.83*	-0.897	*-5.34*^{a}	-0.484	*-3.73*^{a}	-0.653	*-3.78*^{a}	-0.670	*-3.45*^{a}
15:45	-1.509	*-5.09*^{a}	-0.930	*-3.19*^{a}	0.088	*0.18*	-0.758	*-1.60*	-0.921	*-5.59*^{a}	-0.450	*-3.07*^{a}	-0.722	*-4.02*^{a}	-0.498	*-2.48*^{b}
16:00	-1.423	*-5.00*^{a}	-1.000	*-2.85*^{a}	-0.701	*-1.36*	-0.331	*-0.74*	-0.964	*-6.07*^{a}	-0.621	*-4.64*^{a}	-0.784	*-4.35*^{a}	-0.562	*-2.66*^{a}
16:15	-1.615	*-5.42*^{a}	-1.340	*-4.38*^{a}	-0.600	*-1.31*	-1.633	*-4.06*^{a}	-1.069	*-5.43*^{a}	-0.851	*-5.76*^{a}	-1.040	*-5.81*^{a}	-0.820	*-3.94*^{a}
Obs.	114,910		114,910		114,910		114,910		136,382		136,382		136,382		136,382	
R^2	11.48%		5.30%		1.37%		1.48%		10.33%		8.80%		3.77%		2.94%	

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