Fragmentation, Competition and Market Quality: A Post-MiFID Analysis

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Abstract

In this paper we study competition between the London Stock Exchange (LSE) and multilateral trading facilities (MTFs) under the Markets in Financial Instruments Directive (MiFID) in FTSE 100 constituents. We find that despite the lack of price protection investors often execute at the best available price. This indicates that price competition is important for investors and that most investors are monitoring multiple markets. In cases where participants do not execute at the best price, we find that liquidity is in general higher and that trades are more informative. When comparing the market quality across trading venues we find remarkable differences. The LSE posts better terms of trade than any MTF. However, implicit trading costs are smaller on MTFs. Our results show that Chi-X, an MTF, contributes more to quote-based information discovery than the LSE but that trades on the LSE carry more private information than on MTFs. This is consistent with the theory, presented in Chowdhry and Nanda (1991), that more informed investors gravitate to the market that is already the largest and confirms some concerns regarding 'cream-skimming'. Finally, we find despite a high level of market fragmentation that the market for FTSE 100 constituents is relatively efficient.

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1. Introduction

Competition for order flow in FTSE 100 securities is fierce and increasing. Within the past two years the London Stock Exchange's share of exchange order flow has fallen from nearly 100% to less than 65% at the end of 2009. The current situation is such that regulators are concerned about price formation in the stocks that make up the FTSE 100, the leading U.K. stock market index.[4] In this paper we study the competition for order flow and market quality, including price discovery and liquidity in FTSE 100 constituents. We investigate the implications of MiFID in FTSE 100 constituents as the MTF market share is highest in these shares.

The Markets in Financial Instruments Directive (MiFID) is designed to promote an integrated and harmonized European financial trading landscape.[5] MiFID increased the competition for order flow between regulated markets (RM) and other trading venues with the repeal of the concentration rule that stipulated the execution of retail orders on RMs. The concentration rule lead to a situation where a single stock exchange dominated in each member state. This situation is different to the U.S. market where markets are more fragmented but virtually integrated via the consolidated tape and the consolidated quotation system. The lack of competition was addressed with the implementation of MiFID on November 1st, 2007 after which orders could be executed away from the RM on multilateral trading facilities (MTF) or system-internalizers (SI).

The MiFID introduced further competition in European security markets with its policy on best execution. Under MiFID best execution is multi-dimensional, in that price is not the only factor. The obligation to define and enforce a best execution policy is placed on intermediares (e.g. brokers or banks), the results of which are unclear. The best execution policy in U.S. securities markets is a best price policy (see: Rule 602 b, Regulation NMS (Reg NMS)), where the onus to enforce the policy is on the trading venue to which an order is routed (see: Rule 611, Reg NMS). These differences can lead to competition on price or on other factors outlined in MiFID such as speed, probability of execution, or probability of settlement. In consequence, the best available price might be traded-through.[6]

[4]Besides potential benefits of MTFs the British Financial Service Authority (FSA) is concerned that 'there is a risk of liquidity fragmenting, and this would present challenges for the quality and efficiency of the market process and the effectiveness of market oversight' (see: http://www.fsa.gov.uk/pages/Library/Communication/PR/2007/083.shtml). The widely used term 'fragmentation' has a negative connotation. However, competition induced fragmentation may be positive. In concequence, we emphasize a neutral use throughout the paper.

[5]Degryse (2009) provides a structured overview of MiFID and highlights some possible implications.

[6]Trade-Through rates for the U.S. market are reported by Hendershott and Jones (2005b) and Battalio et al. (2004). Foucault and Menkveld (2008) provide some statistics for the Dutch stock market.

The important question is whether or not market fragmentation is beneficial for price discovery. We believe that this question is central for the evaluation of European capital markets under MiFID. Efficient prices are a public good and critical to efficient investment and risk management decision making. Conventional wisdom suggests that liquidity begets liquidity, i.e. liquidity externalties arise when traders meet on centralized market places. The consolidation of order flow reduces trading and search costs for investors and thus, could enhance price discovery. Pagano (1989a,b) and Chowdhry and Nanda (1991) show that there are strong incentitives to concentrate order flow if trading is equally costly across trading venues. However, investors might have different preferences. While high frequency traders seek for low-latency network connections, average investors might for example prefer specific pre- or post-trade services. As a result, concentration might be suboptimal.

Initially, MTFs were strongly promoted by large investment banks in order to put pressure on RMs to reduce the explicit costs of trading in Europe. In retrospect, we can say that on the one hand the emergence of MTFs provides all trading venues with strong incentives to innovate, to adopt technologies, and to offer superior services. In addition, the new market partcipants might reduce the monopoly power of liquidity suppliers in the incumbent market. On the other hand, fragmented order flow reduces the liquidity available on one trading venue and might disrupt price discovery. Easley et al. (1996) document 'cream-skimming' of uninformed liquidity orders for the Cinicinnati Stock Exchange and the New York Stock Exchange (NYSE). An adverse selection problem arises leaving the NYSE with the more informed order flow and higher adverse selection risks. The literature on market quality and fragmentation offers inconclusive results. While Mendelson (1987) or Bennett and Wei (2006) show that fragmentation can result in less liquid and less efficient markets, Boehmer and Boehmer (2003) document large improvements in liquidity after the entrance of a new market. A related branch of literature assesses trading costs in different markets and market structures. Battalio et al. (2004) and de Fontnouvelle et al. (2003) for example find lower spreads for multiple listed single equity options. Barclay et al. (2003) provide further evidence for positive effects of increased competition. They study the U.S. equity order flow on electronic communication networks (ECN) and find that ECNs have a positive impact on market quality as trading venues offering better prices are more likely to attract order flow. In a recent working paper Hengelbrock and Theissen (2009) use an event study approach to examine the liquidity effects of the Turquoise market launch and find a positive impact on liquidity. Taken in its entirety the evidence suggests that competition may be good for FTSE 100 stocks. How this competition plays out in the market and which markets survive is an open question.

We contribute to the existing multimarket regulation and trading literature by sheding light on the question of investors' decisions to trade on the primary market or on MTFs. There is to our knowledge surprisingly little literature which analyzes the impact of increased competition on market quality and the price discovery process in European equities. Foucault and Menkveld (2008) study the market entry of EuroSETS on the dutch stock market in May 2004. As predicted by their theorectical model, they find that the stronger competition among liquidity suppliers leads to an increase in depth of the consolidated order book. In addition, they provide empirical evidence that a higher trade-through rate discourages liquidity supply.

Recently, communication and information technology has revolutionized the organization of financial markets and the manner in which financial assets are traded. Nearly all trading venues operate open and centralized limit order books which can be accessed by algorithmic traders and average investors alike. The connectivity between markets also increases with the addition of standardized trading communications protocols to improve communications and with the introduction of regulation, such as MiFID or U.S. Reg NMS, to integrate markets. Algorithmic traders have been shown to have positive effects on the price discovery process and thus, the integration of both equity (Hendershott and Riordan, 2009) and foreign exchange (Chaboud et al., 2009) markets. In consequence, they may be equaling out some of the negative side-effects of increased competition and fragmentation by electronically linking markets.

Methodologically this study is influenced by a number of papers. As in Hasbrouck (1995) we suppose that there is an efficient price per instrument across all trading venues. Assuming that arbitrageurs ensure equal prices, this approach seems practical. To study the price discovery process we derive our methodology primarily from the analyses presented in Hasbrouck (1991a,b, 1995). Our study of investor routing decisions is borrowed from Barclay et al. (2003) and Hendershott and Riordan (2009).

To study competition and market quality in FTSE 100 stocks we collect data on transactions and quotes for April and May, 2009 on the four largest trading venues in the U.K., the LSE, Chi-X, BATS, and Turquoise. We retrieve trade and quote (TAQ) data in FTSE 100 stocks from the Thomson Reuters DataScope Tick History data service operated by the Securities Industry

Research Centre of Asia-Pacific (SIRCA) on behalf of Thomson Reuters.[7] First, we present some results on the determinants of fragmentation but this is not our primary focus. Rather we focus on the individual decisions of investors when routing orders to trading venues. To better understand these decisions and to outline the resulting dynamics, we identify transactions that execute at the best price and those that do not execute at the best price. For each case we study factors that are expected to impact investor routing decisions. We select our observation period primarily due to the lack of major changes in the market during this period. Major market changes could confound our results as the market converges to a new equilibrium level of competition.

The main result of our analyses is that competition for order flow in FTSE 100 constituents is primarily, but not exclusively price-based. The quality of the markets under observation varies. While quoted spreads are lower on the LSE, implicit transaction costs measured as effective spreads are on average smaller on Chi-X, BATS, and Turquoise. In addition, we find a higher trade-through rate for the LSE. Surprisingly, the quoted based contribution to price discovery by Chi-X, the largest MTF, is greater than for the LSE. This adds fuel to the recent discussion surrounding the LSE TradElect system outage.[8] We also find that informed investors behave as expected and trade pre-dominantly on the LSE and Chi-X, the most liquid markets in our sample. More generally, our results suggest that improved technology, a higly competive environement, and regulation have created a dynamic playing field for investors. Summing up, we find little empirical evidence that fragmentation harms market quality and price discovery.

The paper is organized as follows, Section 2 presents the institutional details and the data used throughout the paper. In Section 3 we study the competition between the trading venues and present in-depth results on price and non-price competition. Section 4 presents results on market quality for each trading venue and in Section 5 we conclude.

2. Institutional Details and Data

The traditional market model of primary exchanges was quickly challenged by new entrants like Chi-X, BATS, and Turquoise which are regulated as MTFs under MiFID. MTFs differentiate on technology, trading costs, and the quality of their service. Their market models are adapted to the needs of high-frequency traders by offering low-latency trading with high throughput rates.

[7]We thank SIRCA for providing access to its data archive.
[8]see: LSE outage on November 26th, 2009.

Chi-X, BATS, and Turquoise are regulated by the Financial Securities Association (FSA) under MiFID and passported to provide trading services within Europe. Chi-X started trading about six month ahead of MiFID at the end of March 2007. The full list of FTSE 100 constituents became available on Chi-X starting July 13th, 2007. To date, Chi-X is owned by Instinet, a subsidiary of Nomura Holdings, and a number of international investment banks and broker houses. The market share in UK stocks increased from 8.8% in March 2008 to 14.9% while celebrating its second birthday in March 2009.[9] The market became even more fragmented when Turquoise offered all FTSE 100 instruments for trading in September 2008 and when BATS started trading in all FTSE 100 constituents on November 7th, 2008. While BATS is operated by BATS Europe a subsidiary of the US company BATS Global Markets, Turquoise is operated by Turquoise Services Limited an independently managed firm founded by Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, Merill Lynch, Morgan Stanley, UBS, BNP Paribas, and Société Générale.[10]

We select April and May 2009 as our period of analysis for a number of reasons. First, given that we want to study the effects of competition and regulation on trading behavior and market quality, selecting a period with a stable market structure is important. During April and May there were no meaningful changes to the markets' microstructures, fees, or trading systems. This allows a clean analysis of the current intensity of competition and market quality. In the following paragraphs we present the institutional details of all trading venues as of May 2009. However, we also outline important changes made over the following months until December 2009.

Competing MTFs offer different fee structures, network latencies, and levels of service. However, Chi-X, BATS, and Turquoise provide the same basic market model. They all operate an integrated anonymous limit order book which combines both visible and hidden liquidity.[11] Hidden limit orders are not visible to any investor. These order types add additional liquidity to the order book and minimize the adverse selection risk for informed investors. However, hidden orders have to meet the Large in Scale requirement of MiFID.[12] Priority of orders is enforced

[9]see: http://www.chi-x.com/chi-x-press-releases/Chi-X-Europe-Second-Year-Anniversary.pdf.

[10]The LSE aggreed to merge its dark pool unit Baikal with Turquoise on December 21st, 2009 leaving the LSE with 60% of the new company. The existing shareholders will own 40% of the new company. The aquisition was completed in February 2010.

[11]In addition, all three trading venues operate dark order books. They use the pre-trade transparency waiver available to reference price systems under MiFID. As reference price the Primary Market Best Bid and Offer (PBBO) is used. While Chi-Delta went live on May 25th, 2009, BATS started its separate dark pool on August 7th, 2009. However, we concentrate our analysis on the integrated order books as we have no access to the trade data of the dark pools.

[12]Regulation exempts large in scale orders from the principle of pre-trade transparency. Article 20 of the MiFID Implementing Regulation states the details.

according to the displayed limit of the order, the transparency of an order (visible orders have priority over hidden orders), and the time. Besides displayed limit orders, market orders, and iceberg orders Chi-X, BATS, and Turquoise offer pegged orders, that is, the trading price is determined by linking to a reference price like the European Best Bid and Offer (EBBO) over all markets. Pegged orders can also be hidden. To guarantee investors attractive prices, the matching of orders on all three trading venues is subject to a price check. However, the MTFs apply different tolerance levels. Generally speaking, an order will be rejected if it executes a certain percentage above the European best bid or below the European best offer. All trading venues operate continuous trading over the same trading hours (8:00 a.m. to 4:30 p.m. local time). There are no opening and closing auctions except on Turquoise which runs an opening call auction. The tick size during our sample period was the same as on the primary market, the LSE.

The LSE trades the FTSE 100 constituents on SETS which combines electronic order-driven trading with integrated liquidity provision by market makers. Today, LSE's trading system TradElect allows round-trip times of about 4 milliseconds. Market makers are obliged to add liquidity to the order book. They pay a certain fee but they benefit from lower trading fees in the securities for which they are market makers. According to the LSE, market markers are active in all FTSE 100 constituents. The LSE and the three MTFs adopted a maker/taker pricing model.[13] While an investor is charged at the LSE between 0.45 bps to 0.75 bps for an aggressive order, that is, an incoming order which hits an order that has been placed in the order book, she receives a rebate of up to 0.40 bps for a passive order. A passive execution refers to the case where a limit order is executed which has been hit by an incoming order. The maker/taker fee category depends on the order volume traded each month. While the highest rebate is received above a monthly trading volume of 25 bnGBP, the minimum fee of 0.45 bps per trade is charged with a monthly trading volume above 30 bnGBP. However, there is a minimum fee of 25 pence per trade. Chi-X and BATS offer a maker/taker pricing scheme with a rebate of 0.20 bps and an order fee of 0.30 bps for an agressive order over our sample period. Turquoise has the cheapest fee for an aggressive order with 0.28 bps and a rebate of 0.20 to 0.24 bps per order. The enhanced rebate level on Turquoise is applied for members whose trading volume exceeded a specified threshold in the previous month.

MTFs offer several potential benefits to investors. First, all systems offer a similar speed

[13]The LSE switched back to a traditional fee schedule on September 1st, 2009.

of execution with an average round-trip time for an order of about 0.4 milliseconds. Thus, the latency on a MTF is ten times smaller than on SETS. In fast moving volatile markets MTFs offer smaller execution risks to investors. Trading on the LSE, the price might be different by the time an order reaches the market. Second, MTFs sometimes offer better prices due to hidden liquidity in the order book. Thus, trades may occur on an MTF inside the spread at a fraction above the best bid or below the best ask. However, on the LSE market makers offer additional liquidity by permanently posting quotes with a maximum spread and a minimum size.[14] In consequence, the LSE might offer more depth and thus, smaller implicit execution costs for large trades. Another possible benefit of trading on the LSE might be the choice of the central counterparty (CCP) introduced on December 12th, 2008. It is possible to clear trades through LCH.Clearnet or SIX x-clear. On the MTFs the choice of CCP has not been available before autumn 2009.

To examine the level of fragmentation in UK equities, we concentrate on the primary market, the LSE, and the three largest MTFs namely Chi-X, Bats, and Turquoise. Data is retrieved directly from the Thomson Reuters DataScope Tick History archive operated by SIRCA. Our sample covers 27 trading days from April 20th, 2009 to May 31st, 2009 excluding May 1st, 2009 due to a considerably smaller trading volume.[15] We study equities trading for the 100 stocks that make up the FTSE 100 stock index. We retrieve trades, best bids, and best asks for the instruments in our sample for each distinct trading venue. In addition we collect order book data up to three levels beyond the best bid and ask. Each trade and quote is timestamped to the millisecond and accessible via Thomson Reuters Instrument Code (RIC). Daily data on market capitalization and corporate actions is collected directly from Bloomberg and cross-checked with Thomson Reuters. To assure a clean analysis of the current intensity of competition and market quality, we exclude stocks with corporate actions, missing data, or less than ten trades per trading day during our research period. Table 1 presents the 74 selected stocks according to trading volume quantiles.[16] The trading volume categories are obtained by ranking the firms in the FTSE 100 sample by their average daily trading volume during the sample period. The first category contains the first 25 firms with the highest trading volume (High), the second the next 25 firms (Medium), and the third category 24 low volume firms (Low).

[14] A liquidity provision agreement between Turquoise and its nine investment bank shareholders ended in March 2009. Afterwards Turquoise's market share decreased significantly but recovered during the previous months.

[15] In several European countries the business is closed because of Labour Day.

[16] In a prior version of this paper we analyze 19 trading days from May 1st, 2009 to May 31st, 2009 separated into market capitalization quartiles. However, the results are not significantly different to this paper version.

Insert Table 1 here

The first and last fifteen minutes of the trading day are removed to avoid biases associated with the information processing and inventory management process due to the opening or closing of the markets. The data spans the period between 8:15 a.m. and 4:15 p.m. local time. We use Thomson Reuters' qualifying code to further filter our data. Reported trades of opening, closing, and intraday auctions as well as reported crossing trades and special market maker trades (e.g. non-protected portfolio transactions[17]) are deleted. In addition, we require LSE trades to match the best bid or ask, respectively. In cases where our constraint is not met, we assume reporting errors and eliminate the trade from our data sets. In total we exclude 0.5% of the LSE trades. Since we only have access to trades occurring on the primary market and MTFs, we concentrate our analysis on these venues only. These data do not include trades executed by systematic internalizers, dark pools, and other OTC execution venues.

In order to aligne data streams across different trading venues, we use RICs and the timestamps to the nearest millisecond given in the data. As a robustness check we compare our data stream including the primary exchange, the LSE, Chi-X, BATS, and Turquoise with the Thomson Reuters consolidated European data feed. The data delivers trades and best bid and ask price changes from all order book driven venues trading FTSE 100 stocks. On a tick-by-tick basis we find a small average midpoint difference of 0.0075 pence for FTSE 100 stocks over the sample period between the *xbo*-data stream and our consolidated data. In light of an average tick size of 0.56 pence our robustness check provides evidence for our high data quality.

3. Competition

Stocks listed on the LSE can be traded via a number of alternative trading venues as well as on the LSE. Each has its own set of rules, clients, and technologies. These include rebates for supplying liquidity, low-latency execution systems, and ownership. The ability to attract order flow in FTSE 100 stocks is strongly dependent on innovation in market design at each trading venue and the ability of each market to attract liquidity supply. These two factors relate more

[17]A non-protected portfolio transaction or a fully disclosed portfolio transaction is a transaction of a number of stocks dealt with by one market maker at an agreed discount to the market price.

specifically to price competition (explicit and implicit trading costs) and non-price competition (market microstructure, execution speed, and regulation). In this section we study the competition between trading venues and investors' routing decisions when price appears to be the predominant factor and when price appears to be of lower priority.

Insert Table 2 here

Table 2 reports the descriptive statistics for the entire sample and per trading venue. The average market capitalization is quite large at 17 billion GBP. The results on posted liquidity (*Quoted Spread* and *Quoted Spread Trade*) are calculated as follows: *Quoted Spread* is calculated on a tick-by-tick basis and *Quoted Spread Trade* is the quoted spread recorded for each trade. For a more detailed description see Appendix A.1. The results on posted liquidity indicate that the LSE offers the most competitive terms of trade ex-ante. Ex-post measured liquidity (*Effective Spread*) is larger on MTFs, this might be an indication that MTFs lead in liquidity provision. We discuss these results in more detail in the following section. The average depth at the best bid and ask (*Depth1*) is greater on the LSE but not considerably greater than *Depth1* posted on Chi-X. To account for quoted volume behind the best bid and ask, we use order book data and aggregate the depth at bid and ask prices up to three ticks in the order book (*Depth3*). A similar measure is used by Foucault and Menkveld (2008). More depth allows traders to execute larger trades without impacting the price, which corresponds to higher liquidity. While the average *Depth3* over the sample period for the LSE is 128,286 GBP, the quoted depth three ticks behind the first level is 139,822 GBP for Chi-X. BATS and Turquoise provide a significantly smaller quoted volume. However, we probably underestimate the depth at the bid and ask side due to iceberg orders and hidden liquidity. The trade size variable shows trades are on average larger on the LSE than on the MTFs and might be evidence of clientele effects that may play a role in order-routing decisions. The descriptive statistics indicate that the market dynamics are quite complex and worthy of further study.

How competitive are UK equity markets? This is essentially the same as asking; how fragmented is trading in UK equities? To answer this question we calculate fragmentation measures using trading volumes reported on the LSE, Chi-X, BATS, and Turquoise. We present an overview over daily market shares in Figure 1 and details for trading volume categories in

Table 3.

Insert Figure 1 here

As expected the LSE attracts with a market share of roughly 70% most of the trading volume over the sample period. In Figure 1 we see evidence of a continuing erosion of LSE market share in April and May when the LSE loses about 3.5% of their order flow despite a lack of market level competitive actions. The primary beneficiary is BATS which, nearly doubles its share of trading volume, but remains well behind Chi-X, the largest MTF, which attracts roughly 20% of total order flow in our sample. As shown in Table 3 we find that MTFs possess a higher market share in high trading volume category stocks. The LSE market share increases from 67,83% for high volume stocks to 73,07% in the low volume category. The final column of Table 3 provides the Herfindahl-Hirschman-Index (HHI) as measure of concentration. The index is given by the sum of the squares of the percentage market share of each trading venue and clearly indicates higher concentration for stocks in the low trading volume category.

Insert Table 3 here

In Table 4 we present data on the cross-sectional determinants of market fragmentation. In Panel A we report summary statistics on fragmentation determinants. The market shares for the LSE (MS^{LSE}) and across the MTFs (MS^{MTFs}) are calculated with the total trading volume on a daily basis per instrument. We use market capitalization ($MCAP$) to capture effects relating to the size of a firm and institutional ownership, calculated as the natural logarithm in British Pounds. We include two variables intraday realized volatility (RV^{avg}) and quoted spread (QSP^{avg}) - calculated as the daily average across trading venues - to take company specific volatility and liquidity conditions into account. We include two variables that capture the proportion of trades for which the LSE was alone at the best price ($AtBestA^{LSE}$) and for which an MTF was alone ($AtBestA^{MTFs}$). We expect $AtBestA^{LSE}$ to be a strong positive determinant of LSE market share. We estimate one-way time fixed effects models for $j \in \{LSE,\ MTFs\}$ with Arellano (1987) standard errors as follows:

$$MS^{j}_{i,T} = \alpha^{j} + \beta^{j}_{1}\ \mathrm{MCAP}_{i} + \beta^{j}_{2}\ \mathrm{RV}^{avg}_{i} + \beta^{j}_{3}\ \mathrm{QSP}^{avg}_{i} + \beta^{j}_{4}\ \mathrm{AtBestA}^{j}_{i} + \epsilon^{j}_{i,t} \tag{1}$$

Insert Table 4 here

While Panel A of Table 4 provides some descriptive statistics, we present the results for each model in Panel B, one with $MS_{i,t}^{LSE}$ as the dependent variable and the second with $MS_{i,t}^{MTFs}$ for each individual stock i on a certain trading day T. The results indicate that firm size is a strong negative determinant of LSE market share and is strongly positive for MTFs. This tells us that order flow in larger firms is more likely to be fragmented. The results on firm volatility indicate that more volatile firms remain less fragmented as do less liquid firms. The coefficient for $AtBestA$ indicates that the posting of best prices is a strong positive determinant for the LSE. An interesting result is the coefficient for $AtBestA^{MTFs}$ which is negative but only significant at the 10% level. This might indicate that, in some cases, even when MTFs post strictly better prices than the LSE, investors seem to ignore these and route to the LSE. In the following two sections we take a more in-depth look into price and non-price competition.

3.1. Price Competition

Markets can compete for order flow in numerous ways. They can compete on explicit trading costs, implicit trading costs, infrastructure, and on trading and non-trading services. In this section we study implicit price competition and the sensitivity of investors to quoted prices. The results on cross-sectional determinants show that investors are sensitive to implicit costs, or rather the cost of liquidity.

The most commonly accepted measure of the cost of liquidity is the effective spread. The effective spread is the difference between the transaction price and the quoted midpoint, normalized by the midpoint and multiplied by the trade direction. The trade direction is -1 for market sell and +1 for market buy orders. We use the midpoint of the consolidated orderbook to capture the price dynamics across trading venues (cf. Battalio et al. (2004)). Table 5 presents summary statistics for effective spreads across markets, trading volume quantiles, and for trade size categories. As expected we find that effective spreads across all trading venues are in general higher for larger trades and less frequently traded stocks. Effective spreads for FTSE 100 constituents are quite small, averaging between 2.670 bps and 8.001 bps. The effective spreads on the LSE compared to Chi-X are only greater for small orders in high volume stocks. In contrast, the effective spreads on BATS and Turquoise are statistically significantly lower in almost every trading volume category group than on the LSE and Chi-X. One would typically interpret this as evidence that liquidity is higher on MTFs than on the LSE. We interpret this as evidence that traders or investors require better terms of trade on MTFs before they route their orders. When combined with the data on trading volume for each venue this result makes sense. If an investor requires a much better price before routing to an MTF we would expect trading volume to be lower on the MTFs in general. Also we may interpret the differences in effective spreads as the preference for other services.

Insert Table 5 here

The descriptive results on effective spreads seem to indicate that liquidity is better on MTFs than on the LSE. Effective spreads are conditional on execution and may have been considerably higher had all the transactions been executed on a single MTF. Given that the LSE provided liquidity to roughly 70% of all transaction an average effective spread of 4.046 bps is quite good. The results also demonstrate that price competition is not entirely perfect. Perfect price competition would lead to a situation where effective spreads are equivalent given execution conditions, such as volume and volatility. To examine whether the differences in effective spreads persist after we control for factors that might influence the execution quality, we estimate the following regressions for $j \in \{ChiX,\ BATS,\ Turquoise\}$. In the regressions we control for trade sizes and market conditions at the time of the trade using the effective spread of the primary market, the LSE, as the benchmark:

$$\begin{aligned} ESP^j_{i,t} = \alpha^j_i + \beta^j_1 \text{ mkt1}_{i,t} + \ ... \ + \beta^j_5 \text{ mkt5}_{i,t} + \gamma^j_2 \text{ size2}_{i,t} + \ ... \ + \gamma^j_5 \text{ size5}_{i,t} + \\ \delta^j_1 \text{ QSPmkt}_{i,t} + \delta^j_2 \text{ Dp1tdmkt}_{i,t} + \delta^j_3 \text{ vol15}_{i,t} + \delta^j_4 \text{ rv15}_{i,t} + \epsilon^j_{i,t} \end{aligned} \tag{2}$$

Trade size dummy variables that take the value one for trade sizes between 1 to 499 shares, 500 to 999 shares, 1,000 to 4,999 shares, 5,000 to 9,999 shares, and more than 10,000 shares are *size2*, *size3*, *size4*, and *size5*, respectively. The variables of interest are the trade size dummies interacted with the trading venue dummies (*mkt1* to *mkt5*) whereas the variables take the value one for a trade on Chi-X, BATS, or Turquoise, respectively. *QSPmkt* is the quoted spread in the market of execution and *Dp1tdmkt* the quoted depth in the order book on the side of the trade. *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, we include firm fixed effects and dummy variables for each half-hour.

Insert Table 6 here

The results in Table 6 are consistent with our expectations from the summary statistics in Table 5. We find that effective spreads across all trading volume categories are significantly smaller than on the LSE. However, comparing the LSE with Chi-X, for example, the coefficient on the variable $mkt1$ is only 0.090 bps. Surprisingly, the implicit transaction costs are the smallest on Turquoise. The coefficient on $mkt5$ indicates that transactions on Turquoise for large trades are on average 2.385 bps smaller than on the LSE.

To better understand price-competition dynamics between venues we compile statistics that capture executions where a trading venue is at best and at best alone. Panel A of Table 7 reports results for at best and Panel B for at best alone. The market at best column presents the number of trades where a market was at best for an execution. The rows can be interpreted as probability vectors that sum up to 100%. A clear result is that when the best price is posted on the LSE, they are the most likely to receive the transaction. The results for Chi-X also indicate that investors route orders there when they are at the best with another market.

Insert Table 7 here

BATS and Turquoise are only able to improve the execution probability slightly when at best with another market. Panel B makes more clear the sensitivity of order flow to price. We see that about 96% of order flow is routed to the LSE when they are at the best price alone. Chi-X is again quite competitive in their ability to attract order flow with the best price with about 84% probability of attracting the order flow when they are at best alone. Both BATS and Turquoise are able to dramatically increase the percentage of attracted order flow when posting the best price, but remain well behind Chi-X and the LSE despite posting a strictly better price. This is evidence that investors condition routing decisions on price and non-price factors but are quite price sensitive nonetheless.

To provide a more in-depth analysis of the level of price competition and insight into other potential competitive factors, highlighted in the MiFID best execution regulation, we estimate multinomial logistical regressions for each trading volume category. We select the LSE as the reference level to contrast executions on a MTF and on the primary market, the LSE. The dependent variable is equal to one for trades on multilateral trading facilities (Chi-X, BATS, and Turquoise) and zero for LSE trades. Then, positive coefficients indicate a tendency to execute on the listed MTF rather than on the LSE. The parameters of the following model are estimated by the method of maximum likelihood:

$$\log \frac{\pi_j}{\pi_{LSE}} = \beta_1^j \text{ QSPdiff} + \beta_2^j \text{ rDp1td} + \beta_3^j \text{ rDp3td} + \beta_4^j \text{ sVol} + \beta_5^j \text{ vol15} + \beta_6^j \text{ rv15} + \beta_7^j \text{ mkttd} \tag{3}$$

where $j \in \{ChiX,\ BATS,\ Turquoise\}$. We further control for firm fixed effects and include intraday dummies for each half-hour. The first coefficient, $QSPdiff$, is the most important in terms of price competition. It is calculated as the difference between the consolidated spread and the spread in the market where the execution occurs. The consolidated spread is the the difference between the maximum bid and the minimum ask across all trading venues, normalized by the corresponding midpoint.

Insert Table 9 here

Table 9 shows the regression results for each trading volume category separately. Negative coefficients on $QSPdiff$ indicate a tendancy to execute rather on the LSE than on a MTF. As expected, if liquidity in one of the MTFs worsens, order flow migrates to the LSE. This confirms the previous analysis that price is an important factor but that barring the best price, order flow migrates to the LSE. However, we find a small but positive coefficient on $QSPdiff$ in high volume stocks for Chi-X. $rDp1td$ is calculated as the depth on the bid in the order book for sell orders and on the ask for by orders in the market of execution relative to the total depth across all four trading venues on the order book side of the trade. $rDp3td$ measures the average quoted depth at the best bid (ask) up to three ticks behind the best price in the market of execution relative to all trading venues. We find positive coefficients for $rDp1td$ and $rDp3td$ across MTFs except for high volume stocks on Chi-X. Interestingly, Turquoise order flow is more sensitive to its own relative depth than are BATS and Chi-X. When combined with the results on effective spreads this result makes sense. If an investor requires a higher quoted depth before routing to Turquoise, we would expect on average a smaller effective spread. The variables $sVol$, $rv15$, and $vol15$ are used as control variables, to control for trade size, lagged 15-minute volatility, and lagged 15-minute trading volume in British Pounds. The variables show that larger trades conditionally tend to execute on the MTFs, that when lagged volume is high order flow migrates to the LSE, and that when realized volatility in the market is high, investors tend to trade on MTFs. This result is perhaps due to the speed advantages provided by MTFs over the LSE. Except high volume stocks on Chi-X this evidence is inconclusive in that depending on which trading volume category we analyze. However, the estimations show that lagged volume has a higher influence on routing decisions in low volume stocks. The $mkttd$ variable takes the value of one if the previous trade occurs on the same trading venue with the same trade direction and zero otherwise. It captures the relative tendencies of investors to trade in the same market in the same direction, perhaps indicating static routing decisions for larger orders.

The above analyses show that post-MiFID there is strong competition based on price. This was to be expected given the competitiveness in the provision of banking services. Financial intermediaries including, brokers, banks, and mutual fund companies compete for customers based primarily on the cost of their services. A large portion of this cost is the cost of trading. We see that when the LSE or Chi-X post the best price alone, they are quite likely to attract the order, the same is not necessarily the case for BATS or Turquoise. We do see evidence that all MTFs are able to improve the probability of attracting an (market) order when the market quoted spread relative to consolidated spread across trading venues improve, i.e. as liquidity improves in a market orders migrate there. In the following section we study competition where price seems to play a lower priority in the routing decision.

3.2. Non-Price Competition

MiFID gives leeway to financial services firms in their definition of best execution. Rather than focusing only on price, firms can take into account execution speed, probability of execution, and other factors. The previous analyses show that most routing decisions are made primarily on the basis of price. In this section we present analyses that capture routing dynamics when the best price is not the main criteria, i.e. the best available price across trading venues is traded-through. We quantify the potential savings to investors had they routed their orders to exchanges with the best prices whereas we assume that sufficient depth is available. This also includes potential savings by splitting a single order into smaller orders and routing to multiple venues.

Trade-through statistics on a trade-by-trade basis are presented in terms of the absolute number of trade-throughs and a function of total trading volume in Table 10. We see that in volume terms trade-throughs are much more prevalent. The rows in each table indicate the beneficiary of the trade-through. By beneficiary we mean which market received the order despite posting worse prices.

Insert Table 10 here

The final column *SavingsSum* reports in kGBP the total potential savings by executing strictly at the best price. In terms of the number of trades, the most relevant for a trading venue, the LSE leads in attracting trade-throughs. The results are even more clear in terms of the volume of trade and total potential savings. The total market savings over our sample period are roughly 13.5 million GBP on the LSE, 1.7 million GBP on Chi-X, and less than 300K for both BATS and Turquoise. This could lead to increased liquidity supply on the LSE, something we study in the following market quality section.

The results on trade-throughs should be taken as an indication rather than a definitive statistic. Errors due to uncertainty regarding ordering when aligning quotes and trades across trading venues might distort the results. However, these data are the same used by market participants when making their routing decisions and are subject to the same lags as for investors gathering the information individually.

To better understand the factors that lead to a trade-through we estimate binomial logistical regressions on trade-throughs similar to equation (3) as follows:

$$\begin{aligned}\log \frac{\pi_{TradeThrough}}{\pi_{Trade}} &= \beta_1 \text{ QSP} + \beta_2 \text{ rDp1td} + \beta_3 \text{ rDp3td} + \beta_4 \text{ PI} \\ &\quad \beta_5 \text{ sVol} + \beta_6 \text{ vol15} + \beta_7 \text{ rv15} + \beta_8 \text{ mkttd}\end{aligned} \tag{4}$$

We estimate two different models using conditions in each market (Model A) and in the consolidated market (Model B). Table 11 presents the results of the estimates.

Insert Table 11 here

For quoted spreads we present results using the spread in the consolidated book ($QSPbest$) and in the market of execution ($QSPmkt$). As expected we find that as liquidity increases and $QSPbest$ falls, trade-throughs become more likely. This is due to the fact that when spreads are tight the benefits to search for better terms of trade are likely to fall, therefore making trade-throughs more likely. The results on $QSPmkt$ are consistent with expectations and with the definition of trade-throughs. As the spread in a market increases, independent of the consolidated spread, the likelihood that a trade is not executed at the best in this market increases by definition. While we use the average depth on the order book side of trade across markets, $Dp1tdavg$, in Model A, $Dp1tdmkt$ is the depth at the best bid (ask) for sell (buy) orders in the market of execution. We include further depth variables ($Dp3tdmkt$, $Dp3tdavg$) measuring quoted volume at the best bid (ask) up to three ticks behind best prices. The coefficients on $Dp1tdmkt$ and $Dp1tdavg$ are positive and provide some evidence that the probability of a trade-through increases with more volume at the first order book level. This might be some evidence for investors that value available depth for medium size orders over the best price. In contrast, the results on depth measured up to three order book levels suggest that as $Dp3tdmkt$ or $Dp3tdavg$ fall investors are less concerned with the best price, rather they may be more concerned with trading relatively large sizes. This is mirrored in the results on trade size ($sVol$), which has a positive coefficient in all specifications.

To capture the informedness of an investor submitting a trade, we include the price impact (PI) that measures information ex-post. We make the assumption that an investor knows ex-ante that they are informed and that the ex-post measurement of information is a good proxy for this. We calculate the $PI^j_{i,t}$ for $x \in \{5, 15\}$ as follows:

$$PI^j_{i,t} = D^j_{i,t} * (Mid_{i,t+x} - Mid^j_{i,t})/(Mid^j_{i,t}) \tag{5}$$

where $Mid_{i,t+x}$ is the midpoint of the consolidated order book in t plus five (fifteen) minutes for instrument i and $Mid^j_{i,t}$ the quoted midpoint in the market j where the trade is executed with $j \in \{LSE, ChiX, BATS, Turquoise\}$. $D^j_{i,t}$ denotes the trade direction with -1 for market sell and $+1$ for market buy orders (cf. Lee and Ready (1991)). Consistent with intuition we find that this is positively related to trade-throughs. We would expect that informed investors are on average more likely to value speed over costs when selecting a trading venue. The positive coefficients on $PI5^j_{i,t}$ and $PI15^j_{i,t}$ in both estimation models indicate that this might be the case.

As in the previous models we include variables that capture market conditions. Trade-throughs are more likely when lagged volume is particularly high. However, we do not find any evidence that volatility influences the probabilty of a trade-through. This is in contrast to the simple order-routing results in Table 9 that present evidence of higher volatility leading to investors to route to faster trading venues, i.e. the MTFs. By ignoring the best price in a market investors are essentially optimizing time to execution. The results for volume have a similar interpretation.

4. Price Discovery

The previous section studies competition for order flow. In this section we examine the contribution of each venue to the quote- and trade-based price discovery process. First, we estimate information shares in order to examine the role of each market in the quote-based price discovery process (Hasbrouck, 1995). Second, we perform our analyses in the spirit of Hasbrouck (1991a,b) to isolate the trade-based information of individual trades. That MiFID increased competition for order flow is indisputable, whether or not this is good for prices is a seperate question. With competition comes fragmentation which has often been found to negatively impact market quality generally and price discovery specifically (e.g. Pagano (1989b)). However, Foucault and Menkveld (2008) find that increased competition between liquidity providers could lead to a deeper consolidated order book, which may in turn improve price efficiency.

The introduction of MTFs and their focus on the most liquid FTSE 100 stocks raises some regulatory concerns. First, they might 'cream-skimming' uninformed orders leaving the LSE with the more informed order flow (cf. Easley et al. (1996)). MTFs often use the primary market as reference market and therefore might not contribute to price discovery. These concerns are similar to those raised in Barclay et al. (2003), in which price discovery in NASDAQ stocks is studied. Our results are different in that the LSE, the incumbent market, is organized as an open electronic limit order book, without preferencing agreements. The results are mixed in that we find MTF quotes contribute more to price-discovery than LSE quotes, and that informed trades are more likely to execute on the LSE than on an MTF. The results on informed trades are consistent with the theoretical model presented in Chowdhry and Nanda (1991). They present a multi-market trading model in which informed traders route their trades to the market with the most uninformed traders and highest liquidity, in order to hide their information. The LSE is the most liquid market in our data and as such should attract more informed trades (cf. Chowdhry and Nanda (1991)). This clashes with results presented in Barclay et al. (2003) in which they find more informed trades on ECNs. Barclay et al. (2003) also present results on the total contribution of ECN and NASDAQ prices (trades and quotes) to price discovery. They find that ECNs contribute more in total to price discovery than NASDAQ market-makers. Our results are mixed in that we find more contribution to price discovery from MTFs on a quote basis but more from the LSE in total. We present a more detailed analysis below.

4.1. Information Shares by Trading Venue

To measure the contribution to price discovery of each trading venue we compute information shares for each market. We 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. Using this technique we can identify where new information is incorporated and therefore determine trading venue contributions to price discovery. Thus, the model attempts to determine which trading venue 'moves first'. Formally, the approach relies on co-integration (cf. Hamilton (1994)), each individual price series is integrated, and therefore contains a random walk component. The price difference between a security trading in two markets is covariance stationary, due to arbitrage relationships. The information share attributable to a trading venue is defined as the proportion of information in the common efficient price of each to the innovation in the common efficient price. The information share (IS) of venue j is defined as:

$$IS_j = \frac{\Psi_j^2 \Omega_{jj}}{\Psi \Omega \Psi'} \tag{6}$$

where $j \in \{LSE, ChiX, BATS, Turquoise\}$. Ψ_j^2 represents the contribution of market j to price discovery and $\Psi\Omega\Psi'$ is the variance of the random-walk component of security prices representing the total price discovery (information). As the contemporaneous midpoint of the different trading venues can be equal, there may be correlation between the midpoints and Ψ may not be diagonal. We follow Hasbrouck (1995) to determine upper and lower bounds that minimize or maximize the contribution of each market in the price discovery process. For a more detailed explanation see Appendix A.2.

Information shares are calculated on a daily basis per instrument and are presented in Table 12 for the entire sample and per trading volume category. By construction information shares sum to one. To compare the information contribution of each trading venue we compare the mean contribution $((IS_{upper} + IS_{lower})/2)$ of each venue and present t-statistics using the LSE as a benchmark.

Insert Table 12 here

Given that the LSE has roughly 70 % of the total trading volume and that it is the primary market, we expect it to lead in quote based price discovery. On the contrary, we find that Chi-X contributes more, at the 1% significance level, to price discovery than does the LSE. The mean difference, the midpoint between the upper and lower bound, is 10.15%. When we attribute all contemporaneously correlated information to the LSE we find that Chi-X leads marginally but not statistically significantly. The difference between the LSE's own contribution to price discovery in high volume stocks and low volume stocks does not show significant differences. The mean difference between the LSE and Chi-X is significant over all trading volume categories, meaning that Chi-X contributes generally more quote-based information in these stocks. This result is important as it demonstrates that even in less frequently traded and less liquid stocks MTFs contribute to price formation. Comparing information shares on the LSE and Chi-X, we only find 4 stocks with a significantly higher information share at the 5% level on the LSE and 35 stocks for Chi-X. Our results show that higher price discovery is not simply generated by higher trading activity. The divergence between total trading volume and information share is also documented by Barclay et al. (2003) and Hendershott and Jones (2005a).

The Figures 2 (a) through (d) present a visualization of the impact of innovation in a trading venue to prices in other venues. We see that Chi-X has a larger impact on future prices, i.e. that Chi-X impounds more information than the other venues. In addition, prices on the other trading venues are adjusted quickly to reflect the new information. The price adjustment to innovations on BATS and Turquoise is significantly slower and their impact on future prices is less pronounced than for Chi-X and LSE innovations.

Insert Figure 2 here

4.2. Private Information of Order Flow

In this section we examine the distribution of informed order flow and its contribution to price discovery across trading venues. In general, price discovery can be characterized using quote processes as above and trade processes as follows. We perform analyses presented in Hasbrouck (1991a) and Hasbrouck (1991b). We extend the typically used vector autoregressive (VAR) system to differentiate between different trading venues as in Barclay et al. (2003) or in Hendershott and Jones (2005a). In the estimation we separate trades executed on the LSE, Chi-X, BATS, and Turquoise and thus, their individual impact on the consolidated midpoint process across trading venues. In contrast to Hasbrouck (1991a,b) our VAR extension results in a five-way VAR model. The results of the VAR analysis are the average cumulative response functions for different trading venues over 10 trades estimated separately per instrument and day. The permanent price impact of a trade (Hasbrouck, 1991a) is commonly used in price discovery research and is typically interpreted as representing the private information of investors. For a more in-depth description of the methodology used see Appendix A.3.

The permanent price impact of each trading venue for different trading volume categories is presented in Table 13. Here the results are in contrast to the information shares analysis. We find that trades in the LSE carry more private information. This is consistent with the analysis presented in Chowdhry and Nanda (1991) which states that informed traders will gravitate to the most liquid trading venue. Also consistent with theory and previous research we find that trades in less frequently traded stocks (low volume category) carry more private information.

Insert Table 13 here

Our results on permanent prices impacts show that informed traders predominatly trade on the LSE. Specifically for BATS and Turquoise the information content per trade, i.e. adverse selection costs, are very low. Coupled with the previous results for these two MTFs the evidence supports concerns of 'cream-skimming'. Chi-X is different in that the permanent price impact is relatively high, although significantly lower than on the LSE, and their contribution to price discovery based on quotes is higher than for LSE. This motivates a final analysis of total price discovery below.

Using the VMA representation explained in the Appendix A.3, information can be decomposed into a trade-correlated part for each trading venue and quote-correlated portions (Hasbrouck, 1991b). The results of the variance decomposition are presented in Table 14.

Insert Table 14 here

This table shows the breakdown of information across trading venues for different trading volume categories and information types, i.e. trade and quote-correlated. We see that quote-correlated information, where Chi-X leads the LSE, makes up 44.3% of total impounded information. Trade-correlated information on the LSE leads the MTFs and is statistically greater in all trading volume categories. This result is confirmed by a firm level analysis. In all stocks the trade-correlated information is significantly greater at the 5% level. If we combine the information share and variance decomposition results we find that the LSE leads Chi-X in price discovery (44.3% * 39.76% + 35.1% = 52.7% versus 44.3% * 49.92% + 13.8% = 35.9%). However, on the whole it seems that both the LSE and Chi-X contribute considerably to the price discovery process.

This makes clear the difficulties in assessing information and policy discussion surrounding price discovery in fragmented makes. If we take quote-correlated or public information as a best measure of information Chi-X leads. Using trade-correlated information suggests that the LSE leads. The current truth lies somewhere in the middle. The most important questions is what happens to market quality as fragmentation increases from this point or when Chi-X or the LSE experience an outage.

5. Conclusion

In this paper we study price and non-price competition and price discovery across four trading venues in FTSE 100 constituents. The trading venues include the primary market, the LSE, and the three MTFs Chi-X, BATS, and Turquoise. The results on price competition show that investors prefer MTFs when the bid-ask spread on MTFs decreases and depth increases. This is not surprising but important in that we find evidence that investors condition their trading decisions on general liquidity factors. In addition, it provides evidence that when MTFs post the best price, either alone or with another market, they increase their likelihood of attracting an order. This competition should induce market innovation to attract more order flow, an important MiFID goal.

The results on non-price competition are novel and show that as the information content of trades increases so does the likelihood of ignoring price considerations. This is likely due to investors desire to execute quickly rather than search for a better price on another exchange. The results also show that as the quoted spread falls, and liquidity is higher, investors are more likely to ignore price considerations. This is an indication that when liquidity is high investors trade-off search and liquidity costs.

Our results on market quality suggest that fragmentation of order flow does not harm the efficiency of the price discovery process. There is interaction between orders and the best quotes posted on multiple venues. While the price impact of trades on the LSE is higher and thus, they carry by definition more private information, we find that Chi-X leads the quote-based price discovery. In sum our results point towards the positive impacts of competition and MiFID on market quality and price efficiency.

References

Arellano, M., 1987. Computing robust standard errors for within-groups estimators. Oxford Bulletin of Economics and Statistics 49 (4), 431--434.

Barclay, M., Hendershott, T., 2003. Price discovery and trading after hours. Review of Financial Studies 16 (4), 1041--1073.

Barclay, M., Hendershott, T., McCormick, D., 2003. Competition among trading venues: Information and trading on electronic communications networks. Journal of Finance 58 (6), 2637--2665.

Battalio, R., Hatch, B., Jennings, R., 2004. Toward a national market system for U.S. exchange-listed equity options. Journal of Finance 59 (2), 933--962.

Bennett, P., Wei, L., 2006. Market structure, fragmentation, and market quality. Journal of Financial Markets 9 (1), 49--78.

Bessembinder, H., 2003. Issues in assessing trade execution costs. Journal of Financial Markets 6 (3), 233--257.

Bessembinder, H., Kaufman, H. M., 1997. A cross-exchange comparison of execution costs and information flow for NYSE-listed stocks. Journal of Financial Economics 46 (3), 293--319.

Boehmer, B., Boehmer, E., 2003. Trading your neighbor's ETFs: Competition or fragmentation? Journal of Banking and Finance 27 (9), 1667--1703.

Chaboud, A., Chiquoine, B., Hjalmarsson, E., Vega, C., 2009. The rise of the machines: Algorithmic trading in the foreign exchange market. Working Paper.

Chowdhry, B., Nanda, V., 1991. Multimarket trading and market liquidity. Review of Financial Studies 4 (3), 483--511.

de Fontnouvelle, P., Fishe, R. P. H., Harris, J. H., 2003. The behavior of bid-ask spreads and volume in options markets during the competition for listings in 1999. Journal of Finance 58 (6), 2437--2463.

Degryse, H., 2009. Competition between financial markets in Europe: What can be expected from MiFID? Financial Markets and Portfolio Management 23 (1), 93--103.

Easley, D., Kiefer, N. M., O'Hara, M., 1996. Cream-skimming or profit-sharing? The curious role of purchased order flow. Journal of Finance 51 (3), 811--833.

Foucault, T., Menkveld, A. J., 2008. Competition for order flow and smart order routing systems. Journal of Finance 63 (1), 119--158.

Hamilton, J. L., 1994. Time Series Analysis. Princeton University Press, Princeton.

Hasbrouck, J., 1991a. Measuring the information content of stock trades. Journal of Finance 46 (1), 179--207.

Hasbrouck, J., 1991b. The summary informativeness of stock trades: An econometric analysis. Review of Financial Studies 4 (3), 571--595.

Hasbrouck, J., 1995. One security, many markets: Determining the contributions to price discovery. Journal of Finance 50 (4), 1175--1199.

Hendershott, T., Jones, C. M., 2005a. Island goes dark: Transparency, fragmentation, and regulation. Review of Financial Studies 18 (3), 743--793.

Hendershott, T., Jones, M. J., 2005b. Trade-through prohibitions and market quality. Journal of Financial Markets 8 (1), 1--23.

Hendershott, T., Riordan, R., 2009. Algorithmic trading and information. Working Paper.

Hengelbrock, J., Theissen, E., 2009. Fourteen at one blow: The market entry of Turquoise. Working Paper.

Lee, C. M. C., Ready, M. J., 1991. Inferring trade direction from intraday data. Journal of Finance 46 (2), 733--746.

Madhavan, A., 2000. Market microstructure: A survey. Journal of Financial Markets 3 (3), 205--258.

Mendelson, H., 1987. Consolidation, fragmentation, and market performance. Journal of Financial and Quantitative Analysis 22 (2), 189--207.

Pagano, M., 1989a. Endogenous market thinness and stock price volatility. Review of Economic Studies 56 (2), 269--287.

Pagano, M., 1989b. Trading volume and asset liquidity. Quarterly Journal of Economics 104 (2), 255--274.

A. Appendix: Computational Details

A.1. Liquidity Measures

In this section we provide detail as to the computation of our measures of liquidity. We adapt the Bessembinder and Kaufman (1997) spread calculation in combination with Bessembinder (2003) using the common Lee and Ready (1991) algorithm to infer trade direction. Using Thomson Reuters DataScope Tick History data we calculate quoted spreads as proxy of trading costs for each trading venue separately. However, quoted spreads only capture liquidity for relatively small order sizes. All spread calculations presented below are spreads relative to the price of an instrument in basis points. Let $\text{Ask}^j_{i,t}$ be the ask price for an instrument i at time t for $j \in \{LSE, ChiX, BATS, Turquoise\}$ and $\text{Bid}^j_{i,t}$ the respective bid price. $\text{Mid}^j_{i,t}$ denotes the mid quote, then the quoted half spread is calculated as follows:

$$QuotedSpread^j_{i,t} = (Ask^j_{i,t} - Bid^j_{i,t})/(Mid^j_{i,t} * 2) \tag{7}$$

Quoted spreads are calculated for every price or volume update and each trade during the trading day (*Quoted Spread*). As the second measure we report quoted spreads on a trade-by-trade basis (*Quoted Spread Trade*). The effective spread is the spread that is actually paid when an incoming market order trades against a limit order. It also captures institutional features of a trading venue like hidden liquidity or market depth. Let $\text{Price}^j_{i,t}$ be the execution price on trading venue j then the effective spread is defined as:

$$EffectiveSpread^j_{i,t} = D^j_{i,t} * (Price^j_{i,t} - Mid_{i,t})/Mid_{i,t}) \tag{8}$$

$D^j_{i,t}$ denotes the trade direction with -1 for market sell and $+1$ for market buy orders. $\text{Mid}_{i,t}$ is the midpoint of the consolidated order book across the LSE, Chi-X, BATS, and Turquoise. All liquidity measures are averaged on a daily basis per instrument.

A.2. Information Shares

Information shares are a relative measure to allocate information across markets (Hasbrouck, 1995). The model attempts to determine which trading venue 'moves first'. We use prevailing midpoints of the consolidated order book m_t based on Thomson Reuters DataScope Tick History data to characterize the implicit efficient price. We define the following price vector $p_t = [p^{LSE}_t, p^{ChiX}_t, p^{BATS}_t, p^{TQ}_t]'$ where each p^j_t refers to the same instrument:

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

Then, m_t is supposed to follow a random walk:

$$m_t = m_{t-1} + u_t, \tag{9}$$

where u_t follows a white noise process with $E(u_t) = 0$, $E(u^2 t) = \sigma^2_u$, 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 VMA model:

$$\Delta p_t = \epsilon_t + \psi_1 \epsilon_{t-1} + \psi_2 \epsilon_{t-2} + ... \tag{10}$$

$\epsilon_t = [\epsilon^{LSE}_t, \epsilon^{ChiX}_t, \epsilon^{BATS}_t, \epsilon^{TQ}_t]'$ is a (4x1) 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 in the corresponding market and the ϵ_i are (4x4) matrices. The ϵ_i has the interpretation that its (i, j)-element measures a one-unit increase in ϵ_t upon Δp_t. Thus, the total impact of innovation on prices through k periods is given by the cumulative impulse response function as follows:

$$D_t(k) = E[\Delta p_t + \Delta p_{t+1} + ... + \Delta p_{t+k} | u_t] = \left(\sum_{i=0}^{k} \Psi_i \right) * \epsilon_t \tag{11}$$

where Ψ_0 is the identity matrix.

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:

$$\sigma^2_u = \Psi \Omega \Psi' \tag{12}$$

where $\Omega = Var(\epsilon_t)$ and Ψ is a polynomial in the lag operator. The random walk variance reflects contributions from all four markets:

$$\sigma^2_u = [\Psi^{LSE}, \Psi^{ChiX}, \Psi^{BATS}, \Psi^{TQ}] \begin{bmatrix} \sigma^2_{LSE} & \sigma_{LSE,ChiX} & \sigma_{LSE,BATS} & \sigma_{LSE,TQ} \\ \sigma_{ChiX,LSE} & \sigma^2_{ChiX} & \sigma_{ChiX,BATS} & \sigma_{ChiX,TQ} \\ \sigma_{BATS,LSE} & \sigma_{BATS,ChiX} & \sigma^2_{BATS} & \sigma_{BATS,TQ} \\ \sigma_{TQ,LSE} & \sigma_{TQ,ChiX} & \sigma_{TQ,BATS} & \sigma^2_{TQ} \end{bmatrix} \begin{bmatrix} \Psi^{LSE} \\ \Psi^{ChiX} \\ \Psi^{BATS} \\ \Psi^{TQ} \end{bmatrix}$$

If the covariance matrix is diagonal (that is, when $\sigma^2_{i,j} = 0$) 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 (IS) of the jth market as:

$$IS_j = \frac{\Psi_j^2 \Omega_{jj}}{\Psi \Omega \Psi'} \tag{13}$$

where $j \in \{LSE, ChiX, BATS, Turquoise\}$. Ψ_j^2 represents the contribution of market j to price discovery and $\Psi\Omega\Psi'$ is the variance of the random-walk component of security prices representing the total price discovery (information). As the contemporaneous midpoint of the different trading venues can be equal, there may be correlation between the midpoints. In consequence, Ψ is not diagonal. We 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 on a daily basis per instrument.

A.3. Trade and Quote Correlated Information

Following Hasbrouck (1991a,b) we 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:

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

The estimation is restarted for each trading day and instrument in the sample. Then, we invert the above VAR model to get the vector moving average (VMA) representation:

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

Following Hasbrouck (1991b) the sums of $\sum_{t=0}^{10} a^{LSE}(L)$, $\sum_{t=0}^{10} a^{ChiX}(L)$, $\sum_{t=0}^{10} a^{BATS}(L)$, and $\sum_{t=0}^{10} a^{TQ}(L)$, where L are polynomial lag operators, 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. Trades may contain information at lower frequencies than measured. This measure however 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:

$$\sigma_v^2 = \left(\sum_{i=0}^{10} a_i^r\right)^2 \sigma_{u_1}^2 + \left(\sum_{i=0}^{10} a_i^{LSE}\right)^2 \sigma_{u_2}^2 + \left(\sum_{i=0}^{10} a_i^{ChiX}\right)^2 \sigma_{u_3}^2 + \left(\sum_{i=0}^{10} a_i^{BATS}\right)^2 \sigma_{u_4}^2 + \left(\sum_{i=0}^{10} a_i^{TQ}\right)^2 \sigma_{u_5}^2$$

The information content of quotes is the first term and the trade-correlated portions for LSE the second, for Chi-X the third, for BATS the fourth, and for Turquoise the fifth term. 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.

B. Appendix: Figures

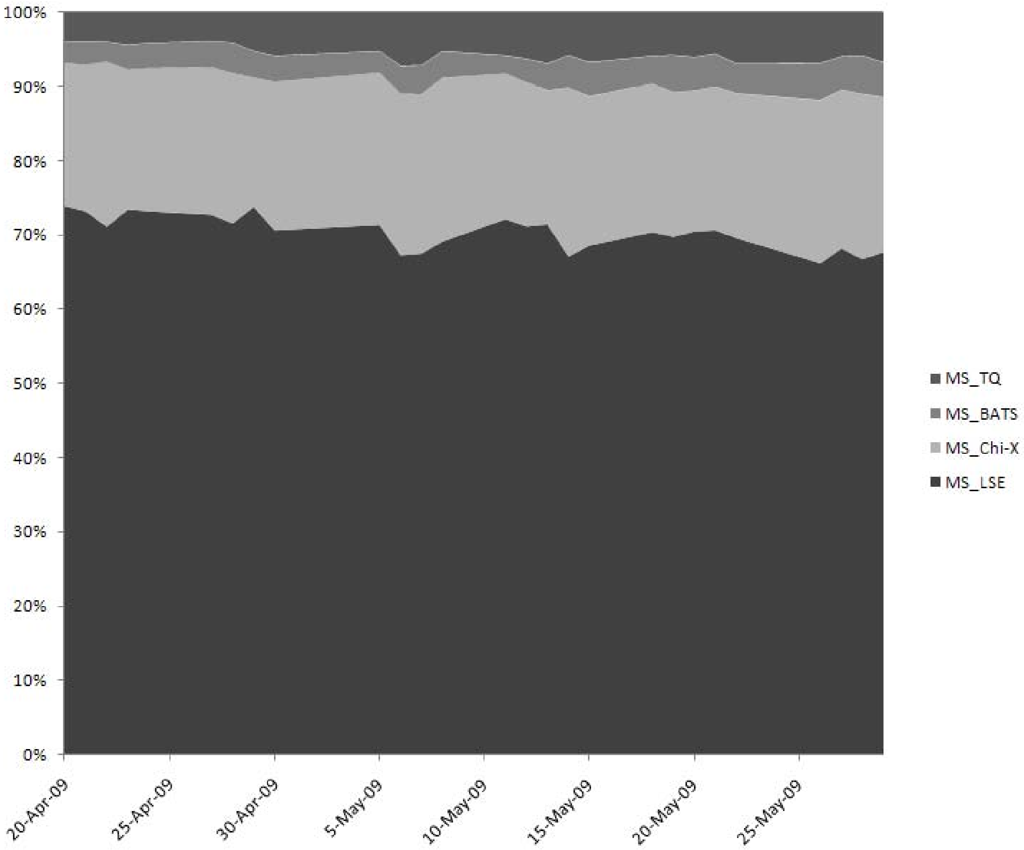
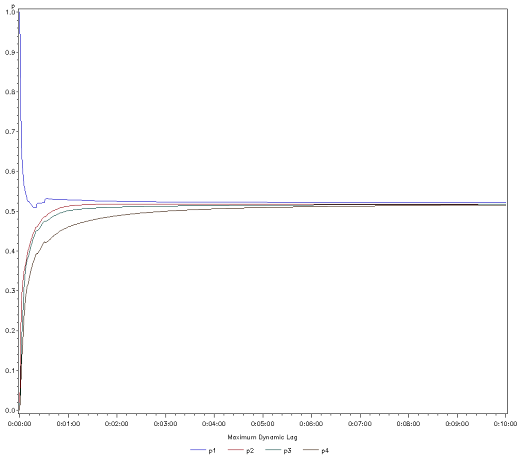
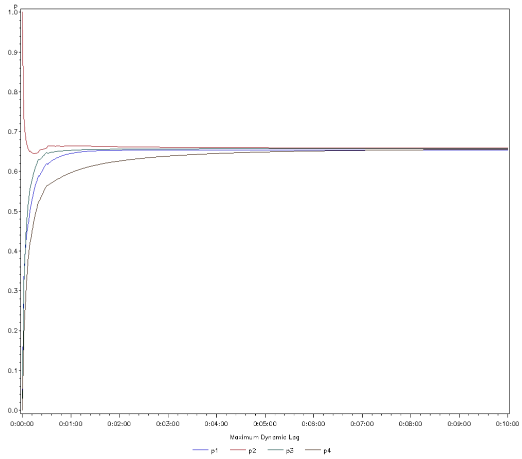


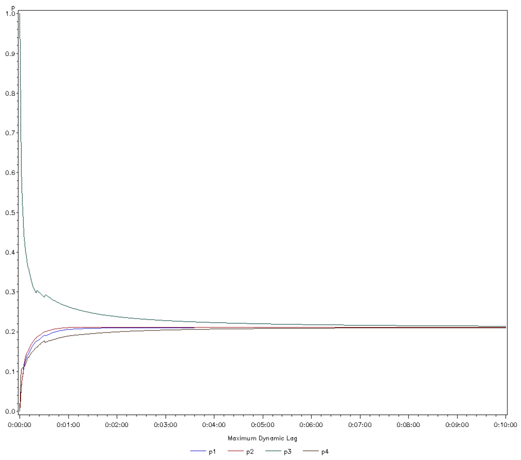
Figure 1: **Market Shares Over Time.** The sample consists of 74 stocks listed in the London Stock Exchange's FTSE 100 segment. The figure presents daily trading volume based market shares of the LSE, Chi-X, BATS, and Turquoise from 20-Apr-2009 to 31-May-2009.



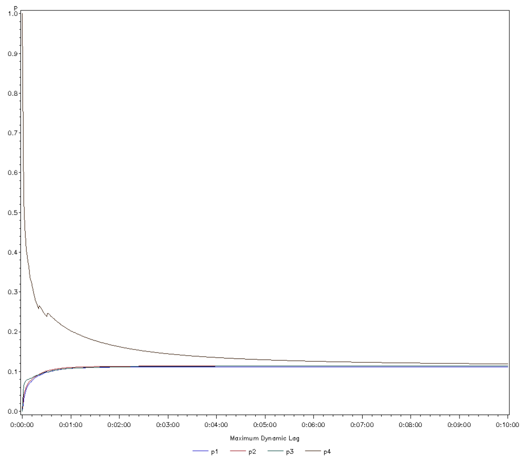
(a) Innovation to the LSE.



(b) Innovation to Chi-X.



(c) Innovation to BATS.



(d) Innovation to Turquoise.

Figure 2: **Cumulative Impulse Response Functions.** The figures present the impact of innovation in a trading venue to prices on the LSE, Chi-X, BATS, and Turquoise. The estimates are based on a vector error correction model of prevailing midpoints according to Hasbrouck (1995).

C. Appendix: Tables

Table 1: **Sample Constituents.** The sample consists of 74 stocks listed in the London Stock Exchange's FTSE 100 segment. The trading volume categories are obtained by ranking the firms in the FTSE 100 sample by their average daily trading volume from 20-Apr-2009 to 31-May-2009. The first category contains the first 25 firms with the highest trading volume (High), the second the next 25 firms (Medium), and the third category 24 low volume firms (Low). The average daily trading volume is given in million British Pounds (MGBP).

High	**Sample Average: 31 MGBP**
HSBC Hldgs, BHP Billiton, Vodafone, Rio Tinto, Barclays, GlaxoSmithKline, AstraZeneca, Xstrata, Anglo American, Royal Dutch Shell B, Tesco, Standard Chartered, British American Tobacco, BG Group, Royal Dutch Shell A, Unilever, Imperial Tobacco Group, Diageo, Reckitt Benckiser Group, Royal Bank of Scotland Group, BAE Systems, Centrica, Aviva, SABMiller	

Medium	**Sample Average: 7 MGBP**
WPP, Kingfisher, Compass Group, Reed Elsevier, Vedanta Resources, BT Group, Tullow Oil, Cadbury, Kazakhmys, Antofagasta, Scottish & Southern Energy, Carnival, Randgold Resources, British Sky Broadcasting Group, Sainsbury (J), British Land Co, Cable & Wireless, Man Group, Thomson Reuters, British Airways, Experian, Autonomy Corporation, Shire, International Power, Smith & Nephew	

Low	**Sample Average: 4 MGBP**
Home Retail Group, InterContinental Hotels Group, Capita Group, Eurasian Natural Resources, RSA Insurance Group, Cairn Energy, Smiths Group, United Utilities Group, Thomas Cook, Group, Invensys, ICAP, Whitbread, Drax Group, Hammerson, Associated British, Foods, TUI Travel, Bunzl, Johnson Matthey, Serco Group, Severn Trent, Sage Group, Rexam, Inmarsat, Standard Life	

Table 2: **Descriptive Statistics.** The sample consists of 74 stocks listed in the London Stock Exchange's FTSE 100 segment. The observation period compromises trading days from 20-April to 31-May-2009. We report sample and descriptive statistics for the LSE, Chi-X, BATS, and Turquoise. All measures are calculated on a daily basis per instrument. We report the mean and the standard deviation in parentheses. Daily market capitalization for each instrument is retrieved from Bloomberg. All spread measures are reported as relative measures in basis points. While the *Quoted Spread* is calculated on a tick-by-tick basis per instrument, the *Quoted Spread Trade* is reported trade-by-trade. The *Effective Spread* is calculated using the consolidated midpoint of the best bid and ask over all markets. While the average *Trade Price* is given in Pence, market capitalization (*Market Cap*), *Turnover*, *Trade Size*, *Depth1*, and *Depth3* are reported in British Pounds (GBP). *Depth1* is half the quoted size at the best bid and ask whereas *Depth3* incorporates the total quoted volume up to three ticks behind best prices.

Sample Statistics				
Market Cap (MGBP)	16.635			
	(24.448)			
Price (per Trade, Pence)	798,58			
	(22.81)			
Descriptive Statistics				
	LSE	Chi-X	BATS	Turquoise
Quoted Spread	6.213	6.634	8.036	13.843
	(2.272)	(2.608)	(6.299)	(15.399)
Quoted Spread Trade	4.708	5.011	5.829	9.084
	(1.691)	(1.858)	(2.401)	(8.951)
Effective Spread	4.046	4.033	3.734	3.665
	(1.549)	(1.549)	(1.524)	(1.695)
Depth1 (GBP)	36,095	31,258	22,033	9,664
	(28,779)	(33,778)	(23,322)	(5,572)
Depth3 (GBP)	128,286	139,822	82,408	27,989
	(110,013)	(156,903)	(89,827)	(27,503)
Turnover (1,000 GBP)	35,040	10,890	2,067	3,126
	(44,414)	(13,759)	(2,840)	(4,473)
Trade Count	2,822	1,424	344	483
	(2,059)	(1,083)	(302)	(481)
Trade Size (GBP)	9,938	5,983	4,681	5,253
	(4,825)	(3,159)	(2,473)	(2,280)

Table 3: **Market Shares.** The sample consists of 74 stocks listed in the London Stock Exchange's FTSE 100 segment. The trading volume categories are obtained by ranking the firms in the FTSE 100 sample by their total trading volume from 20-Apr-2009 to 31-May-2009. The first category contains the first 25 firms with the highest trading volume (High), the second the next 25 firms (Medium), and the third category 24 low volume firms (Low). We report the average daily stock specific trading volume for each category in thousand British Pounds and the corresponding market shares for the LSE, Chi-X, BATS, and Turquoise. In addition, market concentration is measured by the Herfindahl-Hirschman-Index (HHI). The index is given by the sum of the squares of the percentage market share of each trading venue.

Market Shares and Market Concentration									
	LSE		**Chi-X**		**BATS**		**Turquoise**		
Volume Category	**Trading Volume**	**Market Share**	**Trading Volume**	**Market Share**	**Trading Volume**	**Market Share**	**Trading Volume**	**Market Share**	**HHI**
High	76,852	67.83%	24,737	21.76%	4,721	4.21%	7,167	6.20%	51.39%
Medium	18,100	70.11%	5,255	20.34%	997	3.89%	1,477	5.66%	53.87%
Low	9,132	73.07%	2,335	18.53%	418	3.36%	635	5.05%	57.30%

Table 4: **Determinants of Market Shares.** The table presents the trading volume based average daily market share in FTSE 100 stocks of the LSE (MS^{LSE}) and the average market share of Chi-X, BATS, Turquoise (MS^{MTFs}) over the sample period from 20-Apr-2009 to 31-May-2009. We retrieve daily market capitalization per instrument basis from Bloomberg. $MCAP$ is the natural logarithm of daily market capitalization on an instrument basis. RV^{avg} is the average intraday realized volatility in basis points over all four trading venues. QSP^{avg} is the average daily quoted spread. $AtBestA^{LSE}$ stands for the percentage of trades executed on LSE in case of the best available price only over all trading venues. $AtBestA^{MTFs}$ gives the percentage of trades executed on a MTF being the only market with the best available price. We run two separate regressions using a time fixed effects model and robust standard errors (Arellano, 1987) regressing market shares on stock and trading venue characteristics. 'a' denotes significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

Descriptive Statistics				
	Mean	**Std Dev**	**Min**	**Max**
MS^{LSE}	69.88%	6.66%	43.02%	88.24%
MS^{MTFs}	30.12%	6.66%	11.76%	56.98%
MCAP	8.946	1.183	7.194	11.552
RV^{avg}	7.690	17.675	0.003	241.861
QSP^{avg}	8.690	5.403	2.380	90.422
$AtBestA^{LSE}$	38.24%	9.08%	11.83%	68.78%
$AtBestA^{MTFs}$	22.08%	5.65%	5.74%	54.29%

Time Fixed Effects Model				
	LSE		**MTFs**	
	Estimate	**t-stat.**	**Estimate**	**t-stat.**
RSquared	0.35		0.31	
Intercept	0.7474	49.17^{a}	0.1704	12.28^{a}
MCAP	−0.0161	-13.73^{a}	0.0196	16.91^{a}
RV^{avg}	0.0002	2.87^{a}	−0.0002	-2.59^{a}
QSP^{avg}	0.0015	5.78^{a}	−0.0017	-6.39^{a}
AtBestA	0.1625	10.96^{a}	−0.0496	-1.90^{c}

Table 5: **Descriptive Statistics of Effective Spreads.** The sample consists of 74 stocks listed in the London Stock Exchange's FTSE 100 segment. The trading volume categories are obtained by ranking the firms in the FTSE 100 sample by their total trading volume from 20-Apr-2009 to 31-May-2009. The first category contains the first 25 firms with the highest trading volume (High), the second the next 25 firms (Medium), and the third category 24 low volume firms (Low). In addition, we report results for different trade size categories. The average effective spreads - the difference between the transaction price and the quoted midpoint of the consolidated order book, normalized by the consolidated midpoint and multiplied by the trade direction - are reported in basis points per trading venue and trade size categories. The standard deviation is given in parentheses.

	Trading Volume Categories											
Trade Size	**High**				**Medium**				**Low**			
Categories	**LSE**	**Chi-X**	**BATS**	**TQ**	**LSE**	**Chi-X**	**BATS**	**TQ**	**LSE**	**Chi-X**	**BATS**	**TQ**
$<$ **500**	3.154	3.137	2.670	2.807	3.710	3.785	3.587	3.374	4.457	4.623	4.665	4.274
	(1.936)	(1.710)	(1.498)	(1.803)	(0.993)	(0.960)	(1.234)	(1.315)	(1.167)	(1.195)	(1.587)	(1.776)
500 - 999	3.252	3.282	2.949	3.053	3.871	3.894	3.721	3.573	4.636	4.859	4.743	4.552
	(1.851)	(1.748)	(1.767)	(1.938)	(1.005)	(1.040)	(1.281)	(1.384)	(1.102)	(1.355)	(2.179)	(1.788)
1,000 - 4,999	3.518	3.589	3.109	3.000	4.228	4.334	3.790	3.680	5.059	5.389	4.801	4.653
	(1.866)	(1.809)	(1.628)	(2.014)	(1.119)	(1.579)	(1.706)	(1.452)	(1.240)	(1.740)	(2.386)	(2.199)
5,000 - 9,999	3.971	4.297	3.554	3.236	4.761	4.973	3.967	3.293	5.839	6.402	5.117	4.402
	(1.834)	(2.124)	(2.383)	(2.682)	(2.099)	(2.999)	(2.480)	(2.061)	(3.234)	(4.719)	(3.250)	(4.179)
$>$ **10,000**	4.691	5.023	4.125	3.706	6.071	5.281	4.450	3.604	8.001	7.444	4.902	3.937
	(2.269)	(3.055)	(3.047)	(3.497)	(4.132)	(3.405)	(3.210)	(2.628)	(6.631)	(6.575)	(4.379)	(4.842)

Table 6: **Regressions of Effective Spreads.** The sample consists of 74 stocks listed in the London Stock Exchange's FTSE 100 segment. The observation period compromises trading days from 20-Apr-2009 to 31-May-2009. We regress the effective spread - the difference between the transaction price and the quoted midpoint of the consolidated order book, normalized by the consolidated midpoint and multiplied by the trade direction - on trading venue indicators, trade-size dummy variables, and market conditions at the time of the trade. Trade size dummy variables that take the value one for trade sizes between 1 to 499 shares, 500 to 999 shares, 1,000 to 4,999 shares, 5,000 to 9,999 shares, and more than 10,000 shares are *size2*, *size3*, *size4*, and *size5*, respectively. The variables of interest are the trade size dummies interacted with the trading venue dummies (*mkt1* to *mkt5*) whereas the variables take the value one for a trade on Chi-X, BATS, or Turquoise, respectively. *QSPmkt* is the quoted spread and *Dp1tdmkt* the quoted depth in the order book on the side of the trade. *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. Firm fixed effects and dummy variables for each half-hour are not reported. We report Newey West robust standard errors. 'a' denotes significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

	LSE vs. Chi-X		**LSE vs. BATS**		**LSE vs. TQ**	
	Estimate	**t-stat.**	**Estimate**	**t-stat.**	**Estimate**	**t-stat.**
Observations	7,710,097		5,729,010		5,982,031	
RSquared	0.30		0.28		0.32	
mkt1	-0.090	-20.60^a	-0.766	-101.53^a	-1.395	-74.35^a
mkt2	-0.055	-8.97^a	-0.790	-70.24^a	-1.415	-56.42^a
mkt3	-0.083	-17.90^a	-0.901	-97.91^a	-1.861	-91.35^a
mkt4	-0.110	-9.96^a	-0.892	-34.61^a	-2.124	-63.06^a
mkt5	-0.037	-2.09^b	-0.824	-18.62^a	-2.385	-59.85^a
size2	0.062	13.66^a	0.068	14.58^a	0.202	34.73^a
size3	0.275	67.64^a	0.269	62.43^a	0.428	68.68^a
size4	0.441	67.26^a	0.419	61.44^a	0.575	67.59^a
size5	0.680	81.93^a	0.638	73.87^a	0.787	77.20^a
QSPmkt	0.767	772.25^a	0.772	584.65^a	0.632	146.22^a
Dp1tdmkt/10^6	0.000	116.93^a	0.000	97.07^a	0.000	78.97^a
vol15/10^9	-0.102	-34.17^a	-0.099	-28.71^a	0.151	21.80^a
rv15*1.000	0.000	0.87	0.000	1.60	0.000	2.74^a
Firm Dummies	Yes		Yes		Yes	
Time Dummies	Yes		Yes		Yes	

Table 7: **Market Price Quality.** We report absolute and relative frequencies for the LSE, Chi-X, BATS, and Turquoise offering the best available price for FTSE 100 stocks over the sample period from 20-Apr-2009 to 31-May-2009 and the corresponding choice of trading venue. In Panel A we present the case when at least two markets provide the best price (AtBest). In addition, Panel B reports the corresponding statistics for the case that the best price is only available on one trading venue alone (AtBestAlone). The absolute numbers are reported in thousands.

Panel A: Entire Sample - AtBest

Market	Market AtBest	Trade LSE Number	Trade LSE Fraction	Trade Chi-X Number	Trade Chi-X Fraction	Trade BATS Number	Trade BATS Fraction	Trade Turquoise Number	Trade Turquoise Fraction
LSE	5,583	3,095	55.02%	1,676	29.60%	344	5.75%	561	9.64%
Chi-X	5,264	2,547	47.87%	2,076	38.93%	274	4.71%	474	8.50%
BATS	4,413	2,240	49.54%	1,446	31.55%	439	8.74%	503	10.18%
Turquoise	2,232	1,228	53.16%	688	29.00%	135	4.23%	345	13.61%

Panel B: Entire Sample - AtBestAlone

Market	Market AtBestAlone	Trade LSE Number	Trade LSE Fraction	Trade Chi-X Number	Trade Chi-X Fraction	Trade BATS Number	Trade BATS Fraction	Trade Turquoise Number	Trade Turquoise Fraction
LSE	2,197	2,103	95.74%	37	1.68%	6	0.28%	51	2.30%
Chi-X	659	77	11.67%	553	83.84%	6	0.96%	23	3.53%
BATS	430	104	24.05%	62	14.36%	214	49.70%	51	11.91%
Turquoise	299	105	35.09%	49	16.37%	11	3.70%	134	44.84%

Table 8: **Trade Characteristics.** The sample consists of 74 stocks listed in the London Stock Exchange's FTSE 100 segment. The observation period compromises trading days from 20-Apr-2009 to 31-May-2009. We analyze all trades on the LSE, Chi-X, BATS, and Turquoise between 8:30 a.m. and 4:00 p.m local time. While *QSPbest* is the best consolidated spread over all markets, the quoted spread in the market of execution is *QSPmkt*. The difference in spreads between the two types of quoted spreads is *QSPdiff*. The average depth at the best bid for sell orders and the best ask for buy orders across all trading venues is *Dp1tdavg* and *Dp1tdmkt* is the quoted volume at the best bid (ask) in the market where the trade occurs. *Dp3tdmkt* and *Dp3tdavg* measure the quoted volume at the bid (ask) up to three ticks behind the best price at the trading venue where the trade occurs and across all markets, respectively. The depth in the market of trade at the best bid (ask) relative to the average quoted volume at the best bid (ask) over all trading venues is *rDp1td*. *rDp3td* measures the quoted volume at the bid (ask) up to three ticks behind the best price at the trading venue of the trade relative to the average quoted volume at the bid (ask) across all markets. The price impact is the relative difference between the midpoint of the consolidated order book in t plus 5 minutes (*PI5*) and t plus 15 minutes (*PI15*), respectively, and the midpoint in t in basis points. The number of shares traded is *sVol* divided by 1,000. The trading volume in British Pounds/10^9 over all markets during the previous 15 minutes is *vol15*. The realized volatility *rv15* in basis points*1,000 over all markets is calculated from the average midpoint return of the previous 15 minutes to the 15 minutes before. The *mkttd* dummy variable takes the value of one if the previous trade occurs on the same trading venue with the same trading direction and zero otherwise.

Trade Characteristics				
	Mean	**Std Dev**	**Min**	**Max**
Trades	9,294,365			
QSPbest	2.658	3.918	-256.410	67.827
QSPmkt	4.585	5.359	0.000	769.757
QSPdiff	1.947	6.235	-41.426	782.981
Dp1tdavg/10^6	0.024	0.039	7.28E-05	0.700
Dp3tdavg/10^6	0.136	0.160	1.00E-05	3.848
Dp1tdmkt/10^6	0.027	0.031	1.79E-05	3.003
Dp3tdmkt/10^6	0.117	0.113	0.001	1.374
rDp1td	1.204	0.649	0.001	3.902
rDp3td	1.225	0.631	0.000	3.970
PI5	3.952	31.032	-170.170	195.122
PI15	3.645	51.311	-289.855	314.961
sVol/1,000	2.475	10.998	0.001	10,300.000
vol15/10^9	0.373	0.462	3.33E-05	6.382
rv15*1,000	4.621	62.523	0.000	7,192.000
mkttd	0.338	0.473	0.000	1.000

Table 9: **Order-Routing Decisions.** The table presents multinominal logit regressions for the choice of trading venue. The LSE is used as reference category. The dependant variable is equal to zero for LSE trades and one for trades on multilateral trading facilities (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 FTSE 100 sample by their total trading volume from 20-Apr-2009 to 31-May-2009. The first category contains the first 25 firms with the highest trading volume (High), the second the next 25 firms (Medium), and the third category 24 low volume firms (Low). The difference in the quoted spread on a trading venue and the best quoted spread over all markets is *QSPdiff*. The depth at the best bid for sell orders and at the best ask for buy orders in the market of execution relative to the average depth at the best bid or ask over all trading venues is *rDp1td*. *rDp3td* measures the average quoted volume at the bid (ask) up to three ticks behind best prices at the trading venue of execution relative to the quoted volume at the bid (ask) across all markets. The number of shares is *sVol*. The trading volume in British Pounds over all markets during the previous 15 minutes is *vol15*. The realized volatility *rv15* in basis points*1,000 over all markets is calculated from the average midpoint return of the previous 15 minutes to the 15 minutes before. The *mkttd* dummy variable takes the value of one if the previous trade occurs on the same trading venue with the same trading direction and zero otherwise. Firm fixed effects and dummy variables for each half-hour time period are not reported. 'a' denotes significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

		Trading Volume Categories		
Variable	**MKT**	**High**	**Medium**	**Low**
QSPdiff	**TQ**	-0.217^a	-0.112^a	-0.0685^a
		(79,956)	(23,743)	(13,012)
	BATS	-0.119^a	-0.068^a	-0.040^a
		(43,564)	(44,943)	(36,824)
	Chi-X	0.011^a	-0.016^a	-0.0178^a
		(6,110)	(9,623)	(5,762)
rDp1td	**TQ**	0.466^a	0.252^a	0.619^a
		(12,384)	(1,455)	(5,112)
	BATS	0.718^a	0.500^a	0.207^a
		(44,865)	(8,652)	(709)
	Chi-X	0.776^a	0.634^a	0.547^a
		(235,468)	(64,244)	(24,124)
rDp3td	**TQ**	6.706^a	7.166^a	7.390^a
		(578,396)	(278,310)	(163,216)
	BATS	1.739^a	2.732^a	3.618^a
		(140,779)	(124,391)	(116,010)
	Chi-X	-0.650^a	0.427^a	1.244^a
		(105,643)	(18,316)	(95,690)
sVol/1,000	**TQ**	0.033^a	0.056^a	0.025^a
		(2,735)	(923)	(59)
	BATS	0.045^a	0.142^a	0.236^a
		(6,176)	(5,153)	(3,009)
	Chi-X	0.017^a	0.058^a	0.081^a
		(7,384)	(5,997)	(2,518)
vol15/10^9	**TQ**	-0.336^a	-0.642^a	-5.455^a
		(4,683)	(296)	(2,553)
	BATS	-0.129^a	-0.526^a	-4.712^a
		(868)	(268)	(2,792)
	Chi-X	0.076^a	-0.155^a	-2.846^a
		(833)	(72)	(3,225)
rv15*1,000	**TQ**	0.000^a	0.976^a	0.692^a
		(75)	(159)	(55)
	BATS	0.000^a	0.697^a	0.828^a
		(16)	(109)	(101)
	Chi-X	0.000^a	0.142^a	0.304^a
		(155)	(19)	(48)
mkttd	**TQ**	1.212^a	1.467^a	1.502^a
		(62,832)	(31,334)	(14,910)
	BATS	1.810^a	1.919^a	1.843^a
		(117,287)	(50,491)	(25,474)
	Chi-X	0.836^a	0.931^a	0.984^a
		(138,171)	(70,518)	(43,288)
Firm Dummies		Yes	Yes	Yes
Time Dummies		Yes	Yes	Yes
Observations		5,435,291	2,377,040	1,482,034

Table 10: **Trade-Through Statistics.** This table reports statistics for trade-throughs on the LSE, Chi-X, BATS, and Turquoise for FTSE 100 constituents from 20-Apr-2009 to 31-May-2009. Each time when a trade is not executed on the best consolidated bid or ask, we calculate the possible savings by an execution on the best bid or ask over all trading venues. The statistics below shown the number of trade-throughs, the corresponding trading volume in British Pounds (MGBP), and the possible savings (kGBP) compared to a best execution. The numbers are presented separately for each market and trade size categories.

Panel A: Trade-Through Statistics
Entire Sample

	Trade-Throughs		Trading Volume		Savings
	Number	Fraction	Sum	Fraction	Sum
LSE	465,923	8.26%	7,846	11.21%	13,542
Chi-X	223,515	7.86%	1,946	8.94%	1,712
BATS	49,975	7.26%	355	8.59%	288
Turquoise	52,303	5.42%	353	5.66%	256

Panel B: Trade-Through Statistics
Trade Size < 500

	Trade-Throughs		Trading Volume		Savings
	Number	Fraction	Sum	Fraction	Sum
LSE	197,955	10.58%	1,689	34.78%	1,511
Chi-X	118,215	9.75%	706	23.18%	591
BATS	26,559	8.28%	134	17.29%	108
Turquoise	26,424	6.31%	108	10.53%	76

Panel C: Trade-Through Statistics
500 ≤ Trade Size < 1,000

	Trade-Throughs		Trading Volume		Savings
	Number	Fraction	Sum	Fraction	Sum
LSE	91,037	9.36%	1,197	17.96%	1,122
Chi-X	46,008	8.24%	422	12.62%	375
BATS	10,555	7.78%	78	10.01%	66
Turquoise	10,853	2.59%	82	6.79%	60

Panel D: Trade-Through Statistics
1,000 ≤ Trade Size < 5,000

	Trade-Throughs		Trading Volume		Savings
	Number	Fraction	Sum	Fraction	Sum
LSE	144,008	7.06%	2,598	8.76%	2,615
Chi-X	52,871	6.13%	666	6.75%	603
BATS	11,461	6.00%	119	6.59%	96
Turquoise	13,144	4.57%	128	4.43%	93

Panel E: Trade-Through Statistics
5,000 ≤ Trade Size < 10,000

	Trade-Throughs		Trading Volume		Savings
	Number	Fraction	Sum	Fraction	Sum
LSE	20,220	4.71%	618	5.29%	679
Chi-X	4,596	3.64%	96	3.50%	83
BATS	1,088	4.21%	17	4.17%	12
Turquoise	1,163	3.19%	17	2.94%	13

Panel F: Trade-Through Statistics
Trade Size > 10,000

	Trade-Throughs		Trading Volume		Savings
	Number	Fraction	Sum	Fraction	Sum
LSE	12,703	3.88%	1,744	10.18%	7,616
Chi-X	1,825	2.12%	56	2.03%	61
BATS	312	2.12%	7	1.85%	6
Turquoise	719	3.15%	17	3.28%	14

Table 11: **Trade-Throughs.** The table presents bivariate logit regressions when the best available price across markets is traded-through. The dependant variable is equal to one for a trade-through and zero for trades at the best bid and ask, respectively. Chi-Square statistics are reported in parentheses below the estimated log odds ratios. While the best consolidated spread over all markets is *QSPbest*, *QSPmkt* is the quoted spread in the market where the trade occurs. The average depth over all markets in British Pounds is *Dp1tdavg* and *Dp1tdmkt* is the average depth in the market of execution at the best bid for a sell and at the best ask for a buy. *PI5* (*PI15*) is the relative difference between the midpoint of the consolidated order book in t plus 5 minutes (15 minutes) and the midpoint in t in basis points. *Dp3tdavg* and *Dp3tdmkt* measure the quoted volume at the bid (ask) up to three ticks behind the best price across all markets and at the trading venue where the trade occurs, respectively. The number of shares traded is *sVol.* The trading volume in British Pounds over all markets during the previous 15 minutes is *vol15.* The realized volatility *rv15* in basis points*1,000 over all markets is calculated from the average midpoint return of the previous 15 minutes to the 15 minutes before. The *mkttd* dummy variable takes the value of one if the previous trade occurs on the same trading venue with the same trading direction and zero otherwise. Dummy variables for each half-hour time period and firm fixed effects are not reported. 'a' denotes significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

Variable	Model A1	Model A2	Model A3	Model B1	Model B2	Model B3
QSPbest	-0.162^a	-0.163^a	-0.162^a			
	(208,491)	(209,834)	(208,960)			
QSPmkt				0.055^a	0.055^a	0.055^a
				(21,819)	(21,789)	(21,776)
Dp1tdavg/10^6	2.77E-06^a	2.76E-06^a	2.77E-06^a			
	(1,474)	(1,471)	(1,479)			
Dp3tdavg/10^6	-2.05E-06^a	-2.03E-06^a	-2.05E-06^a			
	(3,844)	(3,751)	(3,825)			
Dp1tdmkt/10^6				6.99E-06^a	7.00E-06^a	7.00E-06^a
				(38,988)	(39,027)	(39,013)
Dp3tdmkt/10^6				-7.74E-07^a	-7.73E-07^a	-7.76E-07^a
				(3,232)	(3,228)	(3,244)
PI5		0.004^a			0.004^a	
		(10,450)			(8,418)	
PI15			0.002^a			0.001^a
			(4,575)			(3,795)
sVol/1.000	0.015^a	0.015^a	0.015^a	0.006^a	0.006^a	0.006^a
	(6,842)	(6,654)	(6,778)	(1,482)	(1,413)	(1,462)
vol15/10^9	0.309^a	0.306^a	0.308^a	0.250^a	0.247^a	0.249^a
	(6,505)	(6,316)	(6,437)	(4,186)	(4,081)	(4,147)
rv15*1.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0)	(0)	(0)	(2)	(2)	(2)
mkttd	0.213^a	0.209^a	0.211^a	0.183^a	0.179^a	0.181^a
	(6,081)	(5,852)	(5,982)	(4,746)	(4,549)	(4,661)
Firm Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: **Quote-Based Price Discovery.** In this table we report Hasbrouck (1995) information shares for the LSE, Chi-X, BATS, and Turquoise. The daily measures are calculated from tick data and averaged over the sample period from 20-Apr-2009 to 31-May-2009. While Panel A shows some descriptives for the entire sample, Panel B reports measures for each trading volume category separately. The categories are obtained by ranking the firms in the FTSE 100 sample by their total trading volume over the sample period. The first category contains the first 25 firms with the highest trading volume (High), the second the next 25 firms (Medium), and the third category 24 low volume firms (Low). Using Thompson clustered standard errors we test for the difference in information shares of each market relative to the LSE. In addition, we test for the difference of means between the information shares of the high volume firms and the low volume firms. The t-statistic is calculated by using Newey West standard errors correcting for autocorrelation and heteroskadasticity up to 5 lags. 'a' denotes significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

Panel A: Information Shares for the Entire Sample

		LSE			Chi-X				BATS				Turquoise			
		Lower	**Upper**	**Mean**	**Lower**	**Upper**	**Mean**	**Diff to LSE**	**Lower**	**Upper**	**Mean**	**Diff to LSE**	**Lower**	**Upper**	**Mean**	**Diff to LSE**
All	**Mean**	35.80%	43.73%	39.76%	45.60%	54.23%	49.92%	-10.15%[a]	5.35%	6.82%	6.08%	33.68%[a]	3.90%	4.74%	4.32%	35.44%[a]
	Std. Dev.	13.76%	13.92%	13.84%	14.94%	14.62%	14.78%		5.46%	6.42%	5.94%		4.23%	5.05%	4.64%	

Panel B: Information Shares for Different Trading Volume Categories

		LSE			Chi-X				BATS				Turquoise			
		Lower	**Upper**	**Mean**	**Lower**	**Upper**	**Mean**	**Diff to LSE**	**Lower**	**Upper**	**Mean**	**Diff to LSE**	**Lower**	**Upper**	**Mean**	**Diff to LSE**
High	**Mean**	35.52%	43.99%	39.76%	45.61%	54.85%	50.23%	-10.47%[b]	4.57%	5.97%	5.27%	34.49%[a]	4.33%	5.35%	4.84%	34.92%[a]
	Std. Dev.	16.01%	16.15%	16.08%	16.29%	16.09%	16.19%		5.38%	6.28%	5.83%		4.57%	5.56%	5.07%	
Medium	**Mean**	35.61%	43.45%	39.53%	45.99%	54.51%	50.25%	-10.72%[a]	5.47%	6.91%	6.19%	33.34%[a]	3.71%	4.54%	4.12%	35.41%[a]
	Std. Dev.	12.92%	12.74%	12.83%	14.28%	14.04%	14.16%		5.11%	6.11%	5.61%		4.00%	4.89%	4.45%	
Low	**Mean**	36.27%	43.76%	40.01%	45.19%	53.31%	49.25%	-9.23%[a]	6.03%	7.60%	6.82%	33.20%[a]	3.67%	4.32%	3.99%	36.02%[a]
	Std. Dev.	11.94%	12.52%	12.23%	14.13%	13.54%	13.83%		5.79%	6.77%	6.28%		4.05%	4.57%	4.31%	
High-Low	**Mean**	-1.20%	0.23%	-0.25%	0.42%	1.54%	0.98%		-1.46%	-1.63%	-1.55%		0.66%	1.03%	0.85%	
	t-stat.			-0.22			1.02				-4.42[a]				2.14[b]	

Table 13: **Permanent Price Impact.** The sample consists of 74 stocks listed in the London Stock Exchange's FTSE 100 segment. The observation period compromises trading days from 20-Apr-2009 to 31-May-2009. The table reports descriptive statistics for daily permanent price impacts in basis points according to Hasbrouck (1991a) for the LSE, Chi-X, BATS, and Turquoise. We report the mean and the standard deviation in parentheses. Results are shown for the entire sample and trading volume categories. The categories are obtained by ranking the firms in the FTSE 100 sample by their total trading volume over the sample period. The first category contains the first 25 firms with the highest trading volume (High), the second the next 25 firms (Medium), and the third category 24 low volume firms (Low). Using Thompson clustered standard errors we test for the difference in permanent price impacts of each market relative to the LSE. The difference of means between the high volume firms and the low volume firms is tested for statistical significance using Newey West standard errors correcting for autocorrelation and heteroskadasticity up to 5 lags. 'a' denotes significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

Permanent Price Impact										
	LSE	**Chi-X**			**BATS**			**Turquoise**		
	Mean	**Mean**	**Diff to LSE**	**t-stat.**	**Mean**	**Diff to LSE**	**t-stat.**	**Mean**	**Diff to LSE**	**t-stat.**
Entire Sample	2.414	1.471	0.943	18.82^a	0.628	1.787	22.32^a	0.695	1.719	21.33^a
	0.960	0.626			0.381			0.451		
High	1.924	1.333	0.591	11.05^a	0.615	1.309	12.18^a	0.676	1.248	10.87^a
	0.938	0.734			0.407			0.441		
Medium	2.388	1.434	0.954	17.62^a	0.617	1.771	17.56^a	0.718	1.670	18.83^a
	0.747	0.522			0.328			0.440		
Low	2.953	1.653	1.300	18.55^a	0.652	2.301	22.13^a	0.692	2.261	20.88^a
	0.896	0.556			0.404			0.473		
High-Low	-1.029	-0.320			-0.037			-0.016		
t-stat.	-13.57^a	-7.01^a			-1.65			-0.40		

Table 14: **Quote- and Trade-Correlated Information.** The sample consists of 74 stocks listed in the London Stock Exchange's FTSE 100 segment. The observation period compromises trading days from 20-Apr-2009 to 31-May-2009. Following Hasbrouck (1991b) the table reports the average daily information content of quotes and trades on the LSE, Chi-X, BATS, and Turquoise. We report the mean and the standard deviation in parentheses. Results are shown for the entire sample and trading volume categories. The categories are obtained by ranking the firms in the FTSE 100 sample by their total trading volume over the sample period. The first category contains the first 25 firms with the highest trading volume (High), the second the next 25 firms (Medium), and the third category 24 low volume firms (Low). Using Thompson clustered standard errors we test for the difference in trade-correlated information of each market relative to the LSE. The difference of means between the high volume firms and the low volume firms is tested for statistical significance using Newey West standard errors correcting for autocorrelation and heteroskadasticity up to 5 lags. 'a' denotes significance at the 1% level, 'b' at the 5% level, and 'c' at the 10% level.

Quote- and Trade-Correlated Information											
	Quote-	**Trade-Correlated**									
		LSE	**Chi-X**			**BATS**			**Turquoise**		
	Mean	**Mean**	**Mean**	**Diff to LSE**	**t-stat.**	**Mean**	**Diff to LSE**	**t-stat.**	**Mean**	**Diff to LSE**	**t-stat.**
Entire Sample	0.443	0.351	0.138	0.213	31.67^{a}	0.030	0.322	53.91^{a}	0.038	0.313	53.50^{a}
	0.104	0.079	0.054			0.023			0.032		
High	0.420	0.335	0.163	0.172	17.37^{a}	0.036	0.163	30.04^{a}	0.046	0.289	29.19^{a}
	0.104	0.075	0.049			0.022			0.031		
Medium	0.445	0.355	0.132	0.223	30.42^{a}	0.029	0.132	43.19^{a}	0.039	0.316	44.58^{a}
	0.105	0.075	0.053			0.025			0.034		
Low	0.465	0.364	0.119	0.245	29.41^{a}	0.024	0.119	48.80^{a}	0.028	0.336	53.04^{a}
	0.098	0.083	0.050			0.022			0.029		
High-Low	-0.045	-0.029	0.044			0.012			0.018		
t-stat.	-6.78^{a}	-5.16^{a}	11.29^{a}			10.16^{a}			9.06^{a}		