The paradoxical effects of market fragmentation on adverse selection risk and market efficiency

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Abstract

Unlike the US's Regulation National Market System (RNMS), the EU's Markets in Financial Instruments Directive (MiFID) does not impose a formal exchange trading linkage or guarantee a best execution price. This raises concerns about consolidated market quality in increasingly fragmented European markets. We investigate the impact of visible trading fragmentation on the quality of the London equity market and find a non-linear relationship between fragmentation and adverse selection risk. At moderate levels of fragmentation, order flow competition reduces adverse selection risk and enhances market efficiency by reducing arbitrage opportunities. Contrarily, high levels of fragmentation heighten adverse selection issues.

JEL classification: G10, G14, G15

Keywords: Market fragmentation, Markets in Financial Instruments Directive (MiFID), Multilateral Trading Facilities (MTFs), adverse selection risk, market efficiency

1 Introduction

Over the past decade, entrant trading venues have successfully challenged incumbent national stock exchanges for market share (Ibikunle, 2018). This has resulted in the most fragmented state of financial markets ever observed. This change, mainly concentrated in the European and US markets, has been driven by technology and regulatory shifts in both jurisdictions. For example, the enactment of the Markets in Financial Instruments Directive (MiFID) in 2007, and technological advances in trading systems, have led to an unprecedented increase in the number of trading venues in Europe, with yet unclear implications for price discovery and market quality more generally. The intent of the regulatory reforms was to allow wider access to financial markets and increase competition among trading venues, driving down trading cost. However, trading fragmentation has raised concerns about whether the diversified market landscape could harm price transparency in the markets.

O'Hara and Ye (2011) find that market fragmentation in US equity markets has not been detrimental to market quality. In their study, they describe the US equity trading venues as a single virtual market, with the trading venues serving as multiple entry points. This is a reasonable interpretation given that the market regulation regime in the US guarantees a best execution price, via the so-called trade-through protection, irrespective of the exchange to which an order is submitted. The MiFID regime in Europe offers no such guarantee. Therefore, orders could execute at a price that is inferior to the best available price across multiple venues. Ende and Lutat (2010) document a non-negligible trading cost under sub-optimal order executions due to the absence of a trade-through rule. It implies that trading frictions when accessing multiple trading venues can give rise to inter-market differences in the adverse selection risk faced by uninformed traders. Informed (faster) traders, deploying smart order routing under the MiFID regime, could route their trades to venues with higher levels of uninformed traders and liquidity, increasing the adverse selection risk faced by uninformed traders. Thus, the lack of trade-through protection in Europe could lead to increased adverse selection risk (Hoffmann, 2016).

In the existing theoretical market fragmentation literature, especially those studies examining fragmentation due to trading in opaque trading venues, the degree of adverse selection is identified as 'causing' the market quality characteristics (liquidity and price discovery), effects predicted by market fragmentation models (see as an example, Zhu, 2014) and already examined by the existing empirical studies on market fragmentation (see as examples, Comerton-Forde and Putniņš, 2015; Degryse et al., 2015; Foley and Putniņš, 2016; Nimalendran and Ray, 2014). Therefore, understanding the effect of market fragmentation on adverse selection risk, especially in the European context where no trade-through provisions exist, is critical. In order to fill this void, in this study we investigate the effects of market fragmentation in the UK stock market. Specifically, we present the first set of empirical evidence on whether market fragmentation induces adverse selection risk. For robustness, using the findings from the analysis of the links between adverse selection risk and market fragmentation as a baseline, we also investigate the impact of the current level of market fragmentation on UK stocks on market efficiency.

Our findings relate to some of those documented in the recent market fragmentation literature. Consistent with Degryse et al. (2015), we find a non-linear relationship between fragmentation and adverse selection risk. On the one hand, fragmentation helps to reduce adverse selection risk at low levels of fragmentation. On the other, however, when fragmentation is high, adverse selection risk increases with the level of fragmentation. In line with O'Hara and Ye (2011), we also find that fragmentation facilitates market efficiency by reducing short-term arbitrage opportunities.

This study differs from the existing literature in a number of ways. Firstly, the direct focus on adverse selection risk critically differentiates our study from research that examines the impact of fragmentation on market quality. Secondly, our empirical design allows for measuring aggregate market impact of fragmentation on trading quality over a comparatively long period (2008 – 2014). By employing the longest intraday/ultra-high frequency data time series that has thus far been used to investigate the impact of market fragmentation on trading in financial markets, we are able to control for different time trends and trading conditions. In comparison, Riordan et al. (2011), Gresse (2017), O'Hara and Ye (2011), and Spankowski et al. (2012) use 29-day, 4-month, 6-month and 12-month time series with stock samples smaller than ours. Our data also clearly incorporates years when market fragmentation is deemed to have become fully entrenched in the London market. This is important because a review from the US Securities and Exchange Commission (SEC) argues that the sample in Degryse et al. (2015) covers a period when market fragmentation had not fully set in in the Dutch mid and large stocks. The same criticism may hold for the few other papers that investigate market fragmentation using European stock samples prior to 2011.

2 Literature review

A stream of the theoretical market microstructure literature (see as examples Mendelson, 1987; Cohen et al., 1982; Pagano, 1989) suggests that, in order to maximise market quality, all buyers and sellers should congregate in one consolidated market, and all trades in listed securities should occur within a single exchange. This is because operating single national exchanges yields lower trading costs when compared to a fragmented marketplace. Furthermore, consolidation of the order flow creates economies of scale for liquidity provision. Cohen et al. (1982) show that, due to rising bid-ask spreads and price volatility, off-exchange trading may benefit brokers, but it harms retail investors. The study also suggests that there is a lower probability of order fulfilment in a fragmented market. Consistent with the previous studies, Chowdhry and Nanda (1991) argue that liquidity may be impaired by fragmentation due to information asymmetry; thus implying that fragmentation may lead to increased adverse selection risk. Recent studies, however, argue that concerns about the negative impact of trading fragmentation may have been largely unfounded.

The entry of new venues intensifies the competition for order flow among trading venues. Another stream of the market microstructure literature argues that this increased competition for order flow improves liquidity and market depth, thus implying that market fragmentation has a positive effect on market quality. Foucault and Menkveld (2008) investigate competition between the London Stock Exchange Group (LSEG) and Euronext in the Dutch stock market, whereas before EuroSETS's entry trading volume was largely concentrated in the *Nouveau Systeme Cotation* (NSC), a limit order book operated by Euronext. Foucault and Menkveld (2008) find that both the consolidated order book and the primary exchange's NSC significantly improve following EuroSETS's entry. Similarly, Hengelbrock and Theissen (2009), in their examination of the 2008 entry of Turquoise in 14 European countries, suggest that quoted bid-ask spreads on regulated markets decline following the new entry. These findings are consistent with more recent evidence by Gresse (2017), who finds that increased competition between trading venues is accompanied by a high liquidity provision.

Boneva et al. (2015), like this current study, examine market fragmentation in FTSE 100 stocks. Our work differs from theirs in three respects. Firstly, they examine the impact of fragmentation on market quality measured by volatility, liquidity, and volume, whereas we investigate market fragmentation effects on adverse selection risk and market efficiency. Secondly, as well as a number of other related works on European equity markets' fragmentation (for instance, Riordan et al., 2011; Spankowski et al., 2012; Gresse, 2017), they investigate market quality on the listing market, whereas we create a consolidated order book for our analysis and examine the impact of fragmentation on the aggregate market. The consolidated order book offers a broader view of the market for trading FTSE 100 stocks; it could also yield further insights, especially for policy. From a policy perspective, the aggregate market is the only relevant market, since policy makers must develop rules applying to the whole market within their jurisdictions. As high-tech entrant markets are attracting increasing trading volumes, studies solely focused on the primary exchange (in this case, the London Stock Exchange – LSE) cannot provide a detailed picture of the market. Indeed, Gomber et al. (2012) show that only 20 out of 75 firms in their sample indicate that they only execute trades at the primary exchanges. Thirdly, compared with Boneva et al. (2015) who use weekly FTSE 350 data from 2008 to 2011, we adopt a much richer dataset. Our dataset includes tick-level data, and our regression model incorporates stock-day variables of FTSE 100 stocks, computed from high frequency data of trading activity between 2008 and 2014.

Although a recent development in European markets, trading fragmentation is not a new phenomenon in the US market. Electronic Communication Networks (ECNs), which are similar to the European Multilateral Trading Facilities (MTFs), have been a critical part of the US market infrastructure since the early 1990s, and thus the US evidence on fragmented markets is more extensive. Boehmer and Boehmer (2003) show evidence of increased liquidity when NYSE started to facilitate trading in ETFs listed on the American Stock Exchange. O'Hara and Ye (2011) also show that, although fragmented stocks generate higher short-term volatility, prices appear to be more efficient. Furthermore, fragmentation benefits market quality in terms of increased liquidity and reduced trading cost. Other studies, however, suggest an opposite effect of trading fragmentation. For example, Madhavan (2012) finds that more fragmented stocks were disproportionately affected by the ‘Flash Crash’ of 6 May 2010. He suggests that both volume fragmentation and quote fragmentation are important in explaining the propagation of the crash. Overall, empirical evidence on the impact of fragmentation is inconclusive, and mixed across international markets. Fragmentation can have both positive and negative effects on market quality, although the overall net effect appears to be positive.

3 Data

We conduct our analysis using FTSE 100 index stocks' trading data. The constituent stocks of the FTSE 100 stock index are stocks of the 100 largest firms listed on the LSE, the traditional venue for trading UK-listed stocks. These firms historically account for about 80% of total market capitalisation on the LSE. All FTSE 100 stocks are traded at several venues, and our dataset consists of data from the four main venues where these stocks are traded – the LSE, BATS Europe, Chi-X Europe and Turquoise.[1] The combined trading volume of these four venues accounted for about 98% of the FTSE 100 lit trading value in 2014, the last year in our dataset. We obtain intraday tick data from the Thomson Reuters Tick History (TRTH) database. Our sample dataset covers the period from 1 April 2008 to 30 September 2014. For each year, we only keep the stocks that are consistently part of the FTSE 100 index; i.e. those that have not been affected by the FTSE quarterly index revisions. Given the multi-year nature of the dataset and that quarterly revisions are made to the FTSE 100, there are 118 different stocks in the sample. Specifically, the number of stocks retained for each year ranges from 79 to 86. The dataset includes variables such as the Reuters Identification Code (RIC), date, timestamp, price, volume, bid price, ask price, bid volume, and ask volume. Each trade is allocated corresponding prevailing best bid and ask quotes. Since we only focus on normal trading hours, we delete the opening auction (07:50hrs – 08:00hrs) and closing auction (16:30hrs – 16:35hrs) periods from

[1] Before 20 May 2013, BATS Chi-X Europe only had a licence to operate Multilateral Trading Facilities (MTFs), which are multilateral trading venues allowing for the submission and execution of orders in instruments already listed elsewhere; however, they are not allowed to list new instruments, such as firm shares. Since then, BATS Chi-X Europe has been granted Recognised Investment Exchange (RIE) status. BATS Chi-X could now therefore operate a listing exchange alongside its existing MTF business. The data employed in this paper covers the period before and after BATS Chi-X was granted RIE status. The trading processes of the BATS Chi-X order books/venues employed in this analysis remain essentially the same before and after the transition. Enquiries made with BATS Chi-X confirm that their current order books are still the same as when BATS Chi-X could only operate MTFs; thus, those books are still classic MTFs. Furthermore, achieving the RIE status was only expected to advance BATS Chi-X's fortunes with retail investors. As of June 2016, BATS Trading Limited was still listed on the Committee of European Securities Regulators (CESR) MiFID database as an MTF. Robustness analysis conducted in this paper suggests that our results are unaffected by the granting of the RIE status to BATS Chi-X Europe.

the dataset. Cleaning and merging[2] of the order book data from the four venues yields a consolidated dataset comprising of roughly 1.33 billion trades and 34.42 billion quotes. The 65 months' worth of ultra-high frequency dataset is the largest thus far used to investigate the impact of fragmentation on market quality in the extant literature.

Figure I shows the percentage of monthly traded pound volume for the four trading venues since the introduction over our sample period of 2008 – 2014. Clearly, BATS, Chi-X, and Turquoise have been attracting significant market shares from the LSE since year 2008.

INSERT FIGURES I AND II ABOUT HERE

In November 2011, the trio of Chi-X, BATS and Turquoise attracted a combined market share of 50%; however, since then all have struggled to retain or outperform these market shares over time. Figure II plots the total monthly number of trades across the four trading venues since 2008. Although the highest number of orders are still being executed at LSE, the three high-tech entrants hold the aggregate lead in the competition for order flow.

4 Measures and descriptive statistics

4.1 Probability of an informed trade (PIN)

We employ the information-based trading (PIN) measure as our first proxy of adverse selection risk. This is because the theory that PIN is strongly correlated with adverse selection risk and information asymmetry is well documented and established in the literature (see for example Chung and Li, 2003; Brown et al., 2009). PIN has been applied as a proxy for priced information risk and information asymmetry in both finance and accounting literatures (see for

[2] After cleaning the data and filtering out input errors as in Ibikunle (2015), we use timestamps to match each transaction to a corresponding set of prevailing best bid and ask quotes for each exchange. Thereafter, we concatenate historical transaction files from all four stock exchanges and sort by exchange transaction time to create a 'consolidated order book'. This consolidated order book is a relevant indicator for investors employing smart order routing technology. Hence, we calculate all stock day proxies based on the 'consolidated order book'. Our approach to constructing the consolidated order book is consistent with the recent literature (see as an example, Degryse et al., 2015).

example Vega, 2006; Ellul and Pagano, 2006; Duarte et al., 2008; Chung and Li, 2003). In a more recent study, Lai et al. (2014) examine PIN measures based on a sample of 30,095 firms from 47 countries over a 15-year period. They find that PIN is strongly correlated with firm-level private information. Specifically, PIN is associated with the dispersion of belief about the value of an instrument; such dispersion is only possible due to a lack of transparency regarding the value of the instrument. Aquilina et al. (2017) present a detailed argument for why the existence of information asymmetry in a market implies reduced pricing transparency to the extent of the level of information asymmetry in that market.

Following the existing literature, we employ daily PIN as a measure of daily information asymmetry and an inverse proxy of daily levels of market transparency. The model as specified is based on the expectation that trading between informed traders, liquidity traders, and market makers occurs repeatedly throughout the day. Trading begins with the informed traders acquiring a private signal on a stock's value with a probability of α. Contingent on the arrival of a private signal, bad news will arrive with a probability of δ, and good news arrives with a probability of $(1 - \delta)$. The market makers compute their bid and ask prices, with orders arriving from liquidity traders at the arrival rate ε. Should new private information become available, informed traders will join the trading process, with their orders arriving at the rate μ. Informed traders will thus execute a purchase trade if they receive a good news signal, and sell if the signal is bad news. It should be noted that the setting of different arrival rates for uninformed buyers and sellers does not qualitatively change estimations of the probability that an informed trade has been executed (see Easley et al., 2002).

The PIN model allows us to compute an approximation of the unobservable distribution of trades between informed and uninformed traders by modelling purchases and sales.[3] The 'normal level' of sales and purchases executed within a stock on a given day over several

[3] We infer purchase and sales through the running of Lee and Ready's (1991) trade classification algorithm.

trading cycles is thus interpreted by the model as relatively uninformed trading activity, and this information is employed when estimating ε. An unusual volume of purchase or sale transactions is interpreted as information-based trading, and employed when computing μ. Furthermore, the frequency of intervals during which 'abnormal' levels of purchases and sales are transacted is employed when computing the values of α and δ. These calculations are conducted in a simultaneous fashion by the use of the maximum likelihood estimation method. Supposing that the uninformed and informed trades arrive as a Poisson distribution, the likelihood function for the PIN model for each interval estimated can be expressed as:

$$L\big((B,S)\big|\theta\big) = (1-\alpha)e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!} + \alpha\delta e^{-e_b}\frac{\varepsilon_b^B}{B!}e^{-(\mu+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^S}{S!} + \alpha(1-\delta)e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!}e^{-(\mu+\varepsilon_b)}\frac{(\mu+\varepsilon_b)^B}{B!} \quad (1)$$

where *B* and *S* respectively represent the total number of purchase and sale transactions for each 5-minute trading interval within each trading day; for ease of exposition we have dropped the stock and time subscripts. $\theta = (\alpha, \delta, \mu, \varepsilon)$ is the parameter vector for the structural model. Equation (1) represents a system of distributions in which the possible trades are weighted by the probability of a trading interval with no news $(1 - \alpha)$, a trading interval with good news$(\alpha(1 - \delta))$, or a trading interval with bad news $(\alpha\delta)$. Based on the assumption that this process occurs independently across the different trading periods, Easley et al. (1997) and Easley et al. (1996) calculate the parameter vector estimates using maximum likelihood estimation procedures. Thus, we obtain the parameters for each trading day and for each stock in the sample by maximum likelihood estimation. The PIN for stock *i* on day *t* is therefore computed as:

$$PIN_{i,t} = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \quad (2)$$

Table I reports the descriptive statistics for $PIN_{i,t}$. The standard deviation of the estimates at 0.079 is substantially lower than the mean (median) at 0.173 (0.154), while the interquartile range of the estimates is also low at 0.115 and 0.210. This implies a low level of variation in the probability of informed trading from day to day across all of the stocks in our sample. This is unsurprising since our sample consists of some of the most traded stocks in Europe. Increased levels of trading activity should engender a timely incorporation of information into prices, thus promptly eliminating inefficiencies in the price discovery process. It is expected that the most traded stocks in Europe would generally benefit from such a high level of trading activity; hence, we would expect a low level of variation in informed trading activity across stock-days. The mean estimate of 0.173 implies that roughly 17.30% of the trades in our sample are information-driven.

4.2 Absolute value of autocorrelation in mid-quote return

For robustness, in addition to $PIN_{i,t}$, we use the absolute value of the autocorrelation of short-term return ($Auto_{i,t}$) as a proxy for adverse selection risk. In a theoretically perfectly efficient market, price is unpredictable and thus follows a random walk, ensuring that returns are not correlated. However, in a less efficient market scenario, the gradual incorporation of private information into price leads to a deviation from the random walk, and returns are therefore correlated. Using a dynamic price formation model, Kyle (1985) shows that informed traders can strategically choose optimal trade sizes in order to maximize their expected profits, hence the assumption of a gradual incorporation of private information and of obtaining correlated returns. The actions of informed traders in this sense, evidenced by correlated returns, can therefore be viewed as a source of adverse selection risk for other market participants. We therefore employ the absolute values of 1-minute and 10-second mid-quote return autocorrelation as proxies of adverse selection risk. The return autocorrelation captured occurs because prices are less than fully informationally efficient. The autocorrelation in returns could also be due to under- and over-reaction to information, as well as to a delayed response to information (Comerton-Forde and Putniņš, 2015). By taking the absolute value of the autocorrelation of 1-minute and 10-second mid-quote returns for each stock-day, we capture both under- and over-reaction to new information, with larger values implying higher degrees of inefficiency and adverse selection risk, and vice versa.

In Table I, the descriptive statistics estimates for both variants of $Auto_{i,t}$ suggest that the measure is robust to alternative specifications. The large differentials between the mean and median estimates for both the 1-minute and 10-second returns $Auto_{i,t}$ estimates, as well as the large standard deviations of 0.118 and 0.194 respectively, hint at a higher level of variation across the stock-day estimates than observed for $PIN_{i,t}$.

4.3 Variance ratio

In a further attempt to ensure robustness, we also construct variance ratio as an inverse proxy for market quality. We follow O'Hara and Ye (2011) to construct stock-day variance ratios as follows:

$$VR_{i,t} = |1 - \frac{\sigma^2_{kl;i,t}}{k\sigma^2_{l;i,t}}| \tag{3}$$

where $\sigma^2_{l;i,t}$and $\sigma^2_{kl;i,t}$ are the variances of k-second and kl-second mid-quote returns for a given stock-day. For robustness, we compute $VR_{i,t}$ in two ways: we use a long and short return combination of 1-minute and 10-seconds ($VR_{i,t}$ – 1min), as well as a 5-minute and 1-minute long and short return combination ($VR_{i,t}$ – 5min). In an efficient market, stock price follows a random walk and the variance of returns is a linear function of the return measurement frequency. Furthermore, the variance of returns measured over longer horizons is equal to the sum of variances of shorter horizon returns, as long as the summation of the shorter horizons is equal to that of the longer horizon. Therefore, values closer to zero would imply higher levels of informational efficiency and lower adverse selection risk, while higher values imply worsening efficiency levels and increased probability of being adversely selected by a more informed trader.

4.4 Measure of market fragmentation

We proxy market fragmentation for each stock and for each trading day by using the reciprocal of the Herfindhal-Hirschman Index (HHI). This index is also used by Chlistalla and Lutat (2009), and Degryse et al. (2015). HHI is defined as one divided by the sum of the squared market shares (in daily traded pound volume terms) of the LSE and the other trading venues for the FTSE 100 stocks. The reciprocal of the index explicitly shows the level of fragmentation in the market for each FTSE 100 stock *i* on day *t*. The index is expressed as follows:[4]

$$Frag_{i,t} = \frac{1}{\sum_{k,i,t}\left(\frac{V_{k,i,t}}{\sum_{j,i,t} V_{j,i,t}}\right)^2} \tag{4}$$

where $V_{k,i,t}$ denotes the pound volume of stock i traded on market k on day t, $V_{j,i,t}$ represents the total pound volume of stock *i* traded in all of the markets under observation on day *t*, and $\frac{V_{k,i,t}}{\sum_{j,i,t} V_{j,i,t}}$ is the share of stock *i* traded on market *k* on day *t*. Since we have four trading venues in our sample, including the listing exchange, $Frag_{i,t}$ takes values between one and four. When trades are concentrated in one trading venue the proxy takes values close to one, and when trades are evenly spread across the four venues, this proxy takes values closer to four, the upper bound for the index.

In Table I, the mean estimate for $Frag_{i,t}$ is about 2.3, and the median is 2.38. This shows that, on average, trading activity is not concentrated at a single trading venue, i.e. a

[4] Equation (4), which is effectively defined as 1/HHI, serves as a convex transformation of the HHI. This can lead to outliers in this variable. Hence, we also compute 1-HHI as a proxy for market fragmentation. The results obtained are qualitatively similar to the ones obtained for 1/HHI; for parsimony, we do not report the results employing the latter approach but these are available upon request from the authors.

substantial proportion of trading takes place on platforms other than the LSE in the case of FTSE 100 stocks.

4.5 Other measures

Several other measures are also required in order to execute our empirical design as outlined in Section 5 below. These include liquidity, volatility and trading activity proxies. The first measure, the relative bid-ask spread ($RBAS_{i,t}$), is an inverse proxy for liquidity, and is quantified as the daily mean relative bid-ask spread for stock *i* on day *t*. It is computed for each transaction as the difference between the best prevailing ask and bid prices divided by their midpoint; the mean is computed for each day *t*.

We adopt the realised variance measure of Hansen and Lunde (2006) as a proxy for volatility ($Volatility_{i,t}$). It is computed as the sum of the squares of one-minute returns for stock *i* on day *t*. Finally, we proxy trading activity in two forms. First, we employ the number of transactions executed in stock i on day t as a proxy for trading activity ($TradeCount_{i,t}$). Then, in the spirit of Hendershott et al. (2011), we capture the state of high frequency trading ($Algo_{i,t}$) in the market by scaling the number of messages by the pound volume of transactions in stock *i* on day *t*. Larger estimates would imply a higher level of high frequency trading (HFT) activity.

In Table I, the mean value of $RBAS_{i,t}$ is 0.0945%, indicating that the FTSE 100 stocks in are liquid during the sample period.

In order to reduce the influence of outliers, all stock-day variables are winsorised at the 5% level. This approach is consistent with recent microstructure studies (see as an example, Malceniece et al., 2019).

INSERT TABLE I ABOUT HERE

5 Analysis of the impact of market fragmentation on adverse selection risk

In this section, we analyse the effect of fragmentation on adverse selection risk by estimating a series of stock-day panel regressions, which relate adverse selection risk proxies with a measure of market fragmentation. The general form of our stock-day panel regression model is:

$$Q_{i,t} = a_1 + \beta_1 Frag_{i,t} + \beta_2 Frag^2{}_{i,t} + \beta_3 Log(TradeCount)_{i,t} + \beta_4 Volatility_{i,t}$$

$$+\beta_5 Algo_{i,t} + \beta_6 RBAS_{i,t} + \beta_7 price\_inverse_{i,t} + \beta_8 Time_t + \varepsilon_{i,t} \quad (5)$$

where $Q_{i,t}$ corresponds to one of $PIN_{i,t}$, $Auto_{i,t}$ and $VR_{i,t}$. All variables are computed as described in Section 4. Following Degryse et al. (2015) and Boneva et al. (2015), we include a quadratic term $Frag_{i,t}^2$, in order to account for the possibility of a non-linear relationship between fragmentation and adverse selection risk. In line with O'Hara and Ye (2011), we include the variable $price\_inverse_{i,t}$, which corresponds to one divided by the closing price for stock *i* on day *t*. Finally, as in Comerton-Forde and Putnins (2015), we add $Time_t$, which is a linear time trend starting at zero and increasing by one unit for every date in our sample.

The panel estimations are done in two ways: (i) four one-stage panel least squares regressions (without fixed effects, with stock fixed effects, with date fixed effects, and with both stock and date fixed effects) with panel corrected standard errors (PCSE), and (ii) two instrumental variables (IV) estimation with PCSE. IV approach is employed specifically to address the likelihood of the endogeneity of $Frag_{i,t}$. Endogeneity is a concern because informed traders are more likely to trade in lit markets, while uninformed traders would go on to trade mainly in off-exchange venues (Zhu, 2014). Our IV estimation approaches are closely related with the existing literature. We use two different sets of instruments for robustness. For the first set of $Frag_{i,t}$ and $Frag_{i,t}^2$ instruments, we follow Comerton-Forde and Putniņš (2015), Degryse et al. (2015), Buti et al. (2011) and Hasbrouck and Saar (2013) in using the level of average fragmentation on day *t* for stocks in the same average trading volume size quintile with stock i as an instrument for stock i on day t. In our case, the two endogenous variables $Frag_{i,t}$ and $Frag_{i,t}^2$ are constructed using the average of each variable for all the other stocks in the same stock size quintile; quintile is estimated using average daily pound volume of stocks. This IV approach meets the requirement for an instrument, as the level of fragmentation in each quintile is correlated with the level of fragmentation in the instrumented stock, and it is unlikely that a change in adverse selection risk in stock i causes a large level of fragmentation in other stocks within the same quintile. Therefore, we estimate the following two-stage least squares (2SLS) model using this IV approach:

First stage:

$$Frag_{i,t} = b'_1 X_{i,t} + y'_1 W_{i,t} + e_{i,t} \tag{6}$$

$$Frag_{i,t}^2 = b'_2 X_{i,t} + y'_2 W_{i,t} + e_{i,t} \tag{7}$$

Second stage:

$$Q_{i,t} = \beta_1 \widehat{Frag}_{i,t} + \beta_2 \widehat{Frag}_{i,i}^2 + \gamma'_3 W_{i,t} + \varepsilon_{i,t} \tag{8}$$

Vector $X_{i,t}$ contains two instrumental variables for fragmentation and its quadratic equivalent. $\widehat{Frag}_{i,t}$ and $\widehat{Frag}_{i,t}^2$ are the fitted values of the instruments from the two auxiliary first stage equations. $Q_{i,t}$ corresponds to one of $PIN_{i,t}$, $Auto_{i,t}$ and $VR_{i,t}$. $W_{i,t}$ is the set of the other independent variables in Equation (5). $e_{i,t}$ and $\varepsilon_{i,t}$ are the error terms from first and second stage estimations respectively.

For our second set of instruments we follow Ibikunle (2018), who maximizes the potential for the instrument to be orthogonal to the error terms. We first regress each of the endogenous variables against their corresponding cross-sectional stock averages and the other control variables. We then collect the residuals ($FragRES$ and $Frag^2RES$) and employ them as IVs in 2SLS and GMM estimations. The IVs are expected to be correlated with the endogenous variables and uncorrelated with residuals in Equation (5), since the common cross-sectional component in the stock average has been fully explained by the changes in the endogenous variables, thus yielding the stock dependent factor that is not explained by the cross-sectional average. The IVs are highly correlated with the endogenous variables. We conduct tests to check for the IVs' validity in the regressions for both sets of IVs. We find that the Kleibergen-Paap χ^2 p-value and Cragg-Donald F-statistic reject the under-identification and weak instruments respectively. We also run the Hansen J statistics test for over-identification; the test results suggest that we cannot reject the null hypothesis that over-identifying restrictions are valid. All of the results of our tests are presented in the relevant results tables discussed in subsequent sections.

In order to minimise the possibility that the instruments pick up any general trends in market fragmentation, consistent with Comerton-Forde and Putniņš (2015), $Time_t$ controls for a time trend in the instrumental variable regressions.

Table II presents the correlation matrix for all the variables in the above outlined regression models. The correlation coefficient estimates show that multicollinearity is not of high concern in our estimations.

INSERT TABLE II ABOUT HERE

Table III reports the results from the estimation of Equation (8). The standard panel least squares (with and without fixed effects) results are also reported because evidence from previous papers (see as an example, Comerton-Forde and Putniņš, 2015) implies that endogeneity is more of a concern when causally relating market fragmentation proxies to liquidity rather than to adverse selection risk or price discovery. Panels A, B and C report the results when $Q_{i,t}$ corresponds to $PIN_{i,t}$, $Auto_{i,t}$ and $VR_{i,t}$ respectively. Specifically, for each adverse selection proxy, we present panel regression estimation results for six estimation approaches. Given their consistency, and for parsimony, only the results based on the 1-minute estimation of the adverse selection proxies are presented for $Auto_{i,t}$ and $VR_{i,t}$. The results based on the 5-minute $Auto_{i,t}$ and 10-second $VR_{i,t}$ estimations are presented in Appendix A1.

In Panel A, the coefficients are mostly statistically significant. In addition, the sign and economic magnitude of those coefficients are broadly consistent across the six estimations, thus it appears that our results are robust to alternative estimations approaches. The linear factor $Frag_{i,t}$ has negative coefficients and the quadratic factor has positive coefficients across all estimation approaches, implying that adverse selection first decreases with $Frag_{i,t}$ and then increases as fragmentation attains levels where unimpaired market quality can no longer be sustained. The statistically significant estimates for $Frag_{i,t}$ coefficients range from –0.146 to –0.014, and those for $Frag_{i,t}^2$ range from 0.002 to 0.029. All of the coefficients for both variables are highly statistically significant except the estimates where we control for stock fixed effects estimation only (Column 2, Panel A, Table III).

The first main observation from these estimates is that the current level of market fragmentation, captured by $Frag_{i,t}$, is beneficial for market quality, since it is linked with a reduction in adverse selection risk. Thus, it appears that, although there is no trade-through protection in Europe, sophisticated traders are able to locate and exploit potential arbitrage across platforms. Exploiting such opportunities helps to eliminate them, thereby leading to improved levels of market efficiency and lower risk of informed traders being adversely selected. It could also be that the availability of order execution opportunities on more than one platform makes it possible for orders to be executed in a timely fashion, thus increasing the pace of information incorporation into prices and eliminating adverse selection. Madhavan and Cheng (1997) show that upstairs markets enable transactions that would not otherwise occur in the (main) downstairs market. Thus, the existence of alternative trading venues can improve the probability of order execution and lower adverse selection risk in the aggregate market.

Secondly, the estimates strongly imply the existence of a non-linear relationship between fragmentation and adverse selection risk, irrespective of the estimation approach we employ. Figure III highlights a U-shaped relationship between $PIN_{i,t}$ and $Frag_{i,t}$ under the six estimation approaches, with the inflection points, when adverse selection risk starts to rise, ranging from when 2.17 to 4 (Figure III, Panels A to E).[5] This suggests that the optimal level of market fragmentation using the HHI-based measure lies somewhere between 2.17 and 4. When fragmentation is at or lower than the minimum end of this range, we would expect that the competition for order flow among trading venues benefits all investors through the reducing adverse selection risk. However, when fragmentation is higher than the observed 'optimal' range, it appears that the risk of being adversely selected rises, and implies a reduction in efficient price visibility and market transparency. This result adds to the findings in Boneva et al. (2015), where visible fragmentation shows a U-shaped relationship with volatility, liquidity and volume. Degryse et al. (2015) also report an inverted U-shaped relationship between visible fragmentation and the 'global' market depth for a sample of Dutch stocks.

The estimated inflection points should be interpreted with caution for at least three reasons. Firstly, market fragmentation in FTSE 100 stocks does not appear to be as extreme as some of the thresholds; hence, the estimates are based on regression coefficients computed using data with lower levels of market fragmentation. Secondly, the estimated thresholds are dependent on the coefficient values and thus easily influenced by the estimation approach used. Thirdly, the estimated thresholds could hinge on the liquidity of the stocks investigated; hence, a single point estimate for a group of stocks could be misleading. However, irrespective of the regression estimation approach used, we find consistency in the nature of the relationship between $PIN_{i,t}$ and $Frag_{i,t}$.[6]

INSERT FIGURE III ABOUT HERE

[5] We do not present a plot for the stock fixed effects estimation, because the coefficients are not statistically significant.

[6] For robustness we analyse the impact of the stock-day $Frag_{i,t}$ estimates at the 90th percentile and above on adverse selection risk and find a positive relationship, thus underlining the existence of the U-shaped relationship reported above. For parsimony, the results are not presented in the paper; however, they are available on request.

An examination of the control variables also yields interesting insights. The positive and statistically significant coefficient of $Log(TradeCount_{i,t})$ suggests that informed trading activity is prominent in frequently traded stocks. This finding is consistent with those of Foster and Viswanathan (1993), Engle and Lange (2001), and Alzahrani et al. (2013), in that informed traders could flood the market with orders after a semi-private/private news event. A further reason for the positive relationship between $PIN_{i,t}$ and $Log(TradeCount_{i,t})$ is that informed traders may exploit rising trading activity to camouflage their informed orders. Thus, during periods with high transaction levels per unit of time, one should expect a correspondingly high level of informed trading activity (see Admati and Pfleiderer, 1988). The positive and statistically significant $Volatility_{i,t}$ coefficient values, however, imply that informed trading increases with higher levels of volatility. This is because adverse selection risk is attributable to higher perceived risk, and to the dispersion of beliefs among traders. The volatility coefficient values are thus in line with prior research (see for example Chan and Lakonishok, 1997; Frino et al., 2007).

In Panel B, the $Frag_{i,t}$ and $Frag_{i,t}^2$ coefficient estimates are consistent with those in Panel A. The observed negative (positive) and statistically significant coefficient estimates for the $Frag_{i,t}$ ($Frag_{i,t}^2$) variables are consistent with the expectation that there is a trade-off in the benefits and drawbacks of market fragmentation. Specifically, when market fragmentation exceeds a certain level, fragmentation tends to impair informational efficiency, and therefore increases the risk of uninformed traders being adversely selected.

The positive and statistically significant $Log(TradeCount_{i,t})$ coefficients are in line with the market microstructure literature's view on trades moving prices (see Easley and O'Hara, 1987; Chan and Lakonishok, 1993). The positive and statistically significant coefficient of $Algo_{i,t}$ implies that HFT activity drives an increase in the level of information-based trading activity. In comparison to non-HFTs, HFTs could be viewed as informed, simply because they trade with available information (e.g. a sudden arrest of a firm's CEO for fraudulent activities) at a faster pace than non-HFTs. This is what is referred to as latency arbitrage; it involves the exploitation of a trading time disparity between fast and slow traders, when that trade is executed solely because of a latency advantage. Ibikunle (2018) argues that this speed advantage is tantamount to an information advantage in a high frequency trading world, since the end result remains the same – a set of traders exploit information (whether private or public) ahead of a different set of traders. Thus, exchanges with infrastructures that especially accommodate HFTs tend to display efficient prices ahead of others when instruments are simultaneously traded across those exchanges. This is the case with the analysis of price leadership in the London equity market conducted by Ibikunle (2018). Chaboud et al. (2014) and Brogaard et al. (2014) also show that HFTs enhance informational efficiency by speeding up price discovery and eliminating arbitrage opportunities; this property is consistent with what the classical informed trader in the market microstructure literature does with her trading activity. The $Volatility_{i,t}$ estimates are also consistent with the expectation that increased volatility levels are linked to increases in informed trading (and by extension, the risk of being adversely selected) (see also Domowitz et al., 2001). The positive and statistically significant estimate of $RBAS_{i,t}$ shows that market makers increase their ask prices and lower bid prices when confronted with higher levels of informed trading/adverse selection risk. This result is consistent with Aitken and Frino (1996), Chung et al. (2005), and Frino et al. (2007).[7]

Finally, Panel C presents the results for the regression estimates based on $VR_{i,t}$ as a proxy for adverse selection risk. The estimates are consistent with the results presented in Panels A and B.[8]

[7] In order to minimise the impact of outliers, we also delete the trade-by-trade return "bounceback" larger than 30% from the data and then re-run the regression analysis. This is because such large ''roundtrips'' within such short time frame are unlikely to represent meaningful transactions. The results obtained are qualitatively similar to our baseline results. For parsimony, the results are not presented; however, they are available on request.
[8] We account for the possibility that our results could be driven by developments during the global financial crisis period of 2008 to 2009 in a robustness analysis by excluding the period up until December 2011 (since the effects

6 Analysis of the impact of market fragmentation on market efficiency

Overall, the main conclusion from the analysis of the impact of market fragmentation on adverse selection risk in Section 5 is that, broadly, the latest observed level of market fragmentation in FTSE 100 stocks during our sample period is not detrimental to market quality. This is because $Frag_{i,t}$ is negatively related to the three inverse proxies for market quality that we examine. Therefore, if market fragmentation improves market quality, we would expect to find an increased level of market efficiency in the presence of high levels of market fragmentation within the estimated inflection points. In order to test this hypothesis, we examine the relation between fragmentation and market efficiency. We use the short horizon order imbalance and return predictability regression modelling approach of Chordia et al. (2008), who investigate market efficiency by employing a simple stock level regression of five-minute mid-quote returns on lagged five-minute order imbalances. For our order imbalance measure, we use a pound-based metric, which encapsulates the economic significance of order imbalance. Equation (9) expresses the computation of this measure, where $£BUY$ and $£SELL$ correspond to the 5-minute interval (*t)* pound volume of buy and sell trades respectively; this is computed for each stock separately.[9] We thereafter employ the values in our estimation of Equation (10) below:

$$OIB_{i,t} = \frac{(£BUY - £SELL)}{(£BUY + £SELL)} \tag{9}$$

$$return_{i,t} = \alpha + \beta_1 OIB_{i,t-1} + \beta_2 OIB_{i,t-1} * FRAG_d + Frag_{i,t-1} + \varepsilon_{i,t} \tag{10}$$

where $return_{i,t}$ is the 5-minute return for stock i at 5-minute time *t*, $Frag_{i,t-1}$ is the reciprocal of the HHI index for stock i at 5-minute time interval *t-1*, and $FRAG_d$ is a daily

of the global financial crisis could still be observed until the end of 2011), and estimate our baseline regressions using data from 2012 to 2014. The results (available on request) show that our findings remain unchanged; therefore, our findings are not unduly influenced by the inclusion of the 2008 – 2009 period in the datasets.

[9] The direction of trade is inferred using the Lee and Ready (1991) algorithm.

fragmentation dummy, which takes the value of 1 when the daily $FRAG_{i,t}$ computed in Equation (4) is one standard deviation above the average value for the surrounding (-15, +15) days, and zero otherwise. β_1 is expected to be statistically significant and positive since research suggests that short-term order imbalance contains information about future return (Chordia et al., 2005). If our hypothesis holds, β_2 would be negative, which would imply that order flow competition among the four venues in our sample and an increase in the number of available trading venues improve the timeliness of information incorporation during the trading process, by increasing the speed of the elimination of arbitrage opportunities. Consequently, short horizon return predictability is reduced, and thus market fragmentation enhances market efficiency.

INSERT TABLE IV HERE

Table IV presents the results from the estimation of Equation (10). β_1 (t-statistic) estimate is 1.52×10^{-3} (17.17). This implies that order flow contains information about short horizon asset returns; in this case, five minutes. Specifically, consistent with Chordia et al. (2008), arbitrageurs are able to exploit intraday serial dependence over 5 minutes in their trading activity. The β_2 (t-statistic) is $-4.46\ \times10^{-4}$ (-4.17). The negative and statistically significant β_2 suggests that the ability of lagged order imbalance to predict contemporaneous return decreases when market fragmentation is higher than average. Specifically, in the presence of higher than average levels of market fragmentation, order flow competition across trading venues facilitates market efficiency by reducing short horizon return predictability. This evidence also indicates that market fragmentation at the current level in the market for FTSE 100 stocks does not impair market efficiency. Instead, order flow competition between trading venues facilitates market efficiency by reducing short horizon arbitrage opportunities. This finding is consistent with Storkenmaier and Wagener (2011), who show that quotes across primary exchanges and MTFs are closely linked because competition forces can integrate disconnected trading venues, even in the absence of a trade-through protection regulation. β_1 and β_2 are generally small, which is to be expected given that we focus on a short intraday horizon – five minutes (see Chordia et al., 2008). It is also not surprising that the coefficients are smaller than Chordia et al.'s (2008), as this is linked to our interaction variable being a fragmentation proxy rather than a direct proxy of liquidity. Furthermore, the smaller coefficients are consistent with the intuition that the market becomes more efficient over time as more trading is completed at higher speeds. When trading is done at high speeds, the predictability of returns is eliminated faster. Trading in the London market during our sample period of 2008 – 2014 is more HFT-driven than the 1993 – 2002 US market investigated by Chordia et al. (2008).

Our view of the positive influence of fragmentation on market efficiency is nuanced. Until the introduction of MiFID spurred a significant growth of new trading venues for UK stocks, the LSE was virtually the only venue where UK stocks could be traded. Therefore, it is quite possible that the advent of new venues has led to the execution of orders that otherwise would not have been satisfied by the trading environment on the LSE. This could be due to a number of factors, including restrictions on the capacity for order execution by market makers and broker-dealers on the LSE, or indeed deterrence brought about by the effective monopoly previously enjoyed by the LSE. If unexpressed liquidity and information order requirements of participants are held back by these factors, price discovery will be affected, leading to a reduction in market efficiency. Thus, consistent with our findings, increased opportunities for order execution (indicated by market fragmentation) should improve market efficiency.

7 Conclusion

MiFID ended the quasi-monopoly of primary exchanges across Europe, leading to the introduction of nearly 150 new trading venues, the most prominent of which are MTFs. Since their introduction, MTFs have successfully pried away large shares of the European trading volumes from national exchanges across European equity markets. In contrast to Regulation NMS in the US equity market, MiFID does not impose a formal linkage between trading venues, nor establish a single data consolidator for trade-related information. This lack of integration in trading rightly raises concerns about trading transparency in European markets.

In this paper, we study the impact of the fragmentation of order flow on adverse selection risk and informational efficiency. We obtain ultra-high frequency order book data for the 100 largest UK stocks listed on the LSE and traded at three other recently introduced major trading venues: BATS Europe, Chi-X Europe, and Turquoise. The data obtained covers the sixty-five-month period ending in September 2014. Consistent with the literature (see for example Degryse et al., 2015; Boneva et al., 2015), our results indicate the existence of a quadratic/U-shape relationship between market fragmentation on the one hand and adverse selection risk and informational efficiency on the other. Thus, at the latest observed level of market fragmentation in FTSE 100 stocks during our sample period, market fragmentation helps to reduce adverse selection risk and increase informational efficiency. However, at much higher levels, there is an inflection point of market fragmentation when adverse selection risk will rise with increases in fragmentation; at this point, informational efficiency will also start to deteriorate. Nevertheless, since the historical level of fragmentation is generally lower than the upper limit of an optimal range suggested by our analysis, the implied negative impact of fragmentation on the market has been very limited.

Finally, we further investigate the view that the current levels of market fragmentation have been beneficial for market quality by examining the impact of market fragmentation on market efficiency. We find that fragmentation facilitates market efficiency by eliminating short horizon return predictability and reducing arbitrage opportunities. Our results are in line with Storkenmaier and Wagener (2011) and Menkveld (2013), who suggest that order flow competition across trading venues could act as the basis for the link necessary to minimise arbitrage opportunities, and thus improve market efficiency in a fragmented market.

The findings in this paper have important implications for the debate surrounding trading fragmentation in European equity markets. By finding that competition between trading venues improves aggregate market quality, we show that, despite the lack of a mandated consolidated tape under MiFID, order flow competition effectively links exchanges. Market fragmentation at current levels is therefore a value-creating phenomenon with market quality implications.

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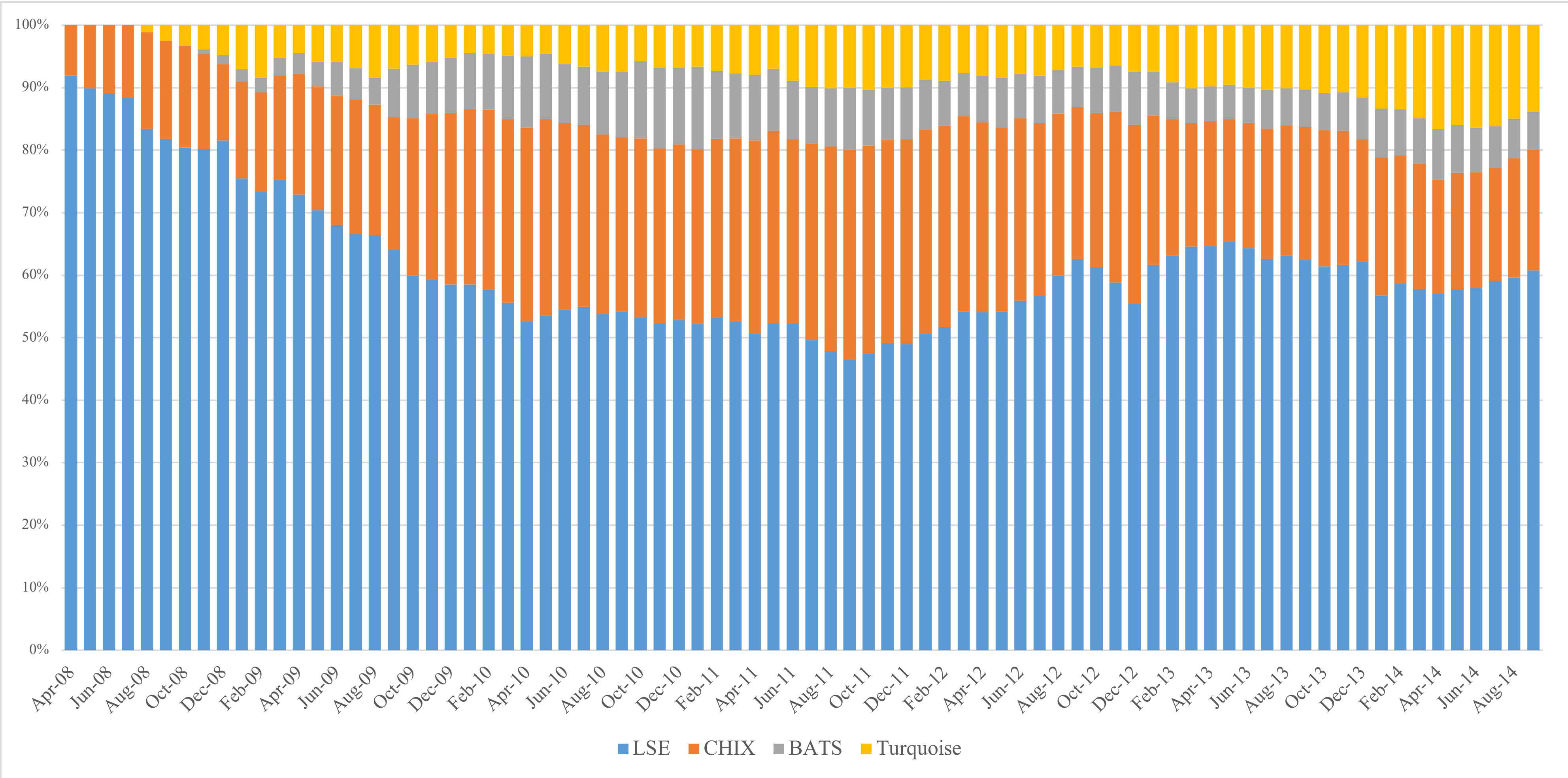
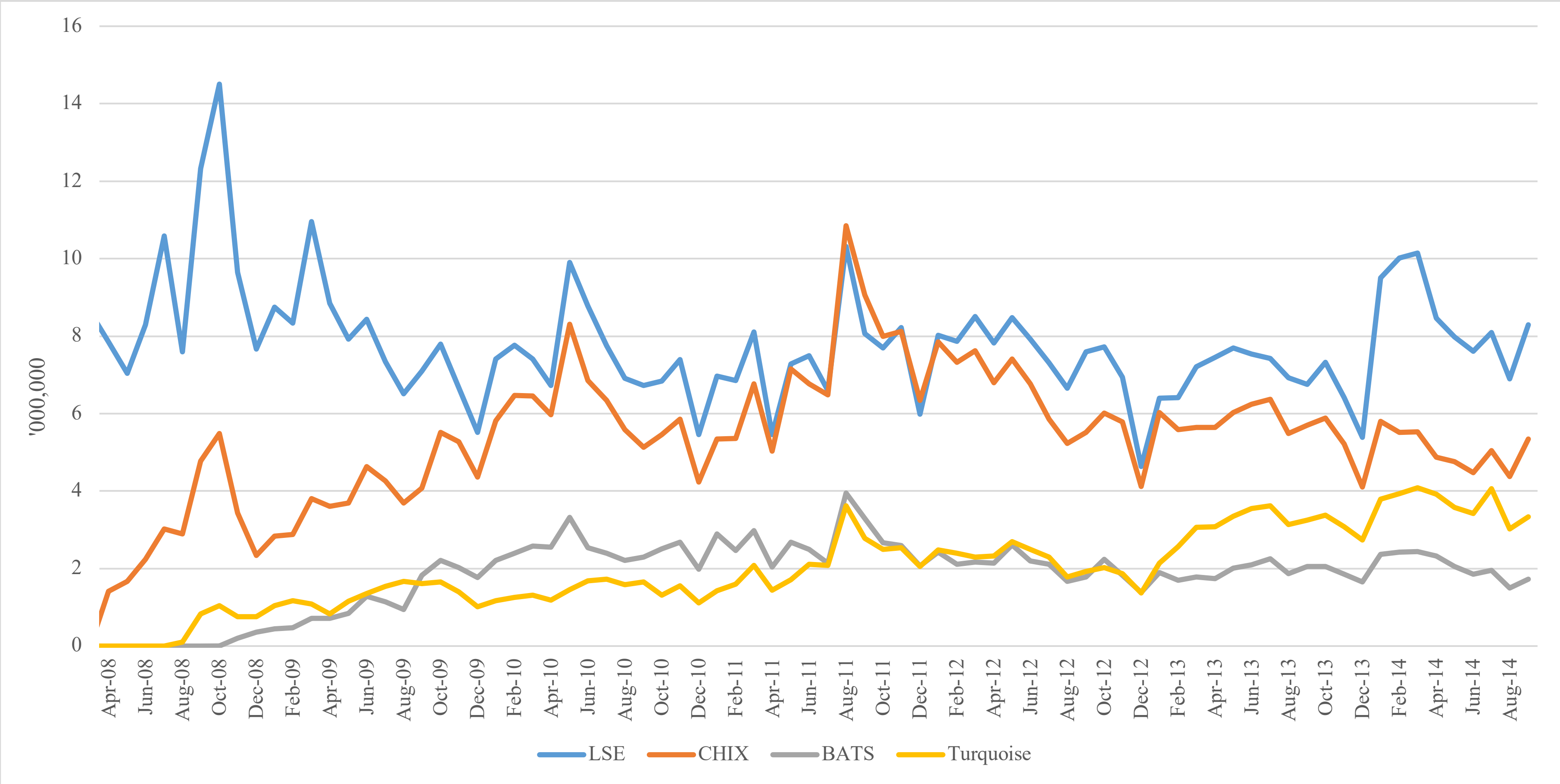
Figure I. Percentage share of trading volume by venue



Note: The figure displays the percentage total monthly trading volume in the primary market, London Stock Exchange (LSE), and the three other trading venues (BATS Europe, Chi-X Europe, and Turquoise) from April 2008 to September 2014.

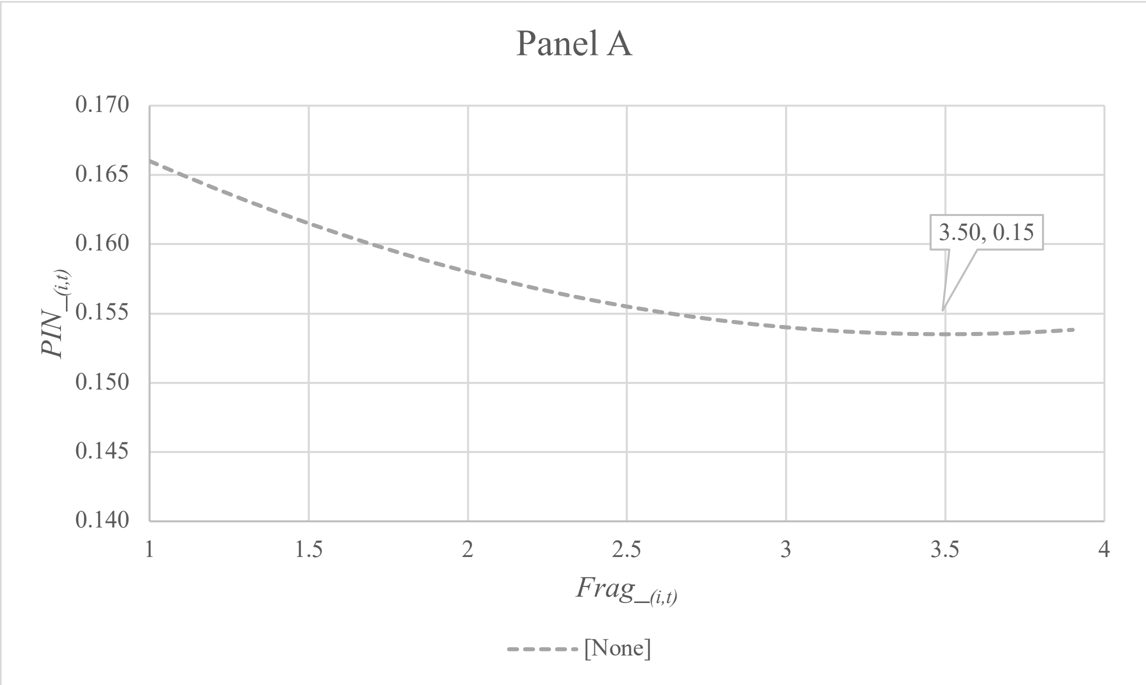
Figure II. Total number of trades by venue before and after the implementation of MiFID



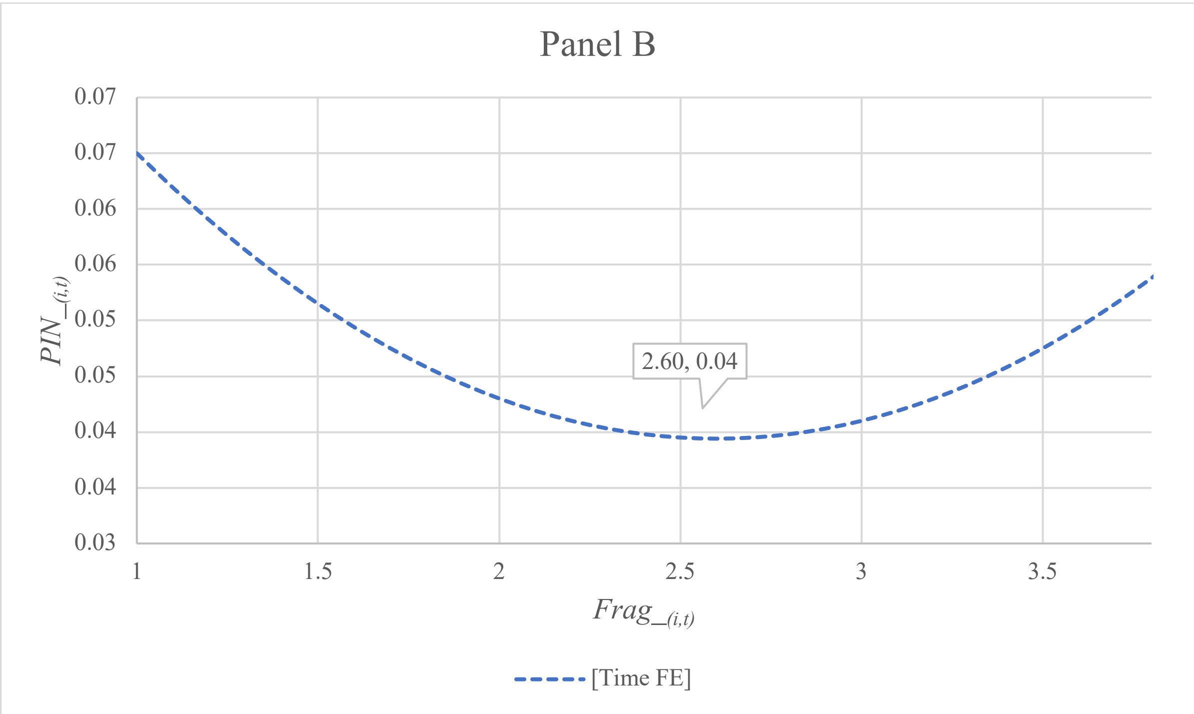
Note: The figure displays the total monthly number of trades across days and stocks for the primary market, London Stock Exchange (LSE), and the three other trading venues (BATS Europe, Chi-X Europe, and Turquoise) from April 2008 to September 2014. The sample comprises of the FTSE 100 stocks trading on the four main exchanges (London Stock Exchange (LSE), BATS Europe, Chi-X Europe, and Turquoise) where the stocks are traded from 1 April 2008 to 30 September 2014.

Figure III. The effects of visible fragmentation on adverse selection risk

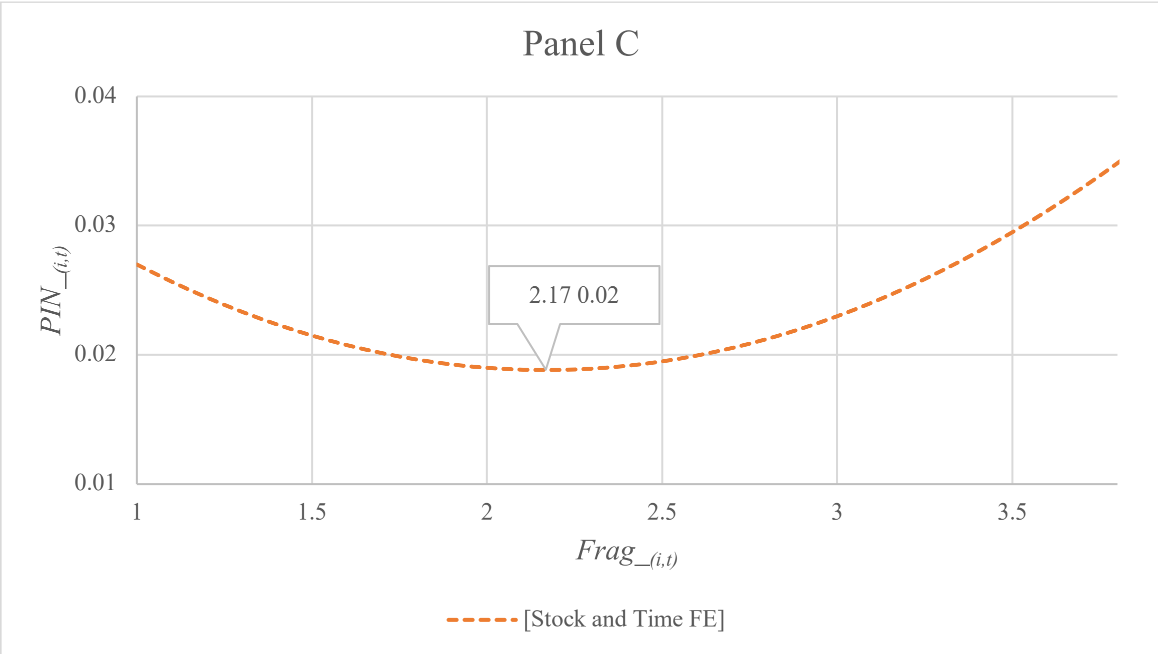
Panel A



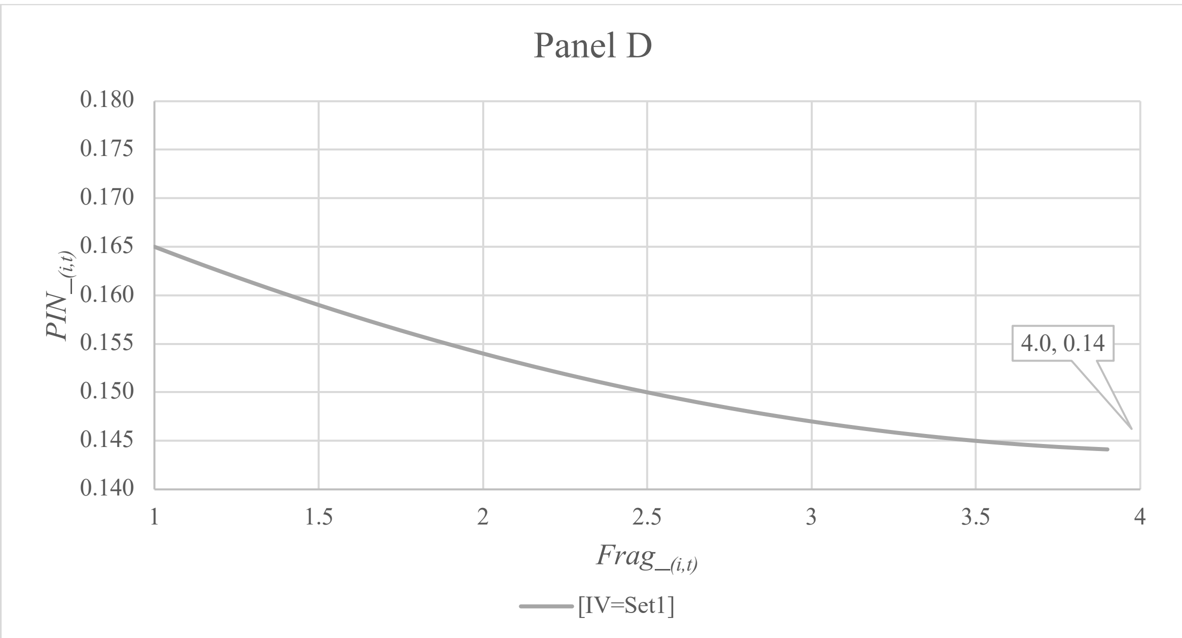
Panel B



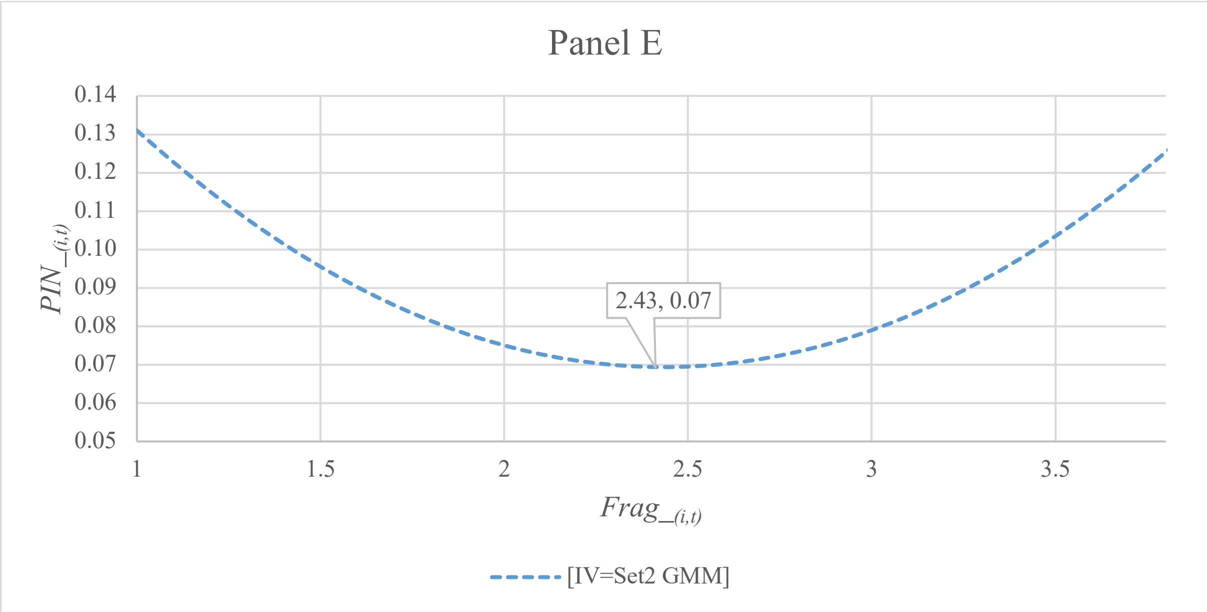
Panel C



Panel D



Panel E



Note: The panels show the implied effect of $Frag_{i,t}$ on $PIN_{i,t}$ using various estimation approaches (see Table III). $PIN_{i,t}$ is the probability of an informed trade in stock *i* at time *t*, while $Frag_{i,t}$ is the level of trading fragmentation in stock *i* at time *t*, and are as defined in Table I. The five panels A – E are based on the following respective regression estimation approaches: panel least squares (PLS), PLS with quarter fixed effects, PLS with stock and quarter fixed effects, two-stage least squares (2SLS) and generalised method of moments (GMM). The sample comprises the FTSE 100 stocks trading on the four main exchanges (London Stock Exchange (LSE), BATS Europe, Chi-X Europe, and Turquoise) where the stocks are traded from 1 April 2008 to 30 September 2014.

Table I. Descriptive statistics

Variable		Mean	Standard deviation	Minimum	25th percentile	Median	75th percentile	Maximum
$PIN_{i,t}$	The probability of an informed trade, computed using the approach of Easley et al. (1996; 1997), for stock *i* on day *t*.	0.173	0.079	0.072	0.115	0.154	0.210	0.375
$Auto_{i,t} - 1min$	The absolute values of the autocorrelation of 1-minute and 10-second mid-quote return for stock *i* on day *t*.	0.118	0.133	0.001	0.031	0.073	0.155	0.693
$Auto_{i,t} - 10second$		0.194	0.175	0.002	0.059	0.139	0.293	0.876
$VR_{i,t} - 1min$	Variance ratio for stock *i* at time *t*.	0.625	0.167	0.122	0.540	0.651	0.742	0.978
$VR_{i,t} - 5min$		0.526	0.201	0.047	0.387	0.531	0.686	0.943
$Frag_{i,t}$	Fragmentation proxy, calculated as the reciprocal of the Herfindahl-Hirschman index of traded pound volume in each venue for stock *i* at time *t*.	2.290	0.618	1.000	1.896	2.378	2.733	3.850
$Log(TradeCount_{i,t})$	Logarithm of number of trades executed for stock *i* on day *t*.	8.690	0.732	7.409	8.167	8.663	9.192	10.109
$Volatility_{i,t}$	Realized variance calculated as the sum of squared one-minute return for stock *i* on day *t*	0.003	0.007	0.000	0.000	0.001	0.002	0.032
$Algo_{i,t}$	Daily number of quote messages scaled by the pound value of transactions for stock *i* on day *t*.	0.007	0.13	0.000	0.003	0.004	0.007	1.062
$RBAS_{i,t}$	The daily mean effective spread, computed as twice the absolute value of the difference between the execution price and the quote midpoint for each trade during the day.	0.095%	0.047	0.034%	0.060%	0.088%	0.113%	0.225%
$price\_inverse_{i,t}$	Inverse of price, computed as one divided by the closing price for stock *i* on day *t*.	0.002	0.002	0.000	0.001	0.001	0.003	0.008

Note: This table defines the variables computed for varying time periods and aggregated across day *t* for each stock *i*, and reports the descriptive statistics. The sample comprises of the FTSE 100 stocks trading on the four main exchanges (London Stock Exchange (LSE), BATS Europe, Chi-X Europe, and Turquoise) where the stocks are traded from 1 April 2008 to 30 September 2014.

Table II. Correlations matrix

	$PIN_{i,t}$	$Auto_{i,t}$-$1min$	$Auto_{i,t}$-$10second$	$VR_{i,t}$-$5min$	$VR_{i,t}$-$1min$	$Frag_{i,t}$	$Log(TradeCount_{i,t})$	$Volatility_{i,t}$	$Algo_{i,t}$	$RBAS_{i,t}$	$price\_inverse_{i,t}$
$PIN_{i,t}$	1										
$Auto_{i,t} - 1min$	-0.036 (<0.0001)	1									
$Auto_{i,t} - 10second$	-0.024 (<0.0001)	0.439 (<0.0001)	1								
$VR_{i,t} - 1min$	-0.007 (0.0131)	0.387 (<0.0001)	0.254 (<0.0001)	1.0000							
$VR_{i,t} - 5min$	-0.034 (<0.0001)	0.350 (<0.0001)	0.169 (<0.0001)	0.501 (<0.0001)	1						
$Frag_{i,t}$	-0.042 (<0.0001)	0.243 (<0.0001)	0.170 (<0.0001)	0.188 (<0.0001)	0.153 (<0.0001)	1					
$Log(TradeCount_{i,t})$	0.010 (0.0003)	0.111 (<0.0001)	0.182 (<0.0001)	-0.280 (<0.0001)	-0.585 (<0.0001)	0.169 (<0.0001)	1				
$Volatility_{i,t}$	0.019 (<0.0001)	0.082 (<0.0001)	0.115 (<0.0001)	0.058 (<0.0001)	0.010 (0.0002)	-0.118 (<0.0001)	0.110 (<0.0001)	1			
$Algo_{i,t}$	0.015 (<0.0001)	-0.0660 (<0.0001)	-0.042 (<0.0001)	0.024 (<0.0001)	0.0715 (<0.0001)	-0.236 (<0.0001)	-0.187 (<0.0001)	0.086 (<0.0001)	1		
$RBAS_{i,t}$	0.013 (<0.0001)	-0.097 (<0.0001)	-0.037 (<0.0001)	0.084 (<0.0001)	0.250 (<0.0001)	-0.392 (<0.0001)	-0.358 (<0.0001)	0.301 (<0.0001)	0.296 (<0.0001)	1	
$price\_inverse_{i,t}$	-0.007 (0.019)	-0.046 (<0.0001)	0.018 (<0.0001)	-0.054 (<0.0001)	-0.036 (<0.0001)	-0.129 (<0.0001)	0.002 (<0.4144)	0.142 (<0.0001)	0.153 (<0.0001)	0.251 (<0.0001)	1

Note: This table reports the correlation coefficients for pairs of all the variables included in stock-day panel regressions. All variables are as defined in Table I. The *t*-statistics are presented in parentheses. The sample comprises of the FTSE 100 stocks trading on the four main exchanges (London Stock Exchange (LSE), BATS Europe, Chi-X Europe, and Turquoise) where the stocks are traded from 1 April 2008 to 30 September 2014.

Table III. Market fragmentation and adverse selection risk

Panel A. Market fragmentation and the probability of an informed trade

	$PIN_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Frag_{i,t}$	-0.014***	-0.001	-0.052***	-0.026***	-0.017***	-0.146***
	(-5.41)	(-0.59)	(-10.67)	(-5.22)	(-3.73)	(-13.03)
${Frag^2}_{i,t}$	0.002***	-0.001	0.010***	0.006***	0.002*	0.029***
	(-3.30)	(-1.06)	(10.00)	(5.25)	(1.72)	(12.36)
$Log(TradeCount_{i,t})$	0.002***	-0.000	0.012***	0.016***	0.000	0.003***
	(5.25)	(-0.78)	(28.47)	(24.84)	(0.90)	(7.53)
$Volatility_{i,t}$	0.157***	0.116***	0.052	-0.032	0.083**	0.179***
	(4.52)	(3.43)	(1.51)	(-0.90)	(2.32)	(5.10)
$Algo_{i,t}$	0.062***	-0.149***	0.143***	-0.068***	-0.193***	0.101***
	(3.29)	(-6.05)	(6.68)	(-2.77)	(-6.87)	(5.05)
$RBAS_{i,t}$	-0.751	0.921***	13.613***	13.376***	3.604***	-1.537**
	(-1.20)	(9.75)	(18.76)	(15.59)	(4.68)	(-2.26)
$price\_inverse_{i,t}$	-0.255***	-0.115	-0.963***	0.722*	-0.272**	-0.245**
	(-3.78)	(-0.95)	(-8.15)	(1.90)	(-2.21)	(-1.97)
$Time_t$					0.004***	0.011***
					(6.31)	(13.41)
$Intercept$	0.178***	0.182***	0.107***	0.047***	0.180***	0.247***
	(39.57)	(29.57)	(18.31)	(6.11)	(26.75)	(28.37)
$\bar{R}$	0.24%	2.37%	3.43%	5.27%	2.31%	0.00%
Observations	127,874	127,874	127,874	127,874	127,874	127,874
Estimation Method	PLS	PLS	PLS	PLS	2SLS	GMM
Fixed Effects	None	Stock	Quarter	Stock and Quarter	Stock	Stock
IV	None	None	None	None	Set1	Set2
Kleibergen-Paap χ^2 p-value					0.00	0.00
Cragg-Donald F statistic					46112.00	5122.00
Hansen J statistic					0.00	0.00

Panel B. Market fragmentation and the autocorrelation of short-term returns

	One-minute $Auto_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Frag_{i,t}$	-0.152*** (-34.78)	-0.143*** (-31.26)	-0.056*** (-6.69)	-0.050*** (-5.84)	-0.498*** (-61.16)	-0.300*** (-31.25)
$Frag^2{}_{i,t}$	0.046*** (46.14)	0.043*** (41.03)	0.009*** (5.13)	0.008*** (4.64)	0.107*** (64.15)	0.066*** (33.61)
$Log(TradeCount_{i,t})$	0.032*** (52.31)	0.047*** (52.93)	0.030*** (42.28)	0.028*** (26.49)	0.061*** (60.48)	0.058*** (61.55)
$Volatility_{i,t}$	1.797*** (23.06)	1.059*** (13.83)	1.573*** (20.95)	0.869*** (12.01)	0.951*** (12.40)	0.912*** (11.96)
$Algo_{i,t}$	0.254*** (7.61)	0.254*** (6.20)	0.171*** (4.62)	0.147*** (3.40)	0.153*** (3.71)	0.062 (1.56)
$RBAS_{i,t}$	4.015*** (3.16)	6.846*** (4.50)	7.994*** (5.72)	24.792*** (15.20)	17.552*** (11.26)	23.964*** (15.07)
$price\_inverse_{i,t}$	0.986*** (4.35)	-2.427*** (-10.36)	0.273** (2.28)	-0.666*** (-3.15)	-1.695*** (-7.24)	-6.237*** (-8.67)
$Time_t$					0.063*** (56.71)	0.047*** (45.06)
$Intercept$	-0.020** (-2.52)	-0.174*** (-16.30)	-0.110*** (-11.04)	-0.117*** (-9.13)	-0.267*** (-22.06)	-0.363*** (-30.08)
$\bar{R}$	9.22%	12.23%	31.04%	32.97%	15.15%	15.07%
Observations	127,874	127,874	127,874	127,874	127,874	127,874
Estimation Method	PLS	PLS	PLS	PLS	2SLS	GMM
Fixed Effects	None	Stock	Quarter	Stock and Quarter	Stock	Stock
IV	None	None	None	None	Set1	Set2

Panel C. Market fragmentation and variance ratio

	One-minute $VR_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Frag_{i,t}$	-0.097*** (-29.22)	-0.112*** (-32.04)	-0.026*** (-6.38)	-0.019*** (-4.58)	-0.551*** (-70.82)	-0.200*** (-29.94)
${Frag^2}_{i,t}$	0.041*** (53.05)	0.041*** (49.79)	0.005*** (5.98)	0.003*** (3.10)	0.125*** (75.41)	0.048*** (34.76)
$Log(TradeCount_{i,t})$	-0.129*** (-252.39)	-0.095*** (-140.05)	-0.029*** (-73.91)	-0.035*** (-63.86)	-0.089*** (-106.15)	-0.082*** (-115.84)
$Volatility_{i,t}$	1.374*** (22.09)	0.902*** (15.66)	2.275*** (51.42)	2.181*** (45.67)	0.875*** (12.20)	0.738*** (12.88)
$Algo_{i,t}$	0.060*** (4.11)	0.121*** (6.92)	-0.121*** (-7.42)	-0.053*** (-3.68)	0.055** (2.42)	-0.187*** (-6.69)
$RBAS_{i,t}$	37.980*** (40.00)	26.167*** (22.40)	29.815*** (41.11)	47.085*** (54.40)	45.193*** (30.48)	43.060*** (37.03)
$price\_inverse_{i,t}$	-2.277*** (-12.79)	-8.070*** (-14.57)	2.550*** (23.70)	2.087*** (6.15)	0.682 (1.03)	-8.137*** (-14.78)
$Time_t$					0.068*** (70.27)	0.047*** (64.45)
$Intercept$	1.698*** (286.78)	1.373*** (160.19)	1.013*** (199.03)	1.040*** (161.07)	1.369*** (122.64)	1.101*** (117.54)
$\bar{R}$	46.77%	52.38%	26.21%	31.66%	54.15%	55.04%
Observations	127,874	127,874	127,874	127,874	127,874	127,874
Estimation Method	PLS	PLS	PLS	PLS	2SLS	GMM
Fixed Effects	None		Stock		Quarter	
IV	None		None		None	

Note: This table shows estimated coefficients results for the following stock day panel regression model:

$$Q_{i,t} = a_1 + \beta_1 Frag_{i,t} + \beta_2 {Frag^2}_{i,t} + \beta_3 Log(TradeCount_{i,t}) + \beta_4 Volatility_{i,t}$$
$$+\beta_5 Algo_{i,t} + \beta_6 RBAS_{i,t} + \beta_7 price\_\ inverse_{i,t} + \beta_8 Time_t + \varepsilon_{i,t}$$

where $Q_{i,t}$ corresponds to one of $PIN_{i,t}$ (Panel A), $Auto_{i,t}$ (Panel B) and $VR_{i,t}$ (Panel C). $PIN_{i,t}$ is the probability of an informed trade for stock *i* on day *t*, and is computed as $PIN_{i,t} = \frac{\alpha\mu}{\alpha\mu+2\varepsilon}$, where α is the probability of informed traders obtaining a private signal, μ is the arrival rate of informed traders, and ε is the arrival rate of uninformed traders; the parameters are estimated through the maximum likelihood estimation of the Easley et al. (1996; 1997) probability of informed trading model. $Auto_{i,t}$ is the one-minute absolute value of the autocorrelation of short-term return for stock *i* on day *t*. $VR_{i,t}$ is the one-minute variance ratio, estimated as $VR_{i,t} = |1 - \frac{\sigma^2_{1minute;i,t}}{6\sigma^2_{10second;i,t}}|$,where $\sigma^2_{1minute;i,t}$and $\sigma^2_{10second;i,t}$ are the variances of 1-minute and 10- second mid-quote returns for stock *i* on day *t*. $Frag_{i,t}$ is the Herfindhal-Hirschman Index (HHI) for stock *i* on day *t* and is estimated as $Frag_{i,t} = \frac{1}{\sum_{k,i,t}\left(\frac{V_{k,i,t}}{\sum_{j,i,t}V_{j,i,t}}\right)^2}$, where $V_{k,i,t}$ denotes the pound volume of stock *i* traded on market *k* on day *t*, $V_{j,i,t}$ represents the total pound volume of stock *i* traded in all of the markets under observation on day *t*, and $\frac{V_{k,i,t}}{\sum_{j,i,t}V_{j,i,t}}$ is the share of stock *i* traded on market *k* on day *t*. $Log(TradeCount_{i,t})$ is the log of the number of transactions executed in stock *i* on day *t*, $Volatility_{i,t}$ is realised variance and is computed as the sum of the squares of one-minute returns for stock *i* on day *t*. $Algo_{i,t}$ is a proxy for high frequency trading and is obtained by scaling the number of quote messages by the pound volume of transactions in stock i on day t. $EBAS_{i,t}$ is the daily mean effective bid-ask spread for stock i on day t, effective bid-ask spread is computed as twice the absolute value of the difference between the execution price and the quote midpoint for each trade during the day. $price\_inverse_{i,t}$ corresponds to one divided by the closing price for stock i on day t. $Time_t$ is a linear time trend starting at zero and increasing for every date in our sample. Two sets of instrumental variables (IVs) are obtained for $Frag_{i,t}$ and $Frag^2{}_{i,t}$; Set 1 is constructed with the average of each endogenous variable over all stocks in the same stock size quintile. Set 2 is constructed by first collecting the within-quintile cross-sectional averages of the trading variables. $Frag_{i,t}$ and $Frag^2{}_{i,t}$ are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in panel least squares frameworks. The residuals from these regressions are each employed as Set 2 IVs. The *t*-statistics are presented in parentheses based on standard errors clustered by stock and quarter. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample comprises of the FTSE 100 stocks trading on the four main exchanges (London Stock Exchange (LSE), BATS Europe, Chi-X Europe, and Turquoise) where the stocks are traded from 1 April 2008 to 30 September 2014. Quintiles are computed on the basis of daily pound volume across the sample period.

Table IV. Market quality test: short-term predictive test

	$return_{i,t}$		$return_{i,t}$	
	Coefficient	*t*-stats	Coefficient	*t*-stats
$OIB_{i,t-1}$	1.52×10^{-3}***	(17.17)	1.38×10^{-3}***	(20.60)
$OIB_{i,t-1} * FRAG_d$	-4.46×10^{-4}***	(-4.17)	-4.07×10^{-4}***	(-4.40)
$Frag_{i,t-1}$			-1.07×10^{-5}***	(-0.64)
Constant	-3.21×10^{-5}***	(-1.38)	-7.51×10^{-6}***	(-0.17)

Note: This table presents the results for following predictive regression:

$$return_{i,t} = \alpha + \beta_1 OIB_{i,t-1} + \beta_2 OIB_{i,t-1} * FRAG_d + Frag_{i,t-1} + \varepsilon_{i,t}$$

$$\text{where } OIB_{i,t} = \frac{(\pounds BUY - \pounds SELL)}{(\pounds BUY + \pounds SELL)}$$

$return_{i,t}$ corresponds to the 5-minute return for stock *i* during 5-minute interval *t*. $OIB_{i,t}$ and $OIB_{i,t-1}$ are measured as the total pound value of buy trades less the total pound volume of sell trades, divided by the total pound volume of all trades during five-minute trading interval *t* and *t-1* respectively. The fragmentation dummy, $FRAG_d$, equals 1.0 when the daily level of fragmentation is at least one standard deviation above the average level of fragmentation for the surrounding days (-15, +15), otherwise zero. ***, ** and * indicate statistical significance at 0.01, 0.05 and 0.1 levels respectively. The sample comprises of the FTSE 100 stocks trading on the four main exchanges (London Stock Exchange (LSE), BATS Europe, Chi-X Europe, and Turquoise) where the stocks are traded from 1 April 2008 to 30 September 2014.

Appendix A1. Market fragmentation and adverse selection risk

Panel A. Market fragmentation and the autocorrelation of short-term returns

	10-second $Auto_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Frag_{i,t}$	-0.221*** (-49.84)	-0.220*** (-47.86)	-0.066*** (-9.36)	-0.069*** (-9.77)	-0.707*** (-89.93)	-0.260*** (-21.05)
${Frag^2}_{i,t}$	0.067*** (64.04)	0.065*** (59.73)	0.011*** (7.90)	0.012*** (8.47)	0.149*** (90.77)	0.059*** (22.66)
$Log(TradeCount_{i,t})$	-0.000 (-0.26)	0.021*** (25.31)	-0.003*** (-4.49)	-0.003*** (-3.85)	0.044*** (44.58)	0.037*** (40.92)
$Volatility_{i,t}$	2.781*** (33.92)	1.831*** (22.96)	2.389*** (31.16)	1.509*** (21.29)	1.662*** (20.84)	1.605*** (20.30)
$Algo_{i,t}$	0.214*** (7.39)	0.285*** (8.05)	0.065** (2.17)	0.121*** (3.29)	0.071* (1.82)	-0.136*** (-2.81)
$RBAS_{i,t}$	45.544*** (34.02)	42.983*** (26.80)	49.439*** (36.75)	68.293*** (43.86)	57.338*** (35.27)	69.153*** (42.97)
$price\_inverse_{i,t}$	-0.448*** (-3.96)	-3.201*** (-13.46)	0.174* (1.85)	-0.540*** (-3.15)	-2.304*** (-10.17)	-4.116*** (-17.18)
$Time_t$					0.092*** (85.86)	0.056*** (50.12)
$Intercept$	0.221*** (28.67)	0.014 (1.38)	0.069*** (8.07)	0.057*** (5.54)	-0.167*** (-14.18)	-0.381*** (-29.84)
$\bar{R}$	12.89%	17.33%	59.45%	61.64%	23.04%	21.23%
Observations	127,874	127,874	127,874	127,874	127,874	127,874
Estimation Method	OLS	OLS	OLS	OLS	2SLS	GMM
Fixed Effects	None	Stock	Quarter	Firm and Quarter	Stock	Stock
IV	None	None	None	None	Set1	Set2

Panel B. Market fragmentation and variance ratio

	5-minute $VR_{i,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Frag_{i,t}$	-0.153*** (-29.49)	-0.136*** (-25.01)	-0.055*** (-5.73)	-0.021** (-2.10)	-0.648*** (-63.22)	-0.273*** (-24.99)
${Frag^2}_{i,t}$	0.055*** (46.60)	0.048*** (39.14)	0.010*** (4.98)	0.003* (1.64)	0.145*** (70.30)	0.063*** (28.16)
$Log(TradeCount_{i,t})$	-0.086*** (-117.16)	-0.061*** (-56.83)	-0.081*** (-93.41)	-0.076*** (-58.03)	-0.048*** (-39.36)	-0.045*** (-40.10)
$Volatility_{i,t}$	2.638*** (31.98)	1.991*** (24.16)	2.295*** (28.30)	1.715*** (21.64)	1.890*** (22.48)	1.790*** (21.58)
$Algo_{i,t}$	0.374*** (11.20)	0.138*** (4.10)	0.332*** (7.88)	0.021 (0.63)	0.075** (2.05)	-0.222*** (-5.03)
$RBAS_{i,t}$	8.974*** (6.06)	9.290*** (5.08)	26.170*** (15.79)	36.558*** (18.22)	20.523*** (10.93)	30.872*** (16.48)
$price\_inverse_{i,t}$	-3.686*** (-13.99)	-17.038*** (-20.91)	-3.039*** (-12.95)	-5.046*** (-6.74)	-7.069*** (-8.60)	-16.384*** (-19.66)
$Time_t$					0.081*** (54.25)	0.061*** (48.55)
$Intercept$	1.300*** (139.99)	1.044*** (81.39)	1.155*** (97.52)	1.056*** (69.18)	1.014*** (68.23)	0.724*** (49.87)
$\bar{R}$	17.39%	20.74%	38.11%	39.82%	24.08%	23.82%
Observations	127,874	127,874	127,874	127,874	127,874	127,874
Estimation Method	OLS	OLS	OLS	OLS	2SLS	GMM
Fixed Effects	None	Stock	Quarter	Firm and Quarter	Stock	Stock
IV	None	None	None	None	Set1	Set2

Note: This table shows estimated coefficients results for the following stock day panel regression model:

$$Q_{i,t} = a_1 + \beta_1 Frag_{i,t} + \beta_2 {Frag^2}_{i,t} + \beta_3 Log(TradeCount_{i,t}) + \beta_4 Volatility_{i,t}$$
$$+\beta_5 Algo_{i,t} + \beta_6 RBAS_{i,t} + \beta_7 price\_inverse_{i,t} + \beta_8 Time_t + \varepsilon_{i,t}$$

where $Q_{i,t}$ corresponds to one of $Auto_{i,t}$ (Panel A) and $VR_{i,t}$ (Panel B). . $Auto_{i,t}$ is the 10-second absolute value of the autocorrelation of short-term return for stock *i* on day *t*. $VR_{i,t}$ is the five-minute variance ratio, estimated as $VR_{i,t} = |1 - \frac{\sigma^2_{5minute;i,t}}{5\sigma^2_{1minute;i,t}}|$,where $\sigma^2_{5minute;i,t}$and $\sigma^2_{1minute;i,t}$ are the variances of 5-minute and 1-minute mid-quote returns for stock *i* on day *t*. All other variables are as defined in Table III. Two sets of instrumental variables (IVs) are obtained for $Frag_{i,t}$ and ${Frag^2}_{i,t}$; Set 1 is constructed with the average of each endogenous variable over all stocks in the same stock size quintile. Set 2 is constructed by first collecting the within-quintile cross-sectional averages of the trading variables. $Frag_{i,t}$ and ${Frag^2}_{i,t}$ are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in panel least squares frameworks. The residuals from these regressions are each employed as Set 2 IVs. The *t*-statistics are presented in parentheses based on standard errors clustered by stock and quarter. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample comprises of the FTSE 100 stocks trading on the four main exchanges (London Stock Exchange (LSE), BATS Europe, Chi-X Europe, and Turquoise) where the stocks are traded from 1 April 2008 to 30 September 2014. Quintiles are computed on the basis of daily pound volume across the sample period from 1 April 2008 to 30 September 2014.

Appendix A2. Construction of the consolidated order book

Stock	Venue	Time	Ask	Bid	Volume
ABC	LSE	09:03:11	10.08	10.05	144
ABC	LSE	09:03:14	10.06	10.03	56
ABC	LSE	09:03:18	10.08	10.06	50
ABC	LSE	09:03:19	10.10	10.05	51
ABC	LSE	09:03:20	10.12	10.07	66
ABC	LSE	09:03:21	10.12	10.07	35
ABC	LSE	09:03:24	10.12	10.07	71
ABC	LSE	09:03:24	10.11	10.07	76
...	...	...	...	...	...

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Stock	Venue	Time	Ask	Bid	Volume
ABC	BATS	09:03:12	10.09	10.05	117
ABC	BATS	09:03:13	10.07	10.04	162
ABC	BATS	09:03:22	10.08	10.06	52
ABC	BATS	09:03:25	10.10	10.05	68
ABC	BATS	09:03:30	10.08	10.05	146
ABC	BATS	09:03:36	10.08	10.07	130
ABC	BATS	09:03:40	10.08	10.07	135
ABC	BATS	09:03:45	10.08	10.07	179
...	...	...	...	...	...

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Stock	Venue	Time	Ask	Bid	Volume
ABC	Chi-X	09:03:05	10.10	10.07	335
ABC	Chi-X	09:03:15	10.13	10.07	129
ABC	Chi-X	09:03:40	10.11	10.07	181
ABC	Chi-X	09:03:49	10.11	10.05	256
ABC	Chi-X	09:03:50	10.11	10.05	201
ABC	Chi-X	09:04:13	10.10	10.06	91
ABC	Chi-X	09:04:15	10.10	10.06	252
ABC	Chi-X	09:04:50	10.10	10.05	388
...	...	...	...	...	...

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Stock	Venue	Time	Ask	Bid	Volume
ABC	Turquoise	09:03:03	10.09	10.06	342
ABC	Turquoise	09:03:09	10.10	10.05	372
ABC	Turquoise	09:03:10	10.09	10.07	213
ABC	Turquoise	09:03:14	10.10	10.03	196
ABC	Turquoise	09:03:20	10.09	10.05	170
ABC	Turquoise	09:04:23	10.10	10.01	373
...	...	...	...	...	...

Stock	Venue	Time	Ask	Bid	Volume	Consolidated
ABC	Turquoise	09:03:03	10.09	10.06	342	YES
ABC	Chi-X	09:03:05	10.10	10.07	335	YES
ABC	Turquoise	09:03:09	10.10	10.05	372	YES
ABC	Turquoise	09:03:10	10.09	10.07	213	YES
ABC	LSE	09:03:11	10.08	10.05	144	YES
ABC	BATS	09:03:12	10.09	10.05	117	YES
ABC	BATS	09:03:13	10.07	10.04	162	YES
ABC	LSE	09:03:14	10.06	10.03	56	YES
...	...	...	...	...	...	...

Note: This figure shows the construction of the consolidated order book. Historical transaction data from all four stock exchanges (LSE, BATS, Chi-X and Turquoise) is concatenated and sorted by exchange transaction time to create a consolidated order book.