

# A Decade in the Life of a Market: Visible Trading Fragmentation, Market Quality and Efficiency

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This Version: January 2016

## Abstract

Unlike the Reg NMS regime in the US, Markets in Financial Instruments Directive (MiFID) does not impose a formal trading linkage or guarantee the best execution price. This raises concerns about consolidated market quality in an increasingly fragmented European trading environment. We investigate the impact of visible trading fragmentation on equity market quality using tick level data of FTSE 100 stocks over the period 2004 to 2014. We find a U-shape relationship between fragmentation and adverse selection costs. At lower levels of fragmentation, order flow competition reduces adverse selection costs and improves market transparency. However, there is a fragmentation threshold where implied adverse selection costs could increase with visible fragmentation. Visible fragmentation also stimulates market efficiency by reducing arbitrage opportunities.

JEL classification: G10, G14, G15

Keywords: MiFID, Multilateral Trading Facilities (MTFs), Market Transparency, Adverse Selection, Probability of informed trading (PIN), Market Efficiency

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## **1. Introduction:**

Over the past decade developed markets in Europe and the US have seen an unprecedented proliferation of new (high-tech) trading venues. As trading volume is attracted from national stock exchanges to the newer venues, regional and national markets have become increasingly fragmented. These changes in the markets follow recent regulatory changes in both Europe and the US. For example, the enactment of the Markets in Financial Instruments Directive (MiFID) in 2007 coupled with technological advances in trading systems have led to the proliferation of trading venues in Europe. Proliferation in turn has accelerated the trading fragmentation, with possible further implications for price discovery and market quality. Expectedly, trading fragmentation has raised concerns whether the diversified market landscape could harm price transparency in the markets. A stream of theoretical literature (See as examples Mendelson, 1987; Cohen et al., 1982; Pagano, 1989) suggest that all buyers and sellers should be congregated in one consolidated market and that all trades in all listed securities should occur in one single exchange. This is because single exchanges have lower costs when compared to a fragmented market place and also the consolidation of the order flow creates economies of scale for the liquidity provision. Cohen et al. (1982) show that off-exchange trading benefits brokers while harming retail investors through higher bid-ask spreads and price volatility. He suggests that there is a lower probability that orders can find a counter party in fragmented market. Chowdhry and Nanda (1991) also argue that liquidity may suffer from fragmentation due to information asymmetry. Their findings indicate that adverse selection costs increase with the number of market listings of an asset.

Recent studies however suggest that concerns about the negative impact of trading fragmentation could have been unfounded. For example, O'Hara and Ye (2011) find that market fragmentation in US equity markets has not necessarily led to the loss of pricing process quality; their analysis presents the US equity trading venues as a single virtual market with multiple entry points (trading venues).

In this paper, we advance the understanding of the impact of market fragmentation on market quality by addressing two issues: first, using a sample of FTSE 100 stocks, we investigate changes in two market quality measures (adverse selection cost and market transparency) in the presence of visible trading fragmentation over a decade. Secondly, we examine the association between market efficiency, measured by short-term return predictability, and level of trading fragmentation over the same period. We find a U-shaped relationship between

fragmentation and adverse selection risk, thus visible fragmentation helps to reduce adverse selection cost and increase market transparency when fragmentation is lower. When fragmentation is higher however, the implied adverse selection cost and market non-transparency potentially increase with fragmentation. The negative impact of fragmentation on curbing transparency is very limited since historical fragmentation is generally smaller than the turning point. We also find that a relatively higher level of fragmentation can facilitate market efficiency by reducing short term arbitrage opportunities. This result is consistent with the hypothesis that visible fragmentation forces liquidity suppliers to disclose trading information and reduce fees (O'Hara and Ye, 2011; Degryse et al., 2015).

Our analysis differs from recent papers, who examine the impact of fragmentation on market quality, in that we focus on an aspects of trading quality yet to be investigated – transparency and short-horizon return predictability as an inverse proxy for market efficiency. For example, our work differs from Koerber et al. (2013), who have also examined fragmentation on FTSE 100 stocks, in three respects. Firstly, they examine the impact of fragmentation on market quality which is measured by volatility, liquidity and volume whereas we test the market transparency. Secondly, they mainly focus their investigation of market quality on the listing market, the LSE, whereas we create a consolidated order book for our analysis. We are of the opinion that the consolidated market environment offers a bigger picture of FTSE 100 stocks market and could yield further insights. Thirdly, compared to Koerber et al. (2013) who use weekly data of FTSE 350 from 2008 to 2011, we adopt a richer dataset. Our dataset includes tick-level data and our regression model incorporates stock-day variables of FTSE 100 stocks over the past decade.

Although European market fragmentation is a relatively more recent phenomenon, by November 2014 more than 150 recently established alternative trading platforms called Multilateral Trading Facilities (MTFs) have been in operation in Europe. Furthermore, several of these venues are successfully challenging the national exchanges for trading market share, and in 2013 an MTF operator, BATS Chi-X Europe (operator of two distinct order books/trading venues – BATS and Chi-X), was the largest trading platform for equity trading in Europe.<sup>1</sup> Under MiFID, trading volume has become increasingly fragmented with trades

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<sup>1</sup> Before 20th May 2013, BATS Chi-X Europe only had a licence to operate MTFs; however, it has since been granted a Recognised Investment Exchange (RIE) status; thus, BATS Chi-X could now operate a listing exchange alongside its existing MTF operating 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 from before and after the transition. Enquiries made with BATS Chi-X

taking place not only on primary exchanges and MTFs but also on various other high tech constructs such as Broker Crossing Networks (BCNs) and Systematic Internalisers (SIs); some of these venues are also dark, i.e. they offer no pre-trade transparency. This development has thus created a very competitive trading environment for platform operators across Europe. The competition among the trading venues is expected to reduce the power of traditional stock exchanges, lead to falling transaction costs and enhance technological innovation. The emergence of these high entrant markets ultimately allows liquidity providers to compete on a finer inter-connected market.

Theory suggests that competition between trading venues can improve market quality (Foucault and Menkveld, 2008). Recent literature has attempted to reveal the impact of fragmentation based on empirical evidence from market depth, liquidity and transaction costs (For example see O'Hara and Ye, 2011; Gresse, 2011; Degryse et al., 2015; Boneva et al., 2015). These papers show positive effects of fragmentation on market quality. However, with the rise of alternative trading venues, fragmentation also increases the costs for monitoring markets in real-time. There is significant concern that trading fragmentation could also be harming market quality by increasing monitoring (and search) costs, non-transparency and adverse selection risk between markets (Madhavan, 1995; Yin, 2005; Hoffmann, 2010). Furthermore, since MiFID does not formally enforce linkage between trading venues and consolidated quote information on a national basis, orders could be permitted to execute at a price that is inferior to the best available price across venues. This differs considerably from the rules in the United States under Reg NMS, which mandates exchanges to re-route orders to other market centres if those are offering a better price (*trade-throughs*). Under MiFID, the primary exchange is accessible by all investors, while access to multiple venues (including MTFs) would normally require the so-called smart order routing system (SORT) that is only available to institutional and professional investors. Although retail investors may be unable to access multiple venues at once, they are still able to trade at individual venues. O'Hara and Ye (2011) explicitly argue that "it is hard to see how a single virtual market can emerge in Europe". Additionally, Ende and Lutat (2010) document a sizeable trading cost under suboptimal order executions due to the absence of a trade-through rule. The access friction to MTFs can give

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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 at June 2015, BATS Trading Limited is still listed on the 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.

rise to inter-market differences in the adverse selection risk faced and non-transparency by liquidity providers. If informed traders are more likely than uninformed traders to be “smart routers”, situations can arise where informed trader could split orders across MTFs and route their trades to the venues with the most uninformed traders and highest liquidity, and therefore increasing the adverse selection cost faced by uninformed traders.

Following concerns regarding lack of trade-through protection and adverse selection risk, another question could be raised regarding whether trading fragmentation does impair market efficiency. In a modern high frequency world, informed algorithm and high-frequency traders prefer to trade across high-tech markets (in Europe these are mainly MTF-type platforms) presumably because they value higher speed of execution and also try to prevent information leakage (Hoffmann, 2010). The informed order flow of informed traders is conditionally and positively autocorrelated, and can give an indication of instrument return during short term intervals (Froot et al., 2001). According to Madhavan (1995) and Nimalendran and Ray (2014), experienced traders are able to profit based on market inefficiency and obtain better execution through their dynamic trading in fragmented markets. Their trading strategies include short-term fundamental information (for example, imminent earnings release) and short-term technical analysis (as an example, front-running strategies and short-term momentum strategies). There is a concern that these experienced traders can locate potential arbitrage opportunities since quotes across regulated markets and MTFs are not closely linked due to the absence of trade-through protection. However, MiFID’s transparency regime mandates MTFs to disclose trade-related information as close to real time as possible. We postulate that if this transparency regime does disclose sufficient trading information content, then, with a high level of trading fragmentation, information on MTFs can spread to other venues. In this case, liquidity providers could adjust quotes against informed traders, decreasing arbitrage opportunity and short-term profitability for informed traders.

Consistent with these concerns, this study focuses on how visible trading fragmentation affects the consolidated market quality for all market participants in related trading venues. Specifically, we investigate the impact of visible fragmentation on measures market transparency and efficiency proxies of FTSE100 stocks in the past 10 years. We study the trades not only from the primary market LSE, but also from the three largest MTFs, BATS, Chi-X and Turquoise. Together, these platforms account for more than 98% of trading volume of FTSE 100 stocks. As high entrant markets are attracting increasingly more trading volume,

focus on a particular on primary exchange cannot provide a full picture of the market.<sup>2</sup> Therefore we construct a global order book by concatenating all trades from four venues. Global measures are relevant to not only investors who are only restricted to primary exchange but also professional traders who can access to Smart Order Routing Technologies (SORT).

We first investigate the relationship between visible fragmentation and market transparency. Market transparency can be considered as an inverse proxy of the levels of adverse selection cost and information asymmetry. Probability of information-based trading (PIN)) (Easley et al., 1996; Easley et al., 1997) is employed here to measure adverse selection risk since they are positively and strongly correlated (Chung and Li, 2003). Furthermore, since research indicates that off-exchange trading will have affect market quality<sup>3</sup>, we also test the impact of off-exchange trading on market transparency. We address the endogeneity of adverse selection by applying instrumental variables (IVs). Our results are robust to different sets of IVs. Turning to the effect of fragmentation on market efficiency, we follow Chordia et al. (2008) in building short horizon tests of the impact of market fragmentation on market efficiency.

Our paper is related to the existing literature on market quality in European equity markets in post-MiFID era. A stream of literature shows that trading fragmentation benefits market quality through increased liquidity and market depth. Foucault and Menkveld (2008) investigate the competition between LSE and Euronext in the Dutch stock market, where prior to EuroSETS's entry trading volume in the Dutch market was largely concentrated in NSC, a limit order book operated by Euronext. Foucault and Menkveld (2008) find that both consolidated order book and primary exchange NSC become significantly deeper after the EuroSETS entry. Hengelbrock and Theissen (2009) also examine the entry of Turquoise in 2008 in 14 European countries. Their findings suggest quoted bid-ask spreads on regulated markets declined following the entry.

Based on sample of stocks on LSE and Euronext exchange, Gresse (2011) finds that the increased competition between trading venues is accompanied with high liquidity provision. Menkveld (2011) examines particular high frequency trading (HFT) activities of Dutch stocks in Chi-X. The results indicate that, firstly, high frequency traders (HFTs) benefit from Chi-X trading platform in terms of lower trading costs. Secondly, the level of market fragmentation is highly determined by the intensity of HFT, because HFTs are likely to spread orders across

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<sup>2</sup> Gomber, Pujol and Wranik (2012) show that only 20 out of 75 execution policies in their sample indicates that they only execute trades at the primary exchanges.

<sup>3</sup> Weaver (2011) shows that off-exchange trade has detrimental effect on market quality by increasing volatility.

markets or to supply liquidity for MTFs. Koerber et al. (2013) employ panel regression on a weekly interval data set to study the impact of fragmentation on the market quality of the London Stock Exchange (LSE). Their market quality metrics include volatility, liquidity and market depth. They find a lower volatility on LSE when there is an order flow competition between MTFs. Their results also suggest that visible fragmentation can reduce market depth on LSE whilst dark trading increase the global trading volume. Degryse et al. (2015) also find a positive impact of visible fragmentation on consolidated liquidity but a negative impact on the liquidity of the primary exchange. Gresse (2014) tests the impact of fragmentation on local liquidity (primary exchange liquidity) and global liquidity of FTSE 100 constituents, CAC 40 constituents, and medium capitalisation stocks of the SBF 80 index before and after the implementation of MiFID. The results show that MiFID introduces value-adding competition; however, large-cap stocks benefit more from fragmentation than small-cap stocks. Gresse (2014)'s study suggests that the introduction of MiFID improves the market quality of LSE and Euronext-listed equities through reduction in transaction costs. Boneva et al. (2015) also examine the effects of fragmentation on FTSE 100 stocks. They find that volatility is lower in a fragmented market for FTSE 100 stocks when compared to the LSE monopoly.

In contrast to Europe, trading fragmentation is not a new phenomenon in the US market. Electronic Communication Networks (ECNs), which are similar to European MTFs, have been a critical part of the US market infrastructure since the early 1990s. Thus the US evidence on fragmented markets is more extensive. Boehmer and Boehmer (2003) show the evidence of increased liquidity when NYSE start to facilitate trading in ETFs listed on the American Stock Exchange. O'Hara and Ye (2011) show that although fragmented stocks generate higher short-term volatility, prices appear to be more efficient. Furthermore, fragmentation benefits market quality in terms of increasing liquidity and reducing trading cost. Other studies suggest an opposite effect of trading fragmentation. For example, Madhavan (2012) find that stocks that experienced greater prior fragmentation were disproportionately affected by the 'Flash Crash' of 6 May 2010. He suggests that 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 effect on market quality. However, existing studies suggest that the positive effects of fragmentation on market quality outweigh its negative effects.

Our paper is also related to another stream of literature, which examines adverse selection and informed trading across electronic markets. Grammig et al. (2001) and Barclay et al. (2003) demonstrate that order flow in electronic market tends to be more informative presumably because informed traders value higher speed and low cost offered by these venues. Hoffmann (2010) examine a sample of French and German stocks trading on both primary markets and Chi-X. Results suggest that Chi-X carries more private information than the primary exchange. The primary exchange offers better quotes but also incurs higher transaction fees. These findings are consistent with (Ibikunle, 2015), who show that Europe's largest high-tech entrant market, BATS Chi-X, appears to lead LSE in the price discovery for LSE-listed stocks by attracting a greater proportion of informed traders in those stocks.

The remainder of this paper is arranged as follows: in next section we discuss the sample selection and descriptive statistics. Section 3 summarises the methodology, Section 4 reports and discusses our findings of fragmentation on adverse selection cost and market transparency. Section 6 looks into the effect of fragmentation on market efficiency and Section 6 concludes.

## **2. Data and Descriptive Statistics**

### *2.1 Dataset*

We focus on constituents of FTSE 100 stocks, which are composed of the 100 largest British firms listed on the LSE. These firms account for about 80% of total market capitalisation on the LSE. All FTSE 100 stocks are traded on several trading venues and our data consists of trading data from the four main markets where these stocks are traded – the LSE, BATS Europe, Chi-X Europe and Turquoise. The total trading volume from these four trading venues account for about 98% of FTSE 100 lit trading value. We obtain intraday tick-by-tick trades data from the Thomson Reuter Tick History (TRTH) database. Our sample dataset starts from 1<sup>st</sup> January 2004 to 30<sup>th</sup> September 2014, for each year of the time series, we only keep the stocks that are consistently part of the FTSE 100 index. The dataset includes variables such as 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 (7:50hrs – 8:00hrs) and the closing auction (16:30hrs – 16:35hrs) periods from the dataset. Dataset cleaning and merging of the order book data from the four venues yield a consolidated dataset comprising of roughly 1.54 billion trades with a total trading value worth 14.29 trillion British pounds Sterling.



## 2.2 *Descriptive statistics*

Table 1 reports descriptive statistics for the stock characteristics and trading activity. The mean value of the effective spread is 0.83 pence; however, there is a huge gap between the third and first quartiles of the liquidity proxy the mean is also much higher than the median value. This suggests an appreciable level of variation across stocks Daily pound volume and daily trades also display similar levels of variation across the quartiles.

[Insert Table 1 here]

Table 2 reports correlations between the key trading variables that will be used in our empirical analysis. It is not surprising to see that daily pound volume is positively related with the number of transaction and median value of trading size. Moreover, daily pound volume is negatively correlated with volatility, algorithm trading activities and effective spread. This is consistent with argument that liquid stocks normally have lower level of adverse selection costs. Table 2 also indicates that the number of trades is positively associated with volatility and negatively associated with the effective spread.

[Insert Table 2 here]

Figure 1 shows the percentage of monthly traded pound volume of four trading venues since the introduction of MiFID. Clearly, BATS, Chi-X and Turquoise started to attract significant market shares from the LSE since about the start of 2008.

[Insert Figure 1 here]

[Insert Figure 2 here]

In November 2011, three MTFs attracted a combined market share of 50%, but have also found the going tougher over time. Figure 2 plots the total monthly number of trades across the four trading venues since 2004. Before the introduction of MiFID, the number of trades on LSE shows an upward trajectory from January 2004 to 2007. Following the introduction of MiFID, three high-tech entrants gradually stymied the rise in aggregate LSE trading figures, although LSE still retains trading dominance. Figure 3 shows the effective bid ask spread (EBAS) from January 2004 to September 2014. Before the introduction of MTFs, the average EBAS tends to be above 0.75 pence. Although there is a spike after the implementation of MTFs, EBAS

quickly falls to and has since remained below 0.75 pence. The declining EBAS suggests that consolidated market liquidity is improving and transaction costs are declining.

[Insert Figure 3 here]

### **3. Measures of Information Asymmetry and Fragmentation**

#### *3.1 PIN, an inverse proxy for market transparency*

We adopt private information-based trading (PIN) as a proxy of adverse selection cost since that the view that PIN is strongly correlated with the 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). Easley et al. (1996) first derive PIN that arise from information asymmetry between informed and uninformed investors. PIN has been applied as a proxy for priced information risk and information asymmetry in both finance and accounting literatures (see for 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.

Following existing literature, we therefore employ daily PIN as a parameter 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 across the day. As shown in Figure 1, trading begins with the informed traders acquiring a private signal on a stock's value with a probability of  $\alpha$ . Contingent on the arrival of a private signal, bad news will arrive with a probability of  $\delta$ , 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  $\varepsilon$ . Should new private information become available informed traders will join the trading process, with their orders arriving at the rate  $\mu$ . Thus, informed traders will execute a purchase trade if they receive a good news signal and sell if the signal is a bad news. Please note 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.<sup>4</sup> Hence, the ‘normal level’ of sales and purchases executed within a stock on a given day over several trading cycles is interpreted as relatively uninformed trading activity by the model, and this information is employed when estimating  $\varepsilon$ . An unusual volume of purchase or sale transactions is interpreted as information-based trading and employed when computing  $\mu$ . Furthermore, the frequency of intervals during which ‘abnormal’ levels of purchase and sale transactions are transacted is employed when computing the values of  $\alpha$  and  $\delta$ . These calculations are conducted in a simultaneous fashion by the use of the maximum likelihood estimation method. Suppose 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:

$$\begin{aligned}
L((B, S) | \theta) = & (1 - \alpha) e^{-\varepsilon_b} \frac{\varepsilon_b^B}{B!} e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!} \\
& + \alpha \delta e^{-\varepsilon_b} \frac{\varepsilon_b^B}{B!} e^{-(\mu + \varepsilon_s)} \frac{(\mu + \varepsilon_s)^S}{S!} \\
& + \alpha (1 - \delta) e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!} e^{-(\mu + \varepsilon_b)} \frac{(\mu + \varepsilon_b)^B}{B!}
\end{aligned} \tag{1}$$

where  $B$  and  $S$  respectively represent the total number of purchase and sale transactions for each one hour trading period within each trading day.  $\theta = (\alpha, \delta, \mu, \varepsilon)$  is the parameter vector for the structural model. Equation (1) represents to a system of distributions in which the possible trades are weighted by the probability of a one hour trading period with no news ( $1 - \alpha$ ), a one hour trading period with good news ( $\alpha (1 - \delta)$ ) or a one hour trading period 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 procedure. Thus we obtain the parameters for each trading day and for each stock in the sample by maximum likelihood estimation. Following Easley et al. (1996) and Easley et al. (1997) PIN is computed as:

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<sup>4</sup> We infer purchase and sales through the running of Lee and Ready’s (1991) trade classification algorithm.

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \quad (2)$$

### 3.2 Measures of Market Fragmentation

Visible fragmentation proxies are computed for each stock and for each trading day by using the reciprocal of the Herfindhal-Hirschman index. This index has been used in Foucault and Menkveld (2008), Chlistalla and Lutat (2009) and Degryse et al. (2015). This index is calculated as one divided by the sum of the squared market shares of the LSE and other trading venues for the FTSE 100 stocks. The reciprocal of this index explicitly shows the level of fragmentation as well as the level of competition among the four trading venues. The index is expressed as follows:

$$FRAG = \frac{1}{\sum_k \left( \frac{V_k}{\sum_j V_j} \right)^2} \quad (3)$$

where  $V_k$  and  $V_j$  denote the pound volumes traded on markets  $k$  and  $j$  respectively,  $V_j$  represents the total pound volume traded in all markets and  $\frac{V_k}{\sum_j V_j}$  is the market share of market  $k$  among those markets.<sup>5</sup> Furthermore, we also test the degree of off-exchange fragmentation since some research has suggested that high-tech entrant markets generate more informed order flows (see for example Grammig et al., 2001; Barclay et al., 2003). This proxy illustrates the fragmentation by calculating how much volume is traded via off-exchange venues, i.e. the other three venues in the sample other than the LSE.

$$FRAG_{EX} = \text{Off - exchange - volume} / \text{Total - volume} \quad (4)$$

Literature suggests that uninformed traders could be pressured off exchange to alternative trading venues by informed traders (See for example Chowdhry and Nanda, 1991). Thus, it is expected that informed trading activity will intensify with increasing volumes being driven off the main exchange. Both fragmentation proxies are computed for each stock and for each trading day.

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<sup>5</sup> Since we have four trading venues in our sample, including listing exchange, the proxy takes values between 1 and 4. 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 4.

Table 3 reports the descriptive statistics for *FRAG*, *FRAG<sub>EX</sub>* and *PIN*. The average *FRAG* 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; there appears to be a good but uneven spread to trading activity across venues for FTSE 100 stocks. Furthermore, the mean value of *FRAG<sub>EX</sub>* is about 0.39, indicating that about 61% of traded volumes are transacted on the listing exchange, the LSE. The average value of *PIN* is 0.1787, which means that roughly about 17.87% of trades are based on private or superior information in our sample. The interquartile range for *PIN* (0.0961) is also less than one standard deviation suggesting that there is a low level of variation across stocks in relation to trading transparency. Figure 4 presents the time series graph of level of *FRAG* and *FRAG<sub>EX</sub>* since implementation of MiFID. It is evident that both *FRAG* and *FRAG<sub>EX</sub>* are increasing over time. *FRAG* begins its lift from around 1 in April 2008 and has gradually risen to over time, recording a maximum value of 3.3 around January 2014. A similar trend is also observed for *FRAG<sub>EX</sub>*. All these patterns indicate an increasingly high level of competition for order flow between the LSE on the one hand and the relatively new high-tech entrants on the other.

[Insert Table 3 here]

[Insert Figure 4 here]

#### 4. Impact of Fragmentation on Market Transparency

In this section, we analyse the effect of fragmentation on market transparency.

##### 4.1 Methodology

The general form of our stock day panel regression model is:

$$PIN_{i,t} = \alpha + \beta_1 Frag_{i,t} + \beta_2 Frag^2_{i,t} + \beta_3 \log(PoundVolume_{i,t}) + \beta_4 \log(TradeCount_{i,t}) + \beta_5 \log(TradeSize_{i,t}) + \beta_6 volatility_{i,t} + \beta_7 Alg o_{i,t} + \beta_8 EBAS_{i,t} + \varepsilon \quad (5)$$

where *PIN* is the probability that a trade is informed, computed as described in Section 3.1; *PIN* is an inverse proxy for market transparency. The proxy for visible fragmentation is *FRAG* and is also computed as described in Section 3.2. Following Degryse et al. (2015) and Boneva et al. (2015), we include a quadratic effect *FRAG<sup>2</sup>* since there could be a trade-off in the benefits and drawbacks of fragmentation. A series of control variables are also included. *Log(PoundVolume)* is the log of total daily pound-volume traded in stock *i*. *Log(TradeSize)* is

the log of median of daily trade size for stock  $i$ .  $\text{Log}(\text{TradeCount})$  is the log of total number of transactions in that day for stock  $i$ .  $\text{Volatility}$  is the daily standard deviation of trade-by-trade return of stock  $i$ . This intraday volatility represents the market risk faced by traders.  $\text{Algo}$  controls for the algorithm trading activity on high-entrant markets. We follow Hendershott et al. (2011) to use the total number of quote changes over pound volume over the in trading day  $i$  from high entrant market as the proxy of the algorithm trading activity. The last control variable is daily effective bid-ask spread,  $\text{EBAS}$ . It is computed as twice the absolute value of the difference between the execution price and the quote midpoint. Effective spread captures the liquidity cost and adverse selection cost faced by market makers.

#### 4.2 Instrumental Variable Approach

Potential endogeneity may raise since informed traders are more likely to want to trade in lit markets, while uninformed would go on to trade mainly in off-exchange venues (Zhu, 2014). To overcome endogeneity issues, we use two different sets of instruments for robustness check. For our first set of instrumental variable, we follow Buti et al. (2011) and Hasbrouck and Saar (2013) to construct the level of fragmentation in a stock-day with the average of fragmentation on that day in all other stocks in the corresponding average trading volume size quintile. In our case, the two endogenous variables  $\text{FRAG}$  and  $\text{FRAG}^2$  are constructed with the average of each variable over all stocks in the same size quintile. This IV approach meets the requirement for instrument because the level of fragmentation in each quintile is correlated with the level of fragmentation in a particular stock and it is unlikely that a change in the informed trading of stock  $i$  causes a larger level of fragmentation in other stocks within the same quintile. Therefore, we estimate the following 2-SLS model:

First stage:

$$\text{FRAG}_{i,t} = \alpha_{1,i} \times d_{q(t)} + \beta'_1 X_{i,t} + y'_1 W_{i,t} + \varepsilon_1 \quad (6)$$

$$\text{FRAG}^2_{i,t} = \alpha_{2,i} \times d_{q(t)} + \beta'_2 X_{i,t} + y'_2 W_{i,t} + \varepsilon_2 \quad (7)$$

Second stage:

$$\text{PIN}_{i,t} = \alpha_i \times \delta_{q(t)} + \beta_1 \hat{\text{FRAG}}_{i,t} + \beta_2 \hat{\text{FRAG}}^2_{i,t} + y'_3 W_{i,t} + \varepsilon_3 \quad (8)$$

Vectors  $X_{i,t}$  contain two instrumental variables.  $\hat{\text{FRAG}}_{i,t}$  and  $\hat{\text{FRAG}}^2_{i,t}$  represent the instrument values from two auxiliary first stage equations and the vector  $W_{i,t}$  is a set of control variables.

For our second set of instruments we follow Ibikunle (2015) who aims to maximize the potential for the instrument to be orthogonal to the error terms. We first regress each of endogenous variables against their corresponding cross-sectional stock averages and the other control variables. Then we collect the residuals (*FragRES* and *Frag<sup>2</sup>RES* for *Frag* and *Frag<sup>2</sup>* respectively) and employ them as IVs in the GMM estimation. The IVs are expected to be correlated with the endogenous variables while 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 for *Frag* and *Frag<sup>2</sup>*, *FragRES* and *Frag<sup>2</sup>RES* are correlated with the endogenous variables (0.4498 and 0.4848 respectively). However, they are statistically and effectively uncorrelated with residuals in equation (5).

### 4.3 Main results

Table 4 reports the coefficients estimated with both stock and quarter fixed effects. Furthermore, we also include two different sets of IV to control for potential endogeneity problems. Most of the coefficients are statistically significant and the sign and economic magnitude of those coefficients are generally consistent across different fixed effects and IVs. Table 4 shows that *PIN* first decreases with *FRAG* and then increases as the linear factor *FRAG* has negative coefficients and the quadratic factor has positive coefficients across all estimation approaches. All the coefficients for both variables are highly statistically significant, thus implying a trade-off in the benefits and drawbacks of visible fragmentation. Figure 5 illustrates this as a U-shape relationship between *PIN* and *FRAG* under two fixed effects and two sets of IVs. The minimum points of *PIN* range from 2.1 to 3 on these panels. This suggests that the optimal level of visible fragmentation lies between 2.1 to 3 using our measure of visible fragmentation as discussed in Section 3.2. When fragmentation is smaller than this optimal level, the negative (positive) relation between *PIN* (market transparency) and *FRAG* suggests that competition among trading venues benefits all investors by reducing adverse selection costs. However, when fragmentation is larger than this optimal level, fragmentation seems harm market transparency without contributing to a decrease in implied adverse selection risks. This finding is in line with Boneva et al. (2015) who find an inverted U-shape relation between visible fragmentation and volatility, liquidity and volume for a sample of UK stocks using weekly interval data. Similarly, Degryse et al. (2015) also report an inverted U-shape relation between visible fragmentation and global market depth for a sample of Dutch stocks.

[Insert Table 4 here]

An examination of the control variables also yield interesting insights. The positive and statistically significant coefficient of  $\text{Log}(\text{PoundVolume})$  suggests that informed trading activity is prominent for heavily traded stocks. In another word, there is a positive effect of global market depth on informed trading activity. This finding is consistent with Foster and Viswanathan (1993). Furthermore, the negative coefficients  $\text{Log}(\text{TradeCount})$  and  $\text{Log}(\text{TradeSize})$  suggest that increased order flow improve trading transparency. The  $\text{Volatility}$  coefficient values however imply market transparency reduces with higher volatility. This is because adverse selection risk is attributed to higher risk and dispersion of beliefs among traders. The volatility coefficient values are consistent with prior research (See for example Chan and Lakonishok, 1997; Frino et al., 2007). The positive and significant coefficient of  $\text{Algo}$  indicates that algorithm trading activity on high entrant market is strongly correlated with informed trading and adverse selection risk. Thus, it appears ATs are usually more informed than slower traders (cf. Ibikunle 2015a). Finally, we find that daily mean  $\text{EBAS}$  has a positive and significant relationship with  $\text{PIN}$ . This is because market makers raise quotes when confronted with informed trades and high adverse selection risk. This result is consistent with Aitken and Frino (1996), Chung et al. (2005) and Frino et al. (2007).

[Insert Figure 5 here]

We now turn to an examination of the effect of off-exchange fragmentation on market transparency. Table 5 reports a positive and significant coefficient for off-exchange trading. Coefficients of  $\text{FRAG}_{\text{EX}}$  are only statistically significant under quarter fixed effects and the first set of IVs. When quarter fixed effect is imposed, the linear and quadratic coefficient of  $\text{FRAG}_{\text{EX}}$  are negative and positive respectively, indicating a U-shape impact curve on adverse selection cost with minimum informed trading level at  $\text{FRAG}_{\text{EX}} = 0.5$ . Conversely, under Set 1 IV, the signs are reversed. Evidence therefore points to both a U-shaped and an inverse U-shaped relationship between  $\text{FRAG}_{\text{EX}}$  and adverse selection costs when our proxy for fragmentation is focused on trading activity off the listing exchange. Except for inconsistent sign of  $\text{FRAG}_{\text{EX}}$ , all control variables yield estimates consistent with Table 4's estimates and signs.

[Insert Table 5 here]



## 5. Fragmentation and Market Efficiency

### 5.1 Methodology

So far we find a U-shaped relation between visible fragmentation and adverse selection cost. Although visible fragmentation helps to reduce adverse selection risk when fragmentation is below a certain level, empirical evidence suggests that implied adverse selection risk could potentially increase with visible fragmentation. Hence, it is valid to assume that disconnected quotes across trading venues can create arbitrage opportunities. Experienced traders may be able to locate these potential arbitrage opportunities since quotes across regulated markets and MTFs are not closely linked due to the absence of a mandatory trade-through protection. To test this hypothesis, we continue to examine the relation between visible fragmentation and market efficiency. We use short horizon order imbalance and return predictability regression modelling approach of Chordia et al. (2008) who investigate market efficiency by employing 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 measure, which encapsulates the economic significance of order imbalance; Equation (9) expresses our computation of this measure, where  $\pounds BUY$  and  $\pounds SELL$  equal the 5-minute pound volume of buy and sell trades in respectively; this is computed for each stock separately.<sup>6</sup> We thereafter employ the values in our estimation of Equation (10) below. In Equation (10),  $return_{i,t}$  corresponds to 5-minute return for stock  $i$  during 5-minute interval  $t$ .

$$OIB\pounds_t = \frac{(\pounds BUY - \pounds SELL)}{(\pounds BUY + \pounds SELL)} \quad (9)$$

$$return_{i,t} = \alpha + \beta_1 OIB_{i,t-1} + \beta_2 OIB_{i,t-1} * FRAG + \varepsilon \quad (10)$$

The fragmentation dummy,  $FRAG$ , takes the value 1 when the either of our fragmentation proxies is one standard deviation above the average value for the trading days over (-15, +15), and zero otherwise.<sup>7</sup> Coefficient of  $\beta_1$  is expected to be statistically significant and positive since research suggests that short term order imbalance contains information about future

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<sup>6</sup> Direction of trade is inferred using Lee and Ready (1991) algorithm.

<sup>7</sup> The model is estimated using both market fragmentation proxies and results presented for both.

return Chordia et al. (2005). Moreover, we should expect to see a negative value of  $\beta_2$ , which would imply that order flow competition among the four venues in our sample reduces arbitrage opportunity and thus market fragmentation enhances market efficiency by reducing short-term return predictability.

[Insert Table 6 here]

## 5.2 Results

Table 6 presents estimated model results for both fragmentation proxies; Panel A shows the results for *FRAG* while B shows the results for *FRAG<sub>EX</sub>*. Firstly, the coefficients on the lagged order imbalance variable are all statistically significant at 1% level, which is consistent with Chordia et al. (2008). This implies that, in a consolidated market, order flow still contains information about short horizon asset returns, in this case, five minutes. The coefficient (t-statistic) of interaction variable *OIB<sub>t</sub>\*FRAG* is -0.000644 (-4.14). This implies that, when the level of visible fragmentation is high, order flow competition across trading venues will facilitate market efficiency by reducing short horizon return predictability. We also find that the coefficient (t-statistic) of interaction variable *OIB<sub>t</sub>\*FRAG<sub>EX</sub>* is -0.000222 (-2.01), implying that with more order flow migrating to MTFs, the London market generally becomes more efficient. Thus, empirical evidence indicates that visible market fragmentation and off-exchange fragmentation do not impair market efficiency. Instead, order flow competition between trading venues facilitates market efficiency by reducing short term arbitrage opportunities. This finding is consistent with Storckenmaier and Wagenerz (2011) who show that quotes across primary exchanges and MTFs are closely linked because competition forces can integrate the disconnected trading venues.

## 6. Conclusion

The Markets in Financial Instrument Directive (MiFID) ended the quasi-monopoly of primary exchanges across Europe. Since their introduction to the European market nomenclature in November 2007, 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 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 the European equity market. In

this paper, we study the impact of competition for visible order flow on market transparency and market efficiency under a consolidated market environment.

We obtain visible high frequency order book data for the 100 largest UK stocks listed on the LSE and traded at three other major recently introduced venues, i.e. BATS Europe, Chi-X Europe and Turquoise; the data obtained covered a ten year period ending in 2014. In order to investigate the impact of fragmentation on global market quality and trading efficiency, we create a single consolidated virtual market by concatenating data from these four venues. Specifically, we use employ probability of informed trading (PIN) as a proxy for adverse selection costs and as an inverse proxy for market transparency. Results obtained suggests that a U-shaped relationship between fragmentation and adverse selection risk. Thus, visible fragmentation helps reduce adverse selection costs and increases market transparency when fragmentation is relatively lower. When fragmentation is higher however, implied adverse selection costs and market opacity potentially increase with fragmentation. However, the negative impact of fragmentation on market transparency is very limited since historical fragmentation is generally smaller than the upper limit of an optimal range suggested by our analysis. This quadratic relationship is in consistent with existing literature (see as examples, Degryse et al., 2014 and Boneva et al., 2015).

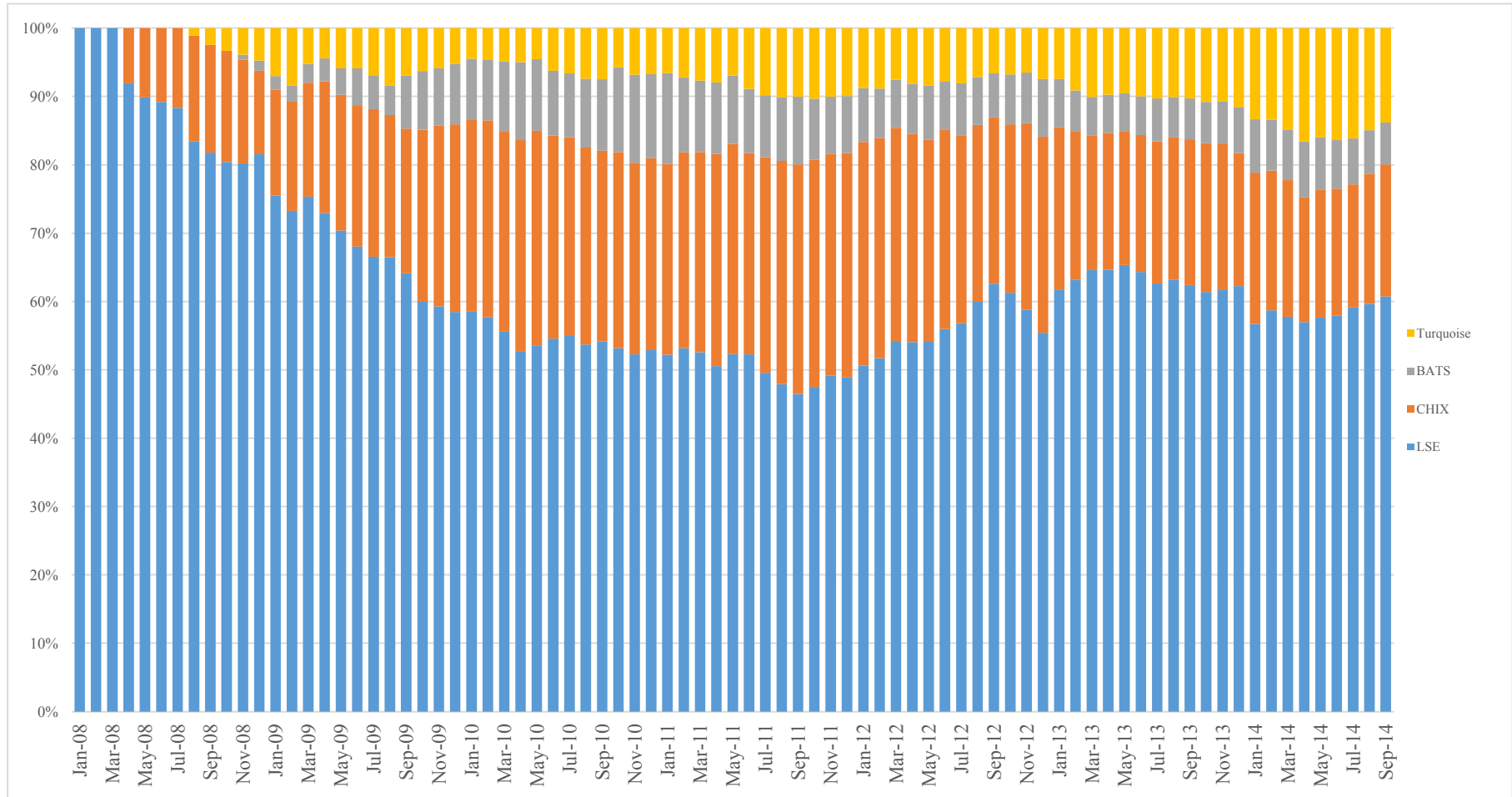
We also make further contributions to the literature by investigating the impact of market fragmentation on market efficiency by adapting Chordia et al. (2008)'s return predictability model to test whether fragmentation reduces short horizon return predictability. We find that fragmentation facilitates market efficiency by eliminating short horizon return predictability and reducing arbitrage opportunities. Our results are consistent with Storckenmaier and Wagenerz (2011) and Menkveld (2013), who argue that order flow competition across trading venues could act as a linkage necessary to minimise arbitrage opportunities.

## Reference:

- Aitken, M., and Frino, A. (1996). Execution costs associated with institutional trades on the Australian stock exchange. *Pacific-Basin Finance Journal*, 4 (1), 45-58.
- Barclay, M. J., Hendershott, T., and McCormick, D. T. (2003). Competition among trading venues: Information and trading on electronic communications networks. *The Journal of Finance*, 58 (6), 2637-2665.
- Boehmer, B., and Boehmer, E. (2003). Trading your neighbor's ETFs: Competition or fragmentation? *Journal of Banking & Finance*, 27 (9), 1667-1703.
- Boneva, L., Linton, O., and Vogt, M. (2015). The effect of fragmentation in trading on market quality in the UK equity market. *Journal of Applied Econometrics*, n/a-n/a.
- Brown, S., Hillegeist, S. A., and Lo, K. (2009). The effect of earnings surprises on information asymmetry. *Journal of Accounting and Economics*, 47 (3), 208-225.
- Buti, S., Rindi, B., and Werner, I. (2011). Diving into dark pool. *Working Paper*.
- Chan, L. K. C., and Lakonishok, J. (1997). Institutional equity trading costs: NYSE versus NASDAQ. *The Journal of Finance*, 52 (2), 713-735.
- Chlistalla, M., and Lutat, M. 2009. The impact of new execution venues on European equity markets' liquidity – the case of Chi-X. In: Nelson, M., Shaw, M. & Strader, T. (eds.) *Value creation in e-business management*. Springer Berlin Heidelberg.
- Chordia, T., Roll, R., and Subrahmanyam, A. (2005). Evidence on the speed of convergence to market efficiency. *Journal of Financial Economics*, 76 (2), 271-292.
- Chordia, T., Roll, R., and Subrahmanyam, A. (2008). Liquidity and market efficiency. *Journal of Financial Economics*, 87 (2), 249-268.
- Chowdhry, B., and Nanda, V. (1991). Multimarket trading and market liquidity. *The Review of Financial Studies*, 4 (3), 483-511.
- Chung, K. H., and Li, M. (2003). Adverse-selection costs and the probability of information-based trading. *Financial Review*, 38 (2), 257-272.
- Chung, K. H., Li, M., and McInish, T. H. (2005). Information-based trading, price impact of trades, and trade autocorrelation. *Journal of Banking & Finance*, 29 (7), 1645-1669.
- Cohen, K. J., Maier, S. F., Schwartz, R. A., and Whitcomb, D. K. (1982). An analysis of the economic justification for consolidation in a secondary security market. *Journal of Banking & Finance*, 6 (1), 117-136.
- Degryse, H., De Jong, F., and Kervel, V. V. (2015). The impact of dark trading and visible fragmentation on market quality. *Review of Finance*, 19, 1587-1622.
- Duarte, J., Han, X., Harford, J., and Young, L. (2008). Information asymmetry, information dissemination and the effect of regulation FD on the cost of capital. *Journal of Financial Economics*, 87 (1), 24-44.
- Easley, D., Hvidkjaer, S., and O'Hara, M. (2002). Is information risk a determinant of asset returns? *The Journal of Finance*, 57 (5), 2185-2221.
- Easley, D., Kiefer, N. M., and O'Hara, M. (1997). The information content of the trading process. *Journal of Empirical Finance*, 4 (2-3), 159-186.
- Easley, D., Kiefer, N. M., O'Hara, M., and Paperman, J. B. (1996). Liquidity, information, and infrequently traded stocks. *The Journal of Finance*, 51 (4), 1405-1436.
- Ellul, A., and Pagano, M. (2006). IPO underpricing and after-market liquidity. *Review of Financial Studies*, 19 (2), 381-421.
- Ende, B., and Lutat, M. (2010). Trade-throughs in European cross-traded equities after transaction costs-empirical evidence for the Euro Stoxx 50. *Working Paper*.
- Foster, F. D., and Viswanathan, S. (1993). Variations in trading volume, return volatility, and trading costs; evidence on recent price formation models. *The Journal of Finance*, 48 (1), 187-211.
- Foucault, T., and Menkveld, A. J. (2008). Competition for order flow and smart order routing systems. *The Journal of Finance*, 63 (1), 119-158.
- Frino, A., Jarnecic, E., and Lepone, A. (2007). The determinants of the price impact of block trades: Further evidence. *Abacus*, 43 (1), 94-106.

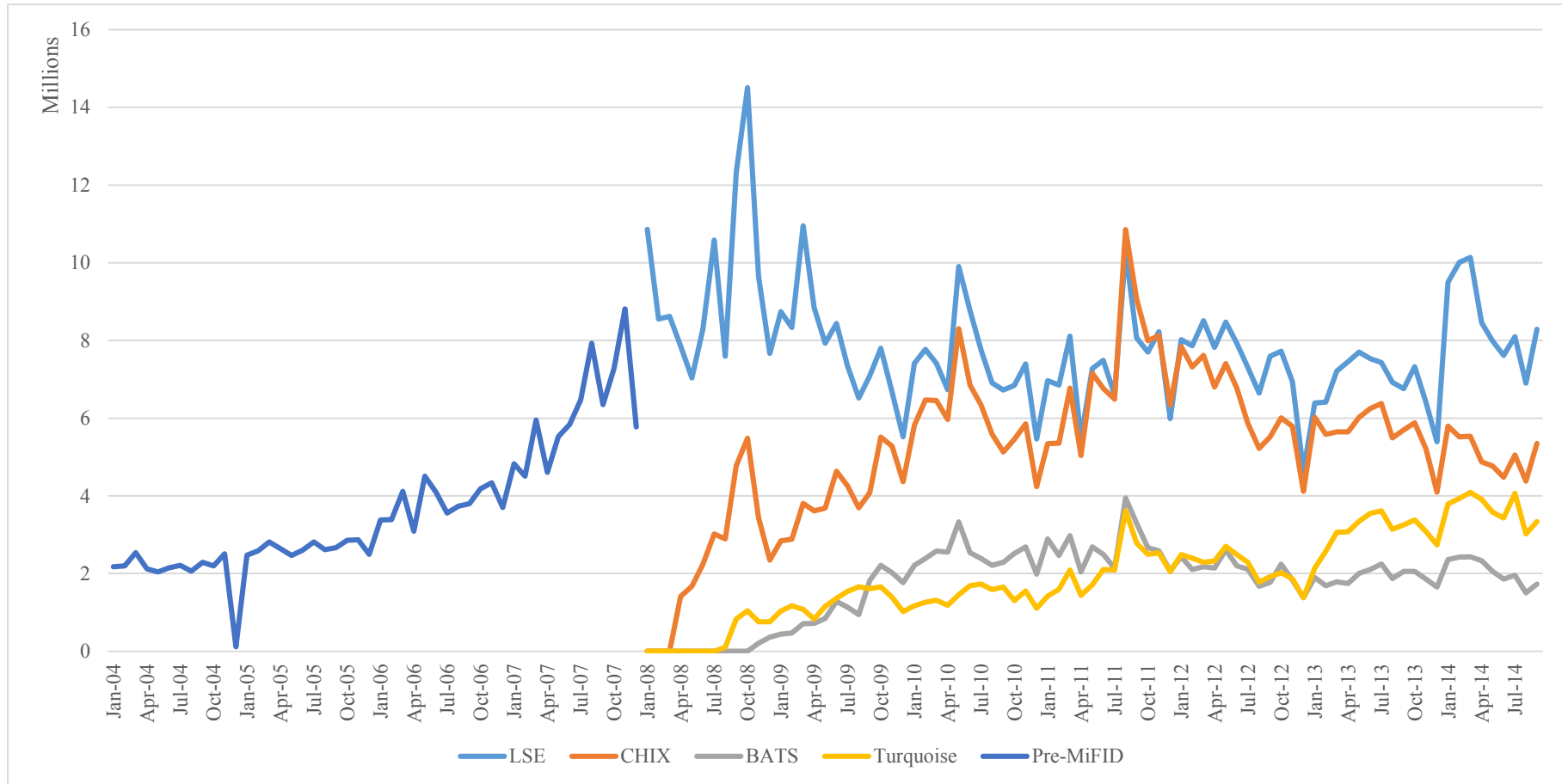
- Froot, K. A., O'connell, P. G. J., and Seasholes, M. S. (2001). The portfolio flows of international investors. *Journal of Financial Economics*, 59 (2), 151-193.
- Grammig, J., Schiereck, D., and Theissen, E. (2001). Knowing me, knowing you:: Trader anonymity and informed trading in parallel markets. *Journal of Financial Markets*, 4 (4), 385-412.
- Gresse, C. (2011). Effects of the competition between multiple trading platforms on market liquidity: Evidence from the mifid experience. *SSRN working paper*.
- Gresse, C. (2014). Effects of lit and dark market fragmentation on liquidity. *Working Paper*.
- Hasbrouck, J., and Saar, G. (2013). Low-latency trading. *Journal of Financial Markets*, 16 (4), 646-679.
- Hendershott, T., Jones, C. M., and Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *The Journal of Finance*, 66 (1), 1-33.
- Hengelbrock, J. O., and Theissen, E. (2009). Fourteen at one blow: The market entry of turquoise. *Working Paper*.
- Hoffmann, P. (2010). Adverse selection, transaction fees, and multi-market trading. *Working Paper*.
- Ibukunle, G. 2015. Competition for order flow and price discovery. *The curious case of high-tech entrants*.
- Koerber, L., Linton, O., and Michael, V. (2013). The effect of fragmentation in trading on market quality in the uk equity market. *Working Paper*.
- Lai, S., Ng, L., and Zhang, B. (2014). Does pin affect equity prices around the world? *Journal of Financial Economics*, 114 (1), 178-195.
- Madhavan, A. (1995). Consolidation, fragmentation, and the disclosure of trading information. *Review of Financial Studies*, 8 (3), 579-603.
- Madhavan, A. (2012). Exchange-traded funds, market structure, and the flash crash. *Financial Analysts Journal*, 68 (4), 20-35.
- Mendelson, H. (1987). Consolidation, fragmentation, and market performance. *The Journal of Financial and Quantitative Analysis*, 22 (2), 189-207.
- Menkveld, A. J. (2011). High frequency trading and the new-market makers. *Working Paper*.
- Menkveld, A. J. (2013). High frequency trading and the new market makers. *Journal of Financial Markets*, 16 (4), 712-740.
- Nimalendran, M., and Ray, S. (2014). Informational linkages between dark and lit trading venues. *Journal of Financial Markets*, 17, 230-261.
- O'Hara, M., and Ye, M. (2011). Is market fragmentation harming market quality? *Journal of Financial Economics*, 100 (3), 459-474.
- Pagano, M. (1989). Trading volume and asset liquidity. *The Quarterly Journal of Economics*, 104 (2), 255-274.
- Storckenmaier, A., and Wagenerz, M. (2011). Do we need a european "national market system"? Competition, arbitrage, and suboptimal executions. *Working Paper*.
- Vega, C. (2006). Stock price reaction to public and private information. *Journal of Financial Economics*, 82 (1), 103-133.
- Yin, X. (2005). A comparison of centralized and fragmented markets with costly search. *The Journal of Finance*, 60 (3), 1567-1590.
- Zhu, H. (2014). Do dark pools harm price discovery? *Review of Financial Studies*, 27, 747-789.

Figure 1. Traded volume in Percentage



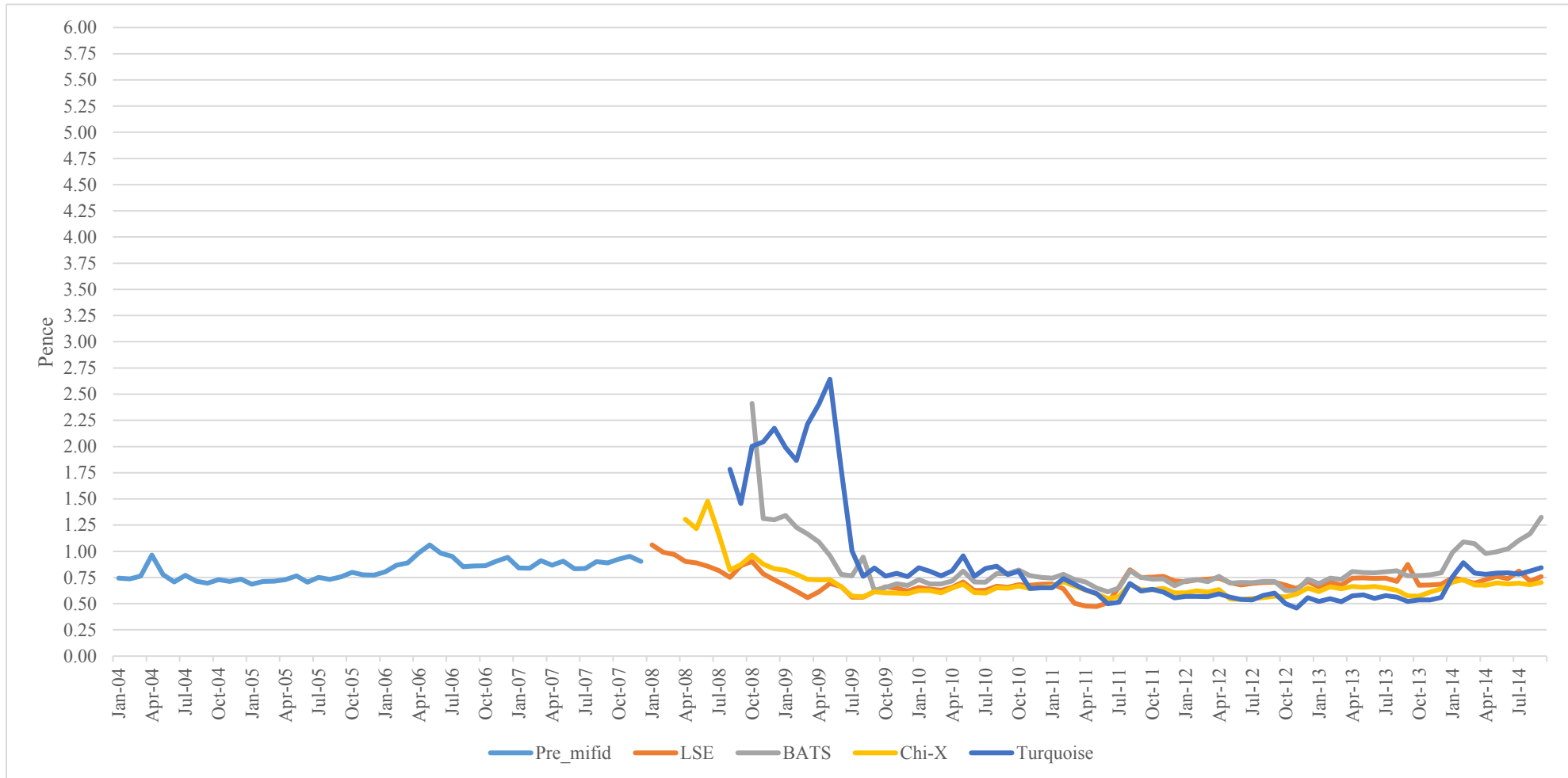
The figure displays the total monthly trading volume in percentage in primary market, LSE and three other trading venues, BATS, Chi-X and Turquoise from January 2008 to September 2014.

Figure 2. Total Number of Trades before and after the implementation of MiFID



The figure displays the total monthly number of trades across days and stocks before and after the implementation of MiFID from January 2004 to September 2014. The number of trades in primary market, LSE and three other trading venues, BATS, Chi-X and Turquoise are plotted in the figure.

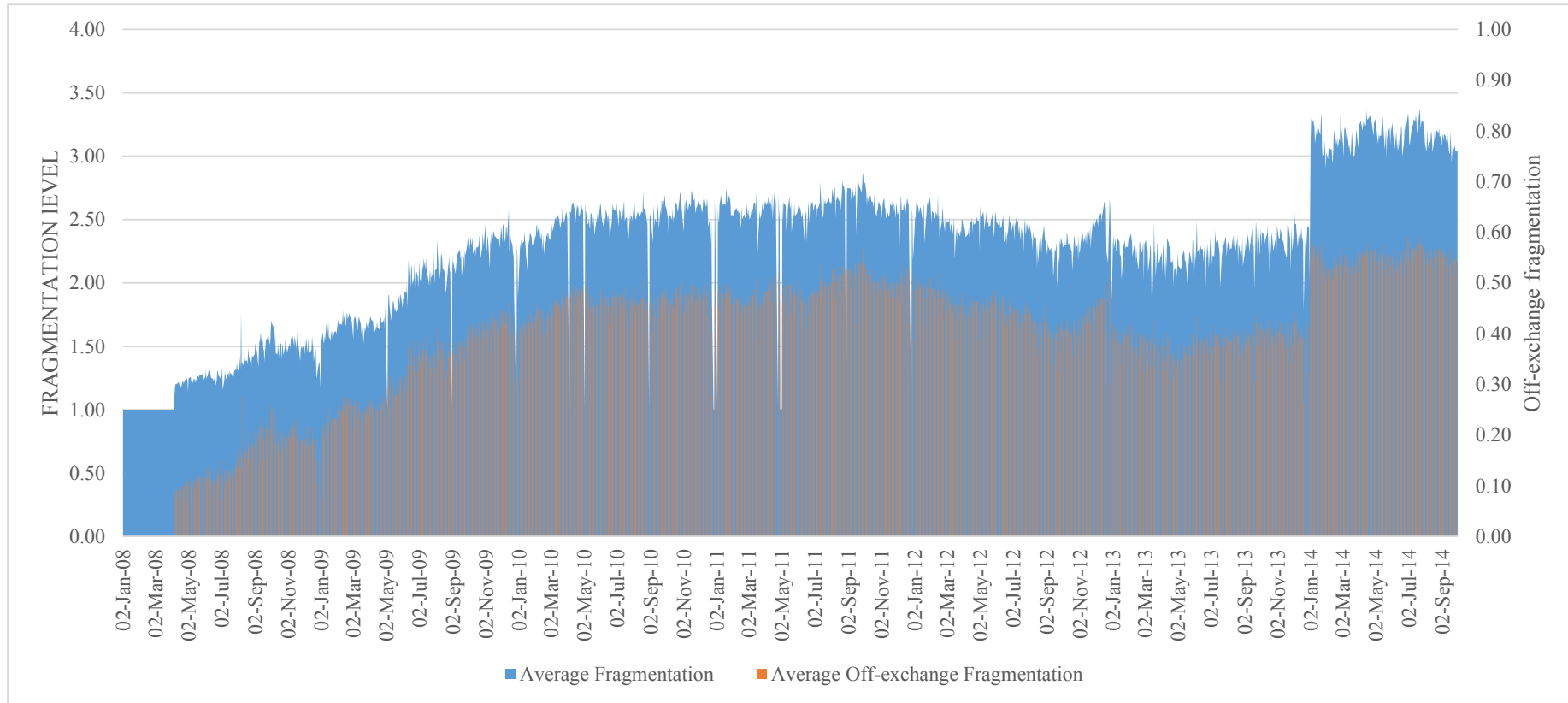
Figure 3. Effective Bid Ask Spread



The figure displays the monthly average value effective bid-ask spread across days and stocks before and after the implementation of MiFID from January 2004 to September 2014. Effective bid-ask spread equals to twice the absolute value of the difference between the execution price and prevailing midpoint at execution. The average values of effective bid ask spread on listing exchange, the LSE and three other venues, BATS, Chi-X and Turquoise are plotted on the figure.

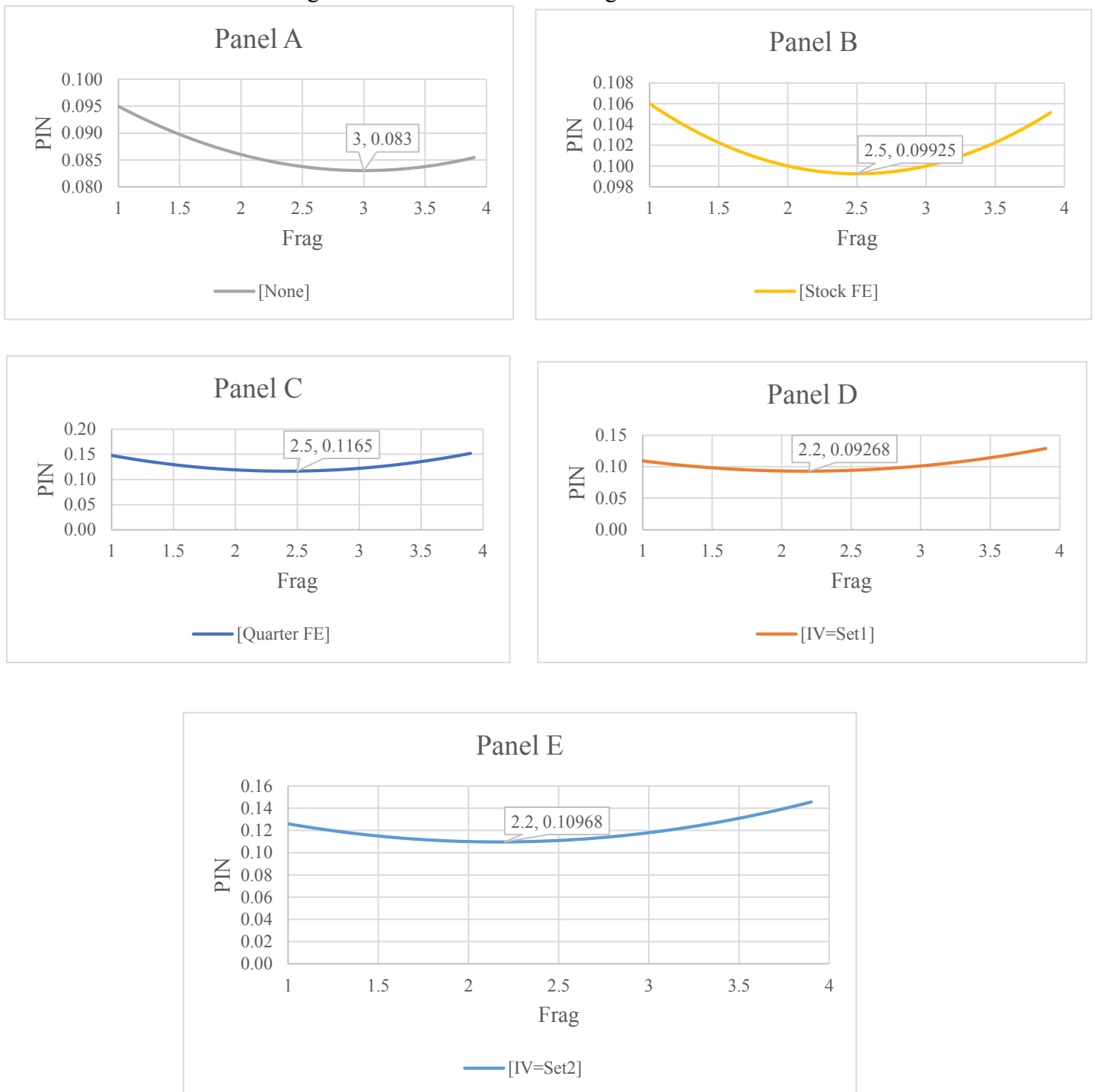


Figure 4. Daily average level of Fragmentation and off-exchange Fragmentation



The figure displays the monthly average overall fragmentation and off-exchange fragmentation from January 2008 to September 2014. Overall fragmentation is calculated as one divided by the sum of the squared market shares of LSE and the three other trading venues, BATS, Chi-X and Turquoise. Off-exchange fragmentation is calculated shares traded off-exchange divided by total shares traded.

Figure 5. The effect of visible fragmentation on PIN



The panels show the implied effect of visible fragmentation on PIN using various estimation approaches. The results are shown for the probability of informed-trading (PIN) displayed on the vertical axis. The horizontal axis shows the level of visible fragmentation. The five panels include regression with no fixed effects, stock fixed-effect, quarter fixed effect and two sets of IVs.

**Table 1. Descriptive Statistics**

This table reports means, standard deviations, and quartile points (25%, Median, 75%) of variables calculated at the stock-day level. *Effective spread* equals twice the absolute value of the difference between the execution price and prevailing midpoint at execution. *Volatility* is the intraday standard deviation of trade-by-trade returns. *Total Daily Pound Volume* is the sum value of daily total pound volume traded of stock *i* on day *t*. *Total Daily Trades* is the daily aggregated value of number of trades of stock *i* on day *t*. The sample comprises the FTSE100 stocks from January 1, 2004 to September 30, 2014

	Mean	Std.dev	25%	Median	75%
Stock characteristics					
Effective spread	0.0083	0.0118	0.0025	0.0063	0.0115
Volatility	0.0070	0.0891	0.0003	0.0004	0.0005
Volumes and Trades					
Total Daily Pound Volume	1.09E+08	4.210E+08	1.900E+07	4.000E+07	1.220E+08
Total Daily Trades (Counts)	8428.43	8300.54	3503.00	5805.00	9966.00

**Table 2. Correlations between independent variables**

This table reports correlations between key trading variables. *log(Pound Volume)* is the log of total daily pound-volume traded in stock *i*; *log(TradeCount)* is the log of total number of transaction of stock *i* on day *t*; *tradesize* is the median of daily trade size of stock *i* on day *t*; *Volatility* is the daily standard deviation of the trade-by-trade return of of stock *i* on day *t*; Finally, *Algo* controls for the algorithm trading activity, it equals the total number of quote changes over pound volume of stock *i* on day *t*. *Effective bid-ask spread* equals twice the absolute value of the difference between the execution price and prevailing midpoint at execution.

	Log(Pound Volume)	Log(TradeCount)	Log(TradeSize)	Volatility	Effective spread
Log(Pound Volume)	1				
Log(TradeCount)	0.5781	1			
Log(TradeSize)	0.8538	0.1856	1		
Volatility	-0.0689	0.0325	-0.1787	1	
Effective spread	-0.0141	-0.1202	0.0494	0.0007	1

**Table 3. Descriptive Statistics of Fragmentation and PIN**

This table reports means, standard deviations, and quartile points (25%, Median, 75%) of variables calculated at the stock-day level. Frag is the overall level of visible fragmentation. This index is calculated as one divided by the sum of the squared market shares of LSE and the three other venues, BATS, Chi-X and Turquoise. This proxy writes as follows:

$$FRAG = \frac{1}{\sum_k (\sum_j V_j)^2}$$

Frag<sub>EX</sub> is the off-exchange market fragmentation and it equals:

$$FRAG_{EX} = \text{Off}^* - \text{exchange} - \text{volume} / \text{Total} - \text{volume}$$

PIN parameters are computed for each stock and time interval by maximising the following likelihood function:

$$\begin{aligned} L((B, S) | \theta) = & (1 - \alpha) e^{-\varepsilon_b} \frac{\varepsilon_b^B}{B!} e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!} \\ & + \alpha \delta e^{-\varepsilon_b} \frac{\varepsilon_b^B}{B!} e^{-(\mu + \varepsilon_s)} \frac{(\mu + \varepsilon_s)^S}{S!} \\ & + \alpha (1 - \delta) e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!} e^{-(\mu + \varepsilon_b)} \frac{(\mu + \varepsilon_b)^B}{B!} \end{aligned}$$

where  $B$  and  $S$  respectively correspond to the total number of buy and sell orders for the day within each trading interval.  $\theta = (\alpha, \delta, \mu, \varepsilon)$  is the parameter vector for the model.  $\alpha$  corresponds to the probability of an information event,  $\delta$  is the conditional probability of a low signal of an information event,  $\mu$  is the arrival rate of informed orders, and  $\varepsilon$  is the arrival rate of uninformed orders. The probability that a trade is informed for each stock and within each interval is then computed as:

$$PIN = \frac{\alpha \mu}{\alpha \mu + 2\varepsilon}$$

The sample comprises the FTSE100 stocks from April, 2008 to September 30, 2014

	Mean	Std.dev	25%	Median	75%
Stock characteristics					
Frag	2.3012	0.6181	1.9049	2.3814	2.7428
Frag <sub>EX</sub>	0.3930	0.1599	0.3092	0.4256	0.5145
PIN	0.1787	0.1016	0.1150	0.1545	0.2111

**Table 4. Effects of Fragmentation on Market Adverse Selection**

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

$$PIN_{i,t} = \alpha + \beta_1 Frag_{i,t} + \beta_2 Frag^2_{i,t} + \beta_3 \log(PoundVolume_{i,t}) + \beta_4 \log(TradeCount_{i,t}) + \beta_5 \log(TradeSize_{i,t}) + \beta_6 volatility_{i,t} + \beta_7 Algo_{i,t} + \beta_8 EBAS_{i,t} + \varepsilon$$

$PIN_{it}$  is an inverse proxy for market transparency for stock  $i$  on day  $t$  and is computed as described in Table 3.  $FRAG$  is as defined in Table 3,  $\log(PoundVolume_{it})$  is the natural logarithm of sum of pound volume traded for stock  $i$  on day  $t$ .  $\log(TradeCount_{it})$  is the log of total number of transaction for stock  $i$  on day  $t$ .  $Volatility$  is the standard deviation of trade-by-trade returns of stock  $i$  on day  $t$ .  $\log(TradeSize_{it})$  is the log of median of daily trade size of stock  $i$  on day  $t$ .  $Algo_{it}$  equals to the total number of quote changes over pound volume of stock  $i$  on day  $t$ .  $EBAS_{it}$  is average effective bid-ask spread of stock  $i$  on day  $t$ . \*\*\*, \*\* and \* indicate statistical significance at 0.01, 0.05 and 0.1 levels respectively.

	PIN				
Frag	-0.018*** (-4.66)	-0.015*** (-3.88)	-0.077*** (-12.06)	-0.052*** (-7.27)	-0.063*** (-2.74)
Frag <sup>2</sup>	0.003*** (3.63)	0.003*** (3.13)	0.016*** (11.59)	0.012*** (6.81)	0.012** (2.50)
Log(PoundVolume)	0.016*** (24.66)	0.016*** (21.83)	0.003*** (3.95)	0.018*** (25.31)	0.015*** (20.61)
Log(TradeCount)	-0.011*** (-17.06)	-0.011*** (-15.41)	0.006*** (6.05)	-0.012*** (-17.97)	-0.009*** (-10.59)
Log(TradeSize)	-0.013*** (-20.34)	-0.013*** (-19.64)	-0.009*** (-6.36)	-0.016*** (-19.60)	-0.012*** (-17.56)
Volatility	0.027*** (5.55)	0.001 (0.15)	0.025*** (4.56)	0.022*** (4.36)	0.028*** (5.73)
Algorithm Trades	0.164*** (6.97)	-0.032 (-1.27)	0.156*** (6.18)	0.180*** (7.15)	0.109*** (3.93)
Mean_EBAS	0.220** (2.46)	0.149* (1.85)	0.283** (2.32)	0.228** (2.45)	0.203** (2.49)
intercept	0.110*** (16.31)	0.118*** (12.38)	0.209*** (21.71)	0.149*** (15.86)	0.166*** (5.75)
Adj_R sqr	0.85%	2.30%	2.57%	0.75%	0.55%
Estimation Method	OLS	OLS	OLS	2SLS	GMM
Fixed Effects	None	Stock	Quarter	None	None
IV	None	None	None	Set1	Set2

**Table 5. Effects of off-exchange Fragmentation on Market Adverse Selection**

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

$$PIN_{i,t} = \alpha + \beta_1 Frag_{EX\ i,t} + \beta_2 Frag_{EX\ i,t}^2 + \beta_3 \log(PoundVolume_{i,t}) + \beta_4 \log(TradeCount_{i,t}) + \beta_5 \log(TradeSize_{i,t}) + \beta_6 volatility_{i,t} + \beta_7 Algo_{i,t} + \beta_8 EBAS_{i,t} + \varepsilon$$

$PIN_{it}$  is an inverse proxy for market transparency for stock  $i$  on day  $t$  and is computed as described in Table 3.  $FRAG_{EX}$  is as defined in Table 3.  $\log(PoundVolume_{it})$  is the natural logarithm of sum of pound volume traded for stock  $i$  on day  $t$ .  $\log(TradeCount_{it})$  is the log of total number of transaction for stock  $i$  on day  $t$ .  $Volatility$  is the standard deviation of trade-by-trade returns of stock  $i$  on day  $t$ .  $\log(TradeSize_{it})$  is the log of median of daily trade size of stock  $i$  on day  $t$ .  $Algo_{it}$  equals to the total number of quote changes over pound volume of stock  $i$  on day  $t$ .  $EBAS_{it}$  is average effective bid-ask spread of stock  $i$  on day  $t$ . \*\*\*,\*\* and \* indicate statistical significance at 0.01, 0.05 and 0.1 levels respectively.

	PIN				
Fragmentation <sub>EX</sub>	-0.018** (-2.38)	-0.010 (-1.30)	-0.173*** (-11.43)	0.173*** (8.71)	0.076 (0.91)
(Fragmentation <sub>EX</sub> ) <sup>2</sup>	-0.002 (-0.15)	-0.010 (-0.81)	0.188*** (10.02)	-0.331*** (-9.61)	-0.106 (-0.97)
Log(PoundVolume)	0.016*** (23.69)	0.016*** (21.00)	0.003*** (3.81)	0.013*** (16.62)	0.017*** (24.04)
Log(TradeCount)	-0.011*** (-16.22)	-0.010*** (-14.29)	0.006*** (6.20)	-0.008*** (-11.88)	-0.012*** (-13.43)
Log(TradeSize)	-0.012*** (-20.02)	-0.012*** (-19.04)	-0.009*** (-6.19)	-0.007*** (-8.07)	-0.012*** (-19.16)
Volatility	0.038*** (6.07)	0.012 (1.58)	-0.010 (-1.30)	0.157*** (11.81)	0.056* (1.94)
Algorithm Trades	0.158*** (6.84)	-0.041 (-1.54)	0.149*** (5.95)	0.092*** (4.34)	0.192*** (6.72)
Mean_EBAS	0.218** (2.45)	0.146* (1.84)	0.285** (2.35)	0.205** (2.29)	0.233** (2.40)
intercept	0.093*** (18.55)	0.100*** (12.35)	0.146*** (18.95)	0.069*** (13.52)	0.075*** (4.92)
Adj_R sq	0.73%	2.31%	2.57%	0.19%	0.63%
Estimation Method	OLS	OLS	OLS	2SLS	GMM
Fixed Effects	None	Stock	Quarter	None	None
IV	None	None	None	Set1	Set2

**Table 6. Market Quality Test: Short-term predictive Test**

Predictive regressions of five-minute returns on lagged order imbalance ( $OIB\mathcal{L}_{t-1}$ ), and lagged order imbalance interacted with a dummy variable for fragmentation.  $OIB\mathcal{L}_t$  is 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  $t$ . The fragmentation dummy,  $FRAG$ , is 1.0 when the daily level of fragmentation is at least one standard deviation above the average level of fragmentation for the surrounding days over (-15, +15), otherwise zero. Panel A presents the results for estimation using fragmentation dummy based on overall level of fragmentation and Panel B uses fragmentation dummy based on only off-exchange fragmentation as a proportion of all trading. \*\*\*,\*\* and \* indicate statistical significance at 0.01, 0.05 and 0.1 levels respectively.

	Panel A			Panel B	
	Coefficient	t-stats		Coefficient	t-stats
$OIB\mathcal{L}_{t-1}$	$1.52 \times 10^{-3}***$	17.17	$OIB\mathcal{L}$	$1.39 \times 10^{-3}***$	14.00
$OIB\mathcal{L}_t$					
$_i*FRAG$	$-6.44 \times 10^{-4}***$	-4.14	$OIB\mathcal{L}*FRAG\_EX$	$-2.22 \times 10^{-4}***$	-2.01
$cons$	$-3.21 \times 10^{-5}***$	-1.38	$cons$	$-3.19 \times 10^{-5}***$	-1.37