UK Equity Market Microstructure in the Age of Machine

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Contents

List of Abbreviations

AT	**Algorithm Trading**
ATs	**Algorithm Traders**
CAPM	**Capital Asset Pricing Model**
DMM	**Designate Market Maker(s)**
HFT	**High-Frequency Trading**
HFTs	**High-Frequency Traders**
IPOs	**Initial Public Offerings**
LSE	**London Stock Exchange**
MiFID	**Markets in Financial Instrument Directives**
MTFs	**Multilateral Trading Facilities**
NBBO	**National Best Bid and Offer**
NYSE	**New York Stock Exchange**
PIN	**Probability of Informed Trading**
Reg NMS	**Regulation National Market System**
RMs	**Regulated Markets**
SEAQ	**Stock Exchange Automated Quotation**
SETS	**Electronic Trading Service**
SIs	**Systematic Internalisations**
SORT	**Smart Order Routing Technology**

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Abstract

Financial markets perform two major functions. The first is the provision of liquidity in order to facilitate direct investment, hedging and diversification; the second is to ensure the efficient price discovery required in order to direct resources to where they can be best utilised within an economy. How well financial markets perform these functions is critical to the financial welfare of every individual in modern economies. As an example, retirement savings across the world are mostly invested in capital markets. Hence, the functioning of financial markets is linked to the standard of living of individuals. Technological advancements and new market regulations have in recent times significantly impacted how financial markets function, with no period in history having witnessed a more rapid pace of change than the last decade. Financial markets have become very complex, with most of the order execution now done by computer algorithms. New high-tech trading venues, such as dark pools, also now play outsized roles in financial markets. A lot of the impacts of these developments are poorly understood. In the EU particularly, the introduction of the Markets in Financial Instruments Directive (MiFID) and advancements in technology have combined to unleash a dramatic transformation of European capital markets. In order to better understand the role of high-tech trading venues in the modern financial markets' trading environment generally and in the UK in particular, I conduct three studies investigating questions linked to the three major developments in financial markets over the past decade; these are algorithmic/high-frequency trading, market fragmentation and dark trading. In the first study, I examine the changing relationship between the price impact of block trades and informed trading, by considering this phenomenon within a high-frequency trading environment on intraday and inter-day bases. I find that the price impact of block trades is stronger during the first hour of trading; this is consistent with the hypothesis that information accumulates overnight during non-trading hours. Furthermore, private information is gradually incorporated into prices despite heightened trading frequency. Evidence suggests that informed traders exploit superior information across trading days, and stocks with lower transparency exhibit stronger information diffusion effects when traded in blocks, thus informed block trading facilitates price discovery. The second study exploits the

regulatory differences between the US and the EU to examine the impact of market fragmentation on dimensions of market quality. Unlike the US's Regulation National Market System, the EU's MiFID does not impose a formal exchange trading linkage or guarantee a best execution price. This has raised concerns about consolidated market quality in increasingly fragmented European markets. The second study therefore investigates the impact of visible trading fragmentation on the quality of the London equity market and find a quadratic relationship between fragmentation and adverse selection costs. At low levels of fragmentation, order flow competition reduces adverse selection costs, improves market transparency and enhances market efficiency by reducing arbitrage opportunities. However, high levels of fragmentation increase adverse selection costs. The final study compares the impact of lit and dark venues' liquidity on market liquidity. I find that compared with lit venues, dark venues proportionally contribute more liquidity to the aggregate market. This is because dark pools facilitate trades that otherwise might not easily have occurred in lit venues when the spread widens and the limit order queue builds up. I also find that informed and algorithmic trading hinder liquidity creation in lit and dark venues, while evidence also suggests that stocks exhibiting low levels of informed trading across the aggregate market drive dark venues' liquidity contribution.

Keyword: Probability of informed trading (PIN), Block trades, Opacity, Price impact, Price discovery, Multilateral Trading Facilities (MTFs), Market transparency, Adverse selection costs, Market efficiency, Dark pools, MiFID, Liquidity commonality, trading liquidity, Algorithm trading , High-frequency trading

1. Introduction and Literature Review

1.1.Introduction

The modern financial markets have changed quickly because of the development of computer science and technology. Advanced technology has provided a high frequency and computer-based trading platform for investors. Automated high-frequency trading (HFT) has grown tremendously in the past 20 years and is responsible for about half of all trading activities at stock exchanges worldwide (Zook and Grote, 2017). At the same time, the market landscape has also altered and new trading rules have been adopted to promote competition and support better price formation. New regimes such as the Markets in Financial Instruments Directive (MiFID) was implemented in Europe to ensure a high degree of harmonised protection for market participants and financial instruments. Technological advancements and new market regulations have in recent times significantly impacted how financial markets function. Financial markets have become very complex, with most of the order execution now done by computer algorithms. New high-tech trading venues, such as dark pools, also now play outsized roles in financial markets.

To better understand the role of high-tech trading venues in the modern financial markets' trading environment generally and in the UK in particular, I conduct three studies investigating questions linked to the three major developments in financial markets over the past decade; these are algorithmic/high-frequency trading, market fragmentation and dark trading. My investigations in this thesis directly contribute to filling the gap in the existing literature. The following paragraphs briefly introduce the contents of the remaining chapters of this thesis.

Chapter 2 provides an institutional background to the subsequent chapters by conducting an analysis of the LSE's Stock Exchange Electronic Trading Service (SETS) and MiFID. The launch of SETS in 1997 led to the transformation of the LSE from a purely quote-driven exchange to a hybrid one, incorporating a quote-drive segment (broker-dealer market) and an order-driven limit order book (SETS). This hardware upgrade provides a centralised electronic order book for participants to compete for order flow. SETS can execute millions of trades a day at sub-second latencies, thereby fostering HFT activities in the UK equity market. About a decade after SETS was launched, MiFID further altered the market landscape by inducing the introduction of more trading venues, leading to even more competition for order flow.

In Chapter 3, I investigate the relationship between informed trading and the price impact of block trades of FTSE100 stocks on the LSE. I aim to answer the question of how informed trading activity facilitates the price discovery process in the HFT era. My contributions here are threefold. First, I present evidence on the information diffusion process in the UK equity market in the HFT era. Existing empirical studies focus on corporate events such as earnings announcement (see for example Vega, 2006) and merger and acquisition (see for example Barclay and Warner, 1993) to control for informed trading activities. This research expands observations of block trades to normal trading hours since informed trading activities occur across trading hours. Second, I find intraday and inter-day patterns of this information diffusion process. The results show that the impounding of information into stock prices is more predominant during the first trading hour than any other time period. Moreover, block trading activity is positively correlated with informed trading activity and informed trading at day$_{t-1}$ can still affect informed traders' block transactions at day$_t$, supporting Foster and Viswanathan (1994) and Hong and Stein (1999) who suggest that private information is gradually incorporated into the price discovery prices. Third, in this chapter, the probability of informed trading (PIN) is constructed to proxy the level of informed trading and firms' financial transparency. The results based on portfolio analysis indicate that informed trading aids price discovery for stocks with less financial transparency. This provides empirical support to Vega's (2006) finding on the high-frequency trading level.

In Chapter 4, I expand the research scope from the LSE to other MTFs to study the policy implications of trading fragmentation under MiFID. This chapter answers the research question regarding how visible trading fragmentation affects market transparency and efficiency. In 2007, MiFID led to an unprecedented increase in the number of trading venues in Europe. Consequently, the market became fragmented since trading venues had to compete with each other to attract order flow. Unlike the US Regulation National Market System (Reg NMS), MiFID does not mandate a formal exchange linkage to guarantee that orders are always executed at the best available price. Some researchers, such as Hoffmann (2010) and O'Hara and Ye (2011), have expressed concern about this potentially sub-optimal trading rule. In this chapter, I present first-order evidence of whether or not visible trading fragmentation induces adverse selection costs and informational inefficiency in the aggregate market. My analysis is conducted on an aggregate market by creating a consolidated order book of FTSE100 stocks traded on the three largest MTFs and the LSE. My dataset covers a ten-year period ending in 2014. This is the first study to assess the impact of fragmentation on the aggregate market for trading Europe's highest volume stocks over such a long period. A quadratic relationship is found between fragmentation and adverse selection risk.

On one hand, visible fragmentation helps to both reduce adverse selection costs and increase market transparency at low levels of fragmentation. On the other hand, however, when fragmentation is high, the implied adverse selection cost and market opacity potentially increase with the level of fragmentation. The results reveal that the negative impact of fragmentation on transparency is very limited. In the second part of the empirical analysis, a short-term return predictability model is employed to test the effect of fragmentation on market efficiency. Results also indicate that order flow competition tends to reduce short-term return predictability, thus enhancing market efficiency. This chapter has important policy implications for the debate surrounding trading fragmentation in European equity markets. Based on the empirical results, market fragmentation should be viewed as a value-creating competition phenomenon that benefits market transparency and price efficiency.

Chapter 5 continues to expand the research scope to MTFs' new type of trading venue, dark pools, which are exempt from publicly displayed bid and offer quotes. The development of dark pools is intended to reduce the transaction costs for wholesale trades based on liquidity reasons. A computer algorithm in dark pools matches dark buy and sell orders without revealing traders' identities and sets execution at the mid-quote of the best bid and ask price derived from the primary market. However, dark pools are criticised for not providing price discovery. Many regulators are concerned that the growth of dark pools may at some point affect the quality of price discovery in lit markets. In Europe, regulators intend to put more restrictions on dark pool trading. MiFID II proposes the introduction of a volume cap for dark pool trading. This restriction is scheduled for implementation at the beginning of 2018. Thus, it is beneficial for regulators and researchers to know more about the implications of dark pool trading. However, it seems that the effects of dark trading on market liquidity remain obscure. Brugler (2015) and Gresse (2017) suggest that dark trading improves the liquidity of FTSE100 stocks. However, based on data from the Toronto Stock Exchange, Foley and Putniņš (2016) do not find evidence that midpoint dark trading consistently benefits market liquidity. In contrast, Degryse et al. (2015) find that dark fragmentation has a detrimental effect on global liquidity. In this chapter, I aim to disentangle the effects of dark trading on aggregate market liquidity by employing an established liquidity commonality model. The results suggest that, compared with lit venues, dark pools proportionally contribute more liquidity when the market-wide liquidity starts to increase. This is because dark venues can facilitate trades that otherwise cannot be traded easily in lit venues. Further tests also show that informed trading activity exerts a stronger negative impact on dark pool liquidity. This finding is in line with Zhu's (2014) study that informed investors face low execution probabilities in dark pools because informed traders typically trade at the same side of the dark pools. This research provides first-order evidence that midpoint dark trading potentially contributes liquidity to the aggregate market.

Chapters 3, 4 and 5 focus on one issue as a stand-alone study. I use FTSE100 stocks as sample data for empirical tests across the three chapters. The next part in this section discusses the literature related to my studies.

1.2. Literature Review

According to Fama's (1970) efficient market hypothesis, if new information about a given stock is released into the public domain, perhaps via an earnings announcement, that information will be incorporated into the stock's price rapidly and rationally; and the trading process should have no effect on the price discovery process. However, in the real world, trading is a complex process. This is because: (1) trades do not arrive simultaneously in the market; and (2) trading information is not symmetric. Based on these factors, market microstructure research has been developed as a branch of finance and economics to explain how trading occurs. Microstructure theories such as inventory-based models and information-based models were developed to explain how market makers set bid-ask spread to compensate for their inventory risk and adverse selection risk.

In relatively more recent literature, O'Hara (2003) suggests that the two main functions of a market are to provide liquidity and encourage price discovery. Liquidity is a measure of traders' possibility to trade. In a liquid market, instruments are traded at the price close to their fundamental value. Conversely, in an illiquid market, buy and sell orders appear to push transaction price up and down. Price discovery is the process by which new information is incorporated to security prices. Effective price discovery is critical as it facilitates pricing quantity and quality of an asset at a specified time and place. Liquidity provision, price discovery and information flow are interrelated and closely linked to the execution system of a financial market. On the micro level, a functional financial market will attract investors to trade fairly-priced stocks. Companies will also rely on stock exchange to launch their initial public offerings

(IPOs), raise capital and manage shareholders' wealth. On the macro level, the depth of security markets links the functioning of the financial system and long-term economic growth. For these reasons, conducting microstructure research has important implications for market design and regulation, especially when technologies have a profound impact on trading regulations. This thesis is motivated by the need to investigate liquidity, price discovery and other market quality issues in the context of modern technology-driven markets. In the next paragraphs, I review the microstructure literature for price discovery and liquidity in financial markets by linking them together with the evolution of the market infrastructure.

Liquidity is the degree to which a larger order can be executed within a short period of time with little or no price impact. According to Harris (1990), liquidity measures have several dimensions including width, depth, immediacy and resiliency. Width is represented by the bid-ask spread, which is the difference between bid and offer prices. Bid-ask spread reflects the cost borne by the traders and the economic gain for market makers. Depth refers to the maximum size of a trade for any given bid-ask spread. Immediacy captures how quickly a given number of shares can be traded at a given cost, and resiliency is a measure of the ability to trade at a minimal price impact (given non-informative trades).

Early theoretical papers find that transaction cost has little impact on security prices because liquidity cost is small compared to equilibrium risk premium (see for example Constantinides, 1986, Aiyagari and Gertler, 1991, Heaton and Lucas, 1996, Vayanos and Vila, 1999). However, Amihud and Mendelson (1986) suggest that the short-term movement of asset prices can reflect liquidity cost. Several studies show a link between asset prices and a variety of liquidity measures such as spreads, depths and volumes (see for example Brennan and Subrahmanyam, 1996, Easley et al., 2002). In this context liquidity studies should be based on a theory of information asymmetry, which assumes that one group of sophisticated traders possess more information than other traders in the market. Well-informed traders tend to exploit the information and then profit at the expense of less-informed traders (Harris, 2003). Easley and O'Hara (1987) and Karpoff (1987) suggest that informed traders are more likely to trade aggressively with their private information rather than exploit it gradually. Blau et al. (2009) hold that informed traders do indeed still prefer block trades for informed trading. Studies also indicate that in the case of private information events, market makers will trade against informed traders in order to reduce the exposure of adverse selection costs by widening the spreads and lowering the market depth. This also implies a negative relationship between informed trading activities and market liquidity.

Beyond the theoretical and empirical studies on the impact of information on liquidity, researchers also seek to answer whether liquidity affects risk diversification. Literature documents the liquidity commonality effect. Chordia et al. (2000), Hasbrouck and Seppi (2001) and Korajczyk and Sadka (2008) find that liquidity commonality exists in the US stock market. This indicates that the liquidity of individual stocks co-vary with market-wide liquidity. Such liquidity commonality forms a systemic component of the risk of individual assets that cannot be diversified away. Karolyi et al. (2012) show that liquidity commonality is stronger in countries with high market volatility and more international investors. This can be explained by the fact that liquidity providers tend to re-evaluate the optimal level of their inventory by buying (selling) and re-setting the bid-ask spread when market-wide liquidity is increasing (decreasing). More recent studies reveal that liquidity commonality also exists in various asset classes, such as bonds (Chordia et al., 2005), options (Cao and Wei, 2010) and commodity markets (Marshall et al., 2012). Chordia et al. (2002b) suggest that, even if such commonality exists, it may still be diversifiable across different asset classes. If an exogenous shock causes a liquidity problem in one market, it may induce a corresponding liquidity inflow in another market. This would suggest only a secondary role for liquidity in affecting the risk of holding an asset (O'Hara, 2003).

However, this is not the case for the other main function of financial markets, i.e. price discovery, which refers to the ability of the market to find an efficient price (O'Hara, 2003). In multiple venues/market settings, the concept of price discovery implies that prices for the same security in different markets should converge in the long run, even if they do deviate from the equilibrium in the short run. Lintner (2009) asserts that price formation shows that financial markets aggregate the beliefs of individual traders, and the market equilibrium price is weighted average of these beliefs.

The evolution of asset price also requires a consideration of the nature of the participants (i.e. whether traders are informed or uninformed, see for example Grossman, 1976). Informed traders know the true value of assets and trade based on their superior information. Uninformed traders have no resources to collect (superior) information, but they know that prices and transaction volume will reflect the information harboured by informed traders. Thus, when they trade against informed traders, uninformed traders will seek compensation for trading under information asymmetry. It is difficult for uninformed traders to diversify information risk as uninformed traders could face an information disadvantage in every asset they hold. In this scenario, simply adding assets will not lead to diversification but increase the potential loss against informed traders. Consequently, conditions for the capital market pricing model (CAPM) will not hold. Under this framework, when informed traders trade, the asset price will reflect all the information to the market and private information will be transmitted from the informed to the uninformed traders. However, uninformed traders tend to trade against informed traders by widening spreads in order to be compensated, thereby undermining market liquidity. In order to minimise transaction costs and illiquidity, informed traders are incentivised to hide their intention by deploying dynamic trading techniques, such as breaking up trades (see for example Kyle, 1985, Admati and Pfleiderer, 1988). As a result, information is gradually incorporated into prices via continuous order flows. Diamond and Verrecchia (1981) show that private information is valuable and the aggregation of this information plays a prominent role in the price discovery process. The literature holds wide ranging views on how market efficiency is connected to liquidity and price discovery. The next two paragraphs will attempt to reconcile these views.

Contrary to the popular view, market efficiency does not require the market price to be equal to asset's true value at every point of the trading time (Damodaran, 2012). All it requires is the deviation part to be unbiased and random. With the advent of granular data sets and powerful computing options, researchers are now able to study information and market efficiency across trading hours and find out where inefficiencies may lie. Chordia et al. (2008) are among the first to analyse return predictability in connection with liquidity and interpret their findings from a market efficiency perspective. In particular, they examine changes in liquidity across three tick size regimes over a 10-year period and document a substantial decline in short-horizon return predictability. More importantly, they show that the short-horizon predictability of stock returns from past order flows can be interpreted as an inverse indicator of market efficiency.

Chordia et al.'s (2008) approach provides a feasible basis for estimating the degree of informational efficiency over time in a security market. Research utilising this methodology is also beginning to appear in the literature. For instance, Aktas et al. (2008) use the predictability relationship between order imbalance and return to examine the effects of insider trading on market efficiency. Others, such as Visaltanachoti and Yang (2010), investigate the speed of convergence to market efficiency for foreign stocks listed on the New York Stock Exchange (NYSE). My study in Chapter 4 is a continuation of the line of research that relates order flow to return predictability. Fama (1970) emphasises a lack of return predictability over a daily horizon as a criterion for market efficiency, whereas market microstructure research defines informational efficiency as the degree to which market prices correctly and quickly reflect new information over shorter periods. Chordia et al. (2005) also analyse return variance ratios and return autocorrelations, and conclude that new information is more effectively incorporated into prices when the market is comparatively more liquid. Thus, when the market is liquid, asset prices are more likely to reflect the true value of assets across trading hours, since short-term arbitrage opportunities are reduced. This view is consistent with the findings of Chordia et al. (2008), who find that return predictability diminishes when the market is liquid.

Both the evolution of the characteristics of market participants (e.g. traders are increasingly using high-frequency trading strategies) and market infrastructure (e.g. the emergence of new market platforms, such as dark pools) have impacted financial markets. High-frequency traders (HFTs) are a subset of algorithm traders (ATs) and could be described as traders who use algorithms to buy and sell stocks at very fast speed (Brogaard et al., 2014). Negative media coverage of HFTs and the “flash crash” on May 6, 2010 raised significant concerns about the role of HFTs in the stability and price efficiency of markets. Recent studies aim to show the role of HFTs in liquidity provision and price discovery. Cao et al. (2009) indicate that HFTs trading is related to two sources of public information: macroeconomic news announcements and imbalances in the limit order book. Boehmer et al. (2015) apply co-location data as a proxy of AT from over 40 stock markets globally. They find that ATs offer market liquidity and improve informational efficiency. Based on proprietary data, Carrion (2013) finds that HFTs are more likely to provide liquidity when it is scarce and consume liquidity when it is ample. Hagströmer and Nordén (2013) classify HFTs into market making HFTs and opportunistic HFTs on NASDAQ-OMX Stockholm. They indicate that HFTs concentrate on either liquidity demanding or liquidity supplying. They also suggest that market making HFTs tend to mitigate intraday price volatility. Brogaard et al. (2014) examine the impact of high-frequency trading (HFT) on NASDAQ and find that HFT improves market efficiency and reduces transitory pricing errors. Subsequently Brogaard et al. (2015) and Brogaard et al. (2017) assert that market liquidity benefits from faster trading speed and that HFT absorbs order imbalance during extreme price movements. The rise of algorithmic trading (AT) has introduced new sources of short-term market behaviour. HFT research is of growing importance in academic finance research and to practitioners in financial markets. Both policy makers and regulators have sought to respond to the technology-induced structural changes in the markets by introducing new policy initiatives and regulations. For example, the EU's Markets in Financial Instruments Directive (MiFID) was enacted with a view to encourage order flow competition and technological innovation. Under this reform, trades could be executed away from the listing exchange such as London Stock Exchange (LSE) within a fragmented market environment, which consists of Multilateral Trading Facilities (MTFs) and Systematic Internalisers (SIs). MTFs generally operate lit venues that are mandated to provide both pre- and post-trade transparency regime and dark venues that are exempt from providing pre-trade transparency.

MiFID has generated a heated debate among regulators about issues related to market fragmentation and concentration. One benefit of fragmentation is increased competition resulting in greater market quality, for example, bid–ask spreads become narrower because of increased order flow competition across venues (see Chapter 4). The introduction of an additional market leads to competitive pressures on market makers and brokers. Also, even though the depth of the main market may decrease, the joint depth of the aggregate market, comprising of all the competing exchanges and the listing exchange may increase (Glosten, 1998). O'Hara and Ye (2011) study market fragmentation in the US equity market and find that increased levels of off-exchange fragmentation are associated with improved market quality in terms of lower transaction cost and faster trading speed.

Based on the Dutch market, Degryse et al. (2015) suggest that visible fragmentation generally benefits market liquidity while dark trading may harm market liquidity in terms of increasing adverse selection cost on the lit markets. Gresse's (2017) study includes FTSE100, CAC40 and SBF 80 stocks in European equity markets. She uses the implementation of MiFID as a natural experiment affecting fragmentation and finds that the marginal benefits of visible fragmentation become lower when an equilibrium level of fragmentation is reached, and that increased visible fragmentation may harm the market depth of smaller company stocks. However, she does not find any detrimental effect of dark trading on market quality.

The foregoing discussion sets the background for the interrelated issues of price discovery and liquidity examined in this thesis. There is a gap in the existing literature regarding how recent market developments on the London equity market, one of the largest markets in the world in terms of market capitalisation, affect market quality. My investigations in this thesis directly contribute to filling this gap. The next chapter discusses key institutional background issues related to the London equity market which has evolved over the past two decades.

2. Background

In this section, I discuss key concepts, developments and regulations that should be understood in advance of reading the empirical chapters (3 – 5) in this thesis.

2.1. Stock Exchange Trading Service

Although the transformation of the financial market architecture in Europe started in the late 1980s, it accelerated throughout the 1990s in preparation for the advent of monetary union. In London, the equity market had operated for about ten years as a pure dealership system. These trading arrangements were criticised for their opacity and the high trading costs incurred by smaller investors. In October 1997, the LSE introduced the Stock Exchange Trading Service in response to increased competition. The launch of SETS represents a transformation in trading regime from a quote-driven market structure, the Stock Exchange Automated Quotation (SEAQ), to an order-driven market structure for all FTSE 100 stocks. This system update allows market participants to compete with dealers and designated market makers (DMMs) in order flow by posting the optimal level of bid and ask prices. Trading runs from 8:00 hours to 16:30 hours, subject to a ten-minute opening call auction from 7:50 to 8:00 hours and a five-minute closing call auction from 16:30 to 16:35. During the pre-open auction, limit and market orders can be entered and deleted at will and all order book data are communicated to the market. Once orders are crossed, indicative uncrossing prices for each instrument are displayed as the opening prices. During the closing auction, limit and market orders can be submitted. If orders are crossed during this period, the uncrossing price is released to the market as the closing price. SETS is among the most transparent of limit order books in major equity markets as every outstanding limit order is displayed. There is also a requirement for immediate publication of details of all trades to participants.

2.1.1. Upstairs and Downstairs Markets

On the LSE, the co-existence of downstairs and upstairs markets offers investors two fundamental trading methods. First, when trading on the downstairs market, investors can contact their dealer to submit a limit or market order to the SETS order book. Second, when trading on the upstairs market, investors can contact a broker-dealer to negotiate a trade with the dealer as a counterparty. Note that the supply of broker-dealer services on the upstairs market is entirely voluntary and unconstrained. There is no registration process and no public display of broker-dealer quotes. The upstairs market is designed to reduce the execution costs, especially for low-volume and illiquid stocks. By negotiating directly with potential counterparties, block traders attempt to achieve a lower execution on the upstairs than on the downstairs market. The downstairs market is independent of the upstairs market, implying that the dealers have no obligation to offer quotes on the order book. In addition, trades in the LSE's upstairs market are privately negotiated and hence have no minimum tick restrictions. However, as dictated by the post-trade transparency regime, dealers on the upstairs market must report the trade information within three minutes of its occurrence.

Several papers study the effects of the electronic limit order book system on the downstairs markets. Barclay et al. (1999) document an increasing trend of liquidity on the NASDAQ following the introduction of the electronic trading system. Naik and Yadav (1999) examine changes in the cost of trading before and after introduction of

SETS. They suggest that SETS has reduced the trading cost because limit orders posting improves public investors' bargaining power in negotiating with dealer firms. They also document the negative externalities across almost all trade sizes for stocks not undergoing the reform. Domowitz et al. (2001) find that a screen system increases market liquidity by reducing trading costs and increasing trading volume in a sample of 42 countries. Anand et al. (2009) report that designated market makers enhance the liquidity of electronic limit order markets in the Stockholm Stock Exchange.

However, other studies suggest that the electronic limit order book system might not be the optimal trading mechanism for thinly traded illiquid stocks due to information asymmetry. Theissen (2002) investigates moderately less liquid stocks on the German stock market and discovers that floor trading's liquidity is less sensitive to return volatility than order book's liquidity. This is because market makers on electronic trading systems are more likely to be exposed to information asymmetry. When they detect information asymmetry, market makers post a wider spread to compensate for the potential information disadvantage. Similarly, Lai (2007) reports that the liquidity of FTSE250 stocks dropped substantially following introduction of the limit order book.

Turning to empirical studies of upstairs markets, Seppi (1990) shows that upstairs markets' lack of anonymity benefits investors who can credibly claim to be trading for liquidity reasons. Madhavan and Cheng (1997) suggest that upstairs dealers can screen out information-based trades. Block traders must convince upstairs dealers that they are uninformed with respect to executing trades in the upstairs market. Later research finds similar results suggesting that upstairs trades are less informative than downstairs trades. Smith et al. (2001), Booth et al. (2002), Jain et al. (2003) and Bessembinder and Venkataraman (2004) study the Toronto, Helsinki, London and Paris Bourse stock exchanges, respectively, and find that upstairs trades tend to have a lower permanent price impact than downstairs trades, which they ascribe to the difference in requirement for anonymity among venues. Booth et al. (2002) study the difference of price discovery between the upstairs and downstairs market using the vector error correction model. They suggest that most stock price discovery occurs on the anonymous order book. Armitage and Ibikunle (2015) conduct an intraday study on price discovery between the upstairs and downstairs markets on the LSE. Their results suggest that the upstairs market accounts for about one fifth of the total price discovery and the price discovery on the upstairs markets is higher in the first and last half hours of the trading day.

2.2.MiFID

The implementation of SETS allows market participants to access electronic order books via remote access without the need for a physical presence on an exchange floor. Since the start of the millennium, fast technology iteration has reduced the cost of accessing electronic order books, allowing more participants to join the trading service to provide liquidity. In Europe, entrepreneurially driven trading venues have started to operate at a much higher speed but at much lower cost than the traditional stock exchanges. To foster competition in European financial markets, the European Parliament and Council implemented the Markets in Financial Instruments Directives in August 2006. MiFID allows the following three types of trading services: (1) regulated markets (RMs), including national stock exchanges like LSE and Deutsche

Börse, (2) MTFs, such as BATS, Chi-X and Turquoise, which are newly established venues competing with RMs. Some MTFs operate two separate order books, a lit order book which is subject to the pre-and post-trade transparency regime and a dark order book complying only with the post-trade transparency regime, (3) systematic internalisers (SIs), which are firms that execute client orders by dealing on their own account outside RMs or MTFs on an organised, systematic and frequent basis.

MTFs are multilateral systems that bring together multiple third-party buying and selling interests in financial instruments. However, they may have differing organisational requirements from those of RMs because most MTFs do not offer listings. MiFID removes the concentration rule under which member states required institutions to route orders to RMs only. This implies that RMs are now exposed to competition from other trading venues, allowing traders to choose the trading systems that best meet their needs.

2.2.1. Pre- and Post-trade Transparency

MiFID mandates pre- and post-trade transparency regimes to maintain market integrity. Pre-trade information gives the market participants the opportunity to continuously observe the market's development and execute transactions at known bid and ask prices and depths for all equity instruments. The post-trade regime dictates that post-trade information must be reported as close to real time as possible and in any case within three minutes of the relevant transaction.

However, the pre-trade transparency does not apply to dark venues operated by MTFs and RMs (e.g. Deutsche Börse). To be specific, a limit order submitted to a lit (or visible) exchange is immediately visible to all market participants and thus has an immediate market impact as market participants revise their beliefs about the fundamental value. In contrast, if the limit order is submitted to a dark venue, participants know nothing about the order until it has been executed. The dark order book enjoys a waiver designed to accommodate the need of wholesale participants to execute large orders at the midpoint of the best bid and offer quotes as the "reference price" derived at RMs. The growth of dark pool trading can be justified by the need to strategically hide trading intentions in an HFT environment. Virtually, all venues allow traders to "hide" all or a portion of their orders on the book, resulting in market liquidity having both displayed and non-displayed components.

2.2.2. Market Fragmentation

MiFID allows trading venues to compete for order flows. This competition also leads to fragmentation of trading among these venues. Such fragmentation may potentially detract from other important Exchange Act objectives, including efficient execution of transactions, best execution of investor orders, price transparency and opportunities for investor orders to interact with each other. Certain rules were set up to maintain market fairness. In the US, the Reg NMS Order Protection Rule requires orders to be executed at the best bids and best offers displayed on the National Best Bid Offer (NBBO) across all lit trading venues. In contrast, MiFID does not require trading centres to be responsible for the best execution. Under MiFID, investment firms are required to take all reasonable steps to obtain the best possible result for their clients, taking into account factors such as costs, speed and likelihood of execution. Simultaneous access to multiple venues would normally require the smart order routing system technology (SORT). Only the biggest brokers can afford to connect to all venues. Although retail investors may be unable to access multiple venues at once, they are still able to trade at individual venues in real time. Consequently, orders might not always be executed at the best available price across trading venues. This lack of trade through protections led O'Hara and Ye (2011, p.472) to remark that *"it is hard to see how a single virtual market can emerge in Europe"*.

Recent literature has attempted to investigate whether trading fragmentation impairs market efficiency. In an HFT environment, informed algorithmic and high-frequency traders prefer to trade across high-tech markets (in Europe, these are mainly MTF-type platforms), presumably because they value the higher speed of execution and seek to prevent information leakage (Hoffmann, 2010). Informed order flow 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 can profit from market inefficiency and obtain better execution through dynamic trading in fragmented markets. Their trading strategies include short-term fundamental information (for example, imminent earnings release) and short-term technical analysis (front-running strategies and short-term momentum strategies). There is a concern among the regulators that these experienced traders may identify potential arbitrage opportunities because quotes across RMs and MTFs are not closely linked due to the absence of trade-through protection. In response to this concern, Chapter 4 investigates the impact of market fragmentation on market quality under MiFID.

2.2.3. Dark Trading

The development of high-frequency electronic trading has facilitated the generation of dark liquidity and the use of dark orders to minimise market impact costs. Although dark pools can meet the needs of wholesale traders by hiding trade intentions, many regulators are concerned that the growth of dark pools may affect the quality of price discovery and liquidity in lit markets. The impact of dark trading on market quality is a complex issue because it simultaneously affects the level of transparency and the fragmentation of informed/uninformed order flow across multiple trading venues.

Ye (2011) and Zhu (2014) provide theoretical frameworks to study the impact of dark trades on market quality. Zhu (2014) develops a model in which dark trades prove to be more attractive to the uninformed. According to his model, dark trading should increase price informativeness but at the expense of greater adverse selection costs in the main market. This is because informed traders are likely to cluster on one side of the dark order book and therefore face low execution probability. In contrast to Zhu (2014), Ye (2012) assumes that the informed trader does not face the problem of low execution probability in dark pools. Hence, when more informed traders migrate to dark venues, the price impact and spread on lit markets are reduced. Based on the sample from the Australian Stock Exchange, Comerton-Forde and Putniņš (2015) find that low levels of dark trading can improve price discovery and decrease spreads, but when the dark volume exceeds 10% of the total trading volume, informational efficiency deteriorates. Ibikunle et al. (2017) study dark trading of FTSE350 stocks from 2010 to 2015 and find results similar to those of Comerton-Forde and Putniņš (2015). Two industry reports, Brandes and Domowitz (2010) and Buchanan et al.

(2011) find that increased participation of dark pools enhances the price discovery process in European markets.

Another stream of literature studies the impact of dark trades on market liquidity. Rindi (2008) models the effects of pre-trade transparency of trader identities. Informed traders are effective liquidity suppliers because they face little or no adverse selection costs. When information acquisition is endogenous and costly, transparency reduces the number of informed traders, which harms the liquidity. Ready (2010) studies monthly volume by stock in three dark pools, Liquidnet, POSIT, and Pipeline, from June 2005 to September 2007. He finds that the market share of these dark pools is less than 1% of the consolidated volume and that the dark pool volume is concentrated in liquid stocks (low spreads, high share volume). Buti et al. (2011) use data from 11 US dark pools and conclude that dark pool activity improves spreads, depth and short-term volatility. Brugler (2015) and Gresse (2017) employ 3-month and 6-month data and find that dark trading and dark fragmentation improve the liquidity of FTSE100 stocks. However, Degryse et al. (2015) report that dark fragmentation has a detrimental effect on the overall market liquidity.

2.3. Markets in Financial Instruments Directive II

Since its implementation in November 2007, MiFID has been the cornerstone of capital markets regulation in Europe. However, since its inception, not all benefits have been fed down to the investors and regulators as envisaged. MiFID II aims to address the shortcomings of the original MiFID release, which has been amended with measures as a result of the lessons learned from the financial crisis. MiFID II will be applied starting 3 January 2018 and trading venues are required to comply with the new requirements from that date. MiFID II seeks to herald further investor protection initiatives by addressing three important reforms in regards to HFT/AT, dark pools and trade transparency regimes.

One goal of MiFID II is to tackle the potential instability caused by ATs and HFTs. To avoid “flash crashes” and ensure a stable market, ATs and HFTs will be required to register as investment firms, disclose their algorithms to the regulator and test them in an approved environment. The algorithms are required to have built-in circuit breakers that “exit” once certain market-relevant criteria are met. Investment firms providing direct market access will also be required to have measures and controls in place to mitigate the risk of markets becoming disorderly due to HFT algorithms. Moreover, cancellation fees will be introduced to mitigate the detrimental effect of HFT strategies such as spoofing and quote stuffing. At the moment, HFTs still play an important role in providing liquidity, especially to the equities market, while MiFID II intends to propose technical rulemakings to encourage HFT liquidity without compromising market fairness and stability. Furthermore, regulators also have confirmed a double volume cap for equity and equity-like products traded in the dark pools. Under this mechanism, the trading volume in a given stock on any venue operating under a dark venue cannot exceed 4% of the total market volume, and the total trading volume under these waivers (across all venues) for a given stock cannot exceed 8% of total market volume. The dark volumes for each venue and the total market volume will be calculated on a stock-specific basis over a rolling 12-month window. If the cap has been breached, dark trading for that stock will be halted for the next 6 months, either in specific trading venues or for all dark pools. It remains to be researched how the market will react to the introduction of such a volume cap.

Finally, MiFID II will expand the trade transparency regimes from only equity instruments to all non-equity instruments, such as fixed income, exchange-traded funds, bonds and structured products on all MTFs' visible order books. MTFs will have to report on a continuous basis the current bid/offer spread, as along with the depth of interest of both equity and non-equity instruments. A requirement to trade certain derivatives on RMs will also be imposed. The trading on a regulated market obligation will apply to financial counterparties and non-financial counterparties. MiFID II aims to strengthen investor protection by establishing a stronger corporate governance regime, especially for HFTs and dark pool traders. MiFID II will stimulate a high degree of trading process changes over the next five years with a significant impact across a wide range of activities.

3. Informed Trading and the Price Impact of Block Trades: A high frequency trading analysis.

3.1. Introduction

The role played by information in the price discovery process is well documented. Early informed trading studies suggest that informed traders prefer using large trades in order to minimise transaction costs and to maximise the profit gained from their informed trading activities. This is because they face competition from other informed traders and their private information could be short-lived (Easley and O'Hara, 1987, Karpoff, 1987). In contrast with this paper, most existing studies on the way private information is incorporated into stock prices through block trades focus mainly on trading evolution around corporate events in order to control for private information. This is because evidence suggests that corporate events can stimulate the pre-announcement drive for acquiring private information (Daley et al., 1995). Permanent price impact measures are usually employed as proxies for the informativeness of block trades, since they reflect observable price adjustment for information.

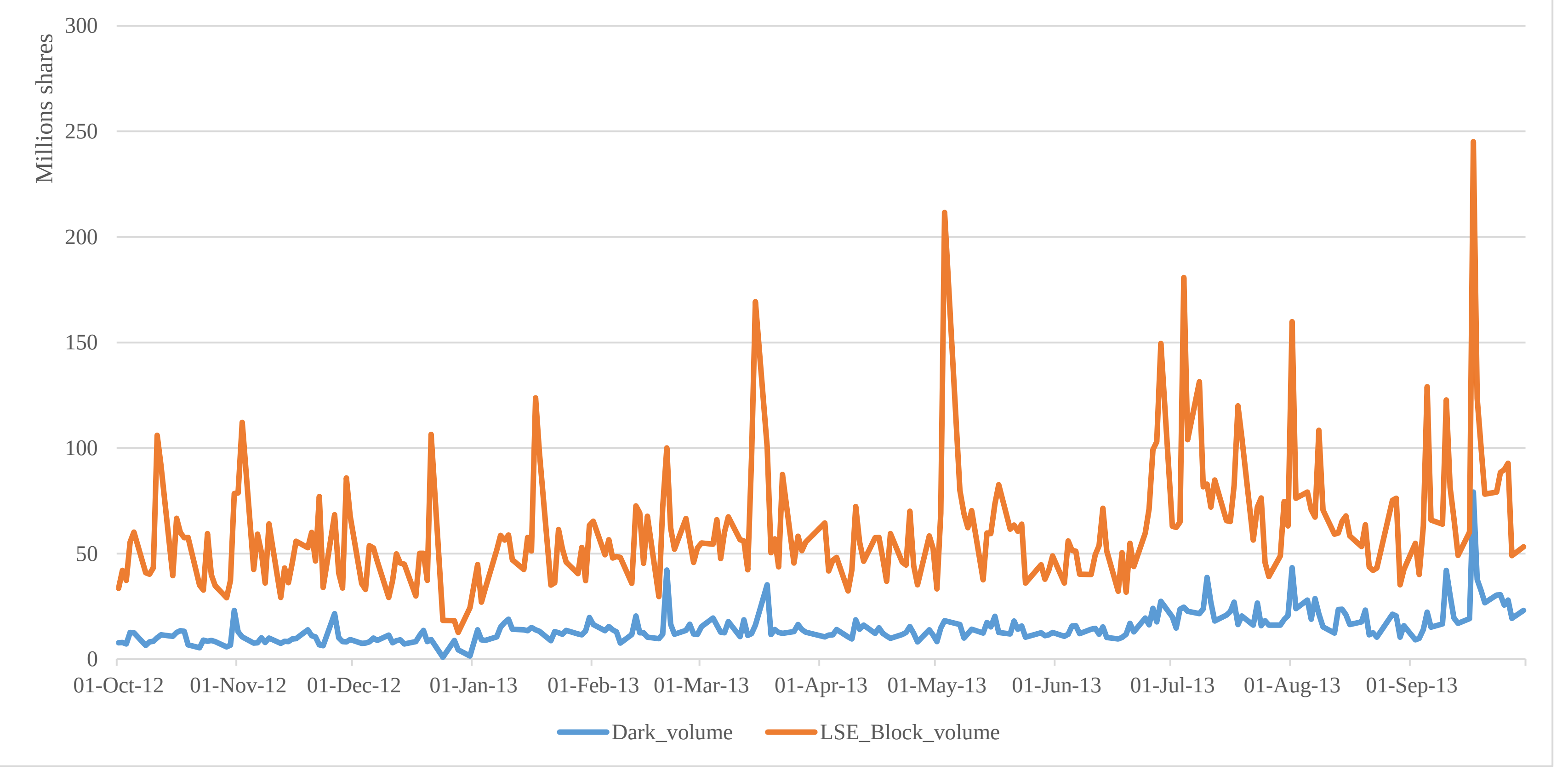
Despite the large volume of existing literature on informed trading, there are several unresolved questions about how and when informed traders choose to employ private information. For example, a stream of literature which includes Kyle (1985), Holden and Subrahmanyam (1992), Foster and Viswanathan (1994) and Hong and Stein (1999), argues that informed traders would employ their private information gradually rather than quickly. However, Easley and O'Hara (1987) and Karpoff (1987) differ, suggesting that informed traders are more likely to aggressively trade with their private information rather than gradually exploit it. Also, Barclay and Warner (1993) and Chakravarty (2001) argue that informed traders are more likely to exploit their information using medium-sized trades, while Blau et al. (2009) hold that informed traders do indeed still prefer block trades for informed trading.

Based on trading data from LSE, this chapter extends the existing literature on the informativeness of block trades and how their execution relates to the incorporation of information in stock prices. It should be noted that although in recent years off-exchange trading such as dark pools has attracted an increasingly portion of order flow from traditional stock exchanges, traditional exchanges still play a dominant role in facilitating block trades. LSE operates both downstairs and upstairs markets. The downstairs market is a consolidated electronic order book where anonymous trading takes place. Compared to dark venues, LSE's downstairs market can offer trading immediacy required by traders in today's markets (Menkveld et al., 2017). By contrast, LSE's upstairs market is a broker-dealer market where brokers/dealers play a search role by locating counterparties for large institutional block trades. Upstairs dealers are obligated to expose negotiated trades to the downstairs floor and to the order book. The upstairs block trades tend to have a lower price impact than down stairs trades because the identity of the counterparties is revealed to upstairs dealers (Booth et al., 2002, Jain et al., 2003, Bessembinder and Venkataraman, 2004). Recent study suggests that the upstairs market plays a more important role in price discovery (Armitage and Ibikunle, 2015). Taken together, LSE is still attractive for institutional block trades. To obtain a better price, the large trader still prefers to send block trades to the upstairs market. I compare the volume of block trades on LSE and dark volume in FTSE100 stocks, using data from October 2012 to September 2013. Figure 3.1

FIGURE 3.1. LSE Block Volume and Dark Volume

The total block trade volume is the sum of daily block trade volume (defined as the largest 1% trade) of FTSE 100 stocks on LSE.

The dark volume is the aggregated dark volume from three largest MTFs, BATS, Chi-X and Turquoise. The time span covered is from 8:00hrs to 16:30hrs over the sample period from 1st to 30th October 2012.



illustrates that block volume on LSE is far larger than the aggregated dark volume of the three largest MTFs in Europe.

In this Chapter, I answer questions such as whether informed traders exploit private information across days rather than immediately, as well as how they alter information use across the trading day. My contributions are three-fold: first, the models employed in this chapter present new empirical evidence on the diffusion process of private information in the UK equity market and in a high-frequency trading environment. Instead of focusing trades around short-term corporate events and insider trading sample, I expand observations of block trades to normal trading periods. This is because informed trading activities occur not only around corporate events but also across regular trading hours.

Second, I find intraday and inter-day patterns within this information diffusion process. The results suggest that the impounding of information into stock prices is stronger in the first trading hour than at other time periods during the normal trading day. Further, informed trading at day t_{-1} could still affect informed traders' block transaction at day t. These results support the theoretical frameworks of Kyle (1985), Holden and Subrahmanyam (1992), Foster and Viswanathan (1994) and Hong and Stein (1999) that suggest that private information is gradually impounded into instrument prices because informed traders slowly exploit the private information across trading days. The results, however, run contrary to the expectation that informed traders quickly take advantage of their private information by trading quickly and aggressively, as suggested by Easley and O'Hara (1987) and Karpoff (1987). It is interesting that high-frequency data from an era that is characterised by short-termism in trading terms could validate theoretical propositions (such as that of Kyle, 1985) from an era in which buy and hold strategies were more orthodox. Third, since PIN also reflects the level of firms' financial transparency (Vega, 2006), I stratify my sample stocks into four portfolios according to the mean value of their daily PINs, and show that the information incorporation process can vary across stocks with different levels of financial transparency. The results imply that the larger the levels of informed trading in a stock, the higher the permanent price impact of block trades. There are several implications of this, including that informed trading aids the price discovery process for less transparent stocks.

Permanent price impact reflects the *lasting* price changes in a stock as a result of a trade; this implies that such trade contains information. Hasbrouck (1991a, 1991b) utilises the vector autoregression (VAR) model to examine the informativeness of trades leading to permanent price impact. Seppi (1992) finds that the permanent price impacts of block trades prior to earnings announcements correlate with quarter earnings surprise. Daley et al. (1995) focus on block trades around the earning announcement periods. They suggest that the permanent price impact of block trades during the five days prior to the earning announcement is larger than during the post-earning announcement period of the same duration. However, Barclay and Warner's (1993) stealth trading hypothesis indicates that, in order to hide information, informed trades are concentrated on the medium size transactions during the pre-tender offer announcement period. Based on three-month audit trail data for a sample of NYSE firms, Chakravarty (2001) finds that institutional traders are more informed, and medium-sized institutional trades are the driving factors in the movement of prices, thus supporting Barclay and Warner’s (1993) findings on the informativeness of medium sized trades.

Other studies including Huang and Masulis (2003), and Alexander and Peterson (2007) also offer evidence on order-splitting strategies from informed traders. Blau et al. (2009) provide a comprehensive explanation of the association between informed trades and block trades. Their results show that informed traders still prefer block trades during the periods of high trading activities because a deep market can provide natural camouflage to hide information. Yang (2009) suggests that informed traders focus on medium sized trades from six to ten days prior to the quarterly earnings announcements. However, informed traders aggressively increase their order size five days before the announcement. Frino and Romano (2010) employ a theoretical model to show that market conditions could determine the size of informed trades. They suggest that information effect plays a role in *weak* bull and bear markets rather than *strong* bull and bear markets. Informed traders are likely to trade large orders when informational profit outweighs the transaction cost in weak bull and bear markets. Saar (2001) suggests that portfolio managers search for block trades based on favourable private information, and rebalance portfolios by selling stocks that have less favourable prospects. Using permanent price impact as an adjustment to private information around corporate events, this research implies that block trade is a powerful indicator for information asymmetry. If a stock is traded based on liquidity reasons rather than information motives, then the price impact of block trade should be relatively small. Hence, the more informative trading is, the bigger its permanent price impact should be (Aktas et al., 2007).

Besides examining trades around corporate events, researchers also investigate the impact of informed trades by looking into insider trading activities. John and Lang (1991) find evidence of signalling theory of dividends by looking at how the information content of dividends may be ‘nuanced’ by inside trading prior to the dividend announcement. Their results reveal that for firms with good growth expectations, the market reacts positively to dividend initiations even when insiders are net sellers. Meulbroek (1992) illustrates that price responds rapidly to illegal insider trading. Lin and Rozeff (1995) examine the speed of price adjustment to private information and find that more than 85% of private information is absorbed within one day. Lakonishok and Lee (2001) examine net purchases and sales from insider trading activities, and their results show statistically significant but economically insignificant market movement around the insider trading activities.

Most informed trading studies mainly focus on the periods around corporate events and insider trading activities, which account for a very small fraction of stocks’ normal trading hours. This chapter is motivated by the need to examine the evolution and impact of informed trading throughout normal trading hours. I also investigate the characterisations of the information diffusion process by testing intraday effects, long-lived information and firms’ various levels of financial transparency. My empirical models are based on the assumption that informed traders prefer to execute block trades. Kyle (1985) and Hong and Stein (1999) explain the gradual information diffusion process using theoretical equilibrium frameworks. These findings are supported by Hong et al.’s (2000) analysis, in which analyst coverage is used to proxy firm-specific information flow. Hong et al. (2000) provide some empirical evidence that stock momentum reflects the gradual diffusion of firm specific information. However, Vega (2006) argues that the analyst coverage is not a good proxy for information flow across traders.

This chapter employs probability of information-based trading (PIN) to proxy the proportion of the unobservable informed trades across normal trading hours. PIN has been elaborated in previous work (see for example Easley et al., 1996a, 1996b, 1997a). Easley et al. (2002) find that a difference of 10% in PIN between two stocks leads to a difference in the excessive returns of 2.5% per annum. This implies that uninformed investors demand a premium to hold stocks with higher information risk. PIN has been extensively used to capture information asymmetry. Easley et al. (2010) use the returns of high and low-PIN portfolios to construct a risk factor which explains portfolio returns. Vega (2006) constructs PIN to test market efficiency, suggesting that the more information investors have about the true value of an asset, the smaller the abnormal return drift. Chung et al. (2005), using a sample of NYSE stocks, examine the relationship between price impacts of all trades, serial correlation in trade direction, and PIN. They find that there is a positive relationship between PIN and permanent price impacts of all trades, and stocks with higher PIN exhibit higher correlations in the trade direction. Their result is consistent with information hypothesis that strategic trading of informed trades results in serially correlated trades.

Based on three months-worth of NYSE and NASDAQ transactions data, Lee and Chung (2009) find a negative relationship between price improvement in NYSE stocks and PIN. This suggests that liquidity providers on the NYSE offer greater price improvements for stocks with a lower PIN. However, Lai et al. (2014) deconstruct PIN into risk component and liquidity component and they find that only the liquidity component is priced. In a recent study, Lai et al. (2014) construct stock-level PINs over a 15-year period in 47 stock markets worldwide. Their results show the variations of PIN between emerging and developed markets. However, they do not find that PIN exhibits explanatory power to expected stock returns in global stock markets.

Consistent with the existing market microstructure literature, I use PIN to proxy informed trades in my analysis of the permanent price impact[1] of block trades. Given the assumption that informed traders execute block trades to exploit superior information, I focus on the association between unobservable informed trading and observable permanent price impact of block trades, in order to determine the informativeness of block trades. My central hypothesis is that, if private information does diffuse into price via block trades, a higher fraction of informed trades will lead to more information being revealed through block trading activity. Hence, the relationship between PIN and the permanent price impact of block purchases (sales) should be positive (negative). The remainder of this chapter is structured as follows: section 2 discusses the data and my econometric methodology; in section 3 I provide analysis of my results and provide extensions to the main analysis; and Section 4 concludes.

[1] I also examine the temporary price impact and the total price impact in this paper. Relevant analyses are presented in subsequent sections.

3.2.Data and Methodology

3.2.1. Data

3.2.1.1. Sample selection

Our data consists of FTSE 100 stocks, which account for about 80% of total market capitalisation on the LSE. The intraday transaction data for this research comes from the Thomson Reuter Tick History (TRTH) Database. My dataset contains 253 trading days from 1st October 2012 to 30th September 2013 and includes variables such as Reuters Identification Code (RIC), date, timestamp, price, volume, bid price, ask price, bid volume and ask volume. Each trade has been allocated corresponding prevailing best bid and ask quotes. Since I only focus on normal trading hours, I delete the opening auction period (7:50hrs – 8:00hrs) and the closing auction period (16:30hrs – 16:35hrs). However, I also spot anomalous observations that are the results of data input errors. In order to minimise data errors, I follow standard practice to exclude observations satisfying the criteria below (see for example Chordia et al., 2001, Ibikunle, 2015a):

1. Transaction price is greater than the prevailing best ask price;
2. The quoted bid price exceeds the quoted ask price;
3. The quoted bid-ask spread exceeds £4;
4. The value of quoted bid-ask spread over transaction price is greater than 0.35;
5. Any of following variables is missing for that observation: price, volume, quoted, bid and ask prices;

6. Transaction is for FTSE 100 stock added to or substituted from the index during the sample period.

After applying these conditions, the final dataset comprises of 44,742,693 transactions, which are restricted to regular trades with eligible best bid and ask prices. I define block trades in line with Frino et al. (2007) as the largest 1% of the trades in each stock. I also classify trades into purchase or sale by using the established Lee and Ready (1991a) tick rule algorithm. Specifically, when the transaction price is higher than the prevailing quote mid-point, I classify the transaction as a buyer-initiated (purchase) trade. If price is the execution price lower than quote mid-point, then I classify it as seller-initiated (sale) trade. If the current and the previous trades are the same price, I classify using the next previous trade. Aitken and Frino (1996) and Lee and Ready (1991a) suggest that the tick rule has an accuracy in excess of 90%. These two classification conditions yield 206,002 block purchases and 246,867 block sales in my final sample.

3.2.1.2. Sample Description

In order to examine trading activity patterns in the sample, I plot the daily volume per minute for the entire trading day from 8:00hrs to 16:30hrs. The log daily volume curve exhibited is U-shaped, which is consistent with previous literature (see as an example, Barclay and Hendershott, 2003). Figure 3.3 shows the average and median trade sizes per minute from 8:00hrs to 16:30hrs. The Figure suggests a higher level of trading during opening and closing periods. I examine these dynamics closely in subsequent analysis.

FIGURE 3.2

Log daily Traded Pound Volume per minute

The average value and median of daily pound volume are computed for each minute for entire sample stocks. I take the log value for the quintile due to the large variability of trading volumes across the trading periods. The time span covered is from 8:00hrs to 16:30hrs over the sample period from 1st October 2012 to 30th.

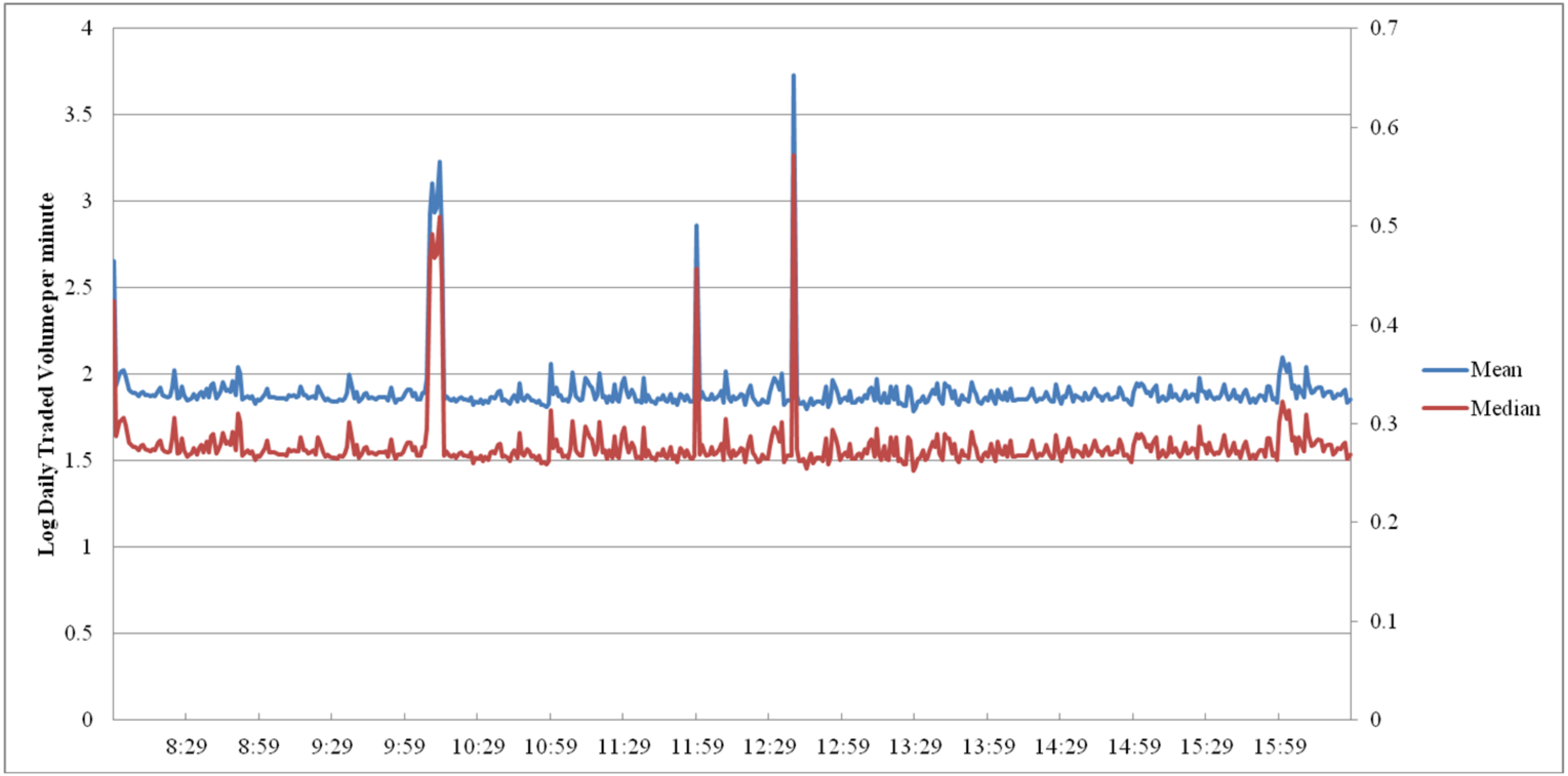


FIGURE 3.3

Log Mean Trade size per minute

The average trade sizes per minute are calculated for entire sample stocks. I take the log value for the quintile due to the large variability of trading volumes across the trading periods. The time span covered is from 8:00hrs to 16:30hrs over the sample period from 1st to 30th October 2012.

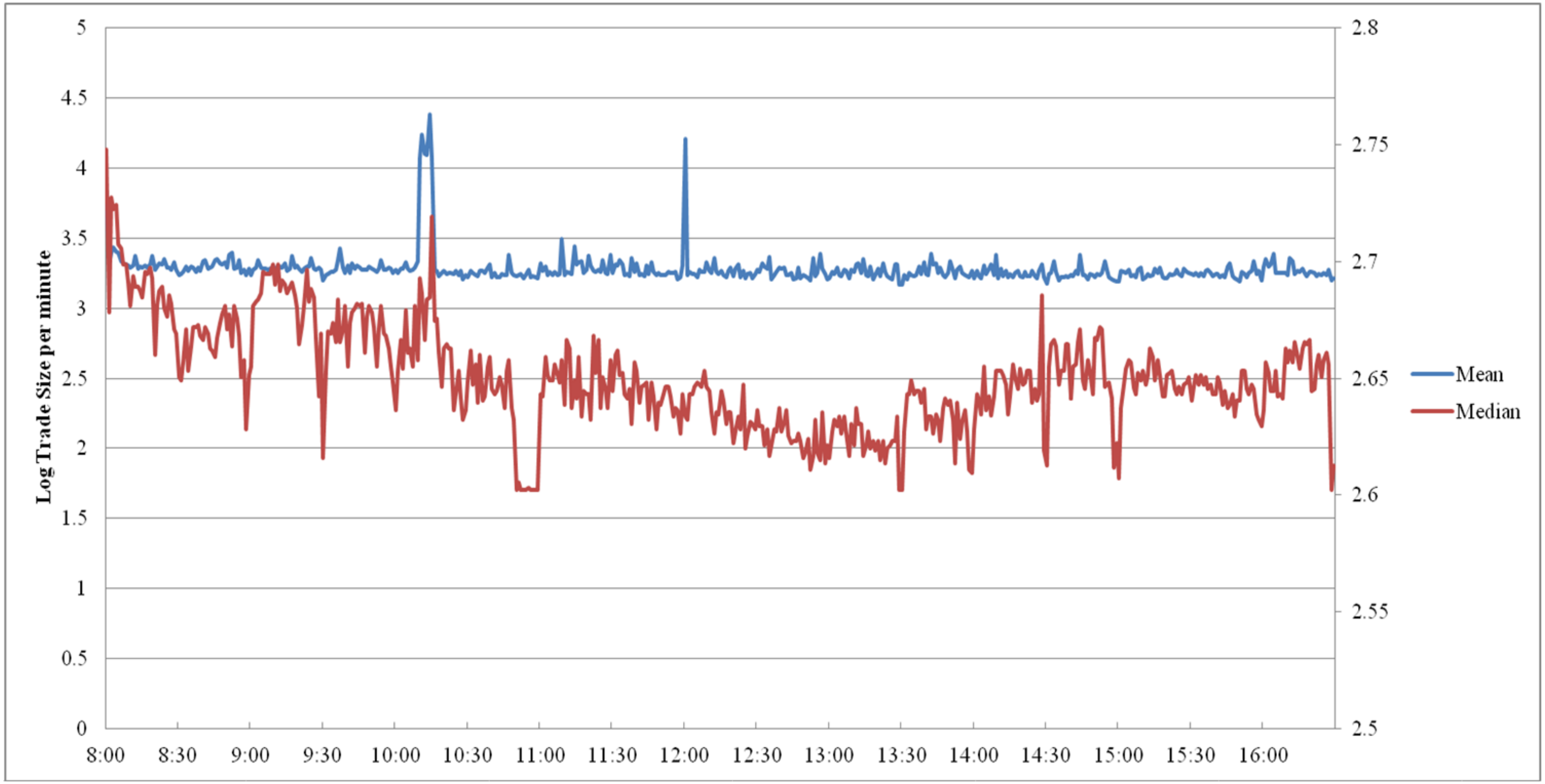


Table 3.1 shows the descriptive data of block trades based on midpoint classification. The average number of shares and average traded values of block sales are greater than those of block purchases. However, the average value of price impact of block purchases is 0.020%, which is more pronounced than the absolute value of the permanent price impact of block sales, at -0.011%. This is significant given that the average price impact is computed from trades occurring at very short intervals of less than 50 seconds in all cases. The impact asymmetry is expected given that prices usually fall after a seller-initiated trade and appreciate after a buyer-initiated trade (see Kraus and Stoll, 1972). The phenomenon is also attributable to the fact that block sales are usually initiated on the basis of a number of factors, one of which is the search for liquidity, while block purchases are more likely to contain firm specific information. This price impact asymmetry is also documented in Keim and Madhavan (1996) and Saar (2001). The BAS average for block sales is larger than that for block purchases. This is surprising given that the literature suggests that spreads are larger for informed trades. Figure 3.4 shows the distribution of the actual size of block trades. The average size of block trades in the sample data is 24111 shares/trades. To capture the block trades for FTSE 100 constituents, I follow Frino et al. (2007) and define block trades as the largest 1% of the transaction for each stock over the sample period. Table 3.2 continue to show more descriptive data of block trades based on midpoint classification. The average number of shares and average traded values of block sales are greater than those of block purchases. However, the average value of price impact of block purchases is 0.020%, which is more pronounced than the absolute value of the permanent price impact of block sales, at -0.011%. This is significant given that the average price impact is computed from trades occurring at very short intervals of less than 50 seconds in all cases. The impact asymmetry is expected given that prices usually fall after a seller-initiated trade and appreciate after a buyer-initiated trade (see Kraus and Stoll, 1972). The phenomenon is also attributable to the fact that block sales are usually initiated on the basis of a number of factors, one of which is the search for liquidity, while block purchases are more likely to contain firm specific information. This price impact asymmetry is also documented in Keim and Madhavan (1996) and Saar (2001). The BAS average for block sales is larger than that for block purchases. This is surprising given that the literature suggests that spreads are larger for informed trades. It is important to point out, however, that the difference between both estimates is small and is not statistically significant at any conventional level. Table 3.3 shows the correlation matrix of the explanatory variables. I observe that there are no econometric multicolinearity issues within the secondary model for the price impact of block trades.

FIGURE 3.4
Distribution chart of block size on LSE.

This figure shows the distribution chart for block trades on LSE between October 2012 and September 2013.

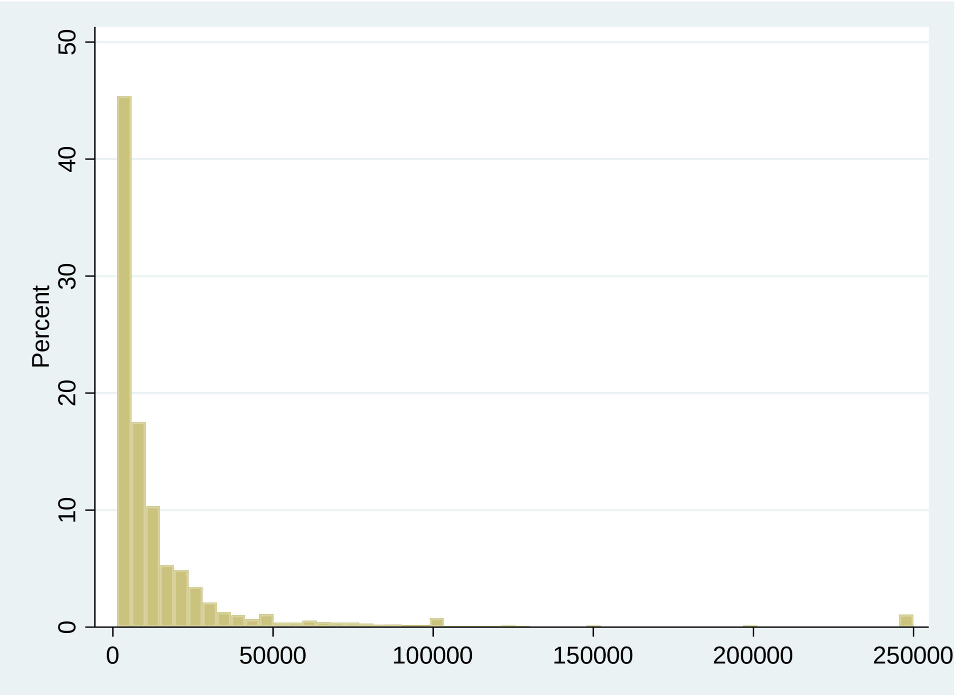


TABLE 3.1
Summary Statistics for Block Trades

This table shows the descriptive statistics for purchase block, sale block and all block trades between October 2012 and September 2013.

	No of trades	BAS (%)	Avg Price Impact (%)	Variance of Price Impact
Block Trades	453,012	0.028	0.000	0.000035
Buy (45.47%)	206,002	0.028	0.020	0.000917
Sell (54.53%)	246,867	0.029	-0.011	0.000007

TABLE 3.2

Correlation matrix of the explanatory variables

This table plots the correlation matrix of the explanatory variables employed in the price impact model in Table 3.4. PIN is the probability of an informed trade, *lnSize* is the natural logarithm of the number of shares per trade, *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place, *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade and *OIB* represents the order imbalance. *BAS* corresponds to the bid-ask spread at the time of the block trade, *Market return* is the daily FTSE100 index return on the day of the block trade, while *Momentum* is the cumulative return of the stock in the five days preceding the block trade.

	PIN	*Ln(size)*	*Volatility*	*Ln(turnover)*	*Market Return*	*Momentum*	*OIB*	*BAS*
PIN	1							
ln(size)	-0.0514	1						
Volatility	-0.011	-0.0088	1					
ln(turnover)	0.1478	-0.1112	-0.0073	1				
Market Return	0.0067	0.0062	0.0444	0.0217	1			
Momentum	0.0218	-0.0369	0.0148	0.0253	0.0114	1		
OIB	0.3191	-0.0321	0.0009	0.0669	0.0039	0.0156	1	
BAS	0.2846	0.0883	-0.0093	0.1225	-0.0018	-0.0343	0.1	1

3.2.2. Methodology

3.2.2.1. The Price Impact Model

I start by constructing three types of price impact that are generally accepted in the literature. These include temporary, permanent and total price impact measures. In the microstructure literature, the permanent price impacts as trading effects on price caused by informed trading, while temporary price impacts usually result from noise or liquidity trading, thus leading to price reversal (see for example Glosten and Harris, 1988, Chan and Lakonishok, 1995, Easley et al., 2002). Block trades demand more liquidity than is likely to be available at current quoted prices. Therefore in order to ensure the execution of such trades against the expressed level of liquidity, it will have to ‘walk’ through the order book. This will result in the move of prices in the trade direction; specifically, purchase trades will force an upward swing and sales will force a downward swing. The temporary impact on the other hand captures the market’s frictional price reaction to the execution of a block trade, which should be reversed soon after the block trade. Equation (3.1) expresses how I measure the temporary price impact as the liquidity effect of executing a block trade. The price deviation on account of an un-informed block trade execution occurs because counterparties at the best expressed corresponding quote are not readily available. The temporary effect is therefore compensation to the counterparties providing the liquidity needed for an un-informed block trade execution. Block purchasers (sellers) offer a price premium (discount) as compensation in order to ensure trade execution.

The permanent impact captures the lasting impact of a block trade execution, that is, the price change that is not reversed within a reasonable timeframe after the block trade execution. The information element of a block trade execution is therefore captured by the permanent impact. The lack of price reversal in this case suggests a learning event in the market, which ultimately results in the discovery of a new price for the traded instrument. Consistent with Holthausen et al. (1990), Gemmill (1996), Frino et al. (2007) and Alzahrani et al. (2013), I employ the five-trade benchmark to calculate the price impact measures. Thus, for temporary price impact (Equation 3.1), I measure the percentage of price reversal after five trades after a block trade execution, and for permanent price impact Equation (3.2) captures the percentage change in price from five trades *before* the block trade to five trades *following* the block trade. The third price impact measure, total impact, captures the total percentage price impact, which includes both the liquidity and the information component. Computing all three measures as percentage returns ensures comparability with existing studies:

$$Temporary\ impact = \frac{P_{t+5} - P_t}{P_t} \tag{3.1}$$

$$Permanent\ impact = \frac{P_{t+5} - P_{t-5}}{P_{t-5}} \tag{3.2}$$

$$Total\ impact = \frac{P_t - P_{t-5}}{P_{t-5}} \tag{3.3}$$

I modify the model of Frino et al. (2007), thereafter employed by Alzahrani et al. (2013), in order to investigate my research questions. I thus estimate the following regression with stock-specific variables:

$$\begin{aligned} \mathrm{Pr}ice\ impact &= \alpha + \beta_1 PIN + \beta_2 \ln Size + \beta_3 Volatility + \beta_4 \ln Turnover + \beta_5 Market return \\ &+ \beta_6 Momentum + \beta_7 BAS + \beta_8 |OIB| + \beta_9 DUM_1 + \beta_{10} DUM_2 + \beta_{11} DUM_3 + \varepsilon \end{aligned} \tag{3.4}$$

where *Price impact* refers to one of three measures: temporary, permanent and total price impacts. *PIN* is a daily approximation of informed trading in every stock as obtained by the maximum likelihood estimation of Equation (3.6) as discussed in Section *2.2.2.* This is the most important variable I study in this chapter. I expect to see a positive (negative) relation between PIN and the permanent price impact of purchase (sale) block trades. This is because price shifts should follow the direction of an informed trade; hence I expect that an informed block purchase (sale) will lead to appreciation (depreciation). *lnSize* is the natural logarithm of the number of shares traded and reported to the nearest millisecond. Based on the established premise that size is related to the information content of a trade (see for example Kraus and Stoll, 1972, Chan and Lakonishok, 1997), I also proxy information content using block trade size.

Volatility is the standard deviation of stock returns on the trading day prior to the block trade. It shows the intraday trading fluctuations in stock prices and therefore reflects the dispersion of beliefs about stock valuation in the market. An increase in volatility of a stock will increase its market risk, leading to larger spreads as well as larger price impact. Since prior contributions also suggest that investor demand for compensation corresponds to stock riskiness (Chan and Lakonishok, 1997, Alzahrani et al., 2013, Frino et al., 2007), I therefore expect a positive relationship between price impact and Volatility. *lnTurnover* is the natural logarithm of the total pound value of stocks traded divided by the pound value of shares outstanding on the trading day prior to the block trade. Turnover is employed by many researchers to measure liquidity in the market (see as examples Lakonishok and Lev, 1987). Investors are expected to demand higher premium to trade illiquid stocks (Amihud and Mendelson, 1986, Brennan and Subrahmanyam, 1996), hence I expect an inverse relationship to exist between price impact and Turnover. This means that when liquidity is higher, there should be lower price impact and vice versa.

Market return is the daily return on the FTSE 100 index. It is included in the regression model because literature has found that most stocks have positive beta (Aitken and Frino, 1996, Chiyachantana et al., 2004, Frino et al., 2007). Thus, a positive relationship is expected to exist between market return and price impact. *Momentum* is calculated as the lagged cumulative daily return for each stock on the five trading days prior to the block trades. Momentum captures the trading trend for each stock.

Thus, higher returns indicate a purchasing trend, and lower returns indicate a selling trend. Saar (2001) argues that the historical performance of stocks is related to their expected price impact asymmetry. Specifically, block trades that are executed following a depreciating price trend will exhibit higher positive asymmetry, and block trades executed following a run of price appreciation should display less price impact, or perhaps negative asymmetry. Specifically, historical cumulative lagged returns correspond to the magnitude of price impact. A positive relationship is therefore expected between momentum and price impact due to the herding effect. *BAS* is the relative bid-ask spread prior to the block trades. I calculate relative bid-ask spread as the ask price prior to the block trade minus the bid price before the block trade, divided by the midpoint of both prices. This measure is a proxy for liquidity, and when liquidity is high, BAS tends to be narrow. Hence, I expect lower price impact when spreads are narrow and larger price impact when they are wide.

OIB corresponds to daily order imbalance. This variable and PIN are new additions to the Frino et al. (2007) price impact model. I compute OIB as shown in Equation (3.5) for each day.[2] According to Chordia et al. (2008) , the extent of the predictability of returns by lagged OIB is an inverse measure of market efficiency. *OIB* in the model is therefore a proxy for how efficiently each stock is being traded.

$$OIB = \left| \frac{\#\,Buy\ trades - \#\,Sell\ trades}{\#\,Buy\ trades + \#\,Sell\ trades} \right| \qquad (3.5)$$

Time dummy variables are used to capture intraday effects of the private information diffusion process. Frino et al. (2007) and Alzahrani et al. (2013) document intraday

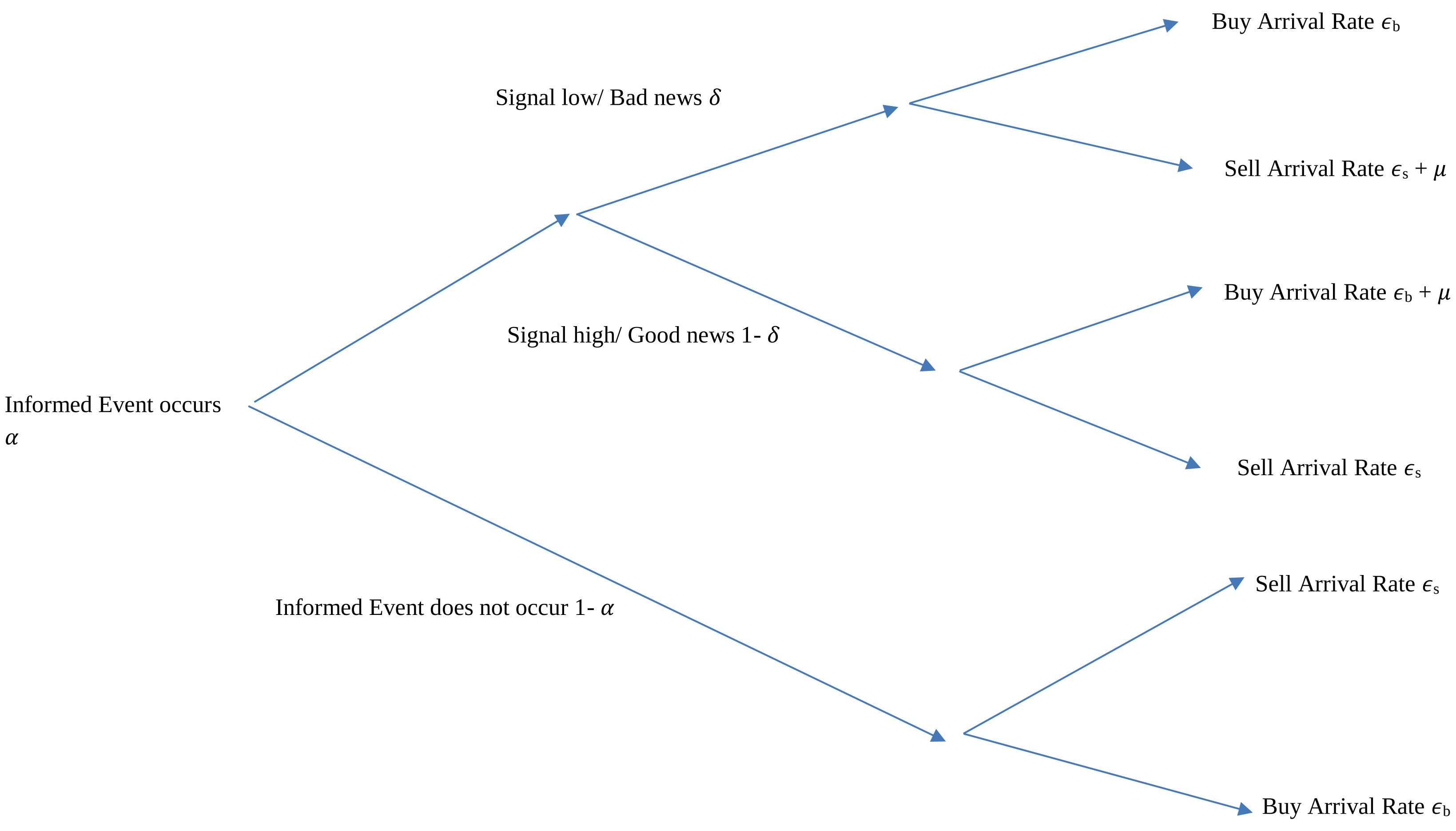
[2] I also compute OIB for each 5-minute period preceding a block trade. The results obtained using the 5-minute OIB measure are not qualitatively different from the main results presented in this paper.

patterns in the price impact of block trades. In this chapter, I employ dummy variables to capture intraday patterns of price effects. DUM_1 equals to one if block trade occurs between 8:00 and 9:00, and is otherwise zero. DUM_2 equals to one if the block trade occurs during 9:00 to 15:30, and is otherwise zero. DUM_3 equals to one if block trade occurs during 15:30 to 16:00, and is otherwise zero. The last trading period (16:00 – 16:30) is not in the regression, as it is the reference group of block trades.

3.2.2.2. The PIN Model

In order to capture the informed trading elements of stock for each day, I compute the daily probabilities of informed trading (PINs) based on the PIN model of Easley et al. (1996a) and Easley et al. (1997b). The model as specified is based on the expectation that trading between informed traders, liquidity traders and market makers occurs repeatedly over numerous trading intervals. As presented in Figure 3.5, trading intervals begin with the informed traders acquiring a private signal on a stock's value with a probability of α. Dependent 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 determine their bid and ask prices, with orders arriving from liquidity traders at the arrival rate ε. If there is a new piece of private information, informed traders will also trade and their orders will arrive at the rate μ. Hence, informed traders will execute a purchase trade should they receive a good news signal and sell if they receive a bad news signal. It is important to point out that the setting of different arrival rates for uninformed buyers and sellers does not qualitatively alter estimations of the probability that an informed trade has been executed (see Easley et al., 2002).

FIGURE 3.5
Tree diagram of the trading process



The PIN model allows us to approximate the unobservable distribution of trades between informed and uninformed traders through the modelling of purchases and sales.[3] Thus, the 'normal level' of sales and purchases executed within a stock on a given day over several intervals is interpreted as an uninformed trade by the model, and this information is employed when estimating ε. An unusual volume of purchase or sale transactions is interpreted as an information-based trade and employed when computing μ. In addition, the frequency of intervals during which 'abnormal' levels of purchase and sale transactions are executed is used when calculating 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:

$$
\begin{aligned}
L((B,S)\mid\theta) = {} & (1-\alpha)e^{-\varepsilon_b}\frac{\varepsilon_b^{B}}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s{}^{S}}{S!} \\
& + \alpha\delta e^{-e_b}\frac{\varepsilon_b{}^{B}}{B!}e^{-(\mu+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^{S}}{S!} \\
& + \alpha(1-\delta)e^{-\varepsilon_s}\frac{\varepsilon_s{}^{S}}{S!}e^{-(\mu+\varepsilon_b)}\frac{(\mu+\varepsilon_b)^{B}}{B!}
\end{aligned}
\tag{3.6}
$$

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 (3.6) corresponds to a mix of

[3] As stated earlier, I infer purchase and sales through the running of Lee and Ready's (1991) trade classification algorithm.

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 ensues independently across the different trading periods, Easley et al. (1996a) and Easley et al. (1997b) compute the parameter vector estimates using maximum likelihood estimation. Hence I obtain the parameters for each trading day and for each stock in the sample by maximum likelihood estimation. I thereafter follow Easley et al. (1996a) and Easley et al. (1997b) to compute PIN as:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \tag{3.7}$$

I include the daily stock-dependent PIN variable into the regression model (3.4).

3.3.Regression Results and Discussion

3.3.1. Preliminary Predictive Analysis

I commence my analysis by first examining the hypothesised relationship between the number/proportion of informed trades and the number of block trades executed on the same day. This is important in order to confirm my assumption that informed traders take advantage of their information by executing block trades. I approximate the number of informed trades occurring for each day by manipulating parameters obtained through the maximum likelihood estimation of the PIN model. Since α corresponds to the probability of information events and arrival rate of informed orders, μ, the number of informed trades may be expressed as the product of α and μ. I therefore estimate the following regression in order to test the assumption that informed traders use block trades as a trading vehicle.

$$\ln(\#\,Block\ trades_t) = \alpha + \beta \ln(\#\,Informed\ trades_t) + \varepsilon \tag{3.8}$$

Table 3.4 shows the statistical results. As expected, the positive and significant coefficient of informed trades indicates that with a 1% increase in the number of informed trades the number of block trades correspondingly increases 1.11% on the same trading day. The adjusted R^2 is about 52.18%, which is high for a univariate estimation. This is an indication that variation in the estimated number of informed trades can be explained by the quantity of block trades. This result is consistent with Easley and O'Hara (1987) and Blau et al. (2009), who suggest that informed traders prefer block trades to exploit private information. However, this result may be viewed to some extent as a contradiction of Barclay and Warner (1993) stealth trading hypothesis, which implies that most of cumulative price changes are due to mid-size trades. One of the explanations could be that Barclay and Warner (1993) focus on trades prior to tender offer events, during which any larger order could easily attract other investors' *unwanted* attention. Informed traders might therefore be more discrete in their exploitation of private information by splitting up large orders. In contrast, during uneventful trading periods informed traders might prefer block trades because they believe the market can absorb large orders without attracting undue attention. The view that stealth trading is mainly prevalent during eventful periods is further emphasised by Yang (2009). Yang (2009) reports that there is an increase in the implementation of stealth trading from around six to ten days prior to the release of quarterly earnings. However, informed traders are likely to aggressively exploit private information through the use of larger trades from about five days prior to the earnings announcements. Despite the inconsistency in the evidence, theoretical and empirical studies generally agree that informed traders are more likely to exploit private information by trading block sizes.

TABLE 3.3
Predictive Analysis Test

This table shows the results of regressing the natural logarithm of the daily number of block trades against the natural logarithm of estimated number of daily informed trades. I use the following model:

$$\ln(\#\,Block\ trades_t) = \alpha + \beta \ln(\#\,Informed\ trades_t) + \varepsilon$$

The coefficients and standard errors (in parentheses) are reported. *** corresponds to statistical significance at the 0.01 level.

	$\ln(\#\,Informed\ trades_t)$	
	Coefficient	*S.E.*
$\ln(\#\,Block\ trades_t)$	1.11***	2.83×10^{-2}
Constant	2.47***	4.98×10^{-2}
Observations	2,007	
R-squared	52.20%	
Adj R-squared	52.18%	

3.3.2. Trading on Information with Block Trades

Following the establishment of a predictive relationship between informed trading and block trades, I now examine the process by which information is compounded in instrument prices via block trading. Panels A, B and C of Table 3.5 present the estimated parameters from Equation (3.4) for all three price impact measures and for block purchases, block sales and all block trades in the sample. For block purchases, PIN shows a positive and statistically significant relationship with both permanent and temporary price impacts. The PIN Permanent price impact of block purchases is 0.000294, while the corresponding temporary price impact is 0.000386. The lesser permanent price impact coefficient estimate implies that the FTSE 100 stocks are less sensitive to informed trades than they are to liquidity trades. Consistent with my expectations, the PIN coefficient estimates for block sales are negative and statistically significant for both the temporary and permanent price impact regressions. As with the block purchases, there is a stronger level of temporary price impact than there is for permanent price impact. The negative (positive) statistically significant coefficient estimates of the PIN coefficients for the block sales (purchases) appear to confirm the information diffusion hypothesis via block trading.

The absolute value of the PIN coefficient against the permanent price impact of block sales is 0.0002, which is smaller than that in block purchases at 0.000294. This level of price impact asymmetry is consistent with previous literature (see for example, Gemmill, 1996) in which there is an implicit assumption that block purchases are more informative than block sales. Conventional explanation for this phenomenon is that, generally, buy trades are more likely to be induced by private information than by liquidity considerations; the motivation is the opposite for sell trades. However, regulations prohibit investors from exploiting negative private information. For example, in the UK the Financial Conduct Authority bans investors from short selling financial service stocks listed on the LSE. The information diffusion process of block purchases will, in all likelihood, be stronger than that of block sales. The estimated

PIN coefficient for the permanent price impact of all block trades is not statistically significant. This is because the coefficient sign is positive for price impact of block purchase and negative for price impact of block sells, while PIN is ranged from zero to one. Thus, PIN cannot statistically explain the variation in price impact when the price impact effects of block purchases and block sales increase simultaneously.

TABLE 3.4
Incorporation of Private Information via Block Trading in FTSE 100 stocks

The relationship between informed trading and block trading is estimated using the following model:

$$\text{Price impact} = \alpha + \beta_1 PIN + \beta_2 \ln Size + \beta_3 Volatility + \beta_4 \ln Turnover + \beta_5 MarketReturn + \beta_6 Momentum + \beta_7 BAS + \beta_8 |OIB| + \beta_9 DUM_1 + \beta_{10} DUM_2 + \beta_{11} DUM_3 + \varepsilon$$

Price impact corresponds to *permanent, temporary* or *total price impact*. *PIN* is the probability of an informed trade. *LnSize* is the natural logarithm of the number of shares per trade; *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place; *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade; *OIB* represents the order imbalance; *BAS* is the bid-ask spread at the time of the block trade; *Market return* is the daily FTSE100 return on the day of the block trade. *Momentum* is the cumulative return of the stock in the five days preceding the block trade. DUM_1 takes the value of 1 if the trade occurs between 8:00 and 9:00; DUM_2 takes the value of 1 if the trade occurs between 9:00 and 15:30; DUM_3 takes the value of 1 if the trade occurs between 15:30 and 16:00. Standard errors are presented in parentheses. Panels A, B and C present results for when permanent price impact, temporary price impact and total price impact are employed as dependent variables respectively. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

	Panel A. Permanent Price Impact			Panel B. Temporary Price Impact			Panel C. Total Price Impact		
	Purchases	*Sales*	*All Trades*	*Purchases*	*Sales*	*All Trades*	*Purchases*	*Sales*	*All Trades*
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
PIN	2.94×10^{-4}***	-2.00×10^{-4}**	6.81×10^{-7}	3.86×10^{-4}***	-8.33×10^{-4}***	-1.43×10^{-4}	1.13×10^{-3}	6.22×10^{-4}***	1.99×10^{-4}*
	(7.74×10^{-5})	(9.01×10^{-5})	(1.00×10^{-4})	(4.64×10^{-5})	(7.38×10^{-5})	(1.40×10^{-4})	(1.14×10^{-3})	(1.01×10^{-4})	(1.19×10^{-4})
Ln(size)	-1.01×10^{-6}	1.13×10^{-5}***	3.94×10^{-6}**	2.31×10^{-6}**	5.88×10^{-6}*	-7.07×10^{-7}	3.89×10^{-5}	4.81×10^{-6}	9.41×10^{-8}
	(1.96×10^{-6})	(2.1×10^{-6})	(1.57×10^{-6})	(1.00×10^{-6})	(3.06×10^{-6})	(6.25×10^{-6})	(4.24×10^{-5})	(3.38×10^{-6})	(3.05×10^{-6})
Volatility	3.02×10^{-5}	1.78×10^{-4}	5.47×10^{-6}	3.26×10^{-4}*	2.41×10^{-3}***	0.01	0.02	-2.17×10^{-3}***	-8.66×10^{-3}***
	(3.33×10^{-4})	(2.92×10^{-4})	(2.50×10^{-4})	(1.93×10^{-4})	(7.55×10^{-4})	(3.57×10^{-3})	(0.02)	(7.24×10^{-4})	(1.79×10^{-3})
Ln(turnover)	1.31×10^{-5} ***	-1.52×10^{-5}***	-1.54×10^{-6}	1.54×10^{-5}***	2.21×10^{-5}***	-3.8×10^{-8}	5.83×10^{-5}	-3.60×10^{-5}***	-7.93×10^{-6}
	(6.25×10^{-6})	(4.13×10^{-6})	(4.55×10^{-6})	(2.31×10^{-6})	(5.95×10^{-6})	(1.11×10^{-5})	(6.28×10^{-5})	(6.43×10^{-6})	(7.62×10^{-6})
Market Return	-8.22×10^{-4} ***	-1.16×10^{-4}	-4.72×10^{-4}*	-9.71×10^{-4}***	5.42×10^{-3}***	1.30×10^{-3}	7.37×10^{-3}	-5.38×10^{-3}***	-2.49×10^{-3}***
	(3.86×10^{-4})	(3.22×10^{-4})	(2.55×10^{-4})	(2.01×10^{-4})	(6.57×10^{-4})	(1.58×10^{-3})	(7.27×10^{-3})	(6.51×10^{-4})	(8.40×10^{-4})
Momentum	1.14×10^{-5}	6.10×10^{-5}***	2.39×10^{-5}	-5.03×10^{-5}***	7.71×10^{-5}***	-1.71×10^{-4}	6.38×10^{-5}	-1.51×10^{-5}	6.77×10^{-5}
	(2.11×10^{-5})	(1.65×10^{-5})	(1.74×10^{-5})	(1.18×10^{-5})	(2.48×10^{-5})	(2.09×10^{-4})	(1.74×10^{-5})	(2.50×10^{-5})	(8.10×10^{-5})
OIB	-1.03×10^{-5}	6.12×10^{-5}	6.81×10^{-5}*	-7.47×10^{-5}***	-2.82×10^{-4}***	-4.05×10^{-4}	3.79×10^{-4}	3.38×10^{-4}***	3.87×10^{-4}***
	(7.00×10^{-5})	(4.12×10^{-5})	(3.89×10^{-5})	(2.40×10^{-5})	(6.96×10^{-5})	(1.41×10^{-4})	(3.40×10^{-4})	(7.18×10^{-5})	(8.86×10^{-5})

BAS	0.42 ***	-0.199***	0.12**	-0.42***	0.96***	0.41***	0.76***	-1.16***	-0.23***
	(0.05)	(0.07)	(0.046)	(0.03)	(0.03)	(0.04)	(0.09)	(0.07)	(0.08)
DUM_1	9.66×10^{-5} ***	-7.92×10^{-5}***	7.20×10^{-6}	5.44×10^{-5}***	-2.46×10^{-4}***	-1.46×10^{-4}***	7.59×10^{-5}**	1.66×10^{-4}***	1.36×10^{-4}***
(8:00 - 9:00)	(1.94×10^{-5})	(1.63×10^{-5})	(1.21×10^{-5})	(9.29×10^{-6})	(1.71×10^{-5})	(2.96×10^{-5})	(3.60×10^{-5})	(2.10×10^{-5})	(2.13×10^{-5})
DUM_2	2.10×10^{-5}***	-3.13×10^{-5}***	-1.10×10^{-5}**	1.20×10^{-5}*	-9.09×10^{-5}***	-1.49×10^{-5}	8.52×10^{-5}	5.99×10^{-5}***	1.19×10^{-5}
(9:00 - 15:30)	(7.78×10^{-6})	(6.07×10^{-6})	(4.85×10^{-6})	(7.31×10^{-6})	(1.41×10^{-5})	(3.06×10^{-5})	(7.50×10^{-5})	($1.37\times10^{-5)}$	(1.65×10^{-5})
DUM_3	1.22×10^{-5}	-3.01×10^{-5}***	-1.19×10^{-5}**	3.42×10^{-7}	-1.44×10^{-4}***	-1.11×10^{-4}***	8.56×10^{-6}	1.13×10^{-4}***	8.22×10^{-5}***
(15:30 - 16:00)	(8.96×10^{-6})	(6.33×10^{-6})	(5.50×10^{-6})	(8.33×10^{-6})	(1.88×10^{-5})	(2.84×10^{-5})	(5.39×10^{-6})	(1.79×10^{-5})	(1.69×10^{-5})
Constant	5.96×10^{-5}	-1.99×10^{-4}***	-6.77×10^{-5}**	1.03×10^{-4}***	6.59×10^{-4}***	2.36×10^{-4}	-1.78×10^{-4}	-8.45×10^{-4}***	-3.55×10^{-4}***
	(5.56×10^{-5})	(3.93×10^{-5})	(3.42×10^{-5})	(2.28×10^{-5})	(6.75×10^{-5})	(1.26×10^{-4})	(1.04×10^{-4})	(6.99×10^{-5})	(8.33×10^{-5})
Observations	206,002	246,867	453,012	206,002	246,867	453,012	206,002	246,867	453,012
R-squared	0.77%	0.34%	0.07%	2.14%	1.40%	0.05%	2.92%	1.89%	0.06%
Adj R-squared	0.76%	0.34%	0.06%	2.14%	1.39%	0.05%	2.92%	1.89%	0.06%

Estimated coefficients for other explanatory variables are largely consistent with existing literature on the price impact of block trades. I find that size has a positive coefficient related to the temporary effect of block purchases, the permanent effect of block sales and all block trades. This suggests that volume has a direct relationship with inventory costs and that price impact is an increasing (decreasing) function of trade size in purchase (sell) block trades (Alzahrani et al., 2013). However, the coefficient for the permanent price impact of block purchases is not significant. In addition, the size variable exhibits intriguing coefficient behaviour. The positive effect of size on permanent impacts indicates that the largest block sales will have smaller price impacts compared with small and medium block sales. This could mean that, within the largest 1% of trades, relatively small trades are more informative. This evidence is in line with Barclay and Warner (1993) findings that informed traders prefer to split their largest orders for execution as medium-sized ones. One plausible aim of this behaviour is to camouflage informed trades as uninformed smaller trades in the order flow. Since there is a consistent general view that large trades imply informed trading, trading in smaller sizes affords the opportunity to avoid detection of informed large orders. Another aim, related to the first, is that a large trade may not necessarily be informed but, since it could be treated as such, a liquidity trader may be inclined to execute it as smaller trades in order to avoid paying a premium or offering a discount.

Volatility exhibits a statistically significant positive relationship with the temporary effect of block purchases and entire block trades. The positive coefficients of temporary price impact of block purchases are in line with literature that states that counterparties will demand higher premium in order to assume higher market risk (see Alzahrani et al., 2013, Chan and Lakonishok, 1997, Frino et al., 2007). However, I also observe some mild and inexplicable inconsistencies which show that volatility is positively related to the temporary price impact of block sales, and negatively related with total price impact of both block sales and all block trades. Given the general lack of statistical analysis of the purchase block trades' volatility coefficient estimates; it appears that the driver of the all block trades coefficient estimates is the evolution of the sale block trades. Turnover has a statistically significant positive effect on the temporary and permanent price impact of block purchase, and a negative effect on permanent price impact of block sales. These estimates imply that higher liquidity can induce a higher permanent price impact in FTSE100 block trades. This result contradicts the argument of Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996) liquidity effect proposition that traders ask for higher premium in order to trade illiquidity stocks. However, my results can be justified as larger block trades can alter perception of the market value of stocks (Alzahrani et al., 2013). Regardless of liquidity constraints, chasing momentum could generate high turnover and, in turn, a price run-up (Chan et al., 1996). I directly examine the effect of momentum in this framework and discuss it below.

Literature suggests that market return should have a positive relationship with price impact. However, my estimates show that market return has a negative effect on the permanent and temporary price impacts of block purchases. The coefficient estimates suggest that there is a reduced price impact for block purchases when market returns rise. The positive and statistically significant market return coefficient for the block sales' temporary price impact is however in line with literature, which suggests a reduced price impact for block sales (see Frino et al., 2007). For momentum, coefficient estimates for total price impact is negative and statistically significant at 0.01, level thus implying that a higher recent price run-up will generate a smaller price impact for block purchases (Saar, 2001). Chiyachantana et al. (2004) make similar inferences based on their analysis; they argue that institutional investors prefer to purchase after days of price run-up in order to induce lower price changes. By contrast, momentum has positive effects on the permanent and temporary price impact measures of block sales, and both coefficient estimates are statistically significant. This reversal sign of momentum variable indicates price reversals associated with block purchases. Positive momentum coefficient estimates suggest that a stock with a momentum trend in its performance is expected to have a lower price impact for block sales. This is in line with my observation regarding the turnover estimates above, as well as with Saar (2001) prediction.

Order imbalance coefficient estimates for total price impact and temporary price impact of block sales and all block trades are all positive and significant. This is because order imbalance measures the daily excess amount of buy orders over sell orders, it conveys information to the market makers and traders about the intraday variations in the order flow and, ultimately, the perceived value of instruments. Higher order imbalance would imply deviation from the norm leading to a perception that the market is inefficient. Thus the coefficient values imply that for block sales, during pockets of inefficiency, there is reduced price impact and even though not statistically significant, the positive block purchase coefficients imply the increasing price impact of total block trades (Chordia et al., 2002a). Bid-ask spread (BAS) is positively related to the price impact of block purchases, and negatively related to the price impact of block sales, with the exception of the permanent price impact. Consistent with Aitken and Frino (1996), results show that when bid-ask spread is wider the price impact is greater for both purchase and block sales.

For intraday effects, dummy variables DUM_1 and DUM_2 in the permanent price impact of block purchases show a positive and significant relationship with price impact. However, the coefficient on DUM_1 is larger than on DUM_2, indicating that the price impact is stronger during the first hour (8:00 – 9:00) than during midday trading hours (9:00 – 15:30). Similarly, dummy variables DUM_1 and DUM_2 in the permanent price impact of block sales show a negative and significant relationship with price impact. Overall, the DUM_1 permanent price impact coefficients for both block purchases and sales are larger than the DUM_1 temporary price impact coefficients. This confirms the expectation that information is accumulated overnight and is thus incorporated into the prices of stocks during the first hour of trading the next day (see also Ibikunle, 2015a).

Our regression model is similar to that of Alzahrani et al. (2013), who study the impacts of block trades in the Saudi Stock Market (SSM). They find that permanent price impact is generally larger than temporary price impact. Their results reveal that most of their independent variables can significantly explain the variations of the permanent price impact, implying that independent variables in their model can, potentially, be used to predict the movement of price impact of block trades. Therefore, they conclude that the SSM is highly sensitive to the informed trades. In contrast, my results are based on a more developed market and a highly liquid sample of FTSE100 stocks, and largely differ from Alzahrani et al. (2013) in that the temporary price impact of block trades is generally more pronounced than the permanent price impact of block purchases. I also find price impact asymmetry such that purchase blocks have higher information diffusion effects than sale blocks. Additionally, not all of the control variables can statistically explain the variation of permanent price impact.

3.3.3. Intraday Patterns

The dummy variables in the full sample regression imply intraday patterns of price impact. To explore this intraday effect of the information diffusion process more keenly, I exogenously split the sample into four time intervals: the first trading hour (8:00hrs – 9:00hrs), middle of the day (9:00hrs – 15:30hrs), the penultimate thirty minutes of trading (15:30hrs – 16:00hrs) and the final thirty minutes of trading (16:00hrs – 16:30hrs). Tables 3.6 and 3.7 show the regression results for block purchases and sales. Panel A in Table 3.6 shows the regression coefficients of the permanent price impact of block purchase. It can be seen that the coefficient of PIN in the first trading hour is 0.000599, which is larger than that of the middle of day trading hours' estimate at 0.000396; both estimates are statistically significant at the 0.05 and 0.01 levels respectively. This indicates that the information diffusion process is strongest during the opening hour, despite the fact that the middle trading period includes six and half hours of the largest volume trading. The observation is also consistent for temporary price impact estimates. These results are in line with Ibikunle (2015a), who argues that a substantial fraction of price discovery occurs during the first trading hour because large amount of new information, held back during the opening auction, is released into the market early on during the continuous trading session of the day. The PIN coefficients for the other trading sub-periods of the day are not statistically significant since, as shown by Ibikunle (2015a), more than 97% of the efficient price discovery occurs prior to the last half hour of trading for FTSE 100 stocks trading on the LSE.

TABLE 3.5

Incorporation of Private Information via Purchase Block Trading in FTSE 100 Stocks across Trading Hours

The relationship between informed trading and purchase block trading across intraday trading intervals is estimated using the following model:

$$\Pr ice\ impact = \alpha + \beta_1 PIN + \beta_2 \ln Size + \beta_3 Volatility + \beta_4 \ln Turnover + \beta_5 Market\mathrm{Re}turn + \beta_6 Momentum + \beta_7 BAS + \beta_8 \,|\, OIB \,| + \varepsilon$$

Price impact corresponds to *permanent*, *temporary* or *total price impact*. *PIN* is the probability of an informed trade. *LnSize* is the natural logarithm of the number of shares per trade; *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place; *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade; *OIB* represents the order imbalance; *BAS* is the bid-ask spread at the time of the block trade; *Market return* is the daily FTSE100 return on the day of the block trade. *Momentum* is the cumulative return of the stock in the five days preceding the block trade. Standard errors are presented in parentheses. Panels A, B and C present results for when permanent price impact, temporary price impact and total price impact are employed as dependent variables respectively. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

	Panel A. Permanent Price Impact				Panel B. Temporary Price Impact				Panel C. Total Price Impact			
	8:00 - 9:00	***9:00 - 15: 30***	***15:30 - 16:00***	***16:00 - 16:30***	***8:00 - 9:00***	***9:00 - 15: 30***	***15:30 - 16:00***	***16:00 - 16:30***	***8:00 - 9:00***	***9:00 - 15: 30***	***15:30 - 16:00***	***16:00 - 16:30***
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
PIN	5.99×10^{-4}**	3.96×10^{-4}***	9.42×10^{-5}	2.37×10^{-4}	3.45×10^{-4}***	3.03×10^{-4}***	1.34×10^{-4}	4.25×10^{-4}	2.50×10^{-4}	9.23×10^{-5}***	-4.04×10^{-5}	-1.90×10^{-4}
	(2.58×10^{-4})	(3.98×10^{-5})	(1.03×10^{-4})	(2.79×10^{-4})	(1.15×10^{-4})	(3.08×10^{-5})	(8.43×10^{-5})	(2.97×10^{-4})	(2.45×10^{-4})	(3.16×10^{-5})	(7.14×10^{-5})	(1.06×10^{-4})
Ln(size)	-9.95×10^{-7}	8.7×10^{-7}	-5.09×10^{-6}*	4.00×10^{-6}	5.23×10^{-6}	7.45×10^{-7}	-2.81×10^{-6}	4.00×10^{-6}	-6.30×10^{-6}	1.2×10^{-7}	-2.28×10^{-6}	-1.01×10^{-7}
	(1.02×10^{-5})	(1.70×10^{-6})	(2.98×10^{-6})	(3.96×10^{-6})	(3.68×10^{-6})	(1.49×10^{-6})	(2.44×10^{-6})	(3.92×10^{-6})	(9.09×10^{-6})	(3.84×10^{-6})	(2.13×10^{-6})	(6.30×10^{-6})
Volatility	1.14×10^{-3}	5.48×10^{-5}	4.65×10^{-4}	6.96×10^{-4}	1.85×10^{-4}	3.05×10^{-4}	5.43×10^{-4}***	4.11×10^{-4}	-1.32×10^{-3}	-2.51×10^{-4}	-7.87×10^{-5}	2.84×10^{-4}
	(1.93×10^{-3})	(2.75×10^{-4})	(6.74×10^{-4})	(5.61×10^{-4})	(8.81×10^{-4})	(2.01×10^{-4})	(4.41×10^{-5})	(4.57×10^{-4})	(1.67×10^{-3})	(1.93×10^{-4})	(4.03×10^{-5})	(3.19×10^{-4})
Ln(turnover)	4.52×10^{-5}	5.68×10^{-6}**	1.05×10^{-5}	2.01×10^{-5}*	4.03×10^{-5}***	8.39×10^{-6}***	8.15×10^{-6}	1.51×10^{-5}	5.30×10^{-6}	-2.72×10^{-6}	2.38×10^{-6}	4.60×10^{-6}
	(3.04×10^{-5})	(2.91×10^{-6})	(7.97×10^{-6})	(1.18×10^{-5})	(6.99×10^{-6})	(1.88×10^{-6})	(5.97×10^{-6})	(1.12×10^{-5})	(2.94×10^{-5})	(2.11×10^{-6})	(4.00×10^{-6})	(3.70×10^{-6})
Market Return	-3.41×10^{-3}*	6.22×10^{-5}	-1.40×10^{-3}	-2.19×10^{-3}***	-2.40×10^{-3}***	-3.41×10^{-4}*	1.91×10^{-3}	-1.61×10^{-3}***	-1.02×10^{-3}	4.03×10^{-4}	5.15×10^{-4}	-5.76×10^{-4}*
	(1.93×10^{-3})	(2.58×10^{-4})	(1.25×10^{-3})	(6.21×10^{-4})	(7.17×10^{-4})	(1.88×10^{-4})	(1.18×10^{-3})	(5.45×10^{-4})	(1.79×10^{-3})	(1.74×10^{-4})	(3.65×10^{-4})	(3.02×10^{-4})
Momentum	1.66×10^{-4}	-4.31×10^{-5}***	1.86×10^{-5}	1.95×10^{-5}	-1.24×10^{-4}**	-4.52×10^{-5}***	-3.44×10^{-6}	1.25×10^{-6}	2.91×10^{-4}***	2.4×10^{-6}	2.23×10^{-5}	1.83×10^{-5}
	(1.13×10^{-4})	(1.62×10^{-5})	(2.57×10^{-5})	(2.47×10^{-5})	(5.12×10^{-5})	(1.16×10^{-5})	(1.58×10^{-3})	(1.67×10^{-5})	(3.93×10^{-5})	(9.09×10^{-6})	(1.76×10^{-5})	(1.23×10^{-5})
OIB	7.73×10^{-4}*	-1.44×10^{-4}***	-4.91×10^{-5}	-1.55×10^{-4}**	5.22×10^{-5}	-9.76×10^{-5}***	-2.14×10^{-5}	-1.25×10^{-4}**	$7.21\times10^{-4*}$	-4.62×10^{-5}**	-2.77×10^{-5}	-3.03×10^{-5}
	(4.22×10^{-4})	(3.40×10^{-5})	(2.54×10^{-5})	(6.68×10^{-5})	(1.11×10^{-3})	(2.41×10^{-5})	(5.25×10^{-5})	(6.04×10^{-5})	(4.07×10^{-4})	(2.35×10^{-5})	(5.38×10^{-5})	(3.26×10^{-5})

BAS	0.54***	0.24***	0.368***	0.24	-0.474***	-0.348***	-0.17***	-0.38*	1.02***	0.59***	0.54***	0.63***
	(0.09)	(0.02)	(0.06)	(0.18)	(0.05)	(0.02)	(0.06)	(0.20)	(0.09)	(0.02)	(0.04)	(0.09)
Constant	2.66×10^{-4}	2.52×10^{-5}	1.65×10^{-4}*	1.74×10^{-4}***	4.12×10^{-4}***	6.94×10^{-5}***	9.23×10^{-5}	7.32×10^{-5}	-1.46×10^{-4}	-4.4×10^{-5}**	7.29×10^{-5}	1.01×10^{-4}***
	(3.02×10^{-4})	(2.81×10^{-5})	(9.17×10^{-5})	(6.74×10^{-5})	(7.91×10^{-5})	(2.85×10^{-5})	(7.18×10^{-5})	(6.08×10^{-5})	(2.98×10^{-4})	(1.90×10^{-5})	(5.62×10^{-5})	(3.42×10^{-5})
Observations	35,490	129,411	15,262	25,839	35,490	129,411	15,262	25,839	35,490	129,411	15,262	25839
R-squared	0.80%	1.00%	1.09%	0.25%	4.42%	1.88%	0.32%	0.31%	2.56%	7.10%	5.53%	10.06%
Adj R-squared	0.78%	1.00%	1.03%	0.22%	4.40%	1.88%	0.27%	0.28%	2.54%	7.10%	5.48%	10.04%

TABLE 3.6

Incorporation of Private Information via Sale Block Trading in FTSE 100 Stocks across Trading Hours

The relationship between informed trading and sale block trading across intraday trading intervals is estimated using the following model:

$$Price\ impact = \alpha + \beta_1 PIN + \beta_2 \ln Size + \beta_3 Volatility + \beta_4 \ln Turnover + \beta_5 Market\ Return + \beta_6 Momentum + \beta_7 BAS + \beta_8 \mid OIB \mid + \varepsilon$$

Price impact corresponds to *permanent, temporary* or *total price impact*. *PIN* is the probability of an informed trade. *LnSize* is the natural logarithm of the number of shares per trade; *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place; *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade; *OIB* represents the order imbalance; *BAS* is the bid-ask spread at the time of the block trade; *Market return* is the daily FTSE100 return on the day of the block trade. *Momentum* is the cumulative return of the stock in the five days preceding the block trade. Standard errors are presented in parentheses. Panels A, B and C present results for when permanent price impact, temporary price impact and total price impact are employed as dependent variables respectively. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

	Panel A. Permanent Price Impact				Panel B. Temporary Price Impact				Panel C. Total Price Impact			
	8:00 - 9:00	***9:00 - 15: 30***	***15:30 - 16:00***	***16:00 - 16:30***	***8:00 - 9:00***	***9:00 - 15: 30***	***15:30 - 16:00***	***16:00 - 16:30***	***8:00 - 9:00***	***9:00 -15: 30***	***15:30 - 16:00***	***16:00 - 16:30***
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
PIN	-1.15×10^{-4}	2.91×10^{-3}	-2.44×10^{-4}***	-1.09×10^{-4}	-2.00×10^{-4}	5.46×10^{-3}	-1.44×10^{-3}***	-1.78×10^{-3}***	3.12×10^{-4}	3.74×10^{-3}	1.17×10^{-3}***	1.70×10^{-3}***
	(2.87×10^{-4})	(2.44×10^{-3})	(8.41×10^{-5})	(1.28×10^{-4})	(1.75×10^{-4})	(0.02)	(3.83×10^{-4})	(2.97×10^{-4})	(2.85×10^{-4})	(2.46×10^{-3})	(3.50×10^{-4})	(2.60×10^{-4})
Ln(size)	3.18×10^{-5}***	2.72×10^{-5}	-5.29×10^{-7}	3.8×10^{-6}	1.39×10^{-5}**	-1.55×10^{-3}*	2.47×10^{-5}**	-5.96×10^{-5}*	1.80×10^{-5}*	8.11×10^{-5}*	-2.50×10^{-5}**	4.58×10^{-5}***
	(8.69×10^{-6})	(3.79×10^{-5})	(1.00×10^{-5})	(3.57×10^{-6})	(6.07×10^{-6})	(8.59×10^{-4})	(1.14×10^{-5})	(3.06×10^{-5})	(9.90×10^{-6})	(4.29×10^{-5})	(1.07×10^{-5})	(1.53×10^{-5})
Volatility	3.52×10^{-3}**	3.56	-1.67×10^{-4}	-1.14×10^{-3}	3.13×10^{-3}*	6.78***	-4.16×10^{-4}	1.12×10^{-2}	4.23×10^{-4}	3.43	1.97×10^{-4}	-6.51×10^{-3}
	(1.47×10^{-3})	(2.51)	(7.26×10^{-4})	(9.87×10^{-4})	(1.84×10^{-3})	(2.24)	(1.43×10^{-3})	(0.01)	(1.97×10^{-3})	(2.51)	(1.52×10^{-3})	(4.68×10^{-3})
Ln(turnover)	-3.81×10^{-5}**	1.29×10^{-3}	-4.93×10^{-6}	-8.93×10^{-6}	3.00×10^{-5}**	3.82×10^{-3}*	3.39×10^{-5}	1.38×10^{-5}	-7.60×10^{-6}	1.23×10^{-3}	-3.76×10^{-5}*	-2.81×10^{-5}
	(1.75×10^{-5})	(9.19×10^{-4})	(6.33×10^{-6})	(6.16×10^{-6})	(1.18×10^{-5})	(2.21×10^{-3})	(2.19×10^{-5})	(3.59×10^{-5})	(1.88×10^{-5})	(9.22×10^{-4})	(2.03×10^{-5})	(2.92×10^{-5})
Market Return	-4.67×10^{-3}***	-9.78×10^{-2}	-1.12×10^{-4}	-1.19×10^{-3}***	3.93×10^{-3}**	0.13	-1.07×10^{-3}	2.26×10^{-3}	-8.47×10^{-3}***	-0.107	8.20×10^{-4}	-1.53×10^{-3}
	(1.62×10^{-3})	(0.07)	(4.87×10^{-4})	(5.44×10^{-4})	(1.39×10^{-3})	(0.17)	(2.24×10^{-3})	(3.71×10^{-3})	(1.85×10^{-3})	(0.07)	(2.10×10^{-3})	(2.24×10^{-3})
Momentum	2.44×10^{-4}***	-2.88×10^{-3}	2.08×10^{-5}	2.99×10^{-5}	1.13×10^{-4}**	6.5×10^{-3}	6.47×10^{-5}	-6.18×10^{-5}	1.32×10^{-4}	-2.87×10^{-3}	-4.19×10^{-5}	7.38×10^{-5}
	(8.18×10^{-5})	(2.06×10^{-3})	(2.80×10^{-5})	(2.68×10^{-5})	(4.72×10^{-5})	(5.56×10^{-3})	(6.48×10^{-5})	(8.26×10^{-5})	(6.95×10^{-4})	(2.08×10^{-3})	(6.18×10^{-5})	(4.56×10^{-5})
OIB	1.63×10^{-4}	1.08×10^{-3}	1.39×10^{-4}*	-1.38×10^{-4}*	2.15×10^{-4}	-0.04**	-2.98×10^{-4}	-1.07×10^{-3}**	-4.26×10^{-5}	1.16×10^{-2}	4.17×10^{-4}	6.27×10^{-4}**

	(2.24×10^{-4})	(7.61×10^{-3})	(7.16×10^{-5})	(7.67×10^{-5})	(2.11×10^{-4})	(0.02)	(2.89×10^{-4})	(5.39×10^{-4})	(2.70×10^{-4})	(7.60×10^{-3})	(2.66×10^{-4})	(3.03×10^{-4})
BAS	-0.29**	-3.77	-0.24***	-0.144	0.89***	5.66	1.035***	1.16***	-1.18***	-5.15**	-1.24***	-1.33***
	(0.14)	(2.62)	(0.05)	(0.12)	(0.05)	(5.34)	(0.22)	(0.16)	(0.13)	(2.61)	(0.20)	(0.15)
Constant	-7.14×10^{-4}***	8.59×10^{-3}	-5.05×10^{-5}	-1.31×10^{-4}**	-3.70×10^{-4}***	0.05*	7.63×10^{-4}***	1.40×10^{-3}***	-3.38×10^{-4}	7.38×10^{-3}	-7.97×10^{-4}***	-1.44×10^{-3}***
	(1.99×10^{-4})	(6.23×10^{-3})	(6.67×10^{-5})	(6.58×10^{-5})	1.38×10^{-4}	(0.02)	(2.33×10^{-4})	(4.17×10^{-4})	(2.15×10^{-4})	(6.26×10^{-3})	(2.22×10^{-4})	(3.07×10^{-4})
Observations	41,492	156,625	18,224	30,476	41,492	156,625	18,224	30,476	41,492	156,625	18,224	30,476
R-squared	0.40%	0.37%	0.79%	0.22%	4.01%	0.30%	0.47%	0.08%	3.58%	0.34%	0.77%	0.29%
Adj R-squared	0.39%	0.36%	0.74%	0.19%	4.00%	0.29%	0.42%	0.05%	3.56%	0.34%	0.73%	0.26%

Results in Table 3.7 are very intriguing because they suggest that, while information diffusion behaviour is strongest during the opening hour for block purchases, block sales do not register statistically significant information diffusion effects until the trading day is truly well under way. The PIN coefficients are only statistically significant for the final two half-hour trading periods of the day. The permanent price impact coefficient for the half-hour period between 15:30-16:00 hours is -0.00024 and is statistically significant at the 0.01 level. For the temporary price impact, the coefficients for the final two half-hour trading periods are -0.0014 and -0.0018 respectively and both are statistically significant at the 0.01 level. The results imply that when informed trading activity is highest in the market, arbitrage traders operate from neutral positions from where they bid for profit opportunities. According to Ibikunle (2015b), informed trading is highest on the LSE during early trading, and decreases as the continuous trading session progresses. Thus, with the reduction in the arbitrage seeking activities of informed traders comes a reduction in purchase trades. The decreases in purchases will allow for increased price impact for block sales, hence the larger information diffusion activity of block sales during the latter end of the continuous trading day. Overall, this section provides evidence that the diffusion process is strong during the opening of the trading session, when trading is most vigorous and there is an increased presence of informed traders (Dufour and Engle (2000). These results also indicate that a liquid and deep market could well facilitate the information diffusion process.

3.3.4. Inter-day patterns (long-lived information)

I now explore the systematic inter-day variations of the information diffusion process. Kyle's (1985) theoretical model suggests that informed traders do not immediately execute trades with all of the information at their disposal; rather, they do so in a gradual manner. This implies that information could be slowly incorporated into prices of instruments over a time frame longer than the length of the trading day. This theoretical position is bolstered by the empirical analysis of Hong et al. (2000). Using analyst coverage as a proxy for firm-specific information inflow, Hong et al. (2000) find that the momentum trend of stocks is caused by the slow impounding of firm-specific information into stock prices. The use of analyst following as a proxy for firm-specific (private) information has been criticised by Vega (2006); in this section, I employ a more generally accepted proxy for private information to examine the hypothesis that private information in trading could be long-lived. Foster and Viswanathan (1993b) also propose a theoretical optimal trading strategy, in which informed traders prefer to trade intensively on common information, and trade less on their private information. Once common information is fully reflected in the stock prices, informed traders then start trading based on private information. This also supports the hypothesis that private information is incorporated into stock prices in a gradual manner. Based on the foregoing submissions, I hypothesize that informed traders will not fully exploit their superior information by the end of an average trading day; they will hold on to it and exploit it during the next trading opportunity (day). According to Holden and Subrahmanyam (1992), informed traders might also try to obtain updated private information during non-trading hours. Then, once the market opens, they may trade aggressively based on yesterday's (re-evaluated) private information. I test this hypothesis by employing the following regression model:

$$\ln\left(\frac{\#\,Block\;trades_t}{\#\,Block\;trades_{t-1}}\right) = \alpha + \beta_1 PIN_{t-1} + \beta_2 Volatility_{t-1} + \beta_3 \ln Turnover_{t-1} + \beta_4 Market\,return_{t-1} + \beta_5 Momentum + \beta_6 \,|OIB|_{t-1} + \varepsilon \tag{3.9}$$

where $\ln\left(\frac{\#\,Block\;trades_t}{\#\,Block\;trades_{t-1}}\right)$ is the natural logarithm of the number of block trades on day_t scaled by the number of block trades on day *t-1*. It reflects the relative change of number of block trades based on the previous trading day. All other variables are as previously defined. I note the limitations of my ability to proxy the overnight private information on day *t-1,* and therefore employ the previous day's PIN as a proxy for existing private information prior to the current trading day.

Table 3.8 presents the regression results from Equation (3.9). Panel A shows the regression results for the entire trading day's block trades, while Panel B is focused only on the first hour of the trading day. The focus on the first hour of trading as an extension of the analysis is based on the expectation that overnight private information is more likely to be traded upon within the first hour of trading. Most of the PIN_{t-1} coefficients in Panels A and B are positive and statistically significant. This indicates that informed traders adjust their block trade positions on day *t* relative to day_{t-1} based on private information gleaned during day *t-1*. In Panel B, the coefficients of PIN_{t-1} of block purchases and sales are larger than the corresponding coefficients of PIN_{t-1} in Panel A. This confirms my expectations that informed traders holding long-lived private information will aim to utilise it by aggressively adjusting their positions during the first trading hour. This is because the longer they hold on to a set of privately acquired information, the more likely it is that they become public before the informed traders could benefit from them (see Foster and Viswanathan, 1993b). Further, the market is at one of its most liquid (in terms of depth) and volatile intervals during the opening period, and therefore informed traders aim to take advantage of this natural camouflage to execute informed block trades. All turnover coefficients in both panels of Table 3.8 are, statistically, highly significant and positive. This implies that informed traders are more willing to adjust their block positions if the stock is very liquid during the previous trading day. This is because a liquid market can easily absorb block trades without causing large price fluctuations. I also observe that in Panel A, market return has statistically significant negative coefficients for purchase and sale block trades. A possible explanation for this could be that when the market is on the rise, informed traders do not adjust their positions by block trades the following day because they may expect a price run-up in their portfolio holdings. Informed traders also may not adjust positions by block sales if they have no liquidity motives to do so.

TABLE 3.7
Inter-day relationship between PIN and Block Trades

This table shows the regression results of the relationship between the inter-day percentage change of number of block trades and the probability of an informed trade. Panel A reports the regression coefficient estimates for block trades sample during the entire continuous trading day, while Panel B reports the regression coefficient estimates for the one-hour period between 08:00 and 09:00hrs. I use the following model:

$$\ln\left(\frac{\#\,Block\ trades_t}{\#\,Block\ trades_{t-1}}\right) = a + b_1 PIN_{t-1} + b_2 Volatility_{t-1} + b_3 \ln Turnover_{t-1} + b_4 Market\ return_{t-1} + b_5 Momentum_{t-1} + b_6 \,|OIB|_{t-1} + e$$

$\ln\left(\frac{\#\,Block\ trades_t}{\#\,Block\ trades_{t-1}}\right)$ corresponds to the natural logarithm of number of block trades at day *t* divided by the number of block trades at day t_{-1}, it depicts the change of number of block trades based on the previous trading day. *PIN* is the probability of an informed trade. *LnSize* is the natural logarithm of the number of shares per trade; *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place; *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade; *OIB* represents the order imbalance; *BAS* is the bid-ask spread at the time of the block trade; *Market return* is the daily FTSE100 return on the day of the block trade. *Momentum* is the cumulative return of the stock in the five days preceding the block trade. Standard errors are presented in parentheses. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

	Panel A. Block Trades during the day			Panel B. Block Trades during the first trading hour (8:00-9:00)		
	Block Purchases	Block Sales	All Block Trades	Block Purchases	Block Sales	All Block Trades
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
PIN_{t-1}	0.25*	0.23*	0.44***	0.41**	0.25	0.35**
	(0.14)	(0.13)	(0.10)	(0.19)	(0.21)	(0.16)
$Turnover_{t-1}$	0.07***	0.07***	0.06***	0.07***	0.04**	0.07***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Momentum	-0.05	-0.05	-0.06	0.01	0.02	-0.04
	(0.05)	(0.06)	(0.04)	(0.07)	(0.07)	(-0.06)
$Volatility_{t-1}$	0.92	0.36	2.51	0.45	-1.77	-1.16
	(2.04)	(1.98)	(1.67)	(0.28)	(3.21)	(2.51)
OIB_{t-1}	0.08	0.06	-0.11	-0.23	-0.45**	-0.22
	(0.14)	(0.15)	(0.11)	(0.19)	(0.21)	(0.16)
$Market\ Return_{t-1}$	-4.84***	-5.15***	0.28	-0.37	2.31	-0.12
	(1.25)	(1.27)	(1.00)	(1.62)	(1.86)	(1.48)
Constant	0.54***	0.58***	0.38***	0.55***	0.35	0.60***
	(0.15)	(0.15)	(0.10)	(0.21)	(0.23)	(0.19)
Observations	9,555	9,224	10,071	6,598	5,360	8,306
R-squared	0.49%	0.51%	0.62%	0.36%	0.23%	0.35%
Adj R-squared	0.47%	0.44%	0.55%	0.28%	0.14%	0.29%

3.3.5. Stock opacity and the incorporation of information

The rate of information compounding for stocks is dependent on the availability of information through trading. I therefore expect that stocks with higher level of transparency will likely have different rates of information incorporation to those that are more opaque. There is an assumption that the more scrutinised a stock is the higher the level of its transparency (see for example, Hong et al.'s (2000) use of analyst coverage as a proxy for information flow). However, this often criticised proxy (see for example, Vega, 2006) reveals nothing about the information impounding process through trading. Using the PIN measure as a proxy for levels of stock trading transparency, I examine how the information incorporation process varies across FTSE 100 stocks with varying levels of transparency. Chung et al. (2005) investigate the relationship between informed trading and trade autocorrelation. Consistent with Easley et al. (1996b), they show that small stocks are associated with high levels of information-based trading. Their results also suggest that a higher probability of informed trading leads to a higher level of serial correlation in trade direction. Vega (2006) also finds that PIN is negatively correlated with firm size. However, the results show that the informed trading variable alone cannot statistically explain the magnitude of post-announcement drift. The results suggest that the more information (both private and public) investors have about the true value of an asset, the smaller the abnormal return drift. This finding is consistent with previous research that small firms' stocks experience greater post-announcement drift than large firms' stocks, since small firms are generally associated with high PINs. This is related to the low level of analyst coverage, large concentration of informed trades, and public news surprise.

Based on the foregoing, I hypothesise that the information diffusion process of high-PIN stocks is stronger than that of low-PIN stocks, since firms with low financial transparency might have more firm-specific information to reveal, and informed trade can facilitate more information into price discovery. I split the sample of FTSE 100 stocks into four portfolios according to the mean value of intraday PIN and estimate Equation (3.4) for each portfolio.

In Table 3.9, Panels A, B and C show the regression results for permanent, temporary and total price impacts of purchase block trades across portfolios. Clearly, PIN coefficients on permanent price impacts increase with the average PIN value in each portfolio. This confirms my expectation that the information diffusion effect is strongest for stocks with lower levels of transparency. However, in the case of block sales, as shown in Table 3.10, there is little evidence to support my hypothesis. It is also related to the fact that block sales are less informative than block purchases, since block sales are more likely to be liquidity-induced rather than information-based when compared to purchase trades. In this section I find that for those firms with relatively low financial transparency, investors and agents who are particularly skilful in analysing public news play an important role in revealing information via block purchases. This result is in line with Vega's (2006) finding that return of high PIN firms is less sensitive to the same size of surprise news than low PIN firms, because the private information should have already been revealed to the market by informed investors across trading periods. Hence, on balance, informed trading plays a positive role in facilitating more information into the price discovery process.

TABLE 3.8

Stock Transparency and Incorporation of Private Information via Purchase Block Trading in FTSE 100 Stocks

The relationship between informed trading and purchase block trading in FTSE 100 stocks with varying levels of stock transparency is estimated using the following model:

$$Pirce\ impact = \alpha + \beta_1 PIN + \beta_2 \ln Size + \beta_3 Volatility + \beta_4 \ln Turnover + \beta_5 Market\mathrm{Re}turn + \beta_6 Momentum + \beta_7 BAS + \beta_8 |OIB| + \beta_9 DUM_1 + \beta_{10} DUM_2 + \beta_{11} DUM_3 + \varepsilon$$

Price impact corresponds to *permanent, temporary* or *total price impact*. *PIN* is the probability of an informed trade. *LnSize* is the natural logarithm of the number of shares per trade; *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place; *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade; *OIB* represents the order imbalance; *BAS* is the bid-ask spread at the time of the block trade; *Market return* is the daily FTSE100 return on the day of the block trade. *Momentum* is the cumulative return of the stock in the five days preceding the block trade. DUM_1 takes the value of 1 if the trade occurs between 8:00 and 9:00; DUM_2 takes the value of 1 if the trade occurs between 9:00 and 15:30; DUM_3 takes the value of 1 if the trade occurs between 15:30 and 16:00. Standard errors are presented in parentheses. PIN estimates are used as proxies for stocks' levels of transparency; on this basis, stocks are partitioned into transparency quartiles/portfolios. The highest (lowest) PIN stocks are designated as Portfolio 1 (4) stocks. Panels A, B and C present results for when permanent price impact, temporary price impact and total price impact are employed as dependent variables respectively. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

	Panel A. Permanent Price Impact				Panel B. Temporary Price Impact				Panel C. Total Price Impact			
	Portfolio1 (High-PIN)	Portfolio2	Portfolio3	Portfolio 4 (Low-PIN)	Portfolio1 (High-PIN)	Portfolio2	Portfolio3	Portfolio 4 (Low-PIN)	Portfolio1 (High-PIN)	Portfolio2	Portfolio3	Portfolio 4 (Low-PIN)
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
PIN	5.46×10^{-4}***	3.65×10^{-4}**	1.84×10^{-4}***	1.84×10^{-4}*	2.15×10^{-5}	-9.21×10^{-5}	1.95×10^{-4}***	8.27×10^{-5}	3.32×10^{-4}	4.56×10^{-4}***	1.13×10^{-5}	4.85×10^{-5}
	(2.64×10^{-4})	(1.51×10^{-4})	(6.81×10^{-5})	(1.08×10^{-4})	(1.52×10^{-4})	(7.08×10^{-5})	(3.07×10^{-5})	(6.43×10^{-5})	(2.08×10^{-4})	(1.38×10^{-4})	(5.56×10^{-5})	(8.31×10^{-5})
Ln(size)	1.43×10^{-5}	8.46×10^{-6}*	-6.16×10^{-6}***	-7.63×10^{-6}*	3.59×10^{-6}	9.99×10^{-6}***	-3.78×10^{-6}***	6.23×10^{-6}*	1.07×10^{-5}	-1.56×10^{-6}	-2.38×10^{-6}	-1.53×10^{-5}***
	(1.27×10^{-5})	(4.74×10^{-6})	(2.13×10^{-6})	(4.34×10^{-6})	(6.35×10^{-6})	(2.34×10^{-6})	(1.29×10^{-6})	(3.39×10^{-7})	(1.17×10^{-5})	(5.71×10^{-6})	(1.59×10^{-6})	(4.18×10^{-6})
Volatility	-5.62×10^{-3}*	8.82×10^{-6}	1.46×10^{-4}	5.68×10^{-4}	2.28×10^{-4}	2.34×10^{-4}	2.50×10^{-4}	6.67×10^{-4}*	-5.89×10^{-3}**	-2.25×10^{-4}	-1.04×10^{-4}	1.18×10^{-4}
	(3.39×10^{-3})	(9.01×10^{-4})	(4.29×10^{-4})	(6.84×10^{-4})	(1.34×10^{-3})	(5.09×10^{-4})	(2.25×10^{-4})	(4.04×10^{-4})	(2.82×10^{-3})	(4.69×10^{-4})	(3.71×10^{-4})	(5.36×10^{-4})
Ln(turnover)	-1.68×10^{-5}	-3.72×10^{-5}***	2.61×10^{-6}	2.11×10^{-5}**	-9.5×10^{-6}	-1.59×10^{-5}***	1.32×10^{-5}***	2.16×10^{-5}***	-7.35×10^{-6}	-2.07×10^{-5}*	-1.05×10^{-5}***	-3.23×10^{-6}
	(3.47×10^{-5})	(1.27×10^{-5})	(4.76×10^{-6})	(9.50×10^{-6})	(1.82×10^{-5})	(6.11×10^{-6})	(1.97×10^{-6})	(6.47×10^{-6})	(2.69×10^{-5})	(1.17×10^{-5})	(4.10×10^{-6})	(9.97×10^{-6})
Market Return	-3.80×10^{-3}*	4.45×10^{-4}	-1.08×10^{-3}***	-5.93×10^{-4}	-2.00×10^{-3}	-7.50×10^{-4}***	-9.32×10^{-4}***	-7.18×10^{-4}*	-1.82×10^{-3}	1.20×10^{-3}	-1.42×10^{-4}	-7.15×10^{-4}
	(2.29×10^{-3})	(1.03×10^{-3})	(3.76×10^{-4})	(6.45×10^{-4})	(1.25×10^{-3})	(1.87×10^{-4})	(2.09×10^{-4})	(4.35×10^{-4})	(1.82×10^{-3})	(9.26×10^{-4})	(3.16×10^{-4})	(6.06×10^{-4})
Momentum	-4.46×10^{-6}	1.08×10^{-4}***	2.45×10^{-5}	-2.11×10^{-5}	-6.30×10^{-5}**	6.07×10^{-6}	3.75×10^{-6}	-6.76×10^{-5}***	5.86×10^{-5}	1.01×10^{-4}***	2.07×10^{-5}	4.88×10^{-5}***
	(5.00×10^{-5})	(4.08×10^{-5})	(1.98×10^{-5})	(3.09×10^{-5})	(2.64×10^{-5})	(2.02×10^{-5})	(1.05×10^{-5})	(2.30×10^{-5})	(4.18×10^{-5})	(3.36×10^{-5})	(1.61×10^{-5})	(2.46×10^{-5})

OIB	-8.10×10^{-4}***	2.37×10^{-4}**	-1.09×10^{-5}	-1.77×10^{-4}*	-1.85×10^{-4}*	-3.21×10^{-5}	-6.38×10^{-5}**	-8.37×10^{-5}*	-6.24×10^{-4}***	2.69×10^{-4}***	5.16×10^{-5}	-8.47×10^{-5}
	(2.16×10^{-4})	(1.07×10^{-4})	(5.01×10^{-5})	(7.73×10^{-5})	(9.64×10^{-5})	(5.52×10^{-5})	(2.79×10^{-5})	(4.44×10^{-5})	(1.87×10^{-4})	(9.41×10^{-5})	(4.48×10^{-5})	(6.85×10^{-5})
BAS	0.45**	0.24**	0.49***	0.488***	-0.39***	-0.55***	-0.54***	-0.38***	0.84***	0.79***	1.03***	0.86***
	(0.19)	(0.12)	(0.09)	(0.07)	(0.08)	(0.05)	(0.04)	(0.07)	(0.15)	(0.13)	(0.09)	(0.09)
DUM_1	4.65×10^{-4}***	1.08×10^{-4}**	3.45×10^{-5}**	8.34×10^{-5}***	1.56×10^{-4}***	7.58×10^{-5}***	7.13×10^{-5}***	4.32×10^{-5}**	3.08×10^{-4}***	3.26×10^{-5}	-3.63×10^{-5}***	1.47×10^{-5}
	(1.15×10^{-4})	(4.48×10^{-5})	(1.70×10^{-5})	(2.69×10^{-5})	(4.88×10^{-5})	(1.96×10^{-5})	(7.04×10^{-6})	(1.82×10^{-5})	(1.04×10^{-4})	(4.78×10^{-5})	(1.55×10^{-5})	(2.73×10^{-5})
DUM_2	7.12×10^{-5}**	6.33×10^{-5}***	4.58×10^{-6}	2.49×10^{-5}***	4.87×10^{-5}**	1.91×10^{-5}**	1.7×10^{-5}***	1.81×10^{-5}**	2.20×10^{-5}	4.41×10^{-5}***	-1.18×10^{-5}***	5.89×10^{-6}
	(2.87×10^{-5})	(1.12×10^{-5})	(6.41×10^{-6})	(9.30×10^{-6})	(2.25×10^{-5})	(8.12×10^{-6})	(5.03×10^{-6})	(8.22×10^{-6})	(1.68×10^{-5})	(8.63×10^{-6})	(3.91×10^{-6})	(6.12×10^{-6})
DUM_3	1.06×10^{-4}***	2.84×10^{-5}**	1.16×10^{-5}	9.87×10^{-6}	6.88×10^{-5}***	1.14×10^{-5}	3.68×10^{-6}	-1.12×10^{-5}	3.71×10^{-5}**	1.72×10^{-5}*	7.89×10^{-6}	4.32×10^{-6}
	(3.05×10^{-5})	(1.37×10^{-5})	(7.84×10^{-6})	(1.11×10^{-5})	(2.58×10^{-5})	(1.02×10^{-5})	(6.25×10^{-6})	(1.44×10^{-5})	(1.72×10^{-5})	(9.77×10^{-6})	(5.16×10^{-6})	(5.08×10^{-6})
Constant	-3.76×10^{-4}	-5.08×10^{-4}***	4.33×10^{-5}	2.07×10^{-4}**	-4.89×10^{-5}	1.07×10^{-5}	1.84×10^{-4}	2.36×10^{-4}***	-3.26×10^{-4}	-5.19×10^{-4}***	-1.54×10^{-4}***	-1.89×10^{-5}
	(3.27×10^{-4})	(1.46×10^{-4})	(5.44×10^{-5})	(9.81×10^{-5})	(1.61×10^{-4})	(6.47×10^{-5})	(2.23×10^{-4})	(6.50×10^{-5})	(2.83×10^{-4})	(1.37×10^{-4})	(5.00×10^{-5})	(9.95×10^{-5})
Observations	15,605	35,665	100,467	54,251	15,605	35,665	100,467	54,251	15,605	35,665	100,467	54,251
R-squared	1.26%	0.31%	0.70%	2.32%	1.53%	3.83%	3.12%	3.75%	3.26%	2.11%	3.24%	8.41%
Adj R-squared	1.19%	0.28%	0.69%	2.30%	1.46%	3.80%	3.11%	3.72%	3.19%	2.08%	3.23%	8.39%

TABLE 3.9

Stock Transparency and Incorporation of Private Information via Sale Block Trading in FTSE 100 Stocks

The relationship between informed trading and sale block trading in FTSE 100 stocks with varying levels of stock transparency is estimated using the following model:

$$Pirce\ impact = \alpha + \beta_1 PIN + \beta_2 \ln Size + \beta_3 Volatility + \beta_4 \ln Turnover + \beta_5 Market\mathrm{Re}turn + \beta_6 Momentum + \beta_7 BAS + \beta_8 |OIB| + \beta_9 DUM_1 + \beta_{10} DUM_2 + \beta_{11} DUM_3 + \varepsilon$$

Price impact corresponds to *permanent, temporary* or *total price impact*. *PIN* is the probability of an informed trade. *LnSize* is the natural logarithm of the number of shares per trade; *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place; *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade; *OIB* represents the order imbalance; *BAS* is the bid-ask spread at the time of the block trade; *Market return* is the daily FTSE100 return on the day of the block trade. *Momentum* is the cumulative return of the stock in the five days preceding the block trade. DUM_1 takes the value of 1 if the trade occurs between 8:00 and 9:00; DUM_2 takes the value of 1 if the trade occurs between 9:00 and 15:30; DUM_3 takes the value of 1 if the trade occurs between 15:30 and 16:00. Standard errors are presented in parentheses. PIN estimates are used as proxies for stocks' levels of transparency; on this basis, stocks are partitioned into transparency quartiles/portfolios. The highest (lowest) PIN stocks are designated as Portfolio 1 (4) stocks. Panels A, B and C present results for when permanent price impact, temporary price impact and total price impact are employed as dependent variables respectively. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

Panel A. Permanent Price Impact

	Portfolio1 (High-PIN)	Portfolio2	Portfolio3	Portfolio 4 (Low-PIN)
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*
PIN	-4.04×10^{-5}	8.14×10^{-5}	2.71×10^{-5}	9.52×10^{-5}
	(1.97×10^{-4})	(1.42×10^{-4})	(7.45×10^{-5})	(1.01×10^{-4})
Ln(size)	1.74×10^{-5}**	2.93×10^{-6}	1.31×10^{-5}***	-1.33×10^{-6}
	(7.70×10^{-6})	(5.09×10^{-6})	(2.28×10^{-6})	(4.94×10^{-6})
Volatility	8.36×10^{-4}	7.96×10^{-5}	-1.13×10^{-4}	1.12×10^{-3}*
	(2.45×10^{-3})	(6.74×10^{-4})	(3.62×10^{-4})	(6.64×10^{-4})
Ln(turnover)	-4.38×10^{-5}**	1.36×10^{-5}	-2.27×10^{-5}***	-5.34×10^{-6}
	(2.05×10^{-5})	(1.51×10^{-5})	(4.01×10^{-6})	(1.27×10^{-5})
Market Return	1.57×10^{-3}	-1.24×10^{-3}	1.56×10^{-5}	-1.93×10^{-4}
	(1.62×10^{-3})	(9.86×10^{-4})	(4.06×10^{-4})	(6.09×10^{-4})
Momentum	5.76×10^{-5}	4.45×10^{-5}	2.23×10^{-5}	9.19×10^{-5}***
	(3.93×10^{-4})	(3.71×10^{-5})	(2.12×10^{-5})	(2.85×10^{-5})
OIB	2.70×10^{-3}**	-7.80×10^{-5}	1.05×10^{-4}**	-6.49×10^{-5}
	(1.54×10^{-4})	(9.52×10^{-5})	(5.26×10^{-5})	(8.44×10^{-5})

Panel B. Temporary Price Impact

	Portfolio1 (High-PIN)	Portfolio2	Portfolio3	Portfolio 4 (Low-PIN)
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*
PIN	3.48×10^{-4}	-7.24×10^{-4}***	-7.84×10^{-4}***	8.60×10^{-4}***
	(2.74×10^{-4})	(2.19×10^{-4})	(1.18×10^{-4})	(1.73×10^{-4})
Ln(size)	1.97×10^{-5}*	-1.69×10^{-6}	-6.64×10^{-8}	1.47×10^{-6}
	(1.07×10^{-5})	(7.30×10^{-6})	(4.37×10^{-6})	(6.15×10^{-6})
Volatility	2.20×10^{-3}	-1.54×10^{-3}*	3.14×10^{-3}***	3.96×10^{-3}***
	(4.90×10^{-3})	(8.30×10^{-4})	(1.09×10^{-3})	(1.79×10^{-3})
Ln(turnover)	9.52×10^{-6}	4.01×10^{-5}**	-1.32×10^{-5}*	1.53×10^{-4}***
	(2.85×10^{-5})	(1.83×10^{-4})	(7.49×10^{-6})	(1.44×10^{-5})
Market Return	6.84×10^{-3}***	8.30×10^{-3}***	5.41×10^{-3}***	2.76×10^{-3}**
	(2.25×10^{-3})	(1.63×10^{-3})	(9.43×10^{-4})	(1.26×10^{-3})
Momentum	6.25×10^{-6}	1.04×10^{-4}**	1.88×10^{-5}	1.12×10^{-4}**
	(5.47×10^{-5})	(5.17×10^{-5})	(1.94×10^{-5})	(4.93×10^{-5})
OIB	-4.37×10^{-5}	1.71×10^{-4}	-2.58×10^{-4}***	-8.69×10^{-4}***
	(2.03×10^{-4})	(1.56×10^{-4})	(1.11×10^{-4})	(1.27×10^{-4})

Panel C. Total Price Impact

	Portfolio1 (High-PIN)	Portfolio2	Portfolio3	Portfolio 4 (Low-PIN)
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*
PIN	3.87×10^{-4}	7.89×10^{-4}	7.96×10^{-4}***	-7.60×10^{-4}***
	(2.84×10^{-4})	(2.30×10^{-4})	(1.28×10^{-4})	(1.71×10^{-4})
Ln(size)	2.07×10^{-6}	4.56×10^{-6}	1.31×10^{-4}***	-2.74×10^{-6}
	(1.11×10^{-5})	(8.00×10^{-6})	(4.62×10^{-6})	(6.86×10^{-6})
Volatility	-1.32×10^{-3}	1.59×10^{-3}**	-3.20×10^{-3}***	-2.74×10^{-3}
	(5.06×10^{-3})	(7.08×10^{-4})	(1.04×10^{-3})	(1.77×10^{-3})
Ln(turnover)	-3.45×10^{-5}	-2.60×10^{-5}	-9.32×10^{-6}	-1.55×10^{-4}***
	(2.95×10^{-5})	(2.17×10^{-5})	(7.59×10^{-6})	(1.70×10^{-5})
Market Return	5.14×10^{-3}	-9.35×10^{-2}***	-5.23×10^{-3}***	-2.79×10^{-3}**
	(2.33×10^{-3})	(1.70×10^{-3})	(9.12×10^{-4})	(1.26×10^{-3})
Momentum	5.03×10^{-5}	-5.72×10^{-5}	4.36×10^{-6}	-1.98×10^{-5}
	(5.66×10^{-5})	(5.21×10^{-5})	(2.42×10^{-5})	(5.02×10^{-5})
OIB	3.13×10^{-4}	-2.48×10^{-4}	3.58×10^{-4}***	7.93×10^{-4}***
	(2.10×10^{-4})	(1.65×10^{-4})	(1.14×10^{-4})	(1.33×10^{-5})

BAS	-0.56***	-0.24***	-0.45***	0.06	0.81***	1.03***	1.27***	0.93***	-1.36***	-1.27***	-1.71***	-0.86***
	(0.04)	(0.10)	(0.11)	(0.13)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)	(0.10)	(0.10)	(0.11)
DUM_1	8.07×10^{-6}	-1.75×10^{-4}***	-3.67×10^{-5}***	-1.00×10^{-4}***	1.34×10^{-5}	-4.65×10^{-5}	-4.08×10^{-4}***	-1.32×10^{-4}***	1.34×10^{-5}	-1.29×10^{-4}**	3.67×10^{-4}***	7.10×10^{-5}*
	(5.66×10^{-5})	(3.84×10^{-5})	(1.71×10^{-5})	(3.53×10^{-5})	(7.89×10^{-5})	(4.44×10^{-5})	(2.36×10^{-5})	(3.47×10^{-5})	(7.41×10^{-5})	(5.04×10^{-5})	(2.65×10^{-5})	(4.23×10^{-5})
DUM_2	2.32×10^{-5}	-4.43×10^{-5}***	-1.68×10^{-4}***	-4.65×10^{-5}***	1.53×10^{-6}***	2.31×10^{-5}	-1.81×10^{-4}***	4.83×10^{-5}*	1.21×10^{-5}	-6.66×10^{-4}**	1.64×10^{-4}***	1.81×10^{-6}
	(4.45×10^{-5})	(1.38×10^{-5})	(6.65×10^{-6})	(1.26×10^{-5})	(5.04×10^{-5})	(3.06×10^{-5})	(2.12×10^{-5})	(2.64×10^{-5})	(4.98×10^{-5})	(2.85×10^{-5})	(2.06×10^{-5})	(2.48×10^{-5})
DUM_3	-1.13×10^{-5}	-3.41×10^{-5}***	-2.38×10^{-5}***	-3.69×10^{-5}***	-1.52×10^{-4}	-1.10×10^{-6}	-2.20×10^{-4}***	-9.66×10^{-5}***	1.40×10^{-4}***	-3.32×10^{-5}	1.93×10^{-4}***	5.95×10^{-5}*
	(2.89×10^{-5})	(1.54×10^{-5})	(8.27×10^{-6})	(1.24×10^{-5})	(6.25×10^{-5})	(4.25×10^{-5})	(2.77×10^{-5})	(3.68×10^{-5})	(6.03×10^{-5})	(3.69×10^{-5})	(2.62×10^{-5})	(3.46×10^{-5})
Constant	5.24×10^{-4}**	-3.14×10^{-5}	-3.30×10^{-4}***	-1.85×10^{-4}	-3.56×10^{-4}	5.72×10^{-4}***	3.79×10^{-4}***	1.38×10^{-3}***	5.33×10^{-4}**	-5.29×10^{-4}**	-6.98×10^{-4}***	-1.53×10^{-3}***
	(2.12×10^{-4})	(1.57×10^{-4})	(5.53×10^{-5})	(1.25×10^{-4})	(3.01×10^{-4})	(1.96×10^{-4})	(8.87×10^{-5})	(1.62×10^{-4})	(2.12×10^{-4})	(2.27×10^{-4})	(8.74×10^{-5})	(1.80×10^{-4})
Observations	17,375	38,831	118,872	71,789	17,375	38,831	118,872	71,789	17,375	38,831	118,872	71,789
R-squared	1.50%	0.43%	0.59%	0.08%	1.64%	1.34%	1.06%	2.46%	3.98%	1.97%	1.62%	2.09%
Adj R-squared	1.44%	0.42%	0.58%	0.08%	1.58%	1.33%	1.05%	2.44%	3.91%	1.96%	1.61%	2.07%

3.4. Conclusion

Previous informed trading studies mainly focus their investigations on corporate events and insider trading activities. I expand the trading data to encompass the entire regular trading hours on the London Stock Exchange and also to focus on an implicit view of informed trading as trading, which is induced by any information not available to the general public. My results show that the number of informed trades is positively related with the number of block trades. The positive (negative) relation between PIN estimates, and the permanent price impact of block purchases (sales), suggests that there exists an impounding of private information via block trading on the LSE. My main research question relates to how the level of trading opacity in a stock affects the incorporation of information through block trading. The evidence I present on the role of stock trading transparency on the information incorporation process suggests that firms with low trading transparency exhibit stronger effects for private information incorporation when compared with those with a high level of trading transparency.

Overall, I support previously held views that informed trading plays a positive role in facilitating the price discovery process through trading in the direction of permanent price impact for both purchase and sale block trades. This finding is consistent with two streams of existing literature: insider trading (see for example John and Lang, 1991) and high-frequency trading (see for example Brogaard et al., 2014). Further contributions made in this chapter include new insights on the intraday and inter-day dynamics of the private information incorporation process. First, I show that impounding of private information into stock prices on the LSE is mostly aggressively propagated during the first hour of trading. This pattern is consistent with evidence from Ibikunle (2015a), as well as with Dufour and Engle (2000), that more informed trades are executed during the highly liquid and informational periods (see also Chordia et al., 2008). However, despite the seemingly rapid private information usage during the trading day, traders also appear to withhold private information longer than a trading day window, such that trading positions are adjusted based on a previous day's private information. I document a linear relationship between the lag PIN variable and the logarithmic of change of number of block trades, which indicates that informed traders adjust their block positions based on historical private information. The combination of intraday and inter-day patterns provides empirical support to previous theoretical work (see for example Foster and Viswanathan, 1994, Hong et al., 2000, Hong and Stein, 1999, Holden and Subrahmanyam, 1992, Kyle, 1985, Lin and Rozeff, 1995) that suggests that informed traders gradually exploit private information rather than trading on its basis over a short time period.

4. Aggregate Market Fragmentation, Adverse Selection and Market Efficiency

4.1. Introduction

Over the past decade, developed markets in Europe and the US have seen an unprecedented proliferation of new (high-tech) trading venues. As newer venues acquire trading volume at the expense of national stock exchanges, markets become even more fragmented at regional and national levels. Observed changes in the markets mainly follow recent regulatory shifts in both Europe and the US. The enactment of the Markets in Financial Instruments Directive (MiFID) in 2007, and technological advances in trading systems, for example, have led to an unprecedented increase in the number of trading venues in Europe. The expansion of the trading field in turn has accelerated trading fragmentation, with possible further implications for price discovery and market quality. Expectedly, trading fragmentation has raised concerns about whether the diversified market landscape could harm price transparency in the markets. This concern has basis in the microstructure literature. A stream of theoretical 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 be congregated in one consolidated market, and all trades in all listed securities should occur in 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 benefits brokers while harming 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 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, argue that concerns about the negative impact of trading fragmentation may have been largely 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 the trading venues serving as multiple entry points. This is a reasonable interpretation given that the US market regulation regime guarantees a best execution price irrespective of the exchange to which an order is submitted. The regime in Europe offers no such guarantee.

In this chapter, I present first order evidence on whether or not market fragmentation induces adverse selection costs, reduced transparency and informational inefficiency in the aggregate market. Thus, I advance the understanding of the impact of market fragmentation on market quality. Firstly, using a sample of FTSE 100 stocks between 2004 and 2014, I investigate the effect of trading fragmentation on the evolution of two market quality measures – adverse selection costs and market transparency. My sample allows us to have a complete picture of the global depth available in the market as I collect intraday tick data from the four main FTSE 100 stock trading venues – the LSE, BATS Europe, Chi-X Europe and Turquoise. The four venues cover more than 95% of the daily trading volume on FTSE 100 stocks during the period under investigation. Secondly, I examine the association between market efficiency and the level of trading fragmentation over the same period. My analysis differs from recent papers, which examine the impact of fragmentation on market quality in that I focus on transparency and use short-horizon return predictability as an inverse proxy for market efficiency – aspects of trading quality – fragmentation nexus yet to be investigated in the reported literature. Perhaps more importantly, my empirical design allows for measuring aggregate market impact of fragmentation on trading quality over a long time period. Similar studies such as Chordia et al. (2008, 2011) underscore the need to examine market trends over time. Therefore, I employ the longest data time series ever used to investigate the impact of market fragmentation on trading in financial markets, allowing us to control for different time trends and trading conditions. By comparison, Riordan et al. (2011), Gresse (2017), O'Hara and Ye (2011), Spankowski et al. (2012) use 29-day, 4-month, 6-month and 12-month time series with stock samples mostly smaller than mine. My analysis is conducted on an aggregate market by creating a consolidated order book featuring order flow and transactions from the exchanges making up the London market for FTSE 100 stocks. Being able to examine the evolution is key to understanding how financial markets develop over time and in relation to contemporaneous events. Thus, for the first time, I can assess the impact of fragmentation on the aggregate market for trading Europe's highest volume stocks.

I find a quadratic relationship between fragmentation and adverse selection risk. On the one hand, visible fragmentation helps to both reduce adverse selection costs and increase market transparency at low levels of fragmentation. On the other hand, however, when fragmentation is high, the implied adverse selection cost and market opacity potentially increase with the level of fragmentation. The negative impact of fragmentation on transparency is very limited, since historical levels of fragmentation are generally smaller than the turning point calculated in this study. I also find that 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 (see also O'Hara and Ye, 2011, Degryse et al., 2015).[4]

Boneva et al. (2015) also examine fragmentation on FTSE 100 stocks but my work differs from theirs in three respects. Firstly, they examine the impact of fragmentation on market quality measured by volatility, liquidity and volume, whereas I investigate its impact on market transparency and adverse selection costs/risk. Secondly, as well as other related works on European equity markets' fragmentation (for instance, Riordan et al., 2011, Spankowski et al., 2012, Gresse, 2017), they focus their investigation of market quality on the listing market. It should be noted that market quality contains several elements, market liquidity, price discovery and pricing efficiency. Market transparency is a crucial element of market quality. As defined by O'Hara (1995), market transparency is "the ability of market participants to observe the information in trading process." A transparent market tends to be more liquid because all investors get equal access to the information and reach an agreement on a fair price. By contrast, in an opaque market, traders are less willing to take the liquidity because of potential information asymmetry. In this case, market makers ask to be

[4] A Securities and Exchange Commission review argues that Degryse et al.'s (2015) sample represents a period when market fragmentation had not fully set in in the Dutch mid and large stocks they use. The same criticism may hold for the few other papers that investigate market fragmentation with European stock samples prior to 2011.

compensated by posting a wider spread. Market transparency is an important issue to consider under a fragmented trading environment. Since trade-through protection is not mandatory across European markets under MiFID I, market access friction gives rise to differences in the adverse selection risk faced by liquidity providers. If informed traders are more likely than uninformed traders to use "smart routers", then information asymmetry may increase across the European markets. This is the reason why I study market transparency in the MiFID I era. In this chapter I also create a consolidated order book for my analysis. The consolidated market environment offers a broader view of the market for trading FTSE 100 stocks, and could yield further insights. Thirdly, compared with Boneva et al. (2015), who use weekly data of FTSE 350 from 2008 to 2011, I adopt a much richer dataset. My dataset includes tick-level data, and my regression model incorporates stock-day variables of FTSE 100 stocks, computed from high-frequency data, over much of the decade from 2004 to 2014.

Although European market fragmentation is a relatively recent phenomenon, by November 2014 more than 150 recently established alternative trading platforms known as Multilateral Trading Facilities (MTFs) were in operation around Europe. Furthermore, several of these venues successfully challenge the established national exchanges for trading market shares, 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.[5] Under MiFID, trading

[5] Before 20th May 2013, BATS Chi-X Europe only had a licence to operate MTFs; however, it has since been granted Recognised Investment Exchange (RIE) status. BATS Chi-X could now, therefore, 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 before and after the transition. Enquiries made with BATS Chi-X confirm that their current order books are still

volume has become increasingly fragmented, with trades 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, that is, they offer no pre-trade transparency. This development has thus created a very competitive trading environment for platform operators across Europe. The competition among trading venues is expected to reduce the power of long-established stock exchanges, leading to falling transaction costs and enhancement of trading-related technological innovation. The emergence of high-tech entrant venues ultimately means that exchange operators now compete in finer inter-connected markets.

Competition between trading venues can improve market quality (Foucault and Menkveld, 2008). Recent literature has attempted to investigate the impact of fragmentation based on empirical evidence from market depth, liquidity and transaction costs (for example see O'Hara and Ye, 2011, Boneva et al., 2015, Gresse, 2017). These papers provide evidence of 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. Such costs relate to acquisition and management of the technology required to do so. There is also a significant concern that trading fragmentation could be harming market quality by increasing

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 was still listed on the CESR MiFID database as an MTF. Robustness analysis conducted in this paper suggests that my results are unaffected by the granting of the RIE status to BATS Chi-X Europe.

monitoring (search) costs, reducing transparency, and increasing adverse selection risk (Madhavan, 1995, Yin, 2005, Hoffmann, 2010).

Furthermore, since MiFID does not formally mandate linkage between trading venues and the release of 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 the Regulation National Market System (Reg NMS), which mandates exchanges to re-route orders to other venues if those offer a better price (*trade-throughs*). Under MiFID the primary exchange is typically accessible to all investors, while simultaneous access to multiple venues (including MTFs) would normally require the so-called Smart Order Routing System (SORT). SORT 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 in real time.

This lack of trade through protections led O'Hara and Ye (2011, p.472) to remark 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 sub-optimal order executions due to the absence of a trade-through rule. Possible trading frictions in accessing MTFs and other newer venues can give rise to inter-market differences in the adverse selection risk faced, and to non-transparency by liquidity providers. If informed traders are more likely than uninformed traders to be "smart routers", informed traders could also split orders across venues, routing their trades to venues with higher levels of uninformed traders and liquidity, and therefore increase the adverse selection cost faced by uninformed traders. The lack of trade-through protection in Europe could therefore be a source of adverse selection risk (Hoffmann, 2010).

A further question to ponder is whether trading fragmentation impairs market efficiency. In a high-frequency world, informed algorithmic and high-frequency traders prefer to trade across high-tech markets (in Europe these are mainly MTF-type platforms), presumably because they value the higher speed of execution and try to prevent information leakage (Hoffmann, 2010). Informed order flow 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 from market inefficiency and obtain better execution through dynamic trading in fragmented markets. Their trading strategies include short-term fundamental information (for example, imminent earnings release) and short-term technical analysis (for 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. I hypothesise 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.

Theoretically, this development improves market quality if trading information is released in a timely manner.

Consistent with the foregoing, this study focuses on how trading fragmentation affects consolidated market quality for all market participants in related trading venues. Specifically, I investigate the impact of fragmentation on measures of market transparency and efficiency for FTSE 100 stocks over a ten year period. Included in my sample are orders executed on the primary market LSE, as well as those executed on the three largest MTFs: BATS, Chi-X and Turquoise. Together, these platforms consistently account for more than 90% of trading volume of FTSE 100 stocks. Thus, the sample is representative of the London market, since FTSE 100 stocks account for more than 80% of capitalisation of the market (see Ibikunle, 2015a). As high entrant markets are attracting increasing trading volumes, focus on just the primary exchange (in this case, the LSE) cannot provide a full picture of the market.[6] I therefore construct a 'global' order book by concatenating all trades from four venues. Global measures are not only relevant to investors who are restricted to trading on the primary exchange, but also to professional traders who use Smart Order Routing Technologies (SORTs).

I 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., 1996b, Easley et al., 1997a) is employed here to

[6] Gomber, P., Pujol, G. & Wranik, A. 2012. Best Execution Implementation and Broker Policies in Fragmentated European Equity Markets. *International Review of Business Research Papers,* 8**,** 144-162. show that only 20 out of 75 firms in their sample indicate that they only execute trades at the primary exchanges.

measure adverse selection risk, since they are positively and strongly correlated (Chung and Li, 2003). For robustness, I also use the absolute value of 60-second mid-quote return autocorrelation as another measure of adverse selection risk. Furthermore, since past studies indicate that off-exchange trading impacts market quality,[7] I also test the effects of off-exchange trading on market transparency. I address the likely endogeneity of adverse selection by applying the instrumental variable approach (IV). My results are robust to different sets of instruments (IVs) and non-IV estimations.

Our study adds to the existing literature on market quality. 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 the LSE and Euronext in the Dutch stock market, where before 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 the consolidated order book and the primary exchange NSC become significantly deeper after EuroSETS's 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 decline following the entry.

Based on a sample of stocks trading on the LSE and Euronext, Gresse (2017) finds that increased competition between trading venues is accompanied by a high liquidity provision. Menkveld (2013) examines high-frequency trading activity in Dutch stocks on Chi-X. The results indicate that, firstly, high frequency traders benefit from Chi-

[7] Weaver (2011) shows that off-exchange trade has a detrimental effect on market quality by increasing volatility.

X’s trading platform in terms of lower trading costs. Secondly, the level of market fragmentation is determined by the intensity of HFT, because HFTs are likely to spread orders across markets or to supply liquidity for MTFs. Boneva et al. (2015) employ a panel regression analysis of a weekly interval dataset in studying the impact of fragmentation on the market quality of the LSE. Their market quality metrics include volatility, liquidity and market depth. They find lower volatility on the LSE when there is order flow competition between MTFs. Their results also suggest that visible fragmentation reduces market depth on the LSE, whilst dark trading increases 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 (2017) 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 the introduction of MiFID could be linked to value-adding competition; however, large cap stocks benefit from fragmentation more than small cap stocks. Gresse's (2017) study suggests that the introduction of MiFID improves market quality on the LSE and for Euronext-listed equities through a reduction in transaction costs.

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, 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 the 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, however existing studies suggest that the positive effects outweigh the negatives.

Our study is also related to a 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 markets tends to be more informative, presumably because informed traders value the higher speed and low cost offered by these venues. Hoffmann (2010) examines a sample of French and German stocks trading on both primary markets and the entrant 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 (2015c), who shows that Europe’s largest high-tech entrant market, BATS Chi-X Europe, leads LSE in the price discovery process for LSE-listed stocks by attracting a greater proportion of informed traders in those stocks.

The remainder of this chapter is arranged as follows. In Section 2, I discuss the sample selection and descriptive statistics. Section 3 summarises the methodology, and Section 4 reports and discusses my findings of fragmentation on adverse selection cost and market transparency. Section 5 looks into the effect of fragmentation on market efficiency, and Section 6 concludes.

4.2. Data and Descriptive Statistics

4.2.1. Data

I focus on constituents of FTSE 100 stocks, which are composed of the 100 largest British firms listed on the LSE. These firms historically account for about 80% of total market capitalisation on the LSE. All FTSE 100 stocks are traded at several venues, and my dataset consists of data from the four main venues where these stocks are traded – the LSE, BATS Europe, Chi-X Europe and Turquoise. The total trading volume from these four trading venues accounted for about 98% of the FTSE 100 lit trading value in 2014. I obtain intraday tick data from the Thomson Reuters Tick History (TRTH) database. My sample dataset covers the period from 1 January 2004 to 30 September 2014. For each year, I 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[8]. The dataset includes variables such as the Reuters Identification

[8] It is very common to filter out the stocks that are dropped from the index composition. For example, Gresse (2015) studies how lit and dark fragmentation affects market liquidity. After removing the stocks that are not consistently in the index, she has only 51 stocks in the FTSE 100 index. Similarly, Degryrse (2015) applies this filter to maintain consistency in the index composition. O'Hara and Ye (2011) filter out sample stocks with low trading activity and trading price below $5. This leaves them with about 70% of the stocks in the NYSE and Nasdaq index.

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 I only focus on normal trading hours, I delete the opening auction (07:50hrs – 08:00hrs) and closing auction (16:30hrs – 16:35hrs) periods from the dataset. Cleaning and merging of the order book data from the four venues yields a consolidated dataset comprising of roughly 1.54 billion trades, with a total trading value worth 14.29 trillion British Pounds Sterling. While a dataset in excess of 10 years allows us to observe the evolution of fragmentation, for most of my analysis, I only employ data for periods when data shows that trading fragmentation has fully set into the market. Thus, my regression analysis incorporates data for the seven-year period spanning 2008 to 2014. This time series is the longest used to investigate the impact of fragmentation on market quality in the literature.

4.2.2. Descriptive statistics

Table 4.1 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. These observations suggest an appreciable level of variation across stocks. The daily pound volume and daily trades' variables also display similar levels of variation across the quartiles.

Table 4.2 reports correlations between the key trading variables employed in my empirical analysis. It is not surprising to see that daily pound volume is positively related to the number of transactions 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 the argument that liquid stocks normally have lower adverse selection costs.

Table 4.1. 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*, while Trade size is the average pound value per trade on day *t*. The sample comprises the FTSE100 stocks from 1 January 2004 to 30 September 2014

	Mean	Std.dev	Min	25%	Median	75%	Max
Stock characteristics							
Effective spread	0.0083	0.0118	7.61E-05	0.0025	0.0063	0.0115	2.71
Algorithm Trading	0.0066	0.0145	0.0000	0.0025	0.0043	0.0072	1.71
Volatility	0.0070	0.0891	0.0001	0.0003	0.0004	0.0005	1.68
Volumes and Trades							
Total Pound Volume	2.160E+08	4.210E+08	1.27E+05	1.900E+07	4.000E+07	1.220E+08	2.72E+09
Total Trades (Counts)	8428.43	8300.54	26.00	3503.00	5805.00	9966.00	1.43E+05
Trade size Median	4.052E+04	1.053E+05	19.00	2.448E+03	3.400E+03	5.260E+03	9.86E+05

Table 4.2. Correlations matrix for independent variables

This table reports correlations between key trading variables. *Log(PoundVolume)* is the log of total daily pound-volume traded in stock *i*; *Log(TradeCount)* is the log of total number of transactions of stock *i* on day *t*; *Log(Tradesize)* is the log of median of daily trade size of stock *i* on day *t*; *Volatility* is the daily standard deviation of the trade-by-trade return of stock *i* on day *t*; *EBAS* is average effective bid-ask spread of stock *i* on day *t.* Finally, *Algo* controls for the algorithm trading activity, and equals the total number of quote changes over pound volume of stock *i* on day *t*. P-values are presented in parentheses.

	Log(Pound Volume)	Log(TradeCount)	Log(TradeSize)	Volatility	EBAS	Algo
Log(Pound Volume)	1.000	0.577	0.854	-0.069	-0.014	-0.315
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Log(TradeCount)	0.577	1.000	0.185	0.033	-0.120	-0.230
	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(<.0001)
Log(TradeSize)	0.854	0.185	1.000	-0.179	0.049	-0.223
	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)
Volatility	-0.069	0.033	-0.179	1.000	0.001	0.003
	(<.0001)	(<.0001)	(<.0001)		(0.767)	(0.338)
EBAS	-0.014	-0.120	0.049	0.001	1.000	0.005
	(<.0001)	(<.0001)	(<.0001)	(0.767)		(0.053)
Algo	-0.315	-0.230	-0.223	0.003	0.005	1.000
	(<.0001)	(<.0001)	(<.0001)	(0.338)	(0.053)	

Figure 4.1. Percentage share of trading volume by venue

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

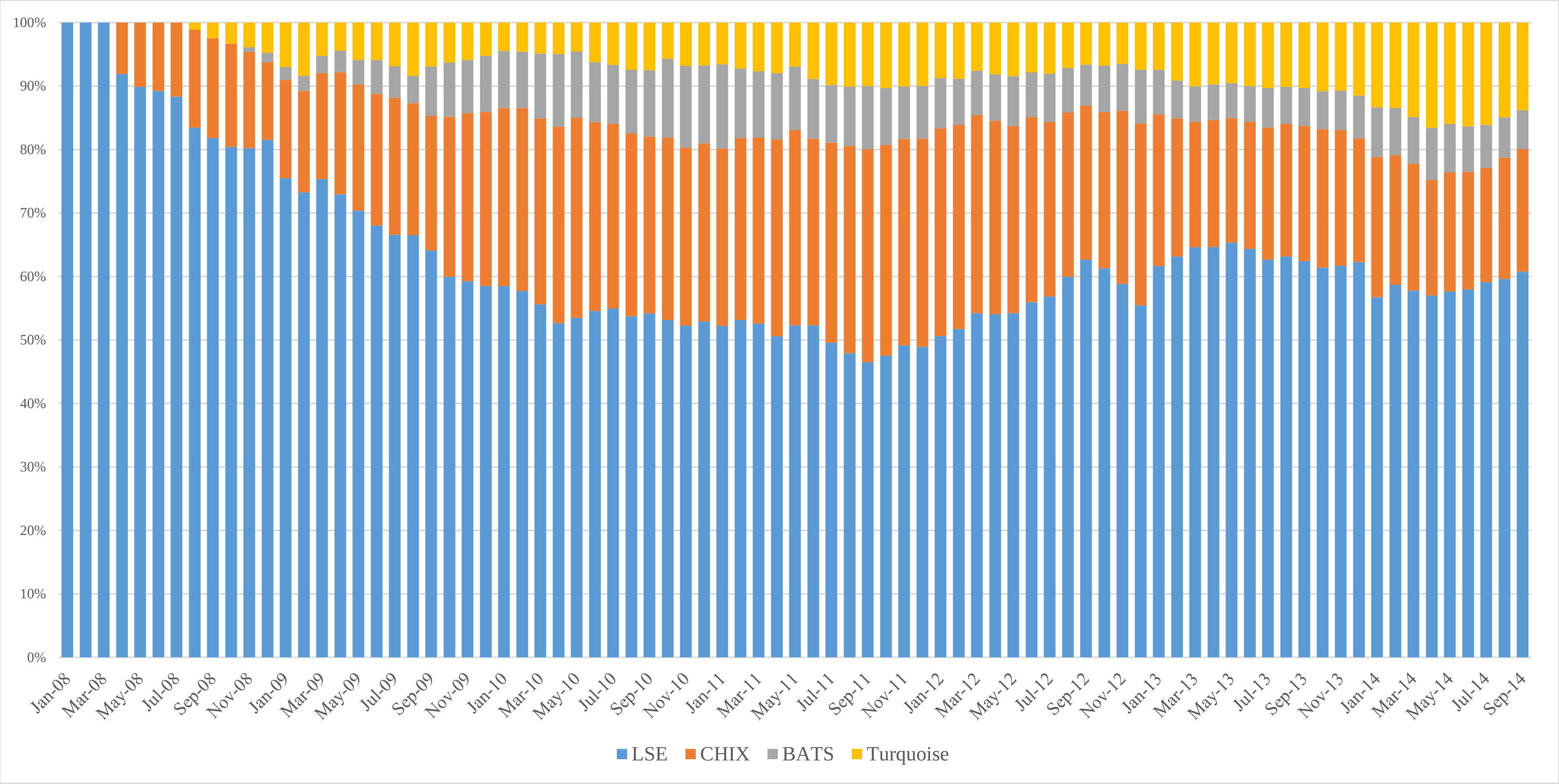


Table 4.2 also indicates that the number of trades is positively associated with volatility, and negatively associated with the effective spread. Thus when there is a higher number of transactions, I would expect to see narrower spreads, leading to a higher level of liquidity and a lower level of adverse selection.

Figure 4.1 shows the percentage of monthly traded pound volume of four trading venues since the introduction of MiFID. Clearly, BATS, Chi-X and Turquoise have been attracting significant market shares from the LSE since around the start of the year 2008.

In November 2011 the three MTFs attracted a combined market share of 50%, but all have since struggled to retain or outperform that threshold over time. Figure 4.2 plots the total monthly number of trades across the four trading venues since 2004. Prior to the introduction of MiFID the number of trades on the LSE shows an upward trajectory, from January 2004 to 2007. Following the introduction of MiFID, the three high-tech entrants gradually stymied the rise in aggregate LSE trading figures, although the LSE still retains trading dominance. Figure 4.3 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 introduction of MTF trading, 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.

Figure 4.2. Total number of trades by venue 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 the primary market, LSE, and three other trading venues, BATS Europe, Chi-X Europe and Turquoise, are plotted in the figure.

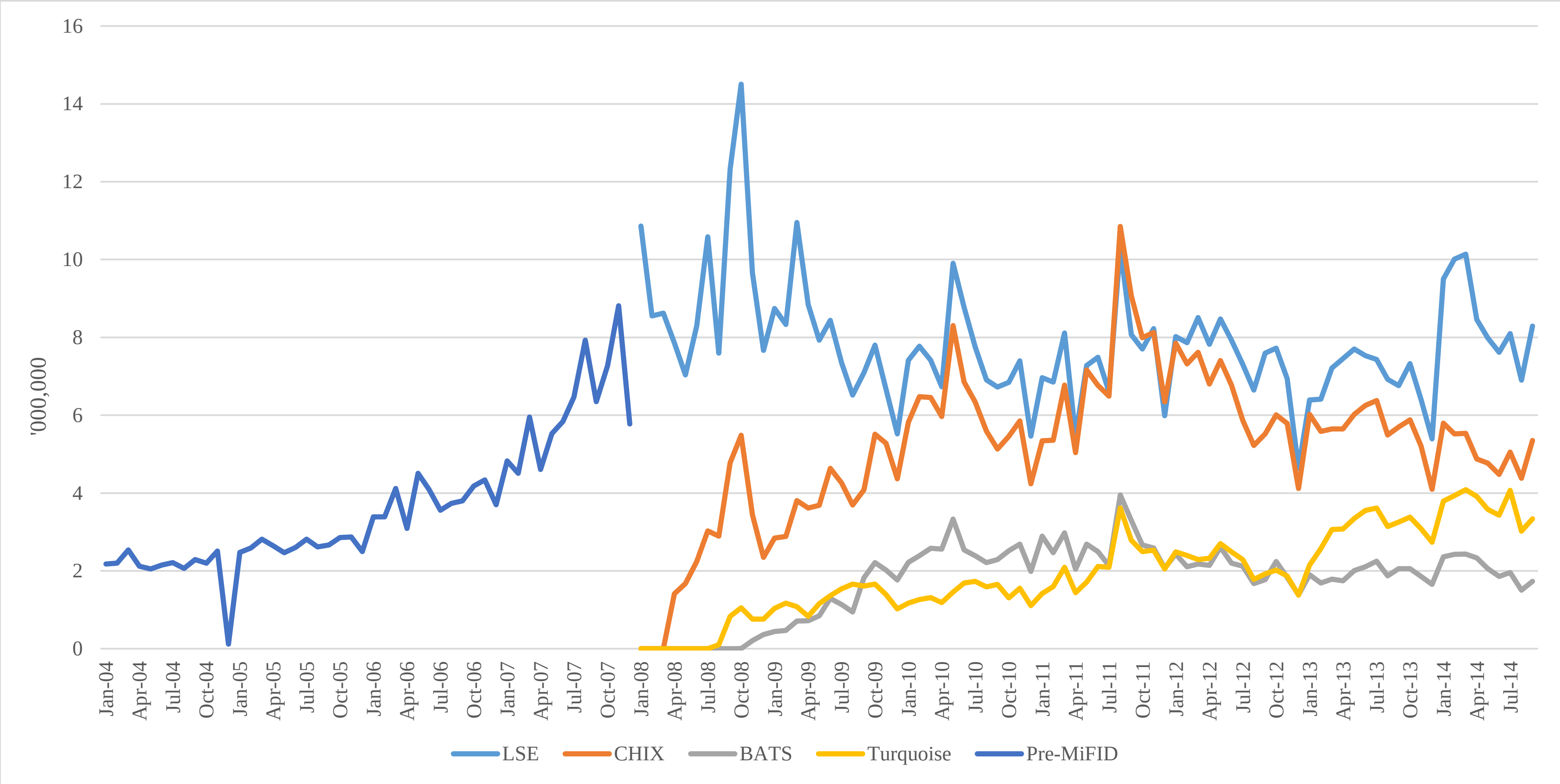
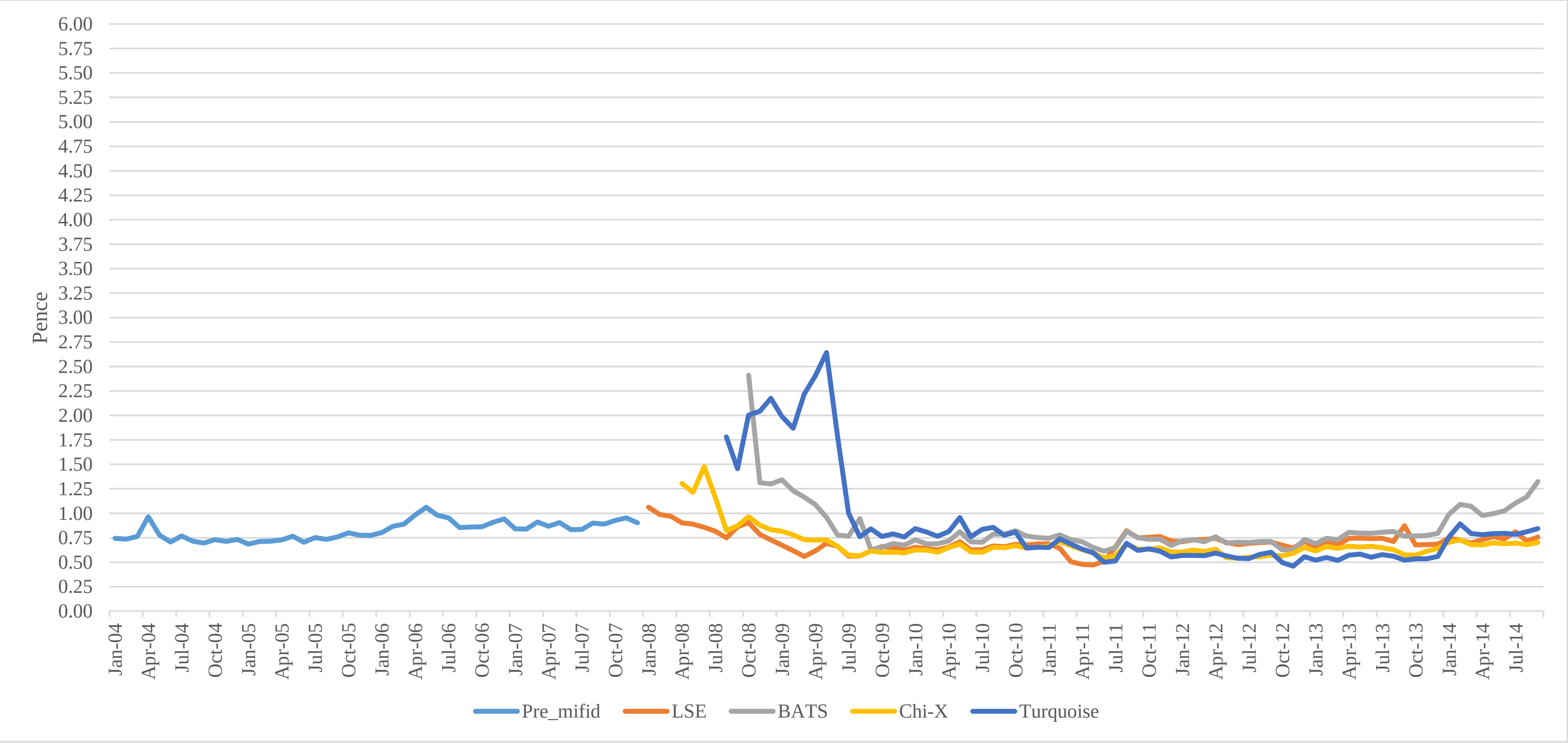


Figure 4.3. Effective bid ask spread by venue

The figure displays the monthly average 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 equates 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 Europe, Chi-X Europe and Turquoise, are plotted on the figure.



4.3. Measures of Information Asymmetry and Fragmentation

4.3.1. PIN, an inverse proxy for market transparency

I adopt the private information-based trading (PIN) measure as a proxy of adverse selection cost, since 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 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, I therefore 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[9]. The 'normal level' of sales and purchases executed within a stock on a given day over several 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:

$$\begin{aligned} L((B,S)\mid\theta) &= (1-\alpha)e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!} + \alpha\delta e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-(\mu-\varepsilon_s)}\frac{(\mu-\varepsilon_s)^S}{S!} \\ &+ \alpha(1-\delta)e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!}e^{-(\mu-\varepsilon_b)}\frac{(\mu-\varepsilon_b)^B}{B!} \end{aligned} \tag{4.01}$$

[9] I infer purchase and sales through the running of Lee and Ready's Lee, C. M. C. & Ready, M. J. 1991b. Inferring Trade Direction from Intraday Data. *The Journal of Finance,* 46**,** 733-746. trade classification algorithm.

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 (4.01) represents 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. (1997a) and Easley et al. (1996b) calculate the parameter vector estimates using maximum likelihood estimation procedures. Thus I obtain the parameters for each trading day and for each stock in the sample by maximum likelihood estimation. PIN is therefore computed as:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \tag{4.02}$$

4.3.2. Absolute value of autocorrelation in mid-quote return

In a theoretically perfect efficient market, price is unpredictable and thus follows a random walk, ensuring that returns are not correlated. However, in a less efficient market scenario, private information being gradually incorporated 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. I therefore employ the absolute value of 1-minute mid-quote return autocorrelation as a proxy of adverse selection risk. The return autocorrelation captured occurs as a result of prices being 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 mid-quote returns for each stock-day I capture both under- and over-reaction to new information, with larger values implying higher degrees of inefficiency, and vice versa.

4.3.3. 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 (HHI). This index is used by Foucault and Menkveld (2008), Chlistalla and Lutat (2009), and Degryse et al. (2015), and is calculated 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 London market. The index is expressed as follows:[10]

[10] Equation (4.03), which is effectively defined as 1/HHI, serves as a convex transformation of the HHI. This can lead to outliers in the independent variable. Hence, I also compute 1-HH1 as a proxy for market fragmentation. The results obtained are qualitatively similar to the ones obtained for 1/HHI; thus, for parsimony, they are not presented in the main draft. They are available in Appendix A.

$$Frag = \frac{1}{\sum_{k}\left(\frac{V_k}{\sum_{j} V_j}\right)^2} \qquad (4.03)$$

where V_k denotes the pound volume traded on markets k, Vj represents the total pound volume traded in all of the markets under observation, and $\frac{V_k}{\sum_j V_j}$ is the market share of market k in the aggregate market, i.e. all markets under consideration combined.[11] I also test the degree of off-exchange fragmentation, since some studies suggest that high-tech entrant markets generate more informed order flows (see for example Grammig et al., 2001, Barclay et al., 2003). This proxy illustrates visible daily fragmentation by calculating how much volume is traded via off-exchange venues each day, i.e. the three venues in the sample other than the LSE. Equation (4.04) is computed at a daily frequency.

$$Frag_{EX} = \frac{Off\text{-}exchange\text{-}volume}{Total\text{-}volume} \qquad (4.04)$$

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, the intensification of informed trading activity could imply a migration of trading volumes from the main exchange. Both fragmentation proxies are computed for each stock and for each trading day.

[11] For ease of exposition, I do not report the subscript for time in Equation (4.03). The index is computed daily. Since I have four trading venues in my sample, including the listing exchange, the proxy 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.

Table 4.3 reports the descriptive statistics for *Frag*, $Frag_{EX}$ 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; i.e. a substantial proportion of trading takes place on platforms other than the LSE in the case of FTSE 100 stocks. Furthermore, the mean value of $Frag_{EX}$ 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, meaning that roughly 17.87% of trades are based on private or superior information in my 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 4.4 presents a time series graph of the level of *Frag* and $Frag_{EX}$ since the implementation of MiFID. It is evident that both *Frag* and $Frag_{EX}$ are increasing over time. *Frag* begins its lift from around 1 in April 2008 and has gradually risen over time, recording a maximum value of 3.3 in January 2014. A similar trend is also observed for $Frag_{EX}$. All these patterns indicate an increasingly high level of competition for order flow between the LSE and the relatively new high-tech entrants.

Table 4.3. Descriptive Statistics: Market 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:

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

$Frag_{EX}$ is the off-exchange market fragmentation:
$$Frag_{EX} = Off\text{-}exchange\text{-}volume / Total\text{-}volume$$

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

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

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. α corresponds to the probability of an information event, δ is the conditional probability of a low signal of an information event, μ is the arrival rate of informed orders, and ε 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:

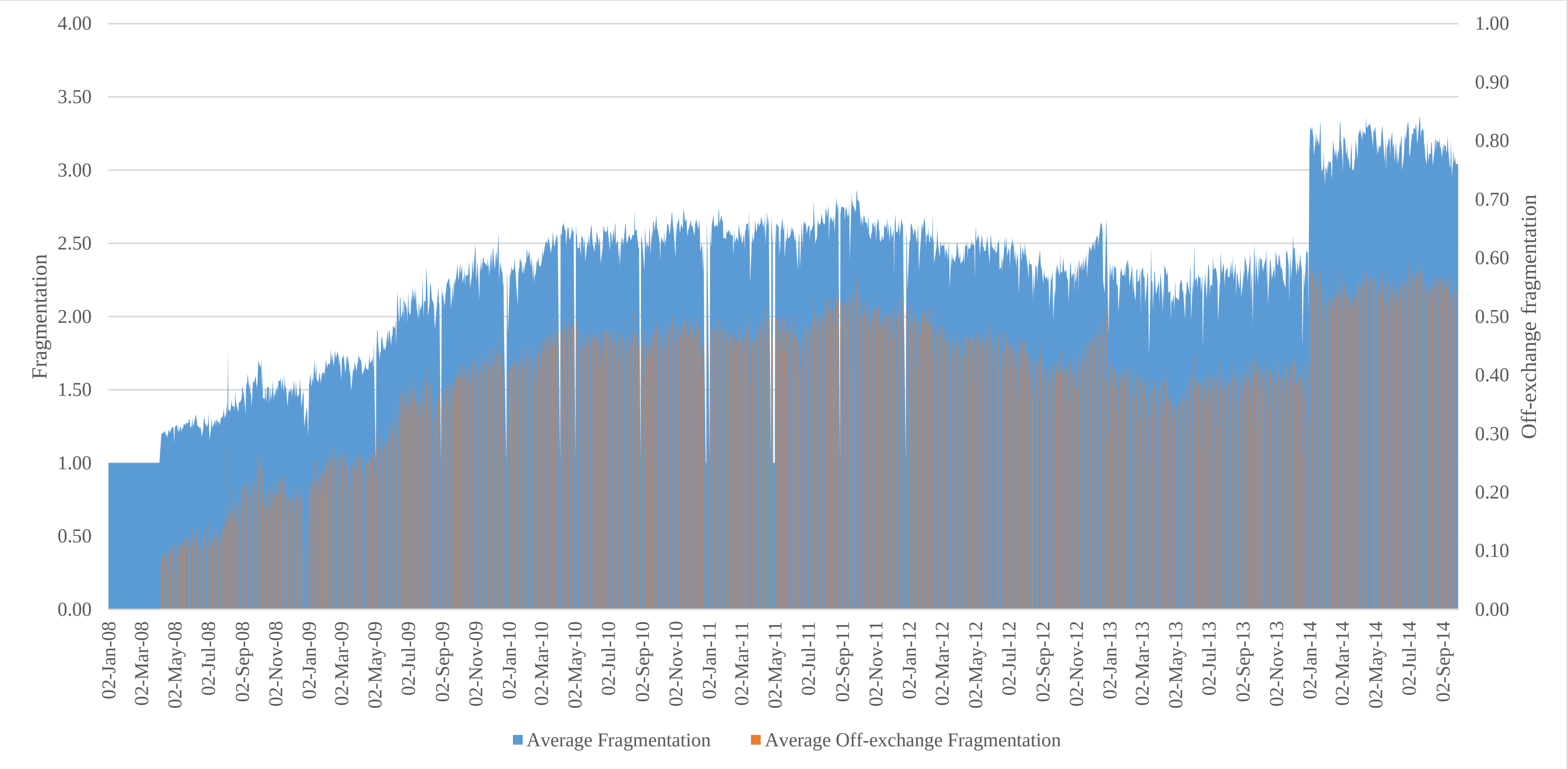
$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}.$$

The sample comprises the FTSE100 stocks from 1 April 2008 to 30 September 2014.

Stock charateristics	Mean	Std.dev	Min	25%	Median	75%	Max
Frag	2.3012	0.6181	1.0000	1.9049	2.3814	2.7428	3.8501
$Frag_{EX}$	0.3930	0.1599	0.0000	0.3092	0.4256	0.5145	0.9980
PIN	0.1787	0.1016	0.0201	0.1150	0.1545	0.2111	0.9799

Figure 4.4. 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 computed as one divided by the sum of the squared market shares of LSE and the three other trading venues, BATS Europe, Chi-X Europe and Turquoise. Off-exchange fragmentation i



4.4. Impact of Fragmentation on Market Transparency

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

4.4.1. Stock Day Panel Regressions

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

$$PIN_{i,t} = \alpha + \beta_1 Frag_{i,t} + \beta_2 Frag^2{}_{i,t} + \beta_3 Log(PoundVolume)_{i,t} + \beta_4 Log(TradeCount)_{i,t} + \beta_5 Log(TradeSize_{i,t}) + \beta_6 Volatility_{i,t} + \beta_7 Algo_{i,t} + \beta_8 EBAS_{i,t} + \beta_9 Price\_inverse_{i,t} + \beta_{10} Time_{i,t} \varepsilon \tag{4.05}$$

where PIN is the probability that a trade is informed, and computed as described in Section 3.1. PIN is thus an inverse proxy for market transparency. The proxy for visible fragmentation is *Frag* and is computed as described in Section 3.2. Following Degryse et al. (2015) and Boneva et al. (2015), I include a quadratic effect $Frag^2$, since there could be a trade-off in the benefits and drawbacks of fragmentation. A series of control variables is 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*. *Log(TradeCount)* is the log of total number of transactions in that day for stock *i*. *Volatility* is the daily standard deviation of trade-by-trade return of stock *i*. This intraday volatility represents the market risk faced by traders. *Algo* controls for the algorithm trading activity on high-entrant markets, and I follow Hendershott et al. (2011) to compute a proxy for this as the total number of quote changes divided by pound volume over the trading day *t*. *EBAS* is the daily mean effective bid-ask spread. It is computed as twice the absolute value of the difference between the execution price and the quote midpoint for each trade during the day, and the mean is computed for each day. *EBAS* captures the liquidity and adverse selection costs faced by market makers. Following O'Hara and Ye (2011), I also add the variable *price_inverse*, which corresponds to one divided by the closing price for stock *i* on day *t*. Finally, in order to minimise the possibility that the instruments pick up any general trends in dark and block trading, I also control for a time trend in the instrumental variable regressions. *Time* depicts the time trend expressed as the log of a linear trending variable starting at zero and increasing by one for every date in the sample, and is employed in the IV regressions only. A similar proxy is applied by Comerton-Forde and Putniņš (2015).

4.4.2. Instrumental Variable Approach

Endogeneity is a concern in my stock-day panel regressions. This is because informed traders are more likely to want to trade in lit markets, while uninformed traders would go on to trade mainly in off-exchange venues (Zhu, 2014). I overcome this issue by employing an instrument variable (IV) approach. I use two different sets of instruments for robustness. For the first set of fragmentation instrumental variables I follow Comerton-Forde and Putniņš (2015), Degryse et al. (2015), 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 my case, the two endogenous variables *Frag* and $Frag^2$ are constructed with the average of each variable over all stocks in the same stock size quintile. 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 informed trading in stock *i* causes a large level of fragmentation in other stocks within the same quintile. The microstructure studies employs this IV method to remove firm-specific reverse causality concerns because the level of fragmentation in each stock quintile is insensitive to concurrent trading in stock *i (Hasbrouck and Saar, 2013).* Therefore, I estimate the following two-stage least squares (2-SLS) model using this IV approach:

First stage:

$$FRAG_{i,t} = b_1^{'} X_{i,t} + y_1^{'} W_{i,t} + e_{1,t} \tag{4.06}$$

$$FRAG^2{}_{i,t} = b_2^{'} X_{i,t} + y_2^{'} W_{i,t} + e_{2,t} \tag{4.07}$$

Second stage:

$$PIN_{i,t} = \beta_1 Fr\hat{a}g_{i,t} + \beta_2 Fr\hat{a}g^2{}_{i,t} + \gamma_3^{'} W_{i,t} + \varepsilon_{i,t} \tag{4.08}$$

Vector $X_{i,t}$ contains two instrumental variables. $Fr\hat{a}g_{i,t}$ and $Fr\hat{a}g^2{}_{i,t}$ represent the instrument values from two auxiliary first stage equations, and the vector $W_{i,t}$ is a set of control variables discussed above. $e_{1,t}$ and $\varepsilon_{i,t}$ are the error terms from first and second stage estimations respectively. The Pearson correlation coefficients between two sets of error terms and potentially endogenous variables are 0.14 and 0.17, suggesting that the IV method applied here appear to be appropriate. Panel A in Table 4.4 shows the results of the first stage regression analysis where two endogenous variables are regressed against IVs and a set of control variables. Columns (1) and (2) report that IVs' coefficients are statistically significant and hence the IVs are strongly correlated with potential potentially endogenous variables. Panel B reports the weak IV and one can see that both the Cragg-Donald Wald F statistic and the Kleibergen-

Paap rk Wald F statistic are greater than the critical values from OLS bias[12]. Therefore, I reject the null hypothesis of weak instruments.

[12] I also conduct the F-statistics of the null hypothesis that the instruments do not enter the first stage regression. The F-statistics for the first and second instrument are 146 and 213 respectively, and therefore both reject the null hypothesis of weak instrumental variables. Similar tests have been conducted in Comerton-Forde and Putnins (2015).

Table 4.4. First stage regression and weak IV test

This table shows estimated first stage regression for the following 2SLS regression model:

$$PIN_{i,t} = \alpha + \beta_1 Frag_{i,t} + \beta_2 Frag^2{}_{i,t} + \beta_3 Log(PoundVolume_{i,t}) + \beta_4 Log(TradeCount_{i,t}) + \beta_5 Log(TradeSize_{i,t}) + \beta_6 Volatility_{i,t} + \beta_7 Algo_{i,t} + \beta_8 EBAS_{i,t} + \beta_9 Price\_inverse_{i,t} + \varepsilon$$

IV is constructed with the average of each endogenous variable over all stocks in the same stock size quintile. $PIN_{i,t}$ is an inverse proxy for market transparency for stock *i* on day *t* and is computed as described in Table 4.3. *Frag* is as defined in Table 4.3, $Log(PoundVolume_{i,t})$ is the natural logarithm of sum of pound volume traded for stock *i* on day *t*. $Log(TradeCount_{i,t})$ is the log of total number of transactions for stock *i* on day *t*. *Volatility* is the standard deviation of trade-by-trade returns of stock *i* on day *t*. $Log(TradeSize_{i,t})$ is the log of median of daily trade size of stock *i* on day *t*. $Algo_{i,t}$ equals the total number of quote changes over pound volume of stock *i* on day *t*. $EBAS_{i,t}$ is average effective bid-ask spread of stock *i* on day *t*. *Price_inverse* is one over the closing price for stock *i* on day *t*. *Time* is the log of linear trending variables starting at zero and incrementing by one for every date in my sample. Instrumental variables (IVs) are obtained for *Frag* and $Frag^2$; The t-statistics are presented in parentheses *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. Quintiles are computed on the basis of daily pound volume across the sample period from 1 April 2008 to 30 September 2014.

Panel A. First stage regression

	(1)	(2)
VARIABLES	Frag	$Frag^2$
IV of Frag	1.808***	5.065***
	(94.09)	(55.73)
IV of $Frag^2$	-0.226***	-0.315***
	(-51.15)	(-15.05)
Log(PoundVolume)	-0.083***	-0.292***
	(-31.26)	(-24.75)
Log(TradeCount)	0.058***	0.123***
	(25.05)	(11.71)
Log(TradeSize)	0.148***	0.705***
	(68.20)	(72.00)
Volatility	0.200***	1.001***
	(12.42)	(14.00)
Algo	-4.294***	-17.124***
	(-14.34)	(-14.15)
EBAS	-0.705**	-3.027**
	(-1.98)	(-2.00)
Price_inverse	-3.570***	-13.733***
	(-9.36)	(-8.16)

Time	0.034***	0.059***
	(16.99)	(6.49)
intercept	-1.037***	-6.226***
	(-46.62)	(-61.57)
Observations	129,241	129,241
R-squared	80%	76%

Panel B. Weak IV test

Chi-sq(1) P-val = 0.0000	
Weak identification test (Cragg-Donald Wald F statistic):	1.70E+04
(Kleibergen-Paap rk Wald F statistic):	1.30E+04
Stock-Yogo weak ID test critical values: 10% maximal IV size	7.03
15% maximal IV size 4.58	
20% maximal IV size 3.95	
25% maximal IV size 3.63	
Source: Stock-Yogo (2005). Reproduced by permission.	
NB: Critical values are for Cragg-Donald F statistic and i.i.d. errors.	

4.4.3. Main results

Table 4.5 reports the coefficients and corresponding t-statistics estimated using the five estimation approaches outlined above. Most of the coefficients are statistically significant. In addition, the sign and economic magnitude of those coefficients are generally consistent across estimations from column (1) to (4), thus it appears that my results are robust. The linear factor *Frag* has negative coefficients and the quadratic factor has positive coefficients across all estimation approaches, implying that *PIN* first decreases with *Frag* and then increases as fragmentation attains levels where unimpaired market quality can no longer be sustained. The estimates for *Frag* coefficients range from –0.071 to –0.015, and those of $Frag^2$ range from 0.003 to 0.013. All but one of the coefficients for both variables are highly statistically significant, suggesting the existence of a non-linear relationship between fragmentation and transparency. Figure 4.5 highlights a U-shaped relationship between *PIN* and *Frag* under the five estimation approaches. The minimum points of *PIN* range from 2.09 to 2.5 on Figure 4.5's panels. This suggests that the optimal level of visible fragmentation lies between 2.09 and 2.5. When fragmentation is smaller than this level, the negative (positive) relationship between market transparency and fragmentation suggests that the competition among trading venues benefits all investors by reducing adverse selection costs. However, when fragmentation is larger than the observed 'optimal' level, the phenomenon appears to harm market transparency without contributing to a decrease in implied adverse selection risks. 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-shape relationship between visible fragmentation and 'global' market depth for a sample of Dutch stocks.

Table 4.5. Market fragmentation and market transparency

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

$$PIN_{i,t} = \alpha + \beta_1 Frag_{i,t} + \beta_2 Frag^2{}_{i,t} + \beta_3 Log(PoundVolume_{i,t}) + \beta_4 Log(TradeCount_{i,t})$$
$$+ \beta_5 Log(TradeSize_{i,t}) + \beta_6 Volatility_{i,t} + \beta_7 Algo_{i,t} + \beta_8 EBAS_{i,t} + \beta_9 Price\_inverse_{i,t} + \varepsilon$$

$PIN_{i,t}$ is an inverse proxy for market transparency for stock *i* on day *t* and is computed as described in Table 4.3. *Frag* is as defined in Table 4.3, *Log(PoundVolume$_{i,t}$)* is the natural logarithm of sum of pound volume traded for stock *i* on day *t*. *Log(TradeCount$_{i,t}$)* is the log of total number of transactions for stock *i* on day *t*. *Volatility* is the standard deviation of trade-by-trade returns of stock *i* on day *t*. *Log(TradeSize$_{i,t}$)* is the log of median of daily trade size of stock *i* on day *t*. $Algo_{i,t}$ equals the total number of quote changes over pound volume of stock *i* on day *t*. $EBAS_{i,t}$ is average effective bid-ask spread of stock *i* on day *t*. *Price_inverse* is one over the closing price for stock *i* on day *t*. *Time* is the log of linear trending variables starting at zero and incrementing by one for every date in my sample. Instrumental variables (IVs) are obtained for *Frag* and $Frag^2$; IV is constructed with the average of each endogenous variable over all stocks in the same stock size quintile. *Frag* and $Frag^2$ are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in panel least squares frameworks. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. Quintiles are computed on the basis of daily pound volume across the sample period from 1 April 2008 to 30 September 2014.

	1	2	3	4
Frag	-0.018***	-0.015***	-0.071***	-0.052***
	(-4.74)	(-3.69)	(-10.97)	(-5.10)
$Frag^2$	0.004***	0.003***	0.015***	0.013***
	(3.80)	(2.92)	(10.70)	(5.49)
Log(PoundVolume)	0.017***	0.018***	0.004***	0.019***
	(25.84)	(23.59)	(4.50)	(24.31)
Log(TradeCount)	-0.011***	-0.010***	0.008***	-0.012***
	(-16.67)	(-13.25)	(7.56)	(-14.93)
Log(TradeSize)	-0.013***	-0.014***	-0.011***	-0.017***
	(-21.46)	(-21.27)	(-8.08)	(-20.53)
Volatility	0.026***	-0.002	0.020***	0.020***
	(5.36)	(-0.27)	(3.80)	(3.99)
Algo	0.175***	-0.085***	0.186***	0.205***
	(7.24)	(-3.15)	(6.99)	(7.83)
EBAS	0.223**	0.139*	0.276**	0.231**
	(2.32)	(1.87)	(2.24)	(2.31)
Price_inverse	0.058	0.006	-0.212*	0.053
	(0.51)	(0.04)	(-1.74)	(0.46)
Time				-0.001
				(-0.79)
intercept	0.097***	0.087***	0.202***	0.138***
	(14.10)	(8.91)	(20.46)	(12.94)
Adj_R sqr	0.90%	2.40%	2.64%	0.76%
Observations	129,241	129,241	129,241	129,241
Estimation Method	OLS	OLS	OLS	2SLS
Fixed Effects	None	Stock	Quarter	None
IV	None	None	None	Yes

An examination of the control variables also yields interesting insights. The positive and statistically significant coefficient of *Log(PoundVolume)* suggests that informed trading activity is prominent for heavily traded stocks. In other words, there is a positive effect of global market depth on informed trading activity. This finding is consistent with those of Foster and Viswanathan (1993b), Engle and Lange (2001), and Alzahrani et al. (2013), in that informed traders could flood into the market after a semi-private news event. Furthermore, the negative coefficients for *Log(TradeCount)* and *Log(TradeSize)* suggest that increased order flow improves trading transparency. This view is consistent with the argument that market quality improves with improved levels of trading liquidity (see for example Tse and Erenburg, 2003, Chordia et al., 2008). The positive and statistically significant estimate of *EBAS* is in keeping with this view. The positive *EBAS* coefficients arise also because market makers raise sell quotes, and lower buy 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). The positive and statistically significant *Volatility* coefficient values, however, imply that market transparency reduces with higher levels of volatility. This is because adverse selection risk is attributable to higher perceived risk, and to 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 *Algo* under the one stage OLS, quarter-fixed effects and the IV estimations indicates that algorithm trading activity on high entrant markets is strongly correlated with informed trading and adverse selection risk. Thus, it appears that algorithm traders (ATs) are usually more informed than slower traders (see Ibikunle, 2015a). I also find that daily mean *EBAS* has a positive and significant relationship with *PIN*.

Figure 4.5. Effects of visible fragmentation on market transparency

The panels show the implied effect of visible fragmentation on PIN (proxy for market transparency) 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 various regression estimation approaches: panel least squares with no fixed effects, panel least squares with stock fixed-effects, panel least squares with quarter fixed effects and two-stage least squares using IV. PIN is as defined in Table 4.3, Fragmentation is defined in Figure 4.4. The IV used is defined in Table 4.4.

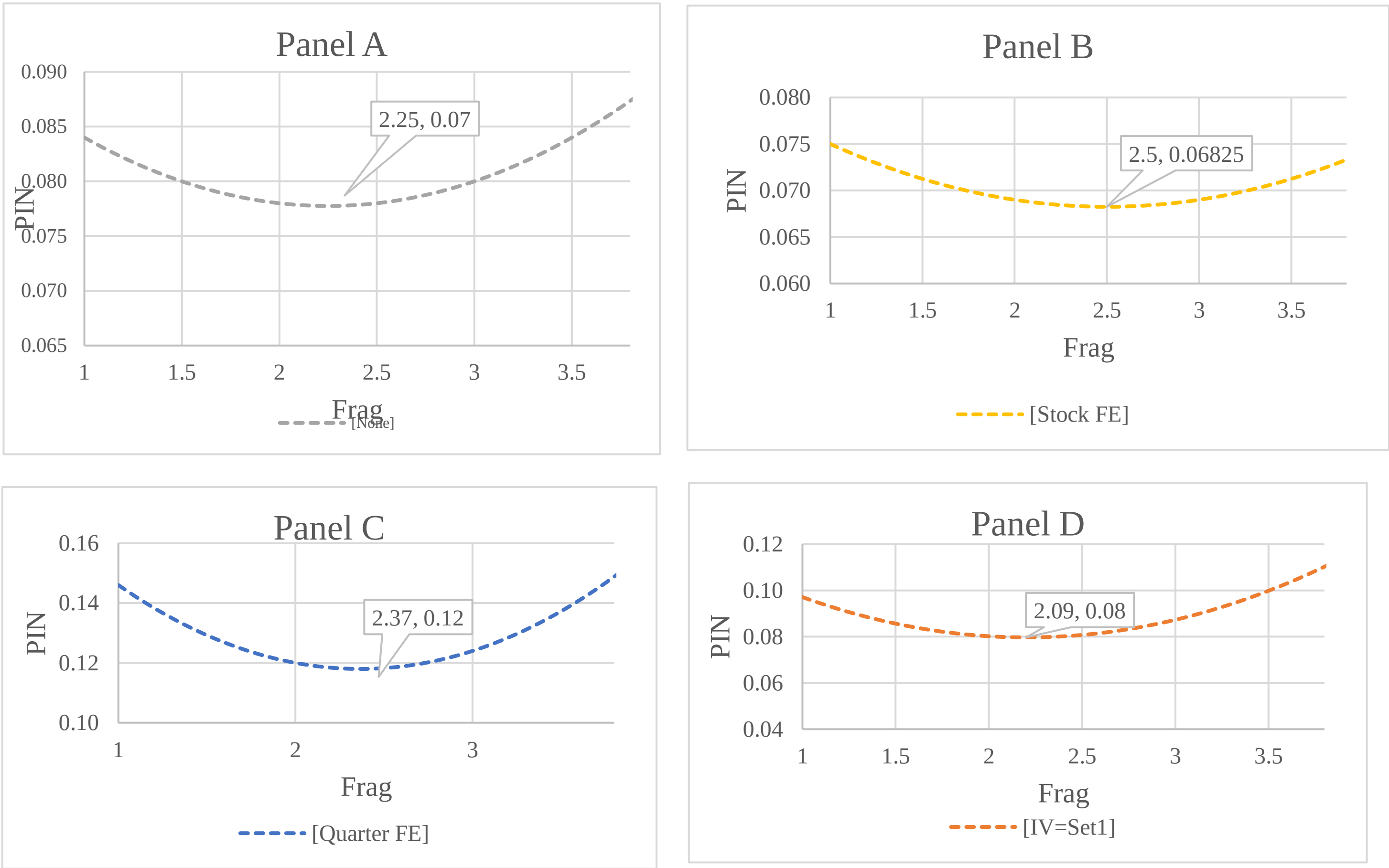


Table 4.6 reports the panel regression estimates of the relationship between levels of fragmentation and absolute value of 1-minute mid-quote autocorrelation. In this table the estimated coefficients in column (1) and (2) are absent in the previously considered PIN-based results. It appears that the signs observed on the coefficients for *Frag* and $Frag^2$ are dependent on whether the estimation approach explicitly accounts for time. Thus, in the estimation with time fixed effects and the IV estimations, which both include time trends, the results are consistent with my hypothesis regarding the impact of fragmentation on market quality. This split result is probably sensible when one considers that autocorrelation in the context of my sample is a function of time. The *Frag* estimates for the time fixed effects and the IV estimates are all statistically significant, and are of a higher magnitude for the IV than the time fixed effects (–0.040). The trend is consistent for the $Frag^2$ estimates at 0.034 for the IV estimation approaches and only 0.007 for the time fixed effects estimation. However, the results are all consistent with the expectation that there is a trade-off in the benefits and drawbacks of visible fragmentation; at higher levels, fragmentation increases adverse selection risk. The *Log(PoundVolume)* coefficients are negative and statistically significant across all of the estimation approaches, which is inconsistent with the results obtained in the PIN regression analysis in Table 4.5. The negative estimates obtained here are more plausible, because one would expect that increasing volume of trade allows for the timely incorporation of new information and thus helps to eliminate adverse selection risk. This aptly explains the negative and statistically significant variables observed for the *EBAS* variable, which is a proxy for liquidity (see Chordia et al., 2008). The same argument could be made for an expectation of negative coefficients for the *Log(TradeCount)* variable; however, the estimates are all positive, implying adverse selection risk increases with higher numbers of trades arriving in the market. This result could be linked to the increased difficulty of screening out informed trades by market markers when transaction volumes rise, thus causing adverse selection to persist and even increase. This could also explain the positive and statistically significant coefficient estimates obtained for the *Algo* variable, since algorithmic trading implies a high volume of transactions. The positive and statistically significant *Log(TradeSize)* coefficients are more in line with the market microstructure literature on the trades that move prices (see Easley and O'Hara, 1987, Chan and Lakonishok, 1993). Larger trade sizes would thus imply informed trading which invariably leads to a higher level of adverse selection risk. The volatility estimates are also consistent with the expectation that increased volatility levels heighten adverse selection risk (see also Domowitz et al., 2001).

I now turn to an examination of the effect of my alternate fragmentation measure, off-exchange fragmentation, on market transparency. The estimation results are presented in Table 4.7. Coefficients of $Frag_{EX}$ are statistically significant under different estimations, except for stock fixed effects estimation approaches. All coefficients are negative as expected except in the case of the IV estimation in column (4). This inconsistency is also replicated for the $Frag_{EX}^2$ coefficients. Specifically, the inconsistencies relate to the stock fixed effects and the IV estimations. When the estimation is made with no fixed effects, with time fixed effects, the estimates are consistent with my earlier findings which indicate a U-shaped impact curve on adverse selection cost. Conversely, under the IV estimation the signs are reversed; the results are not statistically significant for the stock fixed effects. Evidence therefore points to both a U-shaped and an inverse U-shaped relationship between $Frag_{EX}$ and adverse selection costs when my proxy for fragmentation is focused on trading activity off the listing exchange. With the exception of the inconsistent sign for $Frag_{EX}$, most of control variables yield consistent and statistically significant estimates with Table 4.5's results.

Table 4.6. Market fragmentation and adverse selection risk

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

$$Auto_{i,t} = \alpha + \beta_1 Frag_{i,t} + \beta_2 Frag^2_{i,t} + \beta_3 Log(PoundVolume_{i,t}) + \beta_4 Log(TradeCount_{i,t})$$
$$+ \beta_5 Log(TradeSize_{i,t}) + \beta_6 Volatility_{i,t} + \beta_7 Algo_{i,t} + \beta_8 EBAS_{i,t} + \beta_9 Price\_inverse_{i,t} + \varepsilon$$

$Auto_{i,t}$ is the absolute value of 1 – minute mid-quote return autocorrelation, and it is a proxy of adverse selection risk for each stock in each day. *Frag* is as defined in Table 4.3. *Log($PoundVolume_{i,t}$)* is the natural logarithm of sum of pound volume traded for stock *i* on day *t*. *Log($TradeCount_{i,t}$)* is the log of total number of transactions for stock *i* on day *t*. *Volatility* is the standard deviation of trade-by-trade returns of stock *i* on day *t*. *Log($TradeSize_{i,t}$)* is the log of median of daily trade size of stock *i* on day *t*. *$Algo_{i,t}$* equals the total number of quote changes over pound volume of stock *i* on day *t*. *$EBAS_{i,t}$* is average effective bid-ask spread of stock *i* on day *t*. *Price_inverse* is one over the closing price for stock *i* on day *t*. *Time* is the log of linear trending variables starting at zero and incrementing by one for every date in my sample. Instrumental variables (IVs) are obtained for *Frag* and *$Frag^2$*; IV is constructed with the average of each endogenous variable over all stocks in the same stock size quintile. *Frag* and *$Frag^2$* are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in panel least squares frameworks. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. Quintiles are computed on the basis of daily pound volume across the sample period from 1 April 2008 to 30 September 2014.

	1	2	3	4
Frag	0.134***	0.139***	-0.040***	-0.263***
	(30.57)	(31.47)	(-5.12)	(-23.32)
$Frag^2$	-0.025***	-0.027***	0.007***	0.034***
	(-22.98)	(-25.05)	(4.02)	(13.42)
Log(PoundVolume)	-0.018***	-0.016***	-0.002**	-0.062***
	(-20.63)	(-16.69)	(-2.57)	(-52.60)
Log(TradeCount)	0.035***	0.050***	0.030***	0.084***
	(48.11)	(57.76)	(30.84)	(63.46)
Log(TradeSize)	0.038***	0.036***	-0.027***	0.070***
	(51.89)	(45.79)	(-13.58)	(67.54)
Volatility	0.299***	0.217***	0.178***	0.339***
	(81.98)	(28.73)	(27.59)	(76.73)
Algo	0.471***	0.269***	0.362***	-0.287***
	(11.12)	(6.20)	(6.26)	(-7.86)
EBAS	-0.174***	-0.072**	-0.013	-0.239***
	(-2.83)	(-2.39)	(-0.67)	(-2.62)
Price_inverse	-0.017	-1.195***	-0.532***	-0.746***
	(-0.10)	(-3.09)	(-3.67)	(-3.97)
Time				0.093***
				(60.53)
intercept	-0.362***	-0.513***	0.125***	-0.281***
	(-34.09)	(-34.62)	(7.32)	(-19.42)
Adj_R sqr	9.12%	10.90%	38.50%	11.07%
Observations	129,241	129,241	129,241	129,241
Estimation Method	OLS	OLS	OLS	2SLS
Fixed Effects	None	Stock	Quarter	None
IV	None	None	None	Yes

Table 4.7. Off-exchange market fragmentation and market transparency

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

$$PIN_{i,t} = \alpha + \beta_1 Frag_{EX\,i,t} + \beta_2 Frag_{EX}{}^2{}_{i,t} + \beta_3 Log(PoundVolume_{i,t}) + \beta_4 Log(TradeCount_{i,t})$$
$$+ \beta_5 Log(TradeSize_{i,t}) + \beta_6 Volatility_{i,t} + \beta_7 Algo_{i,t} + \beta_8 EBAS_{i,t} + \beta_9 Price\_inverse_{i,t} + \varepsilon$$

$PIN_{i,t}$ is an inverse proxy for market transparency for stock *i* on day *t* and is computed as described in Table 4.3. $Frag_{EX}$ is as defined in Table 4.3. $Log(PoundVolume_{i,t})$ is the natural logarithm of sum of pound volume traded for stock *i* on day *t*. $Log(TradeCount_{i,t})$ is the log of total number of transactions for stock *i* on day *t*. *Volatility* is the standard deviation of trade-by-trade returns of stock *i* on day *t*. $Log(TradeSize_{i,t})$ is the log of median of daily trade size of stock *i* on day *t*. $Algo_{i,t}$ equals the total number of quote changes over pound volume of stock *i* on day *t*. $EBAS_{i,t}$ is average effective bid-ask spread of stock *i* on day *t*. *Price_inverse* is one over the closing price for stock *i* on day *t*. *Time* is the log of linear trending variables starting at zero and incrementing by one for every date in my sample. Instrumental variables (IVs) are obtained for *Frag* and $Frag^2$; IV is constructed with the average of each endogenous variable over all stocks in the same stock size quintile. *Frag* and $Frag^2$ are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in panel least squares frameworks. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. Quintiles are computed on the basis of daily pound volume across the sample period from 1 April 2008 to 30 September 2014.

	1	2	3	4
$Frag_{EX}$	-0.020***	-0.010	-0.160***	0.292***
	(-2.59)	(-1.22)	(-10.37)	(10.05)
$Frag_{EX}^2$	0.002	-0.011	0.177***	-0.436***
	(0.21)	(-0.95)	(9.32)	(-10.72)
Log(PoundVolume)	0.017***	0.017***	0.004***	0.017***
	(24.83)	(22.73)	(4.37)	(20.85)
Log(TradeCount)	-0.010***	-0.009***	0.008***	-0.012***
	(-15.86)	(-12.12)	(7.69)	(-14.47)
Log(TradeSize)	-0.012***	-0.013***	-0.011***	-0.009***
	(-21.12)	(-20.79)	(-7.89)	(-12.23)
Volatility	0.035***	0.010	-0.014*	0.162***
	(5.62)	(1.30)	(-1.93)	(12.48)
Algo	0.168***	-0.097***	0.178***	0.136***
	(6.99)	(-3.52)	(6.73)	(5.42)
EBAS	0.220**	0.135*	0.278**	0.204**
	(2.31)	(1.86)	(2.27)	(2.15)
Price_inverse	0.053	0.004	-0.209*	0.012
	(0.47)	(0.02)	(-1.71)	(0.10)
Time				-0.008***
				(-7.59)
intercept	0.080***	0.069***	0.144***	0.073***
	(15.57)	(8.33)	(18.28)	(13.27)
Adj_R sqr	0.91%	2.40%	2.64%	0.12%
Observations	129,241	129,241	129,241	129,241
Estimation Method	OLS	OLS	OLS	2SLS
Fixed Effects	None	Stock	Quarter	None
IV	None	None	None	Yes

Table 4.8 shows the regression estimates of the relationship between autocorrelation of 1-minute mid-quote returns and off-exchange fragmentation, $Frag_{EX}$. As in Table 4.8, the $Frag_{EX}$ and $Frag_{EX}^2$ coefficients do not show consistent results across different types of regressions, despite all estimates being statistically significant. Coefficients show that there is an inverse U-shaped curve under OLS and stock fixed effects. When quarter fixed effects and the IV estimation are imposed, this relationship becomes U-shaped. Again, as in Tables 4.5 and 4.7, most of the other estimated coefficients in Table 4.8 are consistent with the results in Table 4.6. It therefore appears that the issue with the results here is due to my measure of market fragmentation, which focuses on the aggregate pound volume of transactions executed off the main/listing/incumbent exchange, the LSE. At best this measure encapsulates the loss of market share by the listing exchange, rather than giving a robust view of the state of fragmentation in the market. The results in Tables 4.7 and 4.8 are thus presented to demonstrate the inadequacy of the $Frag_{EX}$ measure in capturing market fragmentation.

Table 4.8. Off-exchange market fragmentation and adverse selection risk

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

$$Auto_{i,t} = \alpha + \beta_1 Frag_{EX\,i,t} + \beta_2 Frag_{EX}{}^2{}_{i,t} + \beta_3 Log(PoundVolume_{i,t}) + \beta_4 Log(TradeCount_{i,t}) + \beta_5 Log(TradeSize_{i,t}) + \beta_6 Volatility_{i,t} + \beta_7 Algo_{i,t} + \beta_8 EBAS_{i,t} + \beta_9 Price\_inverse_{i,t} + \varepsilon$$

$Auto_{i,t}$ is the absolute value of 1-minute mid-quote returns autocorrelation, and it is a proxy of adverse selection risk for each stock in each day. *$Frag_{EX}$* is as defined in Table 4.3. *$Log(PoundVolume_{i,t})$* is the natural logarithm of sum of pound volume traded for stock *i* on day *t*. *$Log(TradeCount_{i,t})$* is the log of total number of transactions for stock *i* on day *t*. *Volatility* is the standard deviation of trade-by-trade returns of stock *i* on day *t*. *$Log(TradeSize_{i,t})$* is the log of median of daily trade size of stock *i* on day *t*. *$Algo_{i,t}$* equals the total number of quote changes over pound volume of stock *i* on day *t*. *$EBAS_{i,t}$* is average effective bid-ask spread of stock *i* on day *t*. *Price_inverse* is one over the closing price for stock *i* on day *t*. *Time* is the log of linear trending variables starting at zero and incrementing by one for every date in my sample. Instrumental variables (IVs) are obtained for *Frag* and *$Frag^2$*; IV is constructed with the average of each endogenous variable over all stocks in the same stock size quintile. *Frag* and *$Frag^2$* are then each individually regressed on their corresponding cross-sectional stock averages and the other control variables in panel least squares frameworks. The t-statistics are presented in parentheses and derived from panel corrected standard errors (PCSE). *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. Quintiles are computed on the basis of daily pound volume across the sample period from 1 April 2008 to 30 September 2014.

	1	2	3	4
$Frag_{EX}$	0.277***	0.273***	-0.119***	-3.720***
	(33.26)	(32.66)	(-6.59)	(-63.05)
$Frag_{EX}^2$	-0.255***	-0.285***	0.082***	4.808***
	(-17.66)	(-19.67)	(3.79)	(58.50)
Log(PoundVolume)	-0.017***	-0.016***	-0.003***	-0.058***
	(-20.81)	(-17.10)	(-3.42)	(-44.47)
Log(TradeCount)	0.035***	0.050***	0.031***	0.096***
	(47.21)	(56.42)	(31.79)	(61.40)
Log(TradeSize)	0.037***	0.034***	-0.026***	0.028***
	(54.54)	(46.75)	(-13.22)	(23.55)
Volatility	0.325***	0.261***	0.182***	-0.941***
	(50.39)	(28.86)	(22.53)	(-36.27)
Algo	0.429***	0.221***	0.337***	0.312***
	(10.81)	(5.40)	(5.99)	(4.40)
EBAS	-0.180***	-0.086**	-0.017	-0.036
	(-2.85)	(-2.42)	(-0.91)	(-0.50)
Price_inverse	-0.090	-1.302***	-0.572***	-0.134
	(-0.50)	(-3.36)	(-3.92)	(-0.68)
Time				0.165***
				(71.23)
intercept	-0.250***	-0.387***	0.096***	-0.373***
	(-26.59)	(-27.86)	(5.83)	(-30.72)
Adj_R sqr	0.90%	10.82%	38.60%	0.01%
Observations	129,241	129,241	129,241	129,241
Estimation Method	OLS	OLS	OLS	2SLS
Fixed Effects	None	Stock	Quarter	None
IV	None	None	None	Yes

4.5. Fragmentation and Market Efficiency

4.5.1. Predictive Regressions

Thus far I have found a U-shaped relationship between visible fragmentation and adverse selection costs. Although visible fragmentation helps to reduce adverse selection risk when fragmentation is below a certain level, empirical evidence in this chapter suggests that implied adverse selection risk could potentially increase with visible fragmentation. It is therefore fair to assume that disconnected quotes across trading venues can create arbitrage opportunities. Even the most efficient markets do not necessarily reflect all available information at every point of the day (see Fama, 1970, Hillmer and Yu, 1979, Patell and Wolfson, 1984, Chordia et al., 2008). Experienced traders may be able to locate potential arbitrage opportunities, since quotes across regulated markets and MTFs are not closely linked due to the absence of a mandatory exchange trade-through protection. To test this hypothesis, I examine the relationship between visible fragmentation and market efficiency. I use the 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 my order imbalance measure, I use a pound-based metric, which encapsulates the economic significance of order imbalance. Equation (4.09) expresses the computation of this measure, where £BUY and £SELL equal the 5-minute interval pound volume of buy and sell trades respectively; this is computed for each stock separately[13]. I thereafter employ the values in my estimation of Equation (4.10) below. In Equation (4.10), *return*$_{i,t}$ corresponds to the 5-minute return for stock *i* during 5-minute interval *t*:

$$OIB£_t = \frac{(£BUY - £SELL)}{(£BUY + £SELL)} \tag{4.09}$$

$$return_{i,t} = \alpha + \beta_1 OIB_{i,t-1} + \beta_2 OIB_{i,t-1} * FRAG + \varepsilon \tag{4.10}$$

The fragmentation dummy, *Frag*, takes the value 1.0 when either of my fragmentation proxies are one standard deviation above the average value for the trading days over (-15, +15), and zero otherwise[14]. Coefficient of 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). Moreover, I should expect to see a negative value for β_2, which would imply that order flow competition among the four venues in my sample reduces arbitrage opportunity, and thus market fragmentation enhances market efficiency by reducing short-term return predictability.

4.5.2. Results

Table 4.9 presents estimated model results for both fragmentation proxies; Panel A shows the results for *Frag* as the interaction dummy in Equation (4.10), while Panel

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[13] Direction of trade is inferred using the Lee, C. M. C. & Ready, M. J. 1991b. Inferring Trade Direction from Intraday Data. *The Journal of Finance,* 46**,** 733-746. algorithm.
[14] The model is estimated using both market fragmentation proxies and results are presented for both.

B shows the results for $Frag_{EX}$. Firstly, the coefficients on the lagged order imbalance variable are all statistically significant at the 1% level. 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 the interaction variable *OIB£*Frag* is -0.001 (-4.17). 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. I also find that the coefficient (t-statistic) of interaction variable *OIB£** $Frag_{EX}$ is -0.0002 (-2.01), implying that with more order flow migrating to MTFs, the London market generally becomes more efficient. I also include the daily dummy variable *Frag* into the regression model and the results are illustrated in Panel D, E and F. It can be observed that with dummy variable added the results are still consistent in that high level of fragmentation reduce short-term predictability power. Thus, this 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 Storkenmaier and Wagener (2011), who show that quotes across primary exchanges and MTFs are closely linked because competition forces can integrate the disconnected trading venues.

Our view of the positive influence of fragmentation on market efficiency is slightly nuanced. The British economy is one of the largest in the world, and until the introduction of MiFID spurred a significant growth of new trading venues for UK stocks, the LSE was virtually the only venue in which to trade UK stocks. 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 the capacity for order execution by market makers and broker-dealers, 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 my findings, increased opportunities for order execution (indicated by market fragmentation) should improve market efficiency.

Table 4.9. Market quality test: short-term predictive test

Predictive regressions of five-minute returns on lagged order imbalance (*$OIB£_{t-1}$*), and lagged order imbalance interacted with a dummy variable for fragmentation. *$OIB£_t$* 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 a fragmentation dummy based on overall level of fragmentation, and Panel B uses a 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			Panel C	
	Coefficient	t-stats		Coefficient	t-stats		Coefficient	t-stats
$OIB£_{t-1}$	1.52×10^{-3}***	17.17	*OIB£*	1.39×10^{-3}***	14.00	*$OIB£_{t-1}$*	1.20×10^{-3}***	19.85
*$OIB£_{t-1}$*Frag*	-4.46×10^{-4}***	-4.17	*$OIB£*Frag_{EX}$*	-2.22×10^{-4}***	-2.01	*$OIB£_{t-1}$*(1-HHI)*	-2.62×10^{-5}	-0.15
Constant	-3.21×10^{-5}***	-1.38	*Constant*	-3.19×10^{-5}***	-1.37	*Constant*	-6.42×10^{-5}***	-2.30

	Panel D			Panel E			Panel F	
	Coefficient	t-stats		Coefficient	t-stats		Coefficient	t-stats
$OIB£_{t-1}$	1.38×10^{-3}***	20.6	*OIB£*	1.41×10^{-3}***	20.82	*$OIB£_{t-1}$*	1.40×10^{-3}***	20.75
*$OIB£_{t-1}$*Frag*	-4.01×10^{-4}***	-4.4	*$OIB£*Frag_{EX}$*	-5.54×10^{-4}***	-6.55	*$OIB£_{t-1}$*(1-HHI)*	-5.37×10^{-4}***	-6.50
Frag	-8.40×10^{-6}***	-0.51	*$Frag_{EX}$*	1.02×10^{-3}***	-2.26	*Frag*	-9.07×10^{-6}***	-0.54
Constant	-1.25×10^{-5}***	-1.38	*Constant*	1.38×10^{-4}***	2.41	*Constant*	1.08×10^{-5}***	-0.25

4.6. Conclusion

The Markets in Financial Instrument Directive (MiFID) ended the quasi-monopoly of primary exchanges across Europe, leading to the introduction of more than one hundred new trading venues, such as MTFs. 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 the Reg. 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 the European equity market. In this chapter, I study the impact of competition for visible order flow on market transparency and market efficiency under a consolidated market environment. A significant difference between my analysis and previous studies is that I conduct my tests on an aggregate market by creating a consolidated order book featuring order flow and transactions from the exchanges making up the London market for FTSE 100 stocks. Thus, for the first time, I can assess the impact of fragmentation on the aggregate market for trading Europe's highest trading stocks.

I obtain visible high-frequency order book data for the 100 largest UK stocks listed on the LSE and traded at three other recently introduced major venues: BATS Europe, Chi-X Europe and Turquoise. The data obtained covers a ten-year period ending in 2014. In order to investigate the impact of fragmentation on global market quality and trading efficiency, I create a single consolidated virtual market by concatenating data from these four venues. Specifically, I employ probability of informed trading (PIN) and 1-minute mid-quote returns autocorrelation as proxies for adverse selection costs and risk, respectively. PIN is also used as an inverse proxy for market transparency. Results obtained suggest the existence of a quadratic/u-shape relationship between fragmentation and adverse selection risk. Thus, visible fragmentation helps to reduce adverse selection costs and increase market transparency in the aggregate market environment when fragmentation is relatively lower. When fragmentation is higher, however, implied adverse selection costs and market opacity potentially increase with fragmentation. The negative impact of fragmentation on market transparency is, however, very limited, since historical fragmentation is generally smaller than the upper limit of an optimal range suggested by my analysis. This quadratic relationship is consistent with the existing literature relating market quality measures with market fragmentation (see for example Degryse et al., 2015, Boneva et al., 2015).

I also make further contributions to the literature by investigating the impact of market fragmentation on market efficiency; I adapt Chordia et al.'s (2008) return predictability model to test whether fragmentation reduces short horizon return predictability. I find that fragmentation facilitates market efficiency by eliminating short horizon return predictability and reducing arbitrage opportunities. My results are in line with Storkenmaier and Wagener (2011) and Menkveld (2013), who suggest that order flow competition across trading venues could act as a linkage necessary to minimise arbitrage opportunities.

The findings in this chapter have important implications for the debate surrounding trading fragmentation in European equity markets. By showing that competition between trading venues can improve aggregate market quality, the argument could be advanced that, despite the lack of a mandated consolidated tape under MiFID, order flow competition effectively acts as a linkage variable. Therefore, market fragmentation should be viewed as a value-creating competition phenomenon that benefits market transparency and price efficiency.

5. Commonality in Lit and Dark liquidity

5.1. Introduction:

The last decade has seen an unprecedented proliferation of new trading places. For example, in Europe, riding on the back of the implementation of the Markets in Financial Instruments Directive (MiFID) in 2007, more than 100 new trading venues have been established over the last decade. The entrant venues are mostly high tech Multilateral Trading Facilities, enabled by MiFID rules. Many trading venues, including the more established national exchanges, rely on existing MiFID waivers to operate dark order books in addition to the standard and more transparent lit (visible) limit order book. The main advantage of dark order books (or dark pools) over traditional lit markets is the ability to execute large orders anonymously and with minimum price impact, since pre-trade transparency is waived for orders submitted to such platforms. However, recent studies suggest average trade sizes in some European dark pools are comparable to those in the lit market (see for example Ibikunle et al., 2017). The lure of trading with no pre-trade transparency has led to a significant growth in the proportion of dark trading across the developed markets. According to Degryse et al. (2015), approximately 30% to 40% of all orders in the United States and European Blue chip stocks are executed in the dark. Despite the growing popularity of dark pools among a section of market participants, mainly institutional traders, the operation of dark pools has generally been subject to debate and controversy due to their lack of pre-trade transparency. Industry and academic contributors have raised concerns that dark pool trading may tarnish the credibility of primary equity markets, and politicians are increasingly wading into the debate. In a letter from US Senator Kaufman to SEC Chair Schapiro, the Senator notes a need to *"examine whether too much order flow is being shielded from the lit markets by dark venues"*.

In Europe, regulators are seeking to place greater restrictions on dark pool trading. Market in Financial Instruments Directive (MiFID) II proposes the introduction of an 8% cap on the total value of dark trading across all venues. This restriction is scheduled for implementation at the start of 2018, having been delayed by a year. Despite the growing importance of dark venues, very limited finance research offers insight into dark pool liquidity and its impact on market quality. The existing literature shows mixed results regarding the impact of dark trades on market liquidity. For example, Buti et al. (2011) find no supporting evidence that dark pool trading can harm market liquidity. Based on high-frequency data, Brugler (2015) shows that dark trading leads to improved liquidity on the primary exchange. However, Nimalendran and Ray (2014) investigate trading data from one of the 32 US dark venues and find that dark trading is associated with increased price impact and price impact on quoting exchanges. Degryse et al. (2015), using a European sample of stocks, show that dark trading has a detrimental effect on market liquidity.

This chapter examines the dynamics of the liquidity-creation effect in both lit and dark venues by employing a liquidity commonality model. Previous research on liquidity commonality (see for example Chordia et al., 2000, Hasbrouck and Seppi, 2001, Huberman and Halka, 2001) show that the liquidity levels of individual stocks co-vary with overall market liquidity. One likely explanation for this phenomenon is market makers' inventory management. This is because market makers are likely to respond to shifting market prices and order flow by altering their exposure across various assets. This is not the only possible reason for liquidity commonality, as the literature also suggests that the level of commonality between a stock and the wider market may depend on market structure (see for example Brockman and Chung, 2008). However, there has to been no examination of the liquidity commonality in a market fragmented along dark and lit lines. Thus, I present a first order analysis of liquidity commonality between stocks and the wider market in a market fragmented along dark and lit trading lines. I compare and contrast the liquidity commonality between lit and dark venues under different market conditions, over the four-year period from 1st June 2010 to 30th September 2014. This is also the first study to characterise the interactions between dark and lit liquidity in relation to the wider market. Indeed, I pose entirely new questions concerning how dark trading is shaping trading in financial markets.

Specifically, four distinct questions are posed. Firstly, when compared with lit venues, do dark pools have larger or smaller co-movement with market-wide liquidity? Secondly, if such relationship exists, does the observed co-movement improve the market liquidity or does it drain liquidity from the overall market; i.e. do dark pools play a complementary role to lit venues, especially in periods of liquidity constraints or do they exacerbate the constraints? Thirdly, what factors drive co-movement in dark and lit liquidity? Finally, since both Ye (2011) and Zhu (2014) suggest the possibility that informed traders may use dark venues in order to reduce their transactions costs and maximise their information-based profits, I investigate whether variations in dark pool liquidity could be linked with informed trading activities.

The findings are fourfold. First, I find that the degree of dark venues' liquidity commonality with the wider market is larger than that of lit venues, indicating that liquidity effects in dark pools is more pronounced. Further analysis suggests that dark liquidity commonality with the wider market is linked to increasing levels of liquidity in the wider market rather than a decreasing trend. This implies that, when market-wide liquidity starts to increase, dark venues proportionally contribute more liquidity than lit venues. Secondly, results suggest that when limit order spread increases and limit order queue builds up traders are incentivised to route their trades to dark venues. This is an indication of the complementary role played by dark venues in the aggregate market, facilitating trades that otherwise could not be easily executed at lit venues. I also show that informed trading and algorithm trading (AT) reduce liquidity-creation effects in both lit and dark venues. This finding is consistent with the related literature (for example see Zhu, 2014, Comerton-Forde and Putniņš, 2015) in that when an informed event occurs informed traders are likely to gravitate to the same side of the market and trade in the same direction, thereby facing a lower execution probability in the dark than in the lit venue. Hence, lit venues attract traders that are more informed and informed order flows. Finally, I show that the stocks with lower levels of informed trading activity and higher volatility generate stronger liquidity commonality effects in both lit and dark venues.

Overall, this chapter extends the recent empirical literature on dark trading on the one-hand and liquidity commonality in the wider microstructure literature on the other. The overall analysis is timely and has implications for dark pool regulation, given the increasingly intense regulatory constraints being considered for dark pools around the world, especially in the EU. Taken together, the results suggest that dark trading poses little threat to the market liquidity, rather it provides an opportunity for executing orders that otherwise might not have been executed, thereby creating additional liquidity in the aggregate market. The reminder of this chapter is structured as follows: in Section 2, I present a summary of the related literature, section 3 discusses the data, liquidity measures and descriptive statistics, section 4 motivates the methodological approach used in the chapter, section 5 presents and discusses the results, while section 6 concludes.

5.2.Related Literature

Early contributions to the literature model investors' ability and preference for trading in dark pools (or with hidden orders, such as icebergs or trading in upstairs markets) and what effects that might have on market quality. Hendershott and Mendelson (2000) show that lower trading cost is the key determinant of dark pools' competitiveness. Given this, their model suggests that informed traders prefer to use dark pools in order to minimise trading costs. Boulatov and George (2013) examine hidden versus displayed liquidity in the primary market. They show that hiding liquidity-providing orders leads to more aggressive competition among informed traders in providing liquidity, thus improving price discovery. Buti et al. (2016) model the interaction between dark pools and limit order book (LOB); they find that although order flow migrates from the LOB to dark pools, the overall market trading volume increases. Ye (2011) and Zhu (2014), in addition to examining the trading strategies of informed and liquidity traders in the presence of dark pools, explicitly investigate the impact of dark orders on price discovery on the primary exchange. Ye (2011) considers an informed trader who splits orders between a lit exchange and a dark pool, and finds that dark trading reduces price discovery. However, Zhu (2014) finds that informed traders are more likely than uninformed traders to cluster on one side of the market and therefore informed traders face lower execution probability in dark pools than uninformed traders. As a result, informed traders gravitate toward the primary (lit) exchange, while uninformed traders are more likely to trade in the dark venue. Zhu (2014) contends that this self-selection improves price discovery in the lit exchange due to reduced uninformed/noise trades there. Ye (2011) and Zhu (2014) draw different conclusions due to different assumptions on dark venue accessibility. Ye's (2011) model does not allow uninformed traders to choose between competing venues, assuming that they trade perpetually on the (lit) primary exchange and hence the role of uninformed traders in dark pools is missing from the model. In contrast, Zhu (2014) model allows for self-selection of trading venues by both informed and uninformed traders.

Other papers employ various empirical frameworks to identify how dark trading affects price discovery, liquidity, market transparency, volatility and overall market quality. Comerton-Forde and Putniņš (2015) examine the impact of dark trading on price discovery by using a sample of Australian Stock Exchange (ASX) stocks. Their results indicate that at low levels (less than 10%) dark trading does not harm price discovery. Ibikunle et al. (2016), employing a sample of FTSE350 stocks, finds that moderate levels of dark trading are beneficial to the aggregate market through the improvement of overall market transparency and trading noise reduction. They also show that the benefits of dark trading peak when dark trading value attains 15% of the overall market volume. Foley and Putniņš (2016), based on an analysis of a Canadian sample of stocks, also find that lower levels of dark trading improves price efficiency.

Several empirical papers investigate the impact of dark pool trading activity on market liquidity. Kwan et al. (2015) study the impact of Reg NMS Rule 612, which stipulates a decrease in minimum pricing increment from $0.01 to $0.0001 when stock prices fall below $1.00. They show that when the spread is constrained and limit order queue builds up, traders prefer to use dark venues in order to lower their trading costs and increase execution probability. Buti et al. (2011) also show that dark pool trades are positively related to daily volume and market depth and negatively related to market volatility and order imbalance. He and Lepone (2014) examine ASX data and find that dark pool volume is higher when quoted spread at the best bid and ask is wider and the limit order queue is longer, as well as when order imbalance, volatility and adverse selection are lower. They do not find evidence of dark trading harming market quality. Similarly, Brugler (2015) estimates the contemporaneous relationship between dark trading and market depth on the primary exchange (LSE) by employing two months-worth of a proprietary trading dataset. The results show that dark trading improves market liquidity at a high frequency level. However, Nimalendran and Ray (2014), using data from one of the 32 US dark venues, find conflicting results that dark trading is associated with increased price impact on primary exchanges.

Consistent with Nimalendran and Ray (2014), Degryse et al. (2015), analysing trading data for 51 Dutch stocks, find that dark venues attract uninformed order flows and that dark trades are associated with high bid ask spread. Foley and Putniņš's (2016) experiment exploit a mandatory minimum price improvement in dark pools introduced by the Toronto Stock Exchange. They classify all dark trades into ‘one-sided’ (at midpoint) and ‘two-sided’ (at either side of the midpoint) dark trades and show that two-sided dark trading is beneficial to both liquidity and informational efficiency. However, they do not find evidence consistent with midpoint dark trading having a significant effect on market quality. This finding stands in sharp contrast to Ibikunle et al. (2016), who show that in the London market, overall market quality is enhanced by low levels of midpoint dark trading.

5.3. Data and Methodology

5.3.1. Data

The data consists of the constituents of the FTSE100 index from 1st June 2010 to 30 September 2014; the FTSE100 includes the 100 largest firms listed on the LSE and they account for more than 80% of the exchange’s total market capitalisation. My data consists of one primary exchange LSE and the three largest MTFs operating in Europe: BATS Europe, Chi-X Europe and Turquoise. The three latter venues operate both lit and dark order books. I obtain intraday tick data from the Thomson Reuters Tick History (TRTH) database. TRTH provides time and sales tick data, which includes variables such as the Reuters Identification Code (RIC), date, timestamp, price, volume, bid price, ask price, bid volume and ask volume, as well as qualifiers indicating whether a trade is executed in the dark or not. I allocate each trade a pair of corresponding prevailing best bid and ask quotes. Since dark orders are only entertained during normal trading hours, I delete the opening auction (7:50hrs –

8:00hrs) and closing auction (16:30hrs – 16:35hrs) periods from the dataset. In addition to the TRTH, I also obtain daily lit and dark trading data from the Market Quality Dashboard (MQD) database managed by the Capital Markets Cooperative Research Centre, Sydney.[15] Finally, I merge the order book level data for the four trading venues in order to create a single 'global' order book for the London market. Dataset cleaning and merging of the order book data from the four venues yield a consolidated dataset containing 638 million transactions valued at 3.08 trillion British Pounds Sterling executed in 95 stocks over the sample period.

5.3.2. Methodology

5.3.2.1. Main liquidity measures

Liquidity is an important component of the cost of trading and its measures could be multi-dimensional. Microstructure literature usually employs the bid-ask spread as a proxy for liquidity. However, given that dark pools in my dataset do not document the spread since they execute orders using the LSE midpoint for reference, I employ other measures of liquidity. Specifically, five measures aimed at capturing liquidity for lit and dark venues, as well as for the aggregate market are identified. The first two measures are theAmihud (2002) and Florackis et al. (2011) illiquidity ratios; these are inverse proxies of liquidity. In less liquid markets, a given level of volume of shares traded will give rise to a greater price response than in more liquid markets. The Amihud (2002) illiquidity ratio is therefore defined as the ratio of the absolute return

[15] In order to ensure comparability, I ascertain that variables occurring in both datasets are sufficient matches. I are fully satisfied that both datasets are very comparable and are sourced from the same trading venues.

to volume of shares traded. The Amihud (2002) illiquidity ratio is well-established in the microstructure literature and has been extensively used to capture systematic liquidity risk and commonality in liquidity among stocks (see as examples Kamara et al., 2008, Korajczyk and Sadka, 2008). Marshall et al. (2012) also examine a range of liquidity proxies and show that the Amihud ratio performs well in liquidity commonality tests. Thus, for each stock in each day, I compute the Amihud ratio for lit and dark venues and for the aggregate market as shown in Equations (5.01), (5.02) and (5.03) respectively.

$$lit\_Amihud_{i,t} = \left| \frac{r_{close-to-open,i,t}}{lit\_volume_{i,t}} \right| \tag{5.01}$$

$$dark\_Amihud_{i,t} = \left| \frac{r_{close-to-close,i,t}}{dark\_volume_{i,t}} \right| \tag{5.02}$$

$$market\_Amihud_{i,t} = \left| \frac{r_{close-to-open,i,t}}{total\_volume_{i,t}} \right| \tag{5.03}$$

However, I also note that trading volume is likely to be greater for economically larger instruments, thus potentially creating a large firm bias. Therefore, for robustness, I also use the Florackis et al. (2011) illiquidity ratio, in which volume in the Amihud (2002) ratio is replaced by the turnover ratio. Similar to Amihud ratio, Florackis ratio is an illiquidity ratio and measures the level of price impact. Florackis ratio modifies Amihud's ratio by substituting the volume with turnover ratio. Florackis et al. (2011) suggest that the trading volume of each stock in Amihud ratio is positively related to market capitalisation and therefore leading to size bias. The Florackis ratio does not suffer from size bias as stock turnover rate is unlikely to be correlated with stock size.

For each stock in each day, I compute the Florackis ratio for lit and dark venues and the aggregate market as given in Equations (5.03), (5.04) and (5.05) respectively.

$$lit\_Florackis_{i,t} = \left| \frac{r_{close-to-open,i,t}}{(mkt\_cap/lit\_volume)_{i,t}} \right| \tag{5.04}$$

$$dark\_Florackis_{i,t} = \left| \frac{r_{close-to-close,i,t}}{(mkt\_cap/dark\_volume)_{i,t}} \right| \tag{5.05}$$

$$market\_Florackisi_{i,t} = \left| \frac{r_{close-to-open,i,t}}{(mkt\_cap/total\_volume)_{i,t}} \right| \tag{5.06}$$

Other liquidity proxies employed include volume of shares traded, number of transactions/executed orders and pound volume, which represent the market depth dimension of liquidity. Through these variables, I are able to compare the variations in trading liquidity in lit and dark venues since they are positively linked with market liquidity.

5.3.2.2. Descriptive statistics

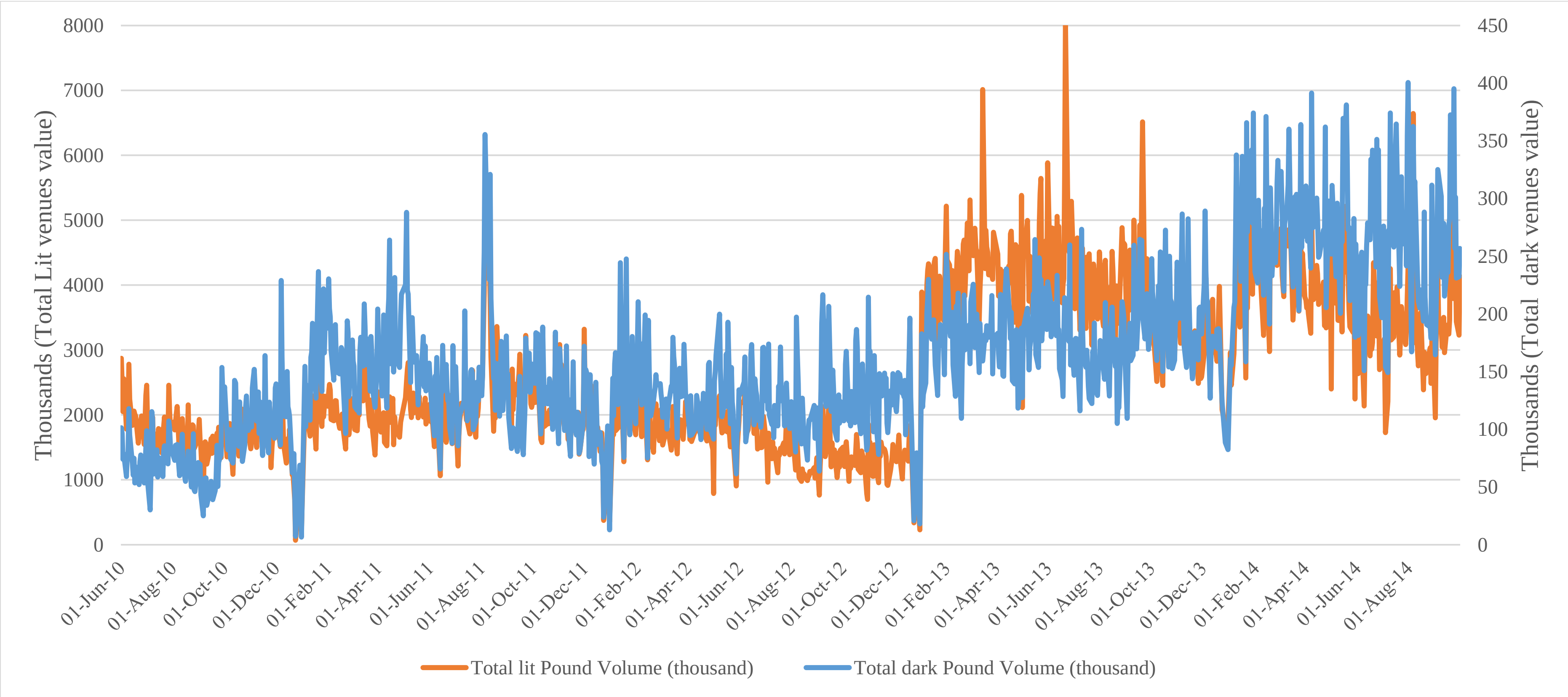
Panel A of Figure 5.1 plots the trading value series for both the lit and dark venues in the London market for the four-year period ending September 2014; all values are in pounds. The cumulative growth in dark trades appears consistent with the trading value for the lit throughout the time series, and for most of the period under consideration the dark trades' growth rate appears larger than that of the aggregate lit venues. Hence, the evidence here is that an increasing proportion of trades are now executed in the dark. Panel B, which plots the dark trading values as percentages of the total market trading value, shows that dark trade values continue to grow as a proportion of total market values. However, the average percentage of dark trading does not exceed 12% during my sample period[16]. Panel C suggests that the average trading size in overall lit and dark values appear to be in lockstep throughout the four-year period. Table 5.1 shows descriptive statistics for key variables. This table shows that lit venues have larger Amihud and Florackis ratio than dark venues. This implies that trading generates a larger impact in lit markets than dark venues. One way of interpreting this estimate is that lit venues are less liquid when compared to dark venues. However, a more apt interpretation is that lit venues attract more informed trades than dark venues, hence the larger price impact generated. Furthermore, given that the dark pools I examine use prices from lit venues as reference prices, it is unlikely that trading in dark venues contribute significantly enough to price discovery for those trades to generate larger impacts than lit venues' trades.

[16] There might be a shift in the dark volume at the beginning of 2013. I will run the analysis year by year to show that my results are not affected by this shift in dark volume.

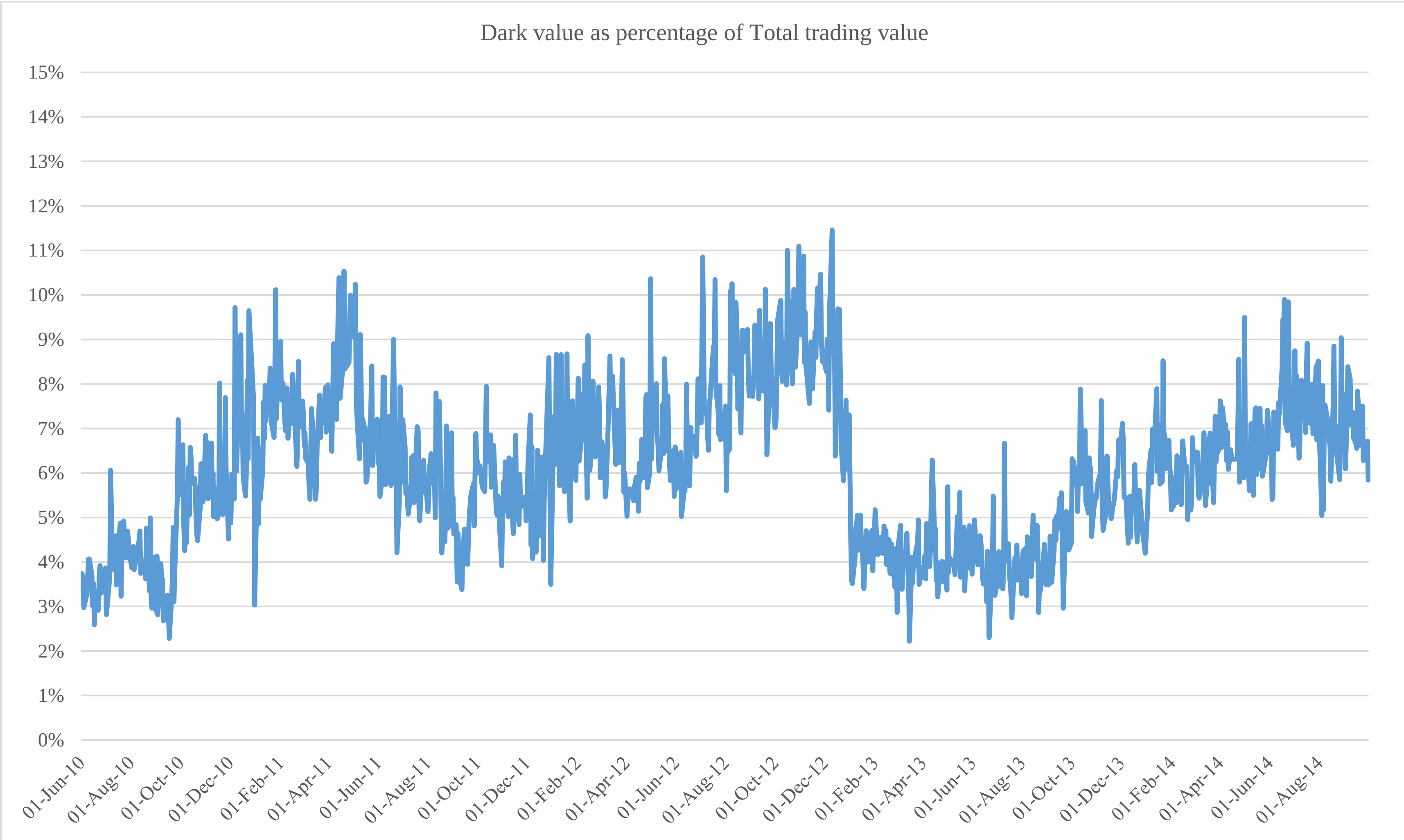
Figure 5.1: Trading values

Panel A plots the lit and dark pound trading values for 95 FTSE 100 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise between 1st June 2010 to 30th September 2014. Panel B plots the pound values for dark as percentages of total market value. Panel C plots the average pound sizes per day of lit and dark trades.

PANEL A



PANEL B



Dark value as percentage of Total trading value
15%
14%
13%
12%
11%
10%
9%
8%
7%
6%
5%
4%
3%
2%
1%
0%
01-Jun-10
01-Aug-10
01-Oct-10
01-Dec-10
01-Feb-11
01-Apr-11
01-Jun-11
01-Aug-11
01-Oct-11
01-Dec-11
01-Feb-12
01-Apr-12
01-Jun-12
01-Aug-12
01-Oct-12
01-Dec-12
01-Feb-13
01-Apr-13
01-Jun-13
01-Aug-13
01-Oct-13
01-Dec-13
01-Feb-14
01-Apr-14
01-Jun-14
01-Aug-14

PANEL C

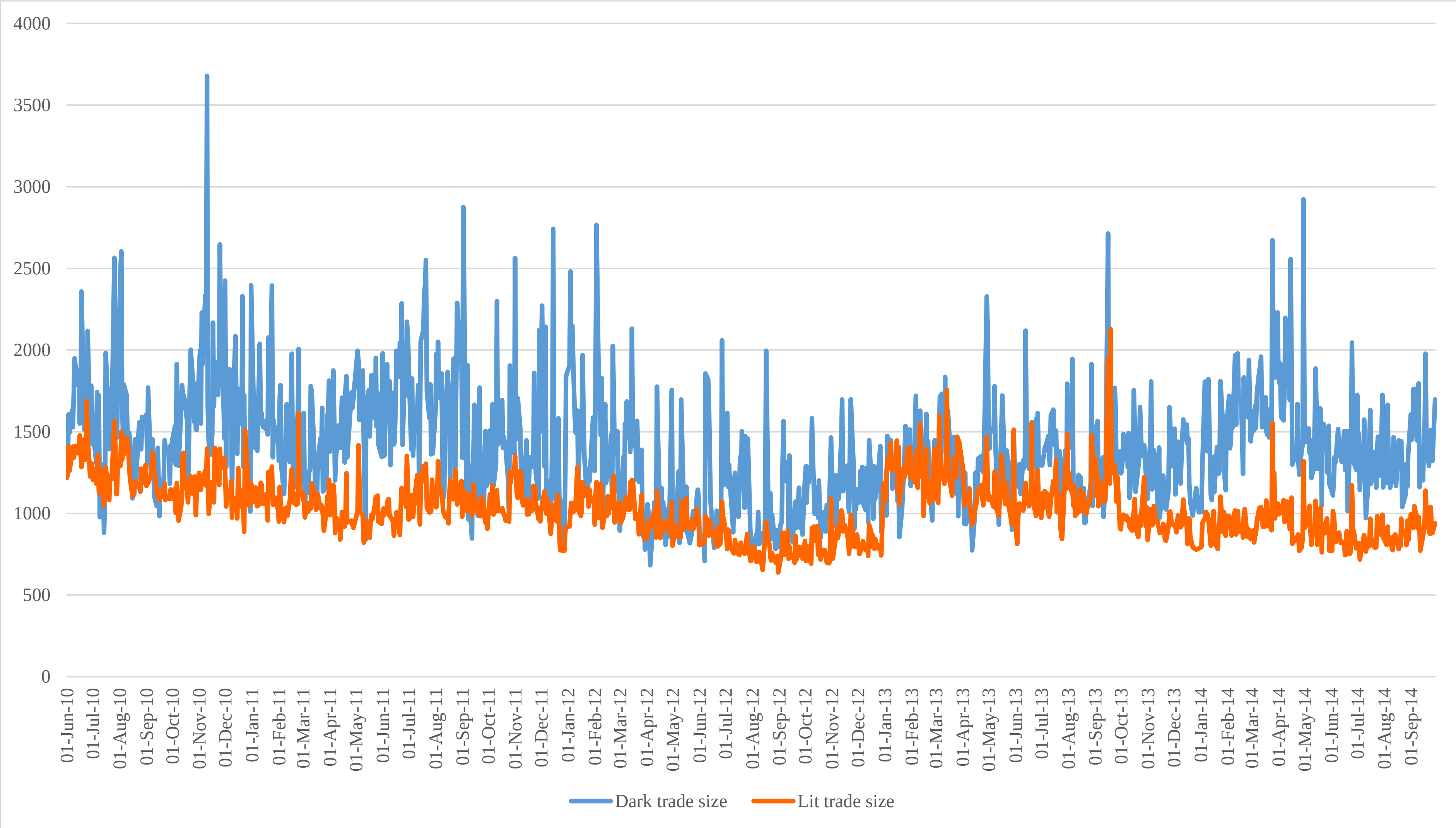

4000
3500
3000
2500
2000
1500
1000
500
0
01-Jun-10
01-Jul-10
01-Aug-10
01-Sep-10
01-Oct-10
01-Nov-10
01-Dec-10
01-Jan-11
01-Feb-11
01-Mar-11
01-Apr-11
01-May-11
01-Jun-11
01-Jul-11
01-Aug-11
01-Sep-11
01-Oct-11
01-Nov-11
01-Dec-11
01-Jan-12
01-Feb-12
01-Mar-12
01-Apr-12
01-May-12
01-Jun-12
01-Jul-12
01-Aug-12
01-Sep-12
01-Oct-12
01-Nov-12
01-Dec-12
01-Jan-13
01-Feb-13
01-Mar-13
01-Apr-13
01-May-13
01-Jun-13
01-Jul-13
01-Aug-13
01-Sep-13
01-Oct-13
01-Nov-13
01-Dec-13
01-Jan-14
01-Feb-14
01-Mar-14
01-Apr-14
01-May-14
01-Jun-14
01-Jul-14
01-Aug-14
01-Sep-14
Dark trade size
Lit trade size

Table 5.1: Descriptive statistics

This table reports means, standard deviations, and quartile points (25%, Median, 75%) for 95 FTSE 100 stocks trading simultaneously on the four main London 'City' exchanges/trading venues; these are the London Stock Exchange, BATS, Chi-X and Turquoise. The sample period covers 1st June 2010 and 30th September 2014. Dark and Lit Amihud are the Amihud ratio for lit and dark venus. These measures write as follows:

$$lit\_Amihud_{i,t} = \left|\frac{r_{close\text{-}to\text{-}open,i,t}}{lit\_volume_{i,t}}\right| \qquad dark\_Amihud_{i,t} = \left|\frac{r_{close\text{-}to\text{-}close,i,t}}{dark\_volume_{i,t}}\right|$$

Lit and dark Florackis ratio is the Florackis ratio for lit and dark venues. These measures write as follows:

$$lit\_Florackis_{i,t} = \left|\frac{r_{close\text{-}to\text{-}open,i,t}}{(mkt\_cap/lit\_volume)_{i,t}}\right| \qquad dark\_Florackisi_{,t} = \left|\frac{r_{close\text{-}to\text{-}close,i,t}}{(mkt\_cap/dark\_volume)_{i,t}}\right|$$

PIN is the Easley et al. (1996, 1997) probability of informed trading measure computed from the parameters yielded by maximising the following likelihood function:

$$L((B,S)\,|\,\theta) = (1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} + \alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^S}{S!}$$
$$+\alpha(1-\delta)e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^B}{B!},$$

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. α corresponds to the probability of an information event, δ is the conditional probability of a low signal of an information event, μ is the arrival rate of informed orders, and ε 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:

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

ALGO is as a proxy for algorithmic trading and is measured as the ratio of messages to trades.

	Percentile					
	25%	50%	75%	95%	mean	std
Dark Amihud	1.65E-08	5.85E-08	1.90E-07	1.18E-06	6.43E-07	3.5477E-05
Lit Amihud	9.15E-10	2.96E-09	8.35E-09	3.43E-08	8.78E-09	7.87E-08
Dark Florackis	2.51E-05	7.97E-05	2.29E-04	1.11E-03	8.12E-04	1.64E-02
Lit Flora Florackis	0.0005	0.0014	0.0033	0.0129	0.0097	0.1170
Dark Volume	47.37	127.90	343.84	1827.19	492.34	1602.55

Lit Volume	990.11	2296.05	5387.60	29880.06	7542.54	20538.06
Number of dark trade	111	223	439	1125	354.98	416.17
Number of lit trades	2985	4931	8826	22330	7356.47	7108.83
Dark £volume (‘000)	442.22	1088.66	2552.05	7740.52	2162.46	3296.88
Lit £volume (‘000)	9176.38	18629.70	41946.64	124107.97	34906.91	44986.42
PIN	0.16	0.22	0.32	0.52	0.25	0.13
ALGO	26.17	38.79	69.35	334.88	99.71	311.93

5.3.2.3. The baseline model

Following Chordia et al.’s (2000), I model the systematic liquidity factors in lit and dark venues by estimating the following time-series regression model.

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \varepsilon_{i,t} \qquad (5.07)$$

Specifically, daily percentage changes in liquidity for an individual stock are regressed against market measures of liquidity. In Equation (5.07), $DL_{i,t}$ is, for stock *i*, the percentage change from trading day $_{t-1}$ to day$_t$ in liquidity as proxied by several variables (including Amihud ratio, Florackis ratio, volume of shares traded, number of trades and pound volume). The volume of shares traded, transaction numbers and pound volume are naturally considered as measures of trading activity rather than traditional measures of liquidity. However, given their high levels of correlation with liquidity variables, I adopt them in this chapter variously as both liquidity proxies and trading activity measures. $DL_{i,t}$ will be tested as lit liquidity and dark liquidity respectively. $DL_{M,t}$, $DL_{M,t-1}$ and $DL_{M,t+1}$ are the concurrent, one-day lag and lead of percentage change in a cross-sectional equally weighted market liquidity proxies of my sample stocks.[17] I examine percentage changes rather than levels for two reasons: firstly, my interest is fundamentally in discovering whether liquidity co-moves, and secondly, time series of liquidity levels are more likely to be plagued by econometric problems. I define the coefficient β_1 as the *elasticity of liquidity commonality* (ELC) as each estimated coefficient in regression Equation (5.07) represents the averaged percentage change in liquidity of each stock given 1% in market liquidity. ELC also measures the co-movent of trading venues' liquidity with market-wide liquidity. I run the regression for both lit and dark venues and obtain the sizes of ELC in lit and dark venues as indicators of which venue exhibit more pronounced co-movement with market-wide liquidity.

[17] In order to reduce the outliers, I follow Korajczyk, R. A. & Sadka, R. 2008. Pricing the commonality across alternative measures of liquidity. *Journal of Financial Economics,* 87**,** 45-72. to 'winsorize' the daily liquidity measures in lit and dark venues using the 1st and 99th percentile.

5.3.2.4. What drives dark pool trading activities

The next step is to examine what drives dark pool liquidity. Previous studies postulate that trades in dark pools and upstairs markets are trades that otherwise might not have easily occurred in traditional lit venues (see for examples Smith et al., 2001, Jain et al., 2003, He and Lepone, 2014, Kwan et al., 2015). Following the existing literature, I argue that, dark pools liquidity is aided by the liquidity constraints in lit venues and thus work as complementary venues to lit venues. Thus, when spreads are wider in lit markets and the queue for order execution is lengthy, traders, especially the uninformed kind, are incentivised to migrate to dark pools where they can trade at the midpoint, ensuring minimum or no price impact. In order to examine this intuition, I design the following model (8) and (9), which captures the relationship between dark venues' share of trading, spread market depth and order queue index in lit markets.

$$DL_{i,t} = \alpha_1 + \beta_1 DBAS_{M,t} + \beta_2 DBAS_{M,t-1} + \beta_3 DBAS_{M,t+1} + \varepsilon_{i,t} \tag{5.08}$$

$$DL_{i,t} = \alpha_1 + \beta_1 DQueue_{M,t} + \beta_2 DQueue_{M,t-1} + \beta_3 DQueue_{M,t+1} + \varepsilon_{i,t} \tag{5.09}$$

In Equation (5.08), $DL_{i,t}$ is, for stock i, the percentage change from trading day_{t-1} to day_t market share variables including volume of shares traded, number of trades and pound volume. $DBAS_{M,t}$, $DBAS_{M,t-1}$ and $DBAS_{M,t+1}$ are the concurrent, one-day lag and lead of percentage change in a cross-sectional equally weighted effective bid ask spread of my sample stocks as observed in lit venues. Effective spread equals twice the absolute value of the difference between transaction price and the corresponding best bid and ask quotes midpoint at the transaction time.

In Equation (5.09), the relationship between order queue and dark trading activities is further examined. Following Kwan et al. (2015) and He and Lepone (2014), I use the market depth at the best bid and ask price as an index of order queue. However, this index is adjusted by message-to-trade-ratio. The reason for including a message-to-trade-ratio adjusted market depth is to minimise the impact of high frequency traders and algorithm traders (ATs), who typically place and cancel bids and offers at high speed. This order queue proxy is calculated as total pound volume of orders submitted at the best bid and ask prices divided by the message to trade ratio (*ALGO*) in the market. $DQueue_{M,t}$, $DQueue_{M,t-1}$ and $DQueue_{M,t+1}$ are the concurrent, one-day lag and lead of percentage change in a cross-sectional equally weighted market queue index of my sample stocks. Estimates from Equations (5.08) and (5.09) offer insights into the impact of liquidity constraints in lit venues on dark pool trading share of trading.

5.3.2.5. Extended Model with Informed trading Factors

Several theoretical papers (see as examples Ye, 2011, Zhu, 2014, Nimalendran and Ray, 2014) examine trading strategies of informed and liquidity traders in the presence of dark pools and the impact of dark trading on price discovery in primary exchanges, under differing conditions. Specifically, the assumptions used in their models' development mainly differ in terms of uninformed traders' ability to access dark pools. However, all of these studies assume that informed traders may use dark pools in order to reduce their transactions costs and maximise profits from their use of private information (Nimalendran and Ray, 2014). Despite a consensus on the theoretical validity of informed traders accessing dark pools, the impact of informed trading on dark venues' liquidity is still an open empirical question. Therefore the analysis in this study is extended to examine this question. In order to study the impact of informed trading on lit and dark liquidity, Equation (5.07) is extended to include two informed trading proxies as shown in Equations (5.12) and (5.13). The first proxy is the probability of informed trading (*PIN*) as computed for the aggregate market. *PIN* can be used to proxy the proportion of the unobservable informed trades across normal trading hours (see for example Easley et al., 1996a, 1996b, 1997a). 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.[18] 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 ε. An unusual volume of purchase or sale transactions is interpreted as information-based trading and used to compute 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 using maximum likelihood estimation. Suppose the arrival of uninformed and informed traders in the market follow a Poisson distribution, the likelihood function for the PIN model for each interval estimated can be expressed as:

$$\begin{aligned} L((B,S)\,|\,\theta) = {} & (1-\alpha)\, e^{-\varepsilon_b} \frac{\varepsilon_b^B}{B!}\, e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!} + \alpha\delta\, e^{-e_b} \frac{\varepsilon_b^B}{B!}\, e^{-(\mu+\varepsilon_s)} \frac{(\mu+\varepsilon_s)^S}{S!} \\ & + \alpha(1-\delta)\, e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!}\, e^{-(\mu+\varepsilon_b)} \frac{(\mu+\varepsilon_b)^B}{B!} \end{aligned} \tag{5.10}$$

[18] I infer purchase and sales by running the Lee and Ready Lee, C. M. C. & Ready, M. J. 1991b. Inferring Trade Direction from Intraday Data. *The Journal of Finance,* 46**,** 733-746. trade classification algorithm.

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 (5.10) represents 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. (1997a) and Easley et al. (1996b) calculate the parameter vector estimates using maximum likelihood estimation procedure. Thus, I obtain the parameters for each trading day and for each stock in the sample by maximum likelihood estimation. Following Easley et al. (1996b) and Easley et al. (1997a), PIN is then computed as:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \tag{5.11}$$

PIN, as computed, technically only proxies informed trading in the lit venues. However, the measure is arguably a direct proxy for informed trading in the overall market rather than in lit venues alone. This is because, as earlier stated, the dark pools included in the sample are midpoint order books; hence, they source execution prices from the lit venue by executing orders against the midpoint or within the spread as posted on lit platforms. This implies that the posted orders at the lit venues effectively relate directly to the dark venues as well. However, for completeness, I employ a second proxy for informed trading. The second informed trading proxy is the ratio of messages to trades (*ALGO*) across all trading venues. This is a typical measure for AT/HFT activity, since ATs/HFTs apply advanced computer power to extract superior information and profit from market movements; thus they arrive at new conclusions regarding shifts in underlying value of instruments faster than most of the rest of the market. Their ability of being able to decipher new information earlier than most other market participants therefore implies that they could be considered as informed traders. This view is consistent with the finding that HFTs can anticipate buying and selling pressure over short horizons (see Hirschey, 2013). Two regression models are run regression in order to avoid a potential multicollinearity problem; thus, PIN and ALGO are used as substitutes in an extension of Equation (5.07).

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \beta_4 PIN_{M,t} + \beta_5 PIN_{M,t-1} + \beta_6 PIN_{M,t+1} + \varepsilon_{i,t} \tag{5.12}$$

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \beta_4 ALGO_{M,t} + \beta_5 ALGO_{M,t-1} + \beta_6 ALGO_{M,t+1} + \varepsilon_{i,t} \tag{5.13}$$

5.3.2.6. Drivers of elasticity of liquidity commonality

Finally, I turn to investigating the drivers of dark liquidity commonality by estimating the following regression model:

$$ECL_{i,t} = \alpha_1 + \beta_1 PRICE_{i,t} + \beta_2 MKT_{i,t} + \beta_3 COUNT_{i,t} + \beta_4 PV_{i,t} + \beta_5 VOLA_{i,t} + \beta_6 Info_{i,t} + \varepsilon_{j,t} \tag{5.14}$$

where ELC is the stock-quarter estimated coefficient, β_1, for stock *i* from Equation (5.07). $PRICE_i$ is the log of quarterly average share price of stock *i*, $COUNT_i$ is the log of quarterly averaged number of transaction of stock *i*, PV_i is the log of quarterly averaged pound volume traded of of stock *i*, $VOLA_i$ is quarterly return volatility for stock *i*, $Info_i$ is the quarterly average of either of two informed trading proxies, *PIN* or *ALGO*.

5.4. Empirical Results and Discussion

This section discusses the results obtained from executing the methodological approaches presented in the preceding section.

5.4.1. Liquidity commonality in lit and dark venues

Table 5.2 reports the regression results for lit and dark venues. Panels A and B indicate that market-wide liquidity is contemporaneously linked with both lit and dark liquidity; however there is a difference in the order of magnitude. In Panel A, the elasticity of liquidity commonality suggests that a 0.01 change in market liquidity $DL_{M,t}$ induces a contemporaneous average percentage change in individual stock liquidity at lit venues ranging from 0.608% to 1.85%, depending on the liquidity proxy, all coefficient estimates for lit venues are significantly different from zero at 0.01 level. The average concurrent coefficients are close to those in Chordia et al.'s (2000) study, which ranges from 0.28% to 1.37%. The coefficients for $DL_{M,t-1}$ and $DL_{M,t+1}$ are smaller (in absolute values), indicating a rapid adjustment in lit liquidity commonality, as $DL_{M,t-1}$ and $DL_{M,t+1}$ are designed to capture any lagged adjustment in commonality. Panel B reports the results for dark liquidity commonality. Results show that individual stock liquidity in dark venues are positively related with market-wide liquidity since all concurrent coefficients are positive and statistically significant at the 0.01 level of statistical significance. The concurrent coefficients of dark liquidity commonality range from 1.225% to 2.407%. depending on the liquidity proxy. Since ELC coefficients of dark venues are larger than the corresponding lit venues ones, individual stocks traded in dark venues appear to exhibit a higher level of liquidity commonality than when they are traded in lit venues. Thus, dark venues have a greater elasticity of liquidity commonality than lit venues. In other words, when market-wide liquidity evolves, dark venues have a larger reaction to market-wide liquidity than lit venues. It should be noted that Amihud and Florackis ratios are inverse proxies of liquidity; hence, when the market starts to gain (lose) liquidity, these two ratios decrease (increase). The other three varibles are positively related with trading liquidity. Furthermore, Panel C demonstrates the difference between the liquidity changes. This result suggests that the daily change in market liquidity generates a significant impact on the difference between daily changes in lit and dark liquidity; when market liquidity starts to rise (deplete), dark liquidity has a more pronounced increase (decrease) than lit liquidity and the difference between lit and dark venues also increases (decreases). This indicates the important role of the dark venue in facilitating liquidity to the market.

Panels A, B, C, D and E in Table 5.3 show the baseline regression results in each year. One can see that the coefficients of $DL_{m,t}$ in dark venues are larger than those in lit venues in each panel. This implies that in each year[19] dark venues consistently exehibit a more pronounced liquidity commonality than lit venues.

[19] Hence the shift in trading volume does not undermine my results in this chapter.

Thus far, I have shown that dark venues have larger liquidity comovement with market liquidity than lit venues. This indicates that dark pools can have two effects on the market; they can help inject liquidity into the market as well as drain liquidity from the market. In order to investigate which case holds, I decompose my liquidity proxies into two parts; i.e. when market-wide liquidity increases and when market-wide liquidity decreases Panel A and B in Table 5.4 show the regression results when market-wide liquidity increases and decreases respectively. When market-wide liquidity is increasing the ELC coefficients in lit and dark venues are greater than the corresponding coefficients for when market-wide liquidity is decreasing. This indicates that, during the sample period, both lit and dark venues are more likely to contribute liquidity to the aggregate market rather than drain it. This is unsurprising given the general tightening of the spread over the past decade in the UK equity market. I further compute a simple ratio of ELC of dark venues to the ELC of lit venues. Since the ratios are all greater than one in both Panels A and B, the result implies that, compared with lit venues, dark venues inject (drain) more liquidity to (from) market when market-wide liquidity is increasing (decreasing). Panel A's ratios range from 1.08 to 2.12 with a mean value of 1.63 and Panel B's multipliers range from 1.22 to 2.10 with a mean of 1.45.

Table 5.2. Baseline results: liquidity commonality in lit and dark venues

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

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \varepsilon_{i,t}$$

$DL_{i,t}$ is, for stock i, the percentage change (D) from trading day$_{t-1}$ to day$_t$ in liquidity variables,including Amihud ratio, Florackis ratio, volume of shares, number of trades and pound volume, for both lit and dark venues. $DL_{i,t}$ will be tested as lit liquiditydark liquidity respectively. Lit and dark Amihud ratio, lit and dark Florackis ratio are computed as described in Table 5.1. $DL_{M,t}$, $DL_{M,t-1}$ and $DL_{M,t+1}$ are the concurrent, one-day lag and lead of percentage change in a cross-sectional equally weighted liquidity proxies including Amihud ratio, Florackis ratio, volume of shares, number of trades and pound volume . The t-statistics are presented in parentheses. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample period covers 1st June 2010 to 30th September 2014.

	Panel A. Lit venues				
VARIABLES	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*
$DL_{M,t}$	1.850***	0.608***	0.933***	1.154***	1.088***
	(26.98)	(21.16)	(110.60)	(133.31)	(125.04)
$DL_{M,t-1}$	-0.120***	-0.094***	-0.000***	-0.000***	-0.000***
	(-2.63)	(-7.04)	(-5.21)	(-4.71)	(-4.01)
$DL_{M,t+1}$	-0.043	-0.036**	0.015**	-0.001	0.013**
	(-0.93)	(-2.25)	(2.51)	(-0.21)	(2.01)
Constant	1.585***	2.275***	0.078***	0.064***	0.071***
	(73.68)	(69.60)	(18.57)	(17.27)	(20.74)
R-squared	2.51%	1.78%	22.77%	28.68%	26.84%

Panel B. Dark venues

VARIABLES	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*
$DL_{m,t}$	2.407***	1.225***	1.700***	1.860***	2.070***
	(19.50)	(18.25)	(36.68)	(47.33)	(39.62)
$DL_{m,t-1}$	0.222**	-0.034	-0.000***	-0.000***	-0.000***
	(2.49)	(-0.97)	(-16.07)	(-18.39)	(-17.03)
$DL_{m,t+1}$	-0.198**	0.016	0.188***	0.150***	0.273***
	(-2.18)	(0.48)	(5.76)	(5.46)	(7.71)
Constant	2.826***	4.283***	0.970***	0.687***	0.923***
	(74.18)	(62.25)	(42.15)	(41.51)	(47.40)
R-squared	1.26%	1.35%	3.74%	6.12%	4.51%

Panel C. Difference (DL_{dark}-DL_{lit})

VARIABLES	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*
$DL_{m,t}$	-0.559***	-0.668***	0.767***	0.707***	0.984***
	(-4.56)	(11.62)	(17.76)	(19.53)	(20.06)
$DL_{m,t-1}$	-0.33***	-0.061**	-3.95E-10***	-0.000000308***	-7.85E-13***
	(-3.67)	(1.88)	(-15.97)	(-18.51)	(-17.19)
$DL_{m,t+1}$	0.175**	-0.062**	0.174***	0.151***	0.260***
	(1.9)	(-1.90)	(5.61)	(5.89)	(7.74)
Constant	-1.217***	-1.97***	0.891***	0.622***	0.852***
	(-31.2)	-(30.45)	(40.93)	(40.06)	(46.01)
R-squared	0.08%	0.42%	1.20%	1.53%	1.47%

Table 5.3. Baseline results in each year

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

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \varepsilon_{i,t}$$

$DL_{i,t}$ is, for stock *i*, the percentage change (D) from trading day_{t-1} to day_t in liquidity variables,including Amihud ratio, Florackis ratio, volume of shares, number of trades and pound volume, for both lit and dark venues. $DL_{i,t}$ will be tested as lit liquiditydark liquidity respectively. Lit and dark Amihud ratio, lit and dark Florackis ratio are computed as described in Table 5.1. $DL_{M,t}$, $DL_{M,t-1}$ and $DL_{M,t+1}$ are the concurrent, one-day lag and lead of percentage change in a cross-sectional equally weighted liquidity proxies including Amihud ratio, Florackis ratio, volume of shares, number of trades and pound volume . The t-statistics are presented in parentheses. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample period covers 1st June 2010 to 30th September 2014.

Panel A. Baseline result in 2010

	Lit venues					Dark venues				
VARIABLES	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*
$DL_{m,t}$	2.12***	0.39***	0.97***	1.13***	1.08***	3.39***	0.47***	2.05***	2.13***	2.35***
	(15.17)	(11.47)	(50.8)	(56.64)	(52.91)	(11.87)	(5.9)	(16.15)	(21.19)	(17.13)
$DL_{m,t-1}$	0.10	-0.10***	0.00	0.00	0.00	0.17	0.04	0.00**	0.00**	0.00
	(0.73)	(-3.23)	(0.25)	(0.54)	(0.29)	(0.63)	(0.6)	(-1.85)	(-1.99)	(-1.23)
$DL_{m,t+1}$	0.27***	-0.041	-0.01	-0.03*	-0.02	0.13	-0.05	0.08	-0.01	0.03
	(2.27)	(-1.24)	(-0.99)	(-1.8)	(-1.51)	(0.55)	(-0.77)	(0.72)	(-0.19)	(0.28)
Constant	1.42***	2.20***	0.05***	0.03*	0.05**	3.23***	4.92***	1.17***	0.81***	1.12***
	(22.58)	(21.28)	(2.92)	(1.7)	(2.57)	(25.02)	(20.55)	(8.83)	(7.01)	(7.27)

Panel B. Baseline result in 2011

	Lit venues					Dark venues				
VARIABLES	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*
$DL_{m,t}$	2.03***	0.45***	0.96***	1.15***	1.11***	2.29***	1.01***	2.01***	2.07***	2.46***
	(17.51)	(14.6)	(67.27)	(77.61)	(72.96)	(10.41)	(13.41)	(21.77)	(28.88)	(24.42)
$DL_{m,t-1}$	-0.21**	-0.07**	-0.00***	-0.00***	-0.00***	-0.18	-0.23***	-0.00***	-0.00***	-0.00***
	(-2.23)	(-2.62)	(-4.28)	(-3.56)	(-3.53)	(-1.01)	(-3.5)	(-5.67)	(-4.97)	-(5.55)
$DL_{m,t+1}$	-0.11	-0.06**	-0.00	-0.02**	0.01	-0.46**	-0.14**	0.20***	0.26***	0.39***
	(-1.17)	(-2.07)	(-0.48)	(-1.85)	(0.82)	(-2.48)	(-2.12)	(2.27)	(3.82)	(4.15)
Constant	1.58***	2.16***	0.10***	0.08***	0.10***	3.21***	4.74***	1.20***	0.76***	1.26***
	(31.3)	(29.93)	(9.05)	(7.98)	(7.81)	(33.41)	(27.34)	(16.07)	(14.39)	(14.46)

Panel C. Baseline result in 2012

	Lit venues					Dark venues				
VARIABLES	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*
$DL_{m,t}$	1.82***	0.49***	1.01***	1.20***	1.13***	2.59***	1.14***	2.16***	2.16***	2.47***
	(16.01)	(12.26)	(72.58)	(77.43)	(72.54)	(13.55)	(13.11)	(30.62)	(33.71)	(30.38)
$DL_{m,t-1}$	-0.17*	-0.04	-0.00***	-0.00***	-0.00*	0.54***	0.01	-0.00***	-0.00	-0.00
	(-1.66)	(-1.26)	(-1.7)	(-2.93)	(-1.67)	(3.1)	(0.23)	(-0.75)	(-0.75)	(-0.87)
$DL_{m,t+1}$	0.07	-0.05*	0.02*	0.00	0.00	-0.18	-0.12	0.18***	0.16***	0.24***
	(0.74)	(-1.64)	(1.64)	(0.44)	(0.27)	(-1.09)	(-1.58)	(2.82)	(2.77)	(3.38)
Constant	1.52***	2.21***	0.07***	0.08***	0.08***	2.55***	4.13***	0.61***	0.45***	0.64***
	(33.27)	(32.08)	(6.59)	(6.5)	(5.51)	(33.32)	(27.61)	(10.71)	(8.03)	(8.18)

Panel D. Baseline result in 2013

	Lit venues					Dark venues				
VARIABLES	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*
$DL_{m,t}$	1.44***	1.23***	0.80	1.14***	0.99***	1.38***	3.39***	1.06***	1.51***	1.27***
	(13.2)	(23.92)	(50.2)	(54.25)	(54.89)	(7.54)	(31.04)	(14.03)	(19.81)	(14.41)
$DL_{m,t-1}$	-0.10	-0.08*	-0.00***	-0.00***	-0.00***	0.74***	0.1145257	-0.00***	-0.00***	-0.00***
	(-1.06)	(-1.85)	(-8.48)	(-5.97)	(-7.77)	(4.37)	(1.12)	(-7.56)	(-5.27)	(-8.78)

VARIABLES	Amihud	Florackis	Volume Of shares	Number of trades	Pound Volume	Amihud	Florackis	Volume Of shares	Number of trades	Pound Volume
$DL_{m,t+1}$	-0.08	0.23***	0.00	-0.02	-0.01	-0.37**	0.70***	0.16**	0.09	0.16**
	(-0.83)	(4.15)	(0.32)	(-1.46)	(-0.87)	(-2.27)	(6.02)	(2.44)	(1.49)	(2.08)
Constant	1.54	2.09***	0.20***	0.18***	0.21***	2.56***	3.44***	1.17***	0.75***	1.40***
	(35.06)	(30.56)	(11.25)	(7.97)	(10.21)	(34.77)	(23.79)	(13.47)	(9.21)	(13.78)

Panel E. Baseline result in 2014

	Lit venues					Dark venues				
VARIABLES	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*
$DL_{m,t}$	1.50***	1.39***	0.80***	1.03***	0.97***	1.79***	1.89***	1.20***	1.33***	1.40***
	(9.57)	(12.3)	(40.98)	(50.06)	(44.63)	(7.29)	(8.58)	(14.06)	(17.81)	(14.4)
$DL_{m,t-1}$	0.02	-0.05	-0.00	-0.00	-0.00	-0.74***	-0.24	-0.00***	-0.00***	-0.00***
	(0.19)	(-0.54)	(-1.39)	(-0.08)	(-0.29)	(-3.38)	(-1.19)	(-3.38)	(-2.43)	(-3.05)
$DL_{m,t+1}$	-0.13	-0.10	0.01	0.01	0.02	-0.14	0.32*	0.24***	0.22***	0.26***
	(-0.97)	(-0.99)	(0.61)	(0.8)	(1.32)	(-0.68)	(1.64)	(3.26)	(3.5)	(3.25)
Constant	1.66***	2.34***	0.08***	0.04**	0.06***	2.55***	4.01***	0.80***	0.52***	0.82***
	(32.28)	(30.89)	(4.4)	(2.00)	(2.79)	(31.86)	(27.19)	(9.14)	(6.33)	(7.83)

Table 5.4. Asymmetry in liquidity commonality in lit and dark venues under different market conditions

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

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \varepsilon_{i,t}$$

$DL_{i,t}$ is, for stock i, the percentage change (D) from trading day$_{t-1}$ to day$_t$ in liquidity variables (including Amihud ratio, Florackis ratio, trading volume, Number of trades and pound volume for both lit and dark venues). $DL_{i,t}$ will be tested as lit liquidity, dark liquidity and market-wide liquidity respectively. Lit and dark Amihud ratio, Lit and dark Florackis ratio are computed as described in Table 5.1. $DL_{M,t}$, $DL_{M,t-1}$ and $DL_{M,t+1}$ are the concurrent, one-day lag and lead of percentage change in a cross-sectional equally weighted liquidity proxies, including Amihud ratio, Florackis ratio, volume of shares, number of trades and pound volume. Panel A reports the results for when market liquidity improves(when Amihud and Florackis ratio decrease, and when volume of shares, number of trades and pound volume increases); Panel B reports the results when market liquidity deteriorates (when Amihud and Florackis ratio increase, and when volume of shares, number of trades and pound volume decrease). The ELC Ratio is the ratio of the ELC coefficient of dark liquidity to the corresponding lit ELC coefficient. The t-statistics are presented in parentheses. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample period covers 1st June 2010 to 30th September 2014.

Panel A. When market liquidity improves

	Lit venues					Dark venues				
	Amihud	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*
$DL_{M,t}$	2.121***	1.436***	1.020***	1.305***	1.205***	2.438***	1.554***	2.096***	2.267***	2.550***
	(13.39)	(9.05)	(60.80)	(75.88)	(71.03)	(7.44)	(4.85)	(22.59)	(27.98)	(24.31)
$DL_{M,t-1}$	-0.180***	-0.008	-0.000***	-0.000***	-0.000***	0.282***	0.099**	-0.000***	-0.000***	-0.000***
	(-3.39)	(-0.52)	(-11.54)	(-4.64)	(-6.35)	(2.74)	(2.56)	(-17.63)	(-15.76)	(-17.79)
$DL_{M,t+1}$	0.063	0.015	0.096***	0.001	0.025**	-0.297***	0.044	0.368***	0.203***	0.379***
	(1.18)	(0.88)	(8.96)	(0.05)	(2.14)	(-2.71)	(1.21)	(6.67)	(3.88)	(5.83)
Constant	1.667***	2.279***	0.106***	0.041***	0.060***	2.822***	3.926***	1.131***	0.710***	1.016***
	(37.42)	(32.12)	(13.92)	(6.14)	(9.56)	(34.09)	(26.92)	(28.88)	(24.33)	(29.55)
ELC Ratio						1.15	1.08	2.05	1.74	2.12

R^2	0.77%	0.25%	15.89%	20.92%	19.10%	0.25%	0.05%	3.66%	5.43%	4.29%

Panel B. When market liquidity deteriorates

	Lit venues					Dark venues				
	Amihud	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*
DL$_{M,t}$	1.853***	0.503***	0.945***	1.066***	1.015***	2.389***	1.058***	1.207***	1.490***	1.239***
	(17.59)	(14.36)	(65.50)	(70.01)	(68.98)	(12.63)	(13.01)	(14.39)	(21.95)	(14.27)
DL$_{M,t-1}$	0.047	-0.130***	0.000***	-0.000	0.000	0.179	-0.334***	-0.000***	-0.000***	-0.000***
	(0.49)	(-2.67)	(5.10)	(-0.16)	(1.18)	(1.01)	(-3.17)	(-4.94)	(-8.51)	(-5.01)
DL$_{M,t+1}$	-0.207**	0.018	-0.043***	-0.027***	-0.017**	-0.005	0.161	-0.004	0.028	0.035
	(-2.38)	(0.38)	(-6.10)	(-3.67)	(-2.38)	(-0.03)	(1.60)	(-0.09)	(0.89)	(0.83)
Constant	1.564***	2.642***	0.049***	0.049***	0.055***	2.866***	4.856***	0.723***	0.553***	0.660***
	(34.16)	(44.02)	(9.16)	(9.61)	(11.78)	(35.23)	(37.57)	(23.94)	(23.97)	(24.65)
ELC Ratio						1.29	2.10	1.28	1.40	1.22
R^2	1.58%	1.19%	9.92%	11.46%	10.96%	0.77%	1.08%	0.65%	1.38%	0.59%

5.4.2. What drives dark pool trading activities

The next step is to test the argument that dark pools may work as complementary venues to traditional (lit) exchanges, especially in the event of worsening liquidity and long limit order queues in lit markets. This is because, such conditions may incentivise traders to migrate to dark pools where they can trade at or within the midpoint with relatively minimal price impact. The estimates from these tests are presented in Table 5.5.

Panel A shows the estimated relationship between market-wide liquidity and trading activity in lit and dark venues. In the lit market, a 1% change in market-wide spread induces approximately 0.3% contemporaneous average percentage change in individual stock trading activity; all the estimates are statistically significant at the 0.01 level. Thus, as liquidity declines in the wider market, there is a marked but unsubstantial increase in trading activity in an average individual stock. In comparison, the increase in trading activity in the dark venues is at least twice, and in some cases, thrice, the magnitude seen in the lit venues. Specifically, in dark pools, a 1% change in market-wide limit order spread induces a contemporaneous change in individual stock trading activity ranging from 0.7% to 0.9%; all coefficients are statistically significant at 0.01 level. This indicates that dark venues are likely to be more attractive than lit venues when liquidity constraints take hold in the aggregate market. This gravitation towards the dark side of the market implies that traders can optimally trade off the execution uncertainty, occasioned by market-wide liquidity constraints, and mid-quote price movement in dark pools against increased transaction costs in the limit order book (Buti et al., 2011, He and Lepone, 2014). Increase in transaction costs is due to the demand for immediacy in a liquidity constrained market.

Table 5.5. What drive dark pool trading activity

This table shows estimated coefficients results for the market mechanism test in the following stock day panel regression model:

$$DL_{i,t} = \alpha_1 + \beta_1 DBAS_{M,t} + \beta_2 DBAS_{M,t-1} + \beta_3 DBAS_{M,t+1} + \varepsilon_{i,t}$$

$$DL_{i,t} = \alpha_1 + \beta_1 DQueue_{M,t} + \beta_2 DQueue_{M,t-1} + \beta_3 DQueue_{M,t+1} + \varepsilon_{i,t}$$

$DL_{i,t}$ is, for stock *i*, the percentage change (D) from trading day_{t-1} to day_t in liquidity variables ,including volume of shares, number of trades and pound volume for both lit and dark venues. $DL_{j,t}$ will be tested as lit liquidity, dark liquidity and market-wide liquidity respectively.. $DBAS_{M,t}$, $DBAS_{M,t-1}$ and $DBAS_{M,t+1}$ represent the concurrent, one-day lag and lead of the percentage change in a cross-sectional equally weighted effective bid-ask spread of my sample stocks. $DQueue_{M,t}$, $DQueue_{M,t-1}$ and $DQueue_{M,t+1}$ represent the concurrent, one-day lag and lead of the percentage change of the message-to-trade ratio adjusted order queue; this is calculated as the market depth at the best bid and ask divided by message-to-trade ratio. The t-statistics are presented in parentheses. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample period covers 1st June 2010 to 30th September 2014.

Panel A. Effective Spread						
	Lit venues			Dark venues		
	Volume Of shares	*Number of trades*	*Pound Volume*	*Volume Of shares*	*Number of trades*	*Pound Volume*
$DBAS_{M,t}$	0.003***	0.003***	0.003***	0.009***	0.007***	0.009***
	(7.28)	(9.34)	(7.4)	(5.04)	(5.53	(5.07)
$DBAS_{M,t-1}$	-0.001***	-0.001***	-0.001***	-0.001	-0.001*	0.00
	(-4.70)	(-6.84)	(-4.44)	(-0.43)	(-1.91)	(-0.38)
$DBAS_{M,t+1}$	-0.022***	-0.016***	-0.023***	-0.038	-0.018	-0.038
	(-4.46)	(-4.17)	(-4.71)	(-1.60)	(-1.19)	(-1.61)
Constant	0.079***	0.063***	0.079***	0.692***	0.449***	0.692***
	(48.76)	(44.66)	(48.84)	(87.88)	(85.19)	(87.91)
R-squared	0.16%	0.26%	0.02%	0.07%	0.09%	0.07%

Panel B. Order Queue

	Lit venues			Dark venues		
	Volume Of shares	*Number of trades*	*Pound Volume*	*Volume Of shares*	*Number of trades*	*Pound Volume*
DQueue$_{M,t}$	0.239***	0.208***	0.241***	1.018***	0.666***	1.025***
	(36.62)	(36.41)	(36.25)	(24.39)	(27.04)	(24.54)
DQueue$_{M,t-1}$	0.00	-0.000	0.000	-0.000***	-0.000***	-0.000***
	(0.53)	(-0.22)	(0.56)	(-4.64)	(-4.85)	(-4.67)
DQueue$_{M,t+1}$	-0.065***	-0.061***	-0.065***	-0.042***	-0.056***	-0.043***
	(-22.10)	(-23.48)	(-22.15)	(-2.83)	(-6.44)	(-2.91)
Constant	0.072***	0.061***	0.072***	0.815***	0.533***	0.816***
	-12.67	(12.24)	(12.70)	(24.48)	(24.75)	(24.53)
R-squared	4.69%	4.74%	4.80%	3.31%	3.23%	3.36%

When the spread widens, the high savings arising from trading at the midpoint attracts traders to move their orders from lit markets to dark pools. This point is also consistent with Madhavan and Cheng (1997) and Smith et al. (2001) who study the role of upstairs market. Similar to dark pools, upstairs markets allow traders to execute large institutional client orders without pre-trade transparency. However, some upstairs markets do have market makers to intermediate trades and upstairs transactions will incur price impact subsequently. Madhavan and Cheng (1997) show that upstairs markets enable transactions that would not otherwise occur in the downstairs market. The key differences between the upstairs markets of old and the modern midpoint dark pool, which I study is that execution prices in the latter are constrained within the downstairs market spread and dark pools are not usually subject to trading intermediation as it conceptually affords complete opacity of trading intentions. Nevertheless, the similarities in the functions of the upstairs markets and dark pools are striking. For example, Smith et al. (2001) show that upstairs markets play a complementary role to the downstairs, because trades are more likely to be executed upstairs when the spread on the downstairs limit order book widens. The estimates as obtained in Table 5.5 suggest that the modern midpoint dark pool performs a similar function, but perhaps even more important is that participation in dark pools is not limited to large institutional traders as is the case for upstairs market. Thus dark pools absorbs those trades that would not be easily executed otherwise, in a similar manner to the upstairs market (see as examples Madhavan and Cheng, 1997, Gresse, 2006).

Panel B in Table 5.5 reports the impact of limit order queue on lit and dark trading activities. With a 1% increase in limit order queue, individual stock trading activities in lit and dark markets will contemporaneously increase from 0.21% to 0.24% and 0.67% to 1.02% respectively, depending on the trading activity proxy. It can be observed that dark venues are likely to be more attractive than lit venues when the order queue in lit venues starts to lengthen. This is consistent with queue jumping hypothesis suggested by Kwan et al. (2015). When order queue builds up, new traders will have to join the queue and wait for their orders to be executed. As a result, the risk of non-execution of newer orders increases. In this case, dark venues become more attractive than lit ones as dark pools may offer liquidity traders the ability to bypass the limit order queues and also allow for faster execution with minimum price impact. Thus, I find that when the spread widens or the order queue lengthens traders may take advantage of the dark venues due to its potentially faster execution and propensity for lower price impact. This implies that dark pools act as complementary trading mechanisms to the traditional lit stock exchanges.

5.4.3. Liquidity and informed trading activities

Next the association between liquidity commonality and informed trading activity is considered. Theoretical studies (see for examples Hendershott and Mendelson, 2000, Ye, 2011, Zhu, 2014, Buti et al., 2016) (see as examples Hendershott and Mendelson, 2000, Ye, 2011, Zhu, 2014, Buti et al., 2016)base their modelling on differing assumptions regarding the accessibility of dark pools to uninformed traders. However, all studies agree that informed traders may aim to execute their orders in dark pools in order to reduce their transactions costs and maximise profits from their information (Nimalendran and Ray, 2014). This issue is empirically examined by extending the baseline model to include informed trading proxies related to the dark pools in my sample.[20] The probability of informed trading (*PIN*) is used here to proxy informed trading activity in the aggregate market. For completeness, I also include the ratio of messages in the market to trade (*ALGO*) in order to capture AT activity from the aggregate market. In order to avoid potential multi-collinearity issues, the base-line regression is executed with these two variables separately.

Table 5.6 shows the regression results based on *PIN*, which shows that in lit venues, the daily changes in market-wide *PIN* has a positive and significant impact on daily change in the illiquidity proxies, Amihud and Florackis ratios and negative impact on the more traditional trading activity variables of volume of shares traded, trading frequency and pound volume factors. The coefficients imply an inverse relationship between liquidity commonality and informed trading. This result is inconsistent with Chordia et al. (2000) who hypothesise that informed trading could result in liquidity commonality because simultaneous holding of superior information could result in correlated demand for liquidity by informed traders. However my result is consistent with Chung et al. (2005) in that market makers post wider spreads and smaller depths for stocks with higher probability of information-based trading in order to account for higher levels of adverse selection risks when informed trading activity rises. Furthermore, the coefficients of dark liquidity show that informed trading activities in lit venues also have a negative impact on dark liquidity commonality and coomonality in relation to the trading activity variables of volume of shares traded, transaction numbers and pound volume. Most importantly, the coefficients of dark liquidity and

[20] This method is similar to Chung, K. H. & Chuwonganant, C. 2014. Uncertainty, market structure, and liquidity. *Journal of Financial Economics,* 113**,** 476-499. who add Chicago Board Option Exchange (CBOE) Market Volatility Index (VIX) into liquidity commonality test.

trading activity commonality are all larger than corresponding ones in lit venues, indicating that informed trading activity in the aggregate market has a larger impact on dark liquidity than lit liquidity. The values for the dark venues are 1.14, 2.78, –0.37, –0.18 and –0.33 for Amihud, Florackis, volume of shares traded , transaction numbers and pound volume respectively. This is unsurprsing and consistent with the self-selection hypothesis (see Zhu, 2014; Comerton-Forde and Putnins, 2015), which implies that informed traders gravitate towards lit venues while uninformed traders are attracted to the dark trading structure. My results imply that while informed trading reduces trading activity in lit markets, it does so to a much larger extent in dark venues.

Table 5.6. Liquidity commonality and informed trading

Panel A and B in Table 5.4 shows estimated coefficients results for the following stock day panel regression model:

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \beta_4 PIN_{M,t} + \beta_5 PIN_{M,t-1} + \beta_6 PIN_{M,t+1} + \varepsilon_{i,t}$$

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \beta_4 ALGO_{M,t} + \beta_5 ALGO_{M,t-1} + \beta_6 ALGO_{M,t+1} + \varepsilon_{i,t}$$

$DL_{I,t}$ is, for stock i, the percentage change (D) from trading day_{t-1} to day_t in liquidity variables ,including Amihud ratio, Florackis ratio, volume of shares, number of trades and pound volume for both lit and dark venues. $DL_{i,t}$ will be tested as lit liquidity, dark liquidity and market-wide liquidity respectively. Lit and dark Amihud ratio, Lit and dark Florackis ratio are computed as described in Table 5.1. $DL_{M,t}$, $DL_{M,t-1}$ and $DL_{M,t+1}$ are the concurrent, one-day lag and lead of the percentage change in a cross-sectional equally weighted liquidity proxies of my sample stocks. $DPIN_{M,t}$, $DPIN_{M,t-1}$ and $DPIN_{M,t+1}$ are the concurrent, one-day lag and lead of percentage change in a cross-sectional equally weighted PIN of the sample stocks. PIN measure is computed as outlined in Table 5.1. $DALGO_{M,t}$, $DALGO_{M,t-1}$ and $DALGO_{M,t+1}$ are the concurrent, one-day lag and lead of percentage change in a cross-sectional equally weighted liquidity proxies of the sample stocks. *ALGO* is as a proxy for algorithmic trading and is measured as the ratio of messages to trades.The t-statistics are presented in parentheses. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample period covers 1st June 2010 to 30th September 2014.

Panel A. PIN

	Lit venues					Dark venues				
	Amihud	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*
$DL_{M,t}$	1.853***	0.512***	0.901***	1.117***	1.052***	2.331***	1.081***	1.541***	1.710***	1.876***
	(26.64)	(18.96)	(106.63)	(128.48)	(120.74)	(18.50)	(16.51)	(35.03)	(45.53)	(38.06)
$DL_{M,t-1}$	-0.093*	-0.102***	0.017***	-0.002	0.010	0.106	-0.063*	0.201***	0.148***	0.265***
	(-1.96)	(-7.32)	(2.70)	(-0.37)	(1.63)	(1.18)	(-1.80)	(6.07)	(5.33)	(7.48)
$DL_{M,t+1}$	-0.044	-0.043***	-0.000***	-0.000***	-0.000***	-0.228**	0.015	-0.000***	-0.000***	-0.000***
	(-0.93)	(-2.69)	(-3.65)	(-3.29)	(-2.77)	(-2.51)	(0.45)	(-14.53)	(-17.08)	(-15.66)
$DPIN_{M,t}$	0.454**	1.604***	-0.053***	-0.006	-0.026*	1.135***	2.784***	-0.368***	-0.181***	-0.325***
	(2.02)	(5.06)	(-3.47)	(-0.45)	(-1.74)	(2.86)	(4.14)	(-4.50)	(-3.37)	(-4.01)
$DPIN_{mMt-1}$	0.165	0.877***	-0.012	0.015	0.017	1.681***	3.037***	-0.121*	-0.025	-0.073
	(0.89)	(3.31)	(-0.89)	(1.34)	(1.32)	(4.95)	(5.06)	(-1.68)	(-0.53)	(-1.01)
$DPIN_{M,t+1}$	0.217	-1.031***	-0.084***	-0.033***	-0.052***	-0.049	-0.885	-0.252***	-0.187***	-0.198***
	(1.13)	(-3.91)	(-6.38)	(-2.98)	(-4.05)	(-0.15)	(-1.50)	(-3.46)	(-3.98)	(-2.73)

Constant	1.572***	2.281***	0.072***	0.059***	0.066***	2.806***	4.223***	0.934***	0.667***	0.897***
	(71.26)	(69.07)	(16.80)	(15.44)	(19.05)	(72.15)	(61.16)	(40.64)	(39.98)	(45.89)
R-squared	2.53%	1.51%	21.32%	26.93%	25.25%	1.34%	1.21%	3.08%	5.20%	3.72%

Panel B. ALGO

	Lit venues					Dark venues				
	Amihud	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*	*Amihud*	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*
$DL_{M,t}$	1.827***	0.585***	0.885***	1.086***	1.030***	2.379***	1.177***	1.557***	1.690***	1.898***
	(26.82)	(20.94)	(77.58)	(75.99)	(79.95)	(19.39)	(17.85)	(30.54)	(35.52)	(32.35)
$DL_{M,t-1}$	-0.122***	-0.083***	0.017**	0.007	0.015*	0.246***	0.004	0.187***	0.162***	0.270***
	(-2.68)	(-6.22)	(2.38)	(0.80)	(1.90)	(2.77)	(0.12)	(5.40)	(5.36)	(7.10)
$DL_{M,t+1}$	-0.052	-0.021	-0.000***	-0.000***	-0.000***	-0.237***	0.023	-0.000***	-0.000***	-0.000***
	(-1.12)	(-1.30)	(-7.32)	(-6.59)	(-6.14)	(-2.59)	(0.68)	(-17.12)	(-19.23)	(-18.03)
$DAlgo_{M,t}$	0.351***	-2.295***	-0.393***	-0.361***	-0.386***	1.608***	-7.377***	-1.161***	-0.900***	-1.146***
	(4.00)	(-5.58)	(-5.39)	(-5.31)	(-5.38)	(4.52)	(-5.02)	(-5.36)	(-5.36)	(-5.35)
$DAlgo_{M,t-1}$	0.167***	0.820***	0.084***	0.087***	0.084***	0.226	1.672***	0.434***	0.325***	0.434***
	(2.86)	(4.03)	(3.43)	(3.66)	(3.49)	(1.57)	(2.86)	(3.98)	(4.11)	(4.01)
$DAlgo_{M,t+1}$	-0.241***	0.156	0.077***	0.078***	0.077***	-0.425***	0.321	0.181***	0.168***	0.185***
	(-3.83)	(1.34)	(3.57)	(3.69)	(3.59)	(-3.49)	(0.91)	(2.90)	(3.25)	(2.96)
Constant	1.575***	2.340***	0.098***	0.082***	0.089***	2.764***	4.541***	1.019***	0.726***	0.970***
	(69.38)	(52.46)	(12.72)	(10.73)	(12.22)	(62.25)	(36.10)	(33.34)	(30.50)	(34.51)
R-squared	2.63%	3.48%	37.16%	44.99%	40.86%	1.67%	4.14%	9.55%	13.95%	10.20%

The results in Panel B, based on an alternate informed trading proxy, ALGO, is consistent with the trend in Panel A. AT activity exerts a negative influence on liquidity in both lit and dark venues. Also as in the case for *PIN*, *ALGO* has a larger negative impact on dark liquidity than on lit liquidity. Together, both *PIN* and *ALGO* have an overall stronger negative impact on dark venues than lit venues, indicating that when informed trading activities increases, lit venues' liquidity is less affected than dark venues. This finding is consistent with Comerton-Forde and Putniņš (2015) and Zhu (2014) that lit venues are more attractive to informed traders whereas dark pools are more attractive to uninformed traders because informed traders are likely to gravitate on the same side of the dark venues and when information event occurs these informed trades face low execution probabilities. As a result, informed trading activities reduce the two-sideness of the dark pools as well as dark liquidity.

5.4.4. Determinants of elasticity of liquidity commonality

In conclusion, I examine the elasticity of liquidity commonality (ELC). My approach is consistent with the earlier analysis presented in the preceding sections. First, I run stock quarter analysis for my baseline regression Equation (5.07), collect the ELC, measured as the coefficients of β_1, and run ELC against quarterly averaged stock attributes. Panel A in Table 5.7 shows the results with *PIN* as informed trading proxy in lit venues. When liquidity is measured by Amihud and Florackis ratios, *PIN* has negative impact on ELC, suggesting that stocks with low levels of informed trading have stronger liquidity correlations with the wider market. Thus, informed trading in an individual stock reduces its liquidity commonality with the wider market. Based on the volume of shares traded , trading frequency and pound volume coefficient estimates, I do not observe that informed trading exerts statistically significant impact on trading activity. In the last column, I show the estimates for the overall lit ELC, which equals to the sum of the β_1 from the baseline models under five different liquidity proxies. The last column shows that informed trading activity reduces the level of liquidity commonality in lit markets when all measures of liquidity are considered in unison, and that volatility tends to increase the level of liquidity commonality. Overall, this section of the results suggests that stocks with low level of informed trading and high level of volatility generate the strongest liquidity commonality with the wider market.

Panel B in Table 5.7 shows the results of dark venues. First, when liquidity is proxied by the Florackis ratio and trading frequency, *PIN* exerts a negative and statistically significant impact on liquidity commonality. Further, when liquidity is proxied by Amihud ratio, volume of shares traded, trading frequency and pound volume, volatility tends to have positive and statistically significant impact on liquidity commonality. The last column suggests that the liquidity commonality in dark venues tends to shrink with increases in informed trading activity. The reduction in liquidity commonality when a stock is traded in the dark is on a magnitude almost three times higher than when the stock is traded in the lit market.

Table 5.7. Stock attributes and elasticity of liquidity commonality

The table reports regression coefficient estimates using a stock-quarter panel. I first run regression for each quarter and collect elasticity of liquidity commonality (ELC), coefficient of β_1 , from baseline regression in model (5). Then, I treat ELC as dependent variables in the following regression:

$$ECL_{i,t} = \alpha_1 + \beta_1 PRICE_{i,t} + \beta_2 MKT_{i,t} + \beta_3 COUNT_{i,t} + \beta_4 PV_{i,t} + \beta_5 VOLA_{i,t} + \beta_6 PIN_{i,t} + \varepsilon_{i,t}$$

$PRICE_i$ is the log of quarterly average share price of stock *i*, $COUNT_i$ is the log of quarterly averaged number of transaction of stock *i*, PV_i is the log of quarterly averaged pound volume traded of of stock *i*, $VOLA_i$ is quarterly volatility of return of stock *i*. PIN_i is quarterly averaged probability of informed trading of stock *i*. PIN measure computed as outlined in Table 5.1.

Panel A. Lit venues						
	Amihud	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*	*Overall_Lit*
PIN	-4.582*	-4.502***	-0.406	0.077	0.308	-9.105***
	(-1.84)	(-3.10)	(-0.90)	(0.20)	(0.83)	(-2.80)
Price	0.076	-0.010	-0.072***	0.007	-0.010	-0.008
	(0.80)	(-0.18)	(-5.58)	(0.57)	(-0.82)	(-0.07)
MKT	0.123	-0.256***	0.015	0.019	0.028	-0.072
	(1.20)	(-3.64)	(0.84)	(1.09)	(1.54)	(-0.49)
Count	-0.600	0.776***	-0.015	0.084	0.003	0.250
	(-1.14)	(3.32)	(-0.22)	(1.42)	(0.05)	(0.38)
Pound Volume	0.135	-0.187	0.091*	-0.034	0.052	0.057
	(0.34)	(-0.96)	(1.71)	(-0.68)	(1.01)	(0.11)
Volatility	1.088***	-0.500***	0.173***	0.085**	0.125***	0.971***
	(3.68)	(-3.54)	(4.23)	(2.08)	(2.94)	(2.69)
Constant	8.234**	2.325	0.442	1.231***	0.117	12.350***
	(2.25)	(1.24)	(0.90)	(2.62)	(0.25)	(2.62)
R-squared	2.05%	4.18%	8.55%	2.05%	4.62%	1.72%

Panel B. Dark Venues

	Amihud	*Florackis*	*Volume Of shares*	*Number of trades*	*Pound Volume*	*Overall_Dark*
PIN	-4.582	-7.911***	-5.111	-3.670**	-4.527	-25.801**
	(-0.85)	(-2.64)	(-1.58)	(-2.01)	(-1.21)	(-2.41)
Price	0.198	0.207**	-0.117	-0.087	-0.046	0.154
	(1.47)	(1.96)	(-1.28)	(-1.51)	(-0.41)	(0.51)
MKT	0.488***	-0.652***	-0.075	0.076	0.027	-0.136
	(3.02)	(-4.27)	(-0.86)	(1.19)	(0.29)	(-0.45)
Count	-0.542	0.873*	-0.607	-0.754**	-0.914	-1.944
	(-0.81)	(1.89)	(-1.02)	(-2.33)	(-1.17)	(-1.09)
Pound Volume	-0.651	0.141	0.723*	0.468*	0.844*	1.524
	(-1.20)	(0.37)	(1.77)	(1.95)	(1.67)	(1.17)
Volatility	1.458***	-0.637**	0.667***	0.625***	0.937***	3.051***
	(3.07)	(-2.32)	(2.77)	(3.52)	(3.61)	(3.51)
Constant	17.610***	2.766	-1.073	1.428	-2.100	18.630
	(3.28)	(0.73)	(-0.27)	(0.62)	(-0.44)	(1.51)
R-squared	2.82%	3.73%	1.67%	1.55%	1.73%	1.75%

5.5.Conclusion

This chapter presents the first set of evidence aimed at informing the understanding of the commonality dynamics between dark pool liquidity and market-wide liquidity. Liquidity comovement of FTSE100 stocks are compared and contrasted in lit and dark venues from June 2010 to September 2014. By employing established liquidity commonality model, I find that, compared with lit venues, dark venues have stronger liquidity commonality. Moreover, this stronger liquidity commonality in dark venues is sourced from increasing trend of the market. My findings suggest that dark venues inject liquidity to the market rather than drain liquidity from the market and, compared with lit venues, dark venues contribute more liquidity to the market. This is because dark venues can facilitate trades that otherwise cannot be easily executed in lit venues in the case of limit order spread widens and order queue bulks up. This finding is consistent with He and Lepone (2014) and Kwan et al. (2015). I further test whether dark liquidity commonality is fuelled by informed trading activities. However, the results suggest that informed trading and AT actually reduce both lit and dark liquidity. Compared with lit liquidity, informed trading and AT generates stronger negative impact on dark pool liquidity. This finding is in line with Zhu (2014) that informed investors face low execution probabilities in crossing networks and dark pools because informed trader typically trade at the same side of the dark pools. My last major finding is that stocks with low level of informed trading and high volatility yield greater liquidity commonality.

This evidence indicates that dark trading in my sample potentially contributes liquidity to the market. This is consistent with Buti et al. (2011), He and Lepone (2014) and Brugler (2015) that dark pool trading seems do not have detrimental impact on market liquidity. Obviously, more theoretical and empirical research is need to uncover the dark pool liquidity mechanism in global equity market. I hope my analysis can help policy makers and academics to draw important implication and implement evidence-based policy recommendation in the future

6. Summary

The beginning of this thesis argues that technology has transformed the financial markets over the past few decades. The recent advance in market structure has received significant attention from regulators, academics, investors and other market participants, with some wondering whether the innovations have outpaced the regulatory structure designed to foster market integrity. However, not much attention has been paid to technological iteration in Europe’s largest equity market, the London equity market, comprising the LSE and several other fast-growing trading platforms. This thesis conducts microstructure analysis to identify the impact of the evolving market structure on market quality.

6.1. Summary of findings

6.1.1. Informed trading and the Price Impact of Block Trades

The first empirical study in Chapter 3 investigates the connection between block trades and informed trading on the LSE under a high-frequency trading environment on an intraday and inter-day basis. This contributes to the literature on the informativeness of block trades and how their execution relates to the incorporation of information into stock prices. My sample data include FTSE100 stocks from 1st October 2012 to 30th September 2013. I define block trades as the largest 1% of the trades in each stock. To obtain the level of informed trading activity, tick data is used to estimate PIN variables.

This chapter reveals three major findings. First, by expanding observations of block trades to normal trading hours, I show that informed trades are positively related to the number of block trades and information can quickly diffuse into stock price through block trades on the LSE. Second, the results indicate that the impounding of information into stock prices is stronger in the first trading hour than at other times during the normal trading day. Moreover, informed trading at day $_{t-1}$ can still affect informed traders' block transaction at day $_{t}$. These results are consistent with the theoretical frameworks of Kyle (1985), Holden and Subrahmanyam (1992), Foster and Viswanathan (1994) and Hong and Stein (1999) that suggest that private information is gradually incorporated into asset prices because informed traders gradually exploit private information across trading days. Third, since PIN is correlated with firm-level financial transparency (Vega, 2006), I stratify sample stocks into four portfolios based on the mean value of their daily PIN and show that the information incorporation process can vary across stocks with different levels of financial transparency. This finding shows that the larger the level of informed trading in a stock, the higher the permanent price impact of block trades. This implies a positive role of informed trading in facilitating the price discovery process as informed traders aid the price discovery process for less transparent stocks.

6.1.2. Aggregate market fragmentation, adverse selection and market efficiency

This chapter aims to investigate the visible market fragmentation introduced by MiFID in 2007. MiFID allows MTFs to compete for order flow, resulting in increasingly fragmented trading volume. Note that MiFID does not formally mandate a linkage between trading venues and the release of consolidated quote information on a national basis; orders are 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 the Reg NMS, which mandates that exchanges re-route orders to other venues if those venues offer a better price (*trade-throughs*). Under MiFID, the primary exchange is typically accessible to all investors, while simultaneous access to multiple venues (including MTFs) normally requires the smart order routing technology. SORT 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 in real time. The trading fragmentation has raised concerns about whether the diversified market landscape can harm price transparency in the markets. In this chapter, I disentangle the effect of trading fragmentation by studying the impact of competition for visible order flow on market transparency and market efficiency under a consolidated market environment.

First, the study examines the relationship between trading fragmentation and market transparency. PIN variables and the one-minute mid-quote returns autocorrelation are employed as proxies for adverse selection costs and risk, respectively. PIN and autocorrelations of intraday return capture informed trading activity and therefore are inverse proxies for market transparency. Results suggest the existence of a quadratic/U-shaped relationship between fragmentation and adverse selection risk. Thus, visible fragmentation helps to reduce adverse selection costs and increase market transparency in the aggregate market environment when fragmentation is relatively lower. However, when fragmentation is higher, implied adverse selection costs and market opacity potentially increase with fragmentation.

The impact of market fragmentation on market efficiency is also investigated by adapting Chordia et al.'s (2008) return predictability model to test whether fragmentation reduces short-horizon return predictability. The study finds that fragmentation facilitates market efficiency by eliminating short-horizon return predictability and reducing arbitrage opportunities. This finding is in line with Storkenmaier and Wagener (2011) and Menkveld (2013), who suggest that order flow competition across trading venues can act as a linkage necessary to minimise arbitrage opportunities.

This chapter has important implications for the debate surrounding trading fragmentation in European equity markets. Empirical evidence shows that market fragmentation should be viewed as a value-creating competition phenomenon that benefits market transparency and price efficiency.

6.1.3. Liquidity commonality in lit and dark venues

This chapter expands the research scope to the dark pool, a less transparent trading venue that does not provide pre-trade transparency. In Europe, regulators have taken the opportunity offered by MiFID II to implement an 8% cap on the total value of dark trading across all venues. This restriction is scheduled for implementation at the beginning of 2018.

This chapter presents a study of the dynamics of the liquidity-creation effect in both lit and dark venues by employing a liquidity commonality model. Previous research in liquidity commonality (see for example Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001) shows that the liquidity levels of individual stocks co-vary with the market-wide liquidity. One explanation for this phenomenon is market makers' inventory management; market makers are likely to respond to shifting market prices and order flow by altering their exposure across various assets. The application of liquidity commonality model reveals that, compared with lit venues, dark venues inject liquidity into the market rather than drain liquidity from the market. This is because dark venues can facilitate trades that otherwise cannot be easily executed in lit venues if the limit order spread widens and the order queue bulks up. This study also tests whether dark liquidity commonality is fuelled by informed trading activities. However, the results suggest that informed trading and AT actually reduce both lit and dark liquidity. Compared with lit liquidity, informed trading and AT have a stronger negative impact on dark pool liquidity. This finding is consistent with Zhu's (2014) finding that informed investors face low execution probabilities in crossing networks and dark pools because informed traders are likely to be clustered on the same side of the dark order book. The last major finding is that stocks with a low level of informed trading and high volatility yield greater liquidity commonality. The evidence indicates that midpoint dark pool trading has no detrimental impact on market liquidity.

6.2.Suggestions for Future Research

The studies described in this thesis have examined the impact of recent technological advances on the London equity market. My studies deliver the view that the evolution of the market structure benefits the market participants. However, the constantly changing market landscape leaves some issues that are not covered in this thesis, for example, the intraday analysis of dark pool trading behaviour. Since most trades in dark pools are based on a computerised algorithm and can be executed within a fraction of a millisecond, the high-frequency relationships between dark pool trading and market quality are of direct importance to regulators tasked with promoting financial stability. For example, institutional investors and intraday traders tend to trade heavily when the market is opening and close their positions when the market is closing. Future research can focus on how institutional investors utilise dark pools on an intraday basis and compare the effects of dark trading during the opening and closing to the rest of the day.

Furthermore, the midpoint dark pool also raises concerns about potential market manipulation. Foley and Putniņš (2016) point out that the midpoint dark trading may reveal information about trading intentions. For example, market participants can predict the direction of trade by submitting a bait/probing order to the midpoint dark pool. The execution time and direction of the bait order can reveal information about forthcoming trades. More empirical studies can investigate the impact of the potential market manipulation of dark pools.

Finally, with the Australian and Canadian authorities having already devised measures to regulate dark pool trading, it is now Europe’s turn to regulate dark pool trading activity. It may seem surprising that MiFID II will implement a one-size-fits-all and inflexible 8% dark volume cap on all stocks. Future researchers might conduct a natural experiment to analyse the effects of dark volume cap, answering the questions such as how dark volume caps improve market quality.

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