Liquidity Providers in the Limit Order Book: Are They Becoming More Informed?*

Yang Yue†

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Abstract

The paper examines the relative informativeness of liquidity providers and demanders in the limit order book (LOB) market after a significant market structure change in 2011 that affected high-frequency traders (HFTs) the most. Using data from a period of mature and relatively saturated high-frequency trading (HFT), the study finds that the relative informativeness of quotes at the best price levels decreases after the event, with the largest reduction observed in the most liquid stock group. Trades become the dominant contributor of information for two large-cap groups. This reduction in quotes informativeness is accompanied by an increase in the adverse selection component of trading costs. Additionally, the transitory price impact for large-cap stocks changes from positive to negative, while mid-cap stocks have experienced a negative impact that decreased further after the event. These results are consistent with previous studies that reported a negative transitory price impact and a lack of competition among liquidity suppliers in recent years. However, the informational content of limit orders at and behind the best price levels on average does not decrease for the most liquid group, suggesting orders behind the best price levels are more informed. The study also argues that limit order users act more like traditional market makers, providing liquidity symmetrically on both sides of the market after the event. Overall, this study highlights the complex interplay between technological changes, liquidity provision, and information asymmetry in modern financial markets.

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†University of Westminster, yuey@westminster.ac.uk.

Contents

1 Introduction

Traditional market microstructure models assume that uninformed market makers provide liquidity and only learn information from the order flow (Kyle, 1985; Glosten and Milgrom, 1985; Easley and O'Hara, 1987). Liquidity demanders, who generate order flows, consist informed traders and liquidity traders (or noise traders). These models are based on the uniform price market where the entire trade is executed at a single price. However, today's market is dominated by an open LOB system where anyone can provide liquidity by submitting discriminatory limit orders, and anyone can demand liquidity by submitting market orders. As a result, liquidity providers and demanders are more diverse and less restricted to certain types.

A growing body of literature suggests that liquidity providers in the LOB market possess information (e.g. Hautsch and Huang, 2012; Cenesizoglu et al., 2022; Fleming et al., 2018; Brogaard et al., 2018). In addition, recent academic articles have reported an increase in stock price informativeness (e.g. Bai et al., 2016; Farboodi et al., 2022; Easley et al., 2022; Brogaard et al., 2022). These findings imply that liquidity suppliers may be more informed than they were in the past. However, it remains unclear whether the rise in price informativeness is mainly attributable to liquidity demanders or liquidity suppliers.

To address this question, this paper focuses on a specific period in which a significant market structure change occurred. By narrowing the sample period, this paper sheds light on changes in the information advantage of liquidity providers. Specifically, this paper focuses on liquidity providers who submit limit orders to the market, and the terms 'liquidity providers', 'liquidity suppliers', and 'market makers' are used interchangeably throughout this paper. Automated trading has emerged as a significant trend over the years, with algorithmic and HFT becoming increasingly popular following the introduction of electronic trading platforms (Friederich and Payne, 2011). HFTs are considered informed traders Menkveld (2016), but there is disagreement over whether they primarily profit from liquidity provision, liquidity taking, or both.[1]

This paper focuses on an event in 2011 when the London Stock Exchange (LSE) upgraded its

[1]For instance, Brogaard et al. (2015) found that HFTs profit from providing liquidity, while Hagströmer and Nordén (2013) observed that the majority of HFTs' transactions are executed through limit orders. Additionally, Brogaard and Garriott (2019) found that most new HFT entrants predominantly supply liquidity. On the other hand, both Hirschey (2021) and Benos and Sagade (2016) found that HFTs benefit more from consuming liquidity. Baron et al. (2017) and Boehmer et al. (2018) nevertheless found that HFTs benefit from both liquidity provision and liquidity taking.

trading system, which was likely to affect HFTs the most due to their sensitivity to trading speed (Menkveld and Zoican, 2017, p. 1189). This event serves as an exogenous shock to HFT, providing an opportunity to study the impact of this change on the relative informativeness of liquidity suppliers and demanders, which in turn sheds light on the changes in the composition of liquidity providers. Previous literature suggests that market automation increases the relative informativeness of liquidity providers (e.g. Hendershott et al., 2011; Riordan and Storkenmaier, 2012), but the event in this paper is more recent, occurring during a mature period of HFT growth. Therefore, the competition between HFTs is likely to be different, potentially leading to different effects on liquidity, welfare, and information asymmetry in the market (Bongaerts and Achter, 2021).

Based on the findings of the baseline analysis using Hasbrouck (1991a,b) information sharing method, this paper finds that the relative informativeness of quotes for the three groups of stocks with varying levels of liquidity and size was diminished after the event, with the largest reduction observed in the most liquid and largest stock group. Trades therefore took over as the dominant contributor of information for two large-cap groups after the event. The decrease in the relative informativeness of quotes is accompanied by an increase in the adverse selection component of trading costs, as evidenced by the increase in the permanent price impact. Meanwhile, transitory price impact for large-cap stocks changes from positive to negative, and mid-cap stocks experienced a negative impact before the event, which decreased even further. Findings in this paper are consistent with those of Yueshen (2021), who reports that the transitory price impact is currently negative and the negative value may be attributed to a lack of competition among liquidity suppliers. These results suggest that HFTs' informational advantage may not necessarily come from their ability to provide liquidity but rather their ability to consume liquidity. The reactions in quoted spread support this argument. Therefore, the rise of HFTs may have contributed to the increase in stock price informativeness in the LOB market, but this may not have necessarily improved the informativeness of quotes at the top of the book.

The method proposed by Hasbrouck (1991a,b) considers only quotes at the best price level and trades. However, Geottler et al. (2009) suggest that orders close to and far from the best prices convey different levels of informativeness. Empirical evidence from Cenesizoglu et al. (2022) further supports this argument. In this study, I employ a method distinct from those used in Pascual and Veredas (2010), Hautsch and Huang (2012), Fleming et al. (2018) and Brogaard et al. (2018) to investigate whether liquidity providers in the book on average are informative about price movement.

Traditional models assume that liquidity providers are uninformed and quote symmetrically on both sides of the market to make a profit. Therefore, the trading cost for buy and sell market orders would be equivalent (Kyle, 1985; Glosten and Milgrom, 1985; Glosten, 1994; Sandås, 2001). The LOB model developed by Sandås (2001) shows that the slope of the LOB corresponds to the permanent price impact in the liquidity provider's pricing function. However, recent studies have demonstrated that the slopes of the LOB on the two sides of the market are asymmetric. Dierker et al. (2016) explain that this asymmetry arises from heterogeneous valuations among liquidity providers. If the slopes are asymmetric, the imbalance indicates whether liquidity providers demand or supply more. A price increase when they demand (supply) more suggests that they are more (less) informed about price movements. Thus, I adopt the slope measure in Sandås (2001) but separate it into the buy-side and sell-side slopes.

I first examined the correlation between the slope of each side of the market and the permanent price impact estimated via the Hasbrouck (1991a). The results showed a low correlation, indicating that the slope may not be a good proxy for the traditional permanent price impact. Furthermore, the bid and ask side slopes were found to be negatively correlated for many stocks, indicating heterogeneous valuations among liquidity providers. To further assess the accuracy of their private valuations of the stock,[2] I conducted a regression analysis using daily returns and order book imbalance as the dependent and explanatory variables, respectively, while controlling for the effects of market orders and firm characteristics. The results revealed a cross-sectional difference in the informativeness of liquidity providers after the system upgrade.

Before the speed-upgrade event, the LOB moved in the same direction as the price movement (i.e., when liquidity providers' buying pressure is higher than the selling pressure, price increases) for all groups of stocks, indicating that liquidity providers in the book on average were informed about price movements. However, after the system upgrade, the informativeness of liquidity providers differed among the three groups of stocks. For the eight FTSE 100 Acc Tick stocks, which are the most liquid and largest firms traded on the LSE, the LOB still moved in the same direction as the price movement. In contrast, for the twenty-nine FTSE 100 stocks, the LOB

[2] In Geottler et al. (2009, p. 71), it is the 'private benefits of trade, accruing to a trader as a result of liquidity shocks or private hedging needs'.

moved in the opposite direction to price movements, indicating a reduction in the informativeness of liquidity providers. For the forty FTSE 250 stocks, the movement of the LOB became unrelated to the price movement, also implying that liquidity suppliers who submit orders at and behind the best prices became relatively less informed after the upgrade.

A noteworthy finding is the negative correlation between permanent price impact and the absolute value of the imbalance between bid and ask slopes holds true for FTSE 100 and FTSE 250 stocks. This suggests that when the adverse selection risk is higher, the LOB is more balanced. On such days, liquidity providers are less informed and behave like traditional market makers who supply liquidity on both sides of the market with equivalent trading costs. Conversely, when the adverse selection risk is relatively lower, the book is less balanced and liquidity providers are relatively more informed. Therefore, the absolute value of the order book imbalance indicates whether liquidity providers are engaging in traditional market-making or are informed about future price movements. After the speed-enhancement, liquidity providers become more like traditional market makers who provide liquidity on both sides of the market.

The paper is organised as follows: Section 2 reviews the relevant literature. Section 3 introduces data and sample construction. Section 4 and 5 respectively examine the impacts of the event on liquidity and activity variables and on the informativeness of quotes and trades at the top of the book. Section 6 and 7 focus on the impact of the event on the informativeness of liquidity providers and demanders by incorporating information behind the best price level. In particular, Section 6 introduces the book imbalance measure which reflects the informativeness of liquidity suppliers. Based on this measure, Section 7 examines the impact of the event on the informativeness of the LOB. The determinants of the order book imbalance are studied in Section 8. Section 9 concludes the paper.

2 Literature review

Symmetry of buy and sell quotes Traditional theories of market microstructure can be categorised into two branches, one that models the adverse selection risk and the other that models the inventory risk for market makers. The former branch, represented by works like Kyle (1985) and Glosten and Milgrom (1985), explains how uninformed liquidity providers assimilate information from past order flows and update their quotes accordingly. These studies show that liquidity is symmetrically distributed around the efficient price, with the exception of Easley and O'Hara (1987), who argues that the quoted spread is not symmetrical around the efficient price. On the other hand, the latter branch of theory, such as Stoll (1978) and Ho and Stoll (1981), focuses on how the uninformed liquidity provider updates their quotes based on changes in their inventory level. Liquidity in these studies is symmetrically distributed around the midquote. In the context of LOB markets, early models like Glosten (1994), Seppi (1997), Biais et al. (2000) assume that liquidity providers are risk-neutral and uninformed, and that their pricing activities on the two sides of the market are symmetrical.

Unbalanced informativeness of buy and sell market orders According to Saar (2001), buyers are more likely to be motivated by information because they can trade as much as they want, whereas sellers face constraints. Empirical studies have provided some insights into the price impact of buys and sells. For instance, Kraus and Stoll (1972), Chan and Lakonishok (1993), Gemmill (1996) and Escribano and Pascual (2006) found that the price impact of a buy is greater than that of a comparable sell. However, Keim and Madhavan (1996) and Bikker et al. (2007) came to a different conclusion, reporting that the price impact of a sell is higher. Collin-Dufresne and Fos (2015) used Schedule 13D filers' trades to examine the validity of different proxies for the adverse selection risks to liquidity providers. They argued that the filers are privately informed buyers and found that all measures of the adverse selection component of trading costs fail to reflect the informed trading, except for the 'directional measures'. When the adverse selection of buy and sell market orders are estimated separately, they are more accurately reflect informed trading. This means that changes in the adverse selection estimated from one side of the book is opposite to changes in the adverse selection estimated from the other side of the book when the asymmetry of the long-term information exist.

Interactions between market and limit orders Although Engle and Patton (2004) did not detect that buy and sell market orders have different effects on midquote dynamics, they have asymmetric impacts on quotes. Specifically, buy (sell) market order has a greater impact on ask (bid) than bid (ask), which is also supported by the evidence in Hautsch and Huang (2012). Ranaldo (2004) found that a larger depth of one side of the market induces market order submission from the same side. He also suggested that agents who intend to sell stocks are likely to be uninformed and providing liquidity.[3]

[3] In his paper, the larger spread for an incoming seller indicates the seller has a higher risk of transacting against an informed trader. He also claims that the information motivated buyers/sellers result in high autocorrelations

Informativeness of the limit orders By employing a Vector Error Correction (VEC) model to assess the permanent impact of limit orders, Hautsch and Huang (2012) found that they significantly influence future price movements, thus contributing to the price discovery process. When examining the impact of HFTs and non-HFTs' market and limit orders, Brogaard et al. (2018) discovered that HFTs' market orders have the least impact on the price discovery process, whilst their limit orders have the most. On the other hand, non-HFTs' market orders demonstrate more informed trading behaviour than their limit orders.

Unbalanced informativeness of the bid- and ask-side of the LOB The primary distinction between limit and market orders is that the former specifies the price at which a market participant intends to trade, while the latter does not specify a particular price.[4] Researchers use order imbalance to evaluate the net demand of liquidity takers (i.e. those who employ market orders). However, this measurement approach does not apply easily to limit orders, as there are different price levels. In Dierker et al. (2016)'s study, a basic model was employed to illustrate that investors' shifts between demand and supply cause a negative correlation between market demand and supply elasticities. This suggests that the aggregate supply elasticity exceeds the aggregate demand elasticity when more investors' private valuations exceed the market price. The slope of the ask- and bid-side of the LOB proxies the aggregate supply and demand elasticities, respectively. Consequently, it can be inferred that the imbalance between the ask- and bid-side slopes indicates the heterogeneous private valuations of investors who employ limit orders.

Pascual and Pascual-Fuster (2014) utilised Hasbrouck (1995)'s information shares method to assess the comparative informativeness of ask and bid quotes. Their findings revealed the presence of asymmetry in a trading session, and the asymmetry is not driven by noise. This indicates that the best ask and bid quotes do not update symmetrically following news. Additionally, the asymmetry is more pronounced when book-based average quotes are used, suggesting that the orders beyond the best quotes does not update symmetrically either. Furthermore, they demonstrated that the asymmetry is due to the order imbalance, with the sell (buy) side of the book leading the price discovery process when the total share/number of the buyer-initiated trades exceed (fell short of) the total share/number of the seller-initiated trades. However, as they noted,

of buy/sell orders. Sell orders have lower autocorrelation.

[4] As in Kyle (1985), limit order is a demand function and the market order is a quantity.

this relationship is weakened by the emergence of high-frequency markets and the increased prevalence of HFTs as new market makers. They also found that the asymmetry between the slopes of the book on two sides of the market was related to the relative informativeness of the quotes.[5] When the slope of the ask-side of the book was higher, the best ask contributed more information to price movements than the best bid. However, in their paper, liquidity providers are only assumed to learn information from liquidity demanders, so they interpreted the slope as the risk exposures of the book. In contrast, liquidity providers in this study potentially possess an advantage in terms of both public and private information compared to liquidity demanders. Therefore, the interpretation of the slope in this paper differs from that in their paper.

The slope measure used in this study is empirically most similar to the 'ex-ante trading costs' studied in Amaya et al. (2018), although the two measures are based on different theoretical models. The difference is that my measure represents the daily average value, which excludes the impact of the efficient price change during the day. Amaya et al. (2018) 's setting also assumes that liquidity providers are uninformed and learn information from the order flows. They discovered that the overall ex-ante trading costs, which are not separated between the bid and ask sides, are informative about price movements. When the two sides are separated, the impacts of the ask- and bid-side trading costs on price movements were asymmetric in 2011. However, the asymmetry became insignificant in 2012 and was claimed to be attributed to the reduced size of the order imbalance. Nonetheless, their results (Table 4, model 3) show that even when the impact of order imbalance is excluded, the effects of trading costs on both sides of the market remained very similar in 2012, suggesting that other factors may be responsible for the asymmetry. This paper also isolates the impact of the order imbalance from the impact of order book imbalance on price movements and examines whether the improvement in trading speed leads to any changes in these impacts. An increase in the impact of order imbalance, accompanied by a decrease in the impact of order book imbalance, would indicate that liquidity demanders are becoming more informed collectively, as the price moves in the same direction as their net demand.

According to Cenesizoglu et al. (2022)'s findings, the slopes of the two sides of the market have opposite effects on returns. Furthermore, the immediate impact of the slope of the higher levels on returns is larger than its cumulative impact, indicating a reversal of the impact. The reversal for the slope of the higher levels is also stronger than for the lower levels. Based on

[5]The slope measure follows Naes and Skjeltorp (2006).

the traditional price impact literature, it can be inferred that the change of the slope of the lower (higher) levels is more related to the information (liquidity) reason. The authors defined the lower levels of the book as the first five price levels. As the slope used in this paper is also measured based on the best five price levels, it is expected that the behaviour of the slope in this paper is comparable to the behaviour of the lower level slope in their paper. That is, the slope in this paper has a permanent impact on price movements.

Using intraday data, Cao et al. (2008) investigated how prices and depth at the best ten levels of the book are associated with future returns. They calculated the imbalance between the ex-ante buy and sell price impacts of trading a hypothetical number of shares, which is similar to the slope imbalance measure used in this paper. However, they emphasized the imbalance of liquidity. They demonstrated that the excess supply (demand) drives the price down (up), mainly due to the liquidity near the top of the book. Faraway orders have the opposite effect but are mostly insignificant. They argue that the positive relationship between excess demand and return is because the more liquid side of the book (i.e. bid) induces market buy orders, resulting in an increase in price. However, they did not clarify what causes the excess demand of liquidity suppliers. This paper suggests that the imbalance between the two sides of the book is mainly due to the heterogeneous private valuations among liquidity suppliers, which complements Cao et al. (2008)'s argument.

In their research on call auctions, Kalay et al. (2004) found that the elasticities of the two sides of the market are not equal, and that the buy limit order has a more significant and permanent price impact than the sell limit order. Building on this work, Kalay and Wohl (2009) developed a measure to capture the buying pressures of liquidity traders in call auctions, based on the slopes of the two sides of the order book. This measure is rooted in the intuition of Hellwig (1980) that only informed traders are price sensitive, while liquidity traders tend to use market orders, which are completely inelastic. By using the slopes of the market orders on the two sides of the book, Kalay and Wohl (2009) was able to proxy for the relative buying or selling pressures of liquidity traders. Their empirical results show that buying pressures have a significant negative relationship with future returns, indicating that liquidity traders are generally uninformative. Additionally, they found that liquidity traders tend to place more sell market orders than buy market orders. In contrast, the slope measure used in this paper captures the elasticity of demand and supply of limit orders during the continuous trading period. Since informed traders are typically price sensitive, the imbalance between the slopes of the two sides of the book is likely to be informative about future price movements.

Theoretical research conducted by Goettler et al. (2009) also provided evidence of the order book imbalance. In their study, the selling pressure was defined as the number of shares posted at the ask. The research found that the slopes of the two sides of the book have opposite effects on expectations about the fundamental values of the asset, and that depth at and away from the best price have distinct effects on future prices. Specifically, when there is a selling pressure (i.e. depth *at* the ask in their paper), future prices will decline, while future prices will increase when depth is *away from* the ask. The effects of the bid side are symmetrical. Notably, as the tick size in their model is one unit, depth is also equivalent to the slope.

3 Data, sample construction and summary statistics

To examine cross-sectionally heterogeneous reactions, I randomly select 8, 30 and 40 stocks from FTSE 100 Acc Tick, the remaining stocks in the FTSE 100 and the FTSE 250 respectively ('F100acc', 'F100' and 'F250' are used onwards to represent three sample groups).[6] The evaluation period covers six weeks before and six weeks after the event, which starts from 04/01/2011 to 31/03/2011. News show that technical issues occurred in the first week after the upgrade. This information is confirmed by the abnormal quotes exhibited in the raw data,[7] so I exclude 18/02/2011 and 25/02/2011.[8]

Data are detailed at the order level, named the 'Rebuild Order Book' (ROB) and purchased from BEDOFIH. It is a direct-feed dataset that contains four files — 'order details', 'order history', 'trade' and 'instrument reference'. Four files record information for all order book activities, including order entries, the subsequent order executions, deletions or modifications, and trades

[6]FTSE 100 Acc Tick is a subset of the FTSE 100 group, which are selected according to the size and the liquidity level of stocks. They are the most liquid stocks, subject to a different tick size table (called 'FTSE100 granular tick'). This segment no longer exists since 2 January 2018, when the MiFID II tick size table was introduced. MiFID II - Directive 2014/65/EU - is the revision of MiFID, applies from 3 January 2018

[7]Negative quoted spreads exhibit in the data and the succeeding spreads are extremely wide (larger than 2 standard deviations).

[8]Comparing to other trading days in our sample, spread on 18/02/2011 is much narrower and the number of negative spread is much higher. Media also reports that serious problems took place on 25/02/2011, which is confirmed by my assessment that spread is wider than other days. So this date is excluded. The nuclear disaster tsunami occurred on 11/03/2011, which, as reported in Conrad et al. (2015), induced a sharp increase in quote updates on the Tokyo Stock Exchange the next day. The strange behaviour is not observed in our data, so both days are kept.

information.[9] Based on these documents, I reconstruct the book at the best five price levels for each stock on each day. This procedure reproduces the market when market participants were making trading decisions. The data is presented with millisecond timestamp.

Only the continuous trading period is considered. Similar to Riordan and Storkenmaier (2012), the first 2 minutes on each trading day are removed to avoid the biases caused by information processing, which then leaves the trading period of 8:02 to 16:30. In addition, off-book trades, such as dark trades and negotiated trades, are not included in the analysis. Hence, trades marked 'automatic' are kept.

Table 1 reports the summary statistics of liquidity and activity variables at the top of the book over the pre-event period. Liquidity measures include time-weighted quoted spread re-scaled by midquote, time-weighted depth re-scaled by the average daily trading volume.[10], and value-weighted effective spread re-scaled by midquote. The detailed calculation for each variable please refer to appendix A.

The cross-sectional heterogeneity is remarkable. The smallest stock in the F100acc group is still bigger than the largest stock in the F100 group, while the average market capitalisation for the largest size group is 56 times that of the smallest size group.

In terms of the average liquidity level, spread-based variables decrease with the equity size, meaning that larger stocks are more liquid than smaller stocks. The effective spread is narrower than the quoted spread for all three groups, suggesting that hidden orders exist and liquidity demanders might be capable of timing the market. On the contrary, depth measured as a fraction of average daily trading volume seems to indicate that the order book at the top is thinner for larger stocks, probably due to the larger trading volume in those stocks.

The standard deviations of liquidity variables for the F100acc and F100 groups are small, meaning there is not much variation in liquidity between stocks in each of the two groups. However, the large differences in liquidity between stocks in the F250 groups can be inferred from the high standard deviations of liquidity variables. Notably, the maximum value of the quoted spread is

[9] For details of the dataset, please refer to `https://www.eurofidai.org/en/high-frequency-data-bedofih` or `https://www.londonstockexchange.com/products-and-services/reference-data/trade/trade-data.htm`

[10] Time-weighted depth is re-scaled by the $ADVolume$. The $ADVolume$ is the average daily volume traded, measured over the pre-event window.

Table 1: Summary statistics

This table presents the daily values of mean, minimum, maximum and standard deviations for quoted spread, effective spread, depth, turnover, numbers of trades, numbers of non-trading events and numbers of cancellation events. Evaluation period is the pre-event period, which is from 04/01/2011 to 11/02/2011. Missing values are deleted.

		Mean	Min	Max	SD	Unit
F100acc	Market Value	58838.23	32061.80	128015.50	25934.71	Million Pounds
	Qspread	4.71	2.38	8.08	1.22	bps
	Depth	0.17	0.05	0.41	0.08	bps
	Espread	3.56	1.83	6.35	1.02	bps
	Turnover	99.65	34.47	240.60	33.29	%
	No. Trades	8424.70	2461.00	21046.00	3809.85	
	AvrTradeSize	1.32	0.61	2.91	0.48	bps
	No. Non-Trades	66940.98	23176	166777	36575.92	
	No. Cancellations	29054.06	9994	72245	16293.28	
F100	Market Value	7180.73	2408.06	20560.95	4601.80	Million Pounds
	Qspread	10.97	4.73	19.02	2.77	bps
	Depth	0.84	0.16	3.43	0.45	bps
	Espread	8.21	3.62	14.64	2.08	bps
	Turnover	99.78	30.57	300.20	38.60	%
	No. Trades	2269.02	477	10269	1181.19	
	AvrTradeSize	5.23	1.63	15.95	2.58	bps
	No. Non-Trades	17504.90	3876	48850	7176.49	
	No. Cancellations	7764.70	1749	22962	3133.30	
F250	Market Value	1050.98	50.67	2841.17	591.50	Million Pounds
	Qspread	35.43	8.24	217.71	27.25	bps
	Depth	3.12	0.17	50.40	4.32	bps
	Espread	24.38	5.55	186.65	20.49	bps
	Turnover	99.76	5.93	688.60	60.92	%
	No. Trades	597.92	14.00	11981.00	705.71	
	AvrTradeSize	38.99	2.72	461.09	46.03	bps
	No. Non-Trades	5481.50	131	80815	5387.00	
	No. Cancellations	2056.69	49	42883	2193.93	

more than six times the average value, implying firm-specific characteristics may exist.

Market participants are apparently more active in large stocks than mid-cap stocks. On average, there are approximately 2.2 non-trading events (i.e. new quote, order cancellation, or order modification) per second for the F100acc group, 0.57 for the F100 group and 0.18 for the F250 group. Among these events, 43.4% are cancellations for the F100acc group and the rate for the F100 group is about the same (44.4%), but falls to 37.5% for the F250 group. Surprisingly, the maximum values of the number of trades, non-trading events and cancellation events for the F250 are larger than the corresponding values for the F100 group. It seems that market participants are very active in some smaller stocks.

Daily turnover measured as a fraction of average daily trading value is almost identical between three groups and are, respectively, 99.65%, 99.78% and 99.76% for the F100acc, F100 and F250. Daily turnover for individual stock in the pre-event period should be the same as its $ADValue$. Three ratios are below 100%, which is likely caused by the rounding issue. For the F250 group, the large spread between the maximum and minimum turnover values suggests that there are days with an exceptionally small amount of trading for certain stocks and days with an exceptionally large amount of trading for certain stocks. The larger standard deviation also reflects this. The average trade size for the F100acc group is only 0.013% of the $ADValue$ and increases to 0.39 % (thirty-fold) for the F250 group. Re-examining depth, average trade size statistics prove that the order book for the F100acc is no thinner than for the F250 group. As for the number of trades per day, the largest stock is more than three- and fourteen-fold of the F100 and the F250 groups respectively, again suggesting that it is more liquid in the F100acc group.

In general, high activity in large stocks might be a sign of a high participation rate on the part of HFTs. However, there is huge variation in the smaller cap group and it can also be seen that market participants are even more active in certain mid-cap securities than large ones. Therefore, it is very likely that liquidity for mid-cap stocks is also affected by the trading system upgrade.

4 The impacts on liquidity and activity variables at the top of the book

This section examines the effects of the speed-upgrading event on liquidity and activity measures based on trade data and data at the first price level in the book in a time-series binary treatment set-up. Liquidity variables include time-weighted quoted spread, time-weighted depth at the first price level, volume-weighted effective spread. Effective spread focus on the liquidity environment after a trade occurs. It measures the materialised and ex-post trading costs. The daily average effective spread is unlikely to be the same as the average quoted spread for two reasons. First, it mitigates biases caused by trading with hidden orders, which the quoted spread cannot capture. Secondly, it reflects investors' ability to time the market (e.g. Admati and Pfleiderer, 1988). Activity variables including the raw number of trading events for a stock on a given day, average trade size,[11] turnover,[12] capitalization of quoting and cancellation events for a stock on a given day and money volume.[13]

To control for confounding effects stemming from the unobserved time-invariant and stock-specific characteristics, stock-specific fixed effect dummies are included. I also include the following variables to control for market conditions: turnover, 5-minute realised variance,[14], the inverse of the daily closing price, and the natural log of the market capitalisation. Adopting these control variables follows Hendershott et al. (2011). The regression function is represented below:

$$L_{i,t} = \alpha_i^{FE} + \beta D_t + \delta' X_{it} + \epsilon_{i,t}, \tag{1}$$

where α_i^{FE} are individual fixed effects on liquidity or activity variables, L denotes the standard liquidity or activity variables, D_t is the event dummy variable, taking value 0 in the first six weeks of the sample and value 1 from 14^{th} February onwards, X_{it} is a vector of control variables, $\epsilon_{i,t}$ is residual. β reflects the impact of the new trading system on the outcome variable L. Standard errors are double-clustered by stock and day.

Table 2 reports the estimates of the impact of the event on liquidity and variables. For large-cap stocks (i.e. the F100acc and F100 groups), it is noticeable that the quoted spread significantly

[11] The average money-volume of a trade on a given day for a stock, scaled by the $ADValue$ and expressed in the basis point. The $ADValue$ is the average daily value traded, measured over the pre-event window.

[12] The sum of value traded on a given day for a stock, scaled by the $ADValue$ and expressed in percentage.

[13] The sum of value traded on a given day for a stock, expressed in £. It should be consistent with turnover.

[14] $Rvar_{i,d} = 1000 * \sum_{t_{5min}=2}^{M} (\log m_{i,d,t_{5min}} - \log m_{i,d,t_{5min}-1})^2$

increases but the effective spread does not have reaction, implying that the liquidity demanders can time the market even though the liquidity condition for the market deteriorates. This is especially the case for the F100 group as the quantity dimension of liquidity, measured by quoted depth, also deteriorates. In contrast, the price dimension of liquidity for the mid-cap group improves as both quoted spread and effective spread significantly narrowed. Effective spread decreases even more than the quoted spread, again pointing to the fact that liquidity demanders better time the market after the system upgrade.

Table 2: The impact of the enhancement of the trading speed on liquidity

This table presents liquidity and activity variables changes after the system-upgrading event based on the equation 1 Dependent variables are daily measures of liquidity variables at the top of the book, including time-weighted quoted spread, time-weighted quoted depth and volume-weighted effective spread. The model includes stock-fixed effect dummies, event dummy and several control variables. The evaluation period covers 6 weeks prior to and 6 weeks after the event, which is from 04/01/2011 to 31/03/2011. 'TO', 'RV', 'InvPrice', 'lnMV', 'Intercept' respectively denote money-turnover, realised variance, the inverse of the daily closing price, the natural log of market captilisation, and the intercept. *t*-statistics in parentheses are based on standard errors that are double-clustered by stock and day. *, **, and *** respectively denote 10%, 5% and 1% significance levels. Results are in basis points.

	F100acc			F100			F250		
	Qspread	Depth	Espread	Qspread	Depth	Espread	Qspread	Depth	Espread
EventDummy	0.119**	-0.001	0.042	0.547***	-0.062***	0.071	-1.617***	-0.107	-1.833***
	(2.217)	(-0.539)	(1.071)	(6.512)	(-5.904)	(1.177)	(-3.375)	(-1.294)	(-4.697)
TO	-2.477***	-0.085**	-1.281**	-5.131***	-0.220	-2.107**	7.813	-0.040	-8.153**
	(-2.869)	(-2.358)	(-2.021)	(-4.240)	(-1.496)	(-2.198)	(1.367)	(-0.131)	(-1.969)
RV	0.204***	-0.008***	0.163***	0.270***	-0.039***	0.282***	0.446*	-0.017***	0.302**
	(5.152)	(-6.203)	(5.294)	(5.802)	(-5.800)	(9.460)	(1.856)	(-2.734)	(2.212)
InvPrice	-0.488***	0.039***	-0.146**	-0.427***	0.181***	-0.139	-3.471***	0.334***	-1.534***
	(-5.903)	(7.524)	(-2.107)	(-2.758)	(7.981)	(-1.267)	(-4.730)	(6.087)	(-4.600)
lnMV	-257.107*	-4.921	-216.911**	-747.524*	-17.641	-354.424	4327.121***	-133.010	422.501
	(-1.763)	(-1.438)	(-2.300)	(-1.954)	(-0.383)	(-1.230)	(3.683)	(-1.012)	(0.467)
Intercept	32.518***	1.092***	17.955**	56.890***	2.688**	26.769***	-32.396	3.635	78.685**
	(3.380)	(2.726)	(2.544)	(5.162)	(2.018)	(3.077)	(-0.761)	(1.539)	(2.535)
N	488	488	488	1769	1769	1769	2440	2440	2440
R-sq	0.7777	0.8846	0.8113	0.7335	0.7898	0.7254	0.8056	0.7810	0.7509
adj. R-sq	0.7721	0.8817	0.8066	0.7284	0.7858	0.7202	0.8021	0.7770	0.7463

The above observations are complemented by changes in market participants' activities. Table 3 shows that for the most liquid group (i.e. F100acc), the average trade size increases and the total number of trades does not change. This is counter-intuitive as quoted spread for this group is wider after the event. However, as the average trading cost, measured by the effective spread, is not changed, the increased trade size further confirms that liquidity demanders are more astute after the event – they only trade when the market is more liquid. For the F100 group, the average trade size does not have reactions, which is consistent with the unchanged effective spread. However, as liquidity deteriorates in both price and quantity dimensions, the opportunities of trading in a liquid market decreases, resulting in a declined number of trades. Interestingly, for mid-cap stocks, the average trade size declines regardless of the improved liquidity. This is reflected in the reduced effective spread.

According to Menkveld and Zoican (2017), changes in quoted spread depend on a stock's news-to-liquidity-trader ratio. If the ratio is above a threshold, high-frequency market maker (HFM, providing liquidity) benefits more from reduced latency by updating stale quotes faster. On the other hand, if the ratio is below the threshold, high-frequency bandit (HFB, consuming liquidity) benefits more from reduced latency, as it gives them more opportunities to pick off HFM. Thus, the observed changes in quoted spread might be explained by these differences in the news-to-liquidity-traders ratio for different stock groups. Specifically, the news-to-liquidity-traders ratio appears to be relatively low (high) for large-cap (mid-cap) stocks.

As for the activity of the limit order at the top of the book, the aggregated number of submissions, modifications and cancellations amplifies, and the order-to-trade ratio is consequently elevated, indicating liquidity suppliers are more capable to update quotes. Nevertheless, the benefit for quote updating does not contribute to the improvement in liquidity provision for large-cap stocks.

5 The impacts on the informativeness of trades and the relative informativeness of trades and quotes

This section first evaluates the permanent price impacts of trades via the Hasbrouck (1991a) method to establish changes in adverse selection risks to liquidity suppliers, then it assess the relative informativeness of trades and quotes. The ROB dataset specifies the trading direction, so I employ the corresponding identifier directly to sign the trade.

5.1 The impacts on the adverse selection risks

The standard methodology for measuring the relative informativeness of quotes and trades was developed by Hasbrouck (1991a). For details on the method, please refer to Appendix B. Generally speaking, according to the impact durations of trades on prices, the price impact can be classified as permanent, transitory, and instantaneous. The permanent price impact reflects the change in the efficient price resulting from a trade, while the instantaneous price impact

Table 3: The impact of the enhancement of the trading speed on activity

This table presents activity variables changes after the system-upgrading event based on the equation 1. Dependent variables include total number of trades, the average trade size measured in money-value and rescaled by $ADValue$, the total number of non-trades events and order-to-trade ratio. The model includes stock-fixed effect dummies, event dummy and several control variables. The evaluation period covers 6 weeks prior to and 6 weeks after the event, which is from 04/01/2011 to 31/03/2011. 'TO', 'RV', 'InvPrice', 'lnMV', 'Intercept' respectively denote money-turnover, realised variance, the inverse of the daily closing price, the natural log of market captilisation, and the intercept. t-statistics in parentheses are based on standard errors that are double-clustered by stock and day. *, **, and *** respectively denote 10%, 5% and 1% significance levels. Results are in basis points.

		Trades	AvrTradeSize	NonTrades	OTR
F100acc	EventDummy	-123.096	0.036**	8298.804***	1.892***
		(-1.077)	(2.397)	(3.955)	(7.786)
	TO	-7846.854***	0.767***	-1.91e+05***	-8.051***
		(-4.359)	(3.725)	(-4.678)	(-2.653)
	RV	183.573**	-0.029***	6330.245**	0.810***
		(2.000)	(-3.611)	(2.202)	(5.631)
	InvPrice	5761.169***	0.342***	16588.107***	-4.159***
		(20.481)	(13.060)	(4.744)	(-9.894)
	lnMV	-7.54e+05***	11.528	-3.49e+07***	-3058.839***
		(-2.944)	(0.562)	(-5.802)	(-5.630)
	Intercept	89876.663***	-7.369***	2.21e+06***	106.430***
		(4.514)	(-3.226)	(4.873)	(3.153)
	N	488	488	488	488
	R-sq	0.9119	0.9019	0.7420	0.6992
	adj. R-sq	0.9097	0.8995	0.7355	0.6916
F100	EventDummy	-63.512***	-0.085	1049.033***	0.387***
		(-2.970)	(-1.570)	(4.423)	(3.270)
	TO	-1080.332***	2.722***	-1.43e+04***	-2.251
		(-2.892)	(3.176)	(-3.834)	(-1.338)
	RV	26.779*	-0.147***	838.798***	0.348***
		(1.666)	(-5.385)	(4.359)	(5.421)
	InvPrice	1447.132***	1.704***	3905.826***	-3.336***
		(22.158)	(13.021)	(10.579)	(-18.442)
	lnMV	-3.05e+04	65.326	1.08e+06	367.310
		(-0.222)	(0.280)	(0.702)	(0.541)
	Intercept	10216.954***	-19.952**	1.34e+05***	30.022*
		(2.977)	(-2.549)	(3.878)	(1.930)
	N	1769	1769	1769	1760
	R-sq	0.8541	0.8471	0.6715	0.4070
	adj. R-sq	0.8513	0.8442	0.6652	0.3956
F250	EventDummy	0.140	-1.717*	1459.719***	2.924***
		(0.008)	(-1.694)	(7.066)	(3.899)
	TO	1.330	-9.295	-849.793	-3.426
		(0.037)	(-1.108)	(-1.469)	(-0.259)
	RV	-6.360	-0.611***	33.454	0.502**
		(-0.829)	(-3.380)	(0.500)	(2.089)
	InvPrice	268.748***	8.843***	728.731***	-4.644***
		(6.053)	(4.952)	(4.069)	(-4.532)
	lnMV	1.09e+05***	-4214.978*	2.47e+06***	1411.477
		(4.458)	(-1.709)	(6.148)	(0.569)
	Intercept	-86.584	111.559*	733.635	35.705
		(-0.309)	(1.751)	(0.163)	(0.359)
	N	2440	2440	2440	2431
	R-sq	0.7397	0.6982	0.4503	0.2371
	adj. R-sq	0.7349	0.6927	0.4402	0.2230

is the change in the observed price immediately after a trade. The transitory price impact is the difference between the two. The three types of price impacts are respectively driven by information held by liquidity demanders, inventory control managed by liquidity suppliers, and the aggregation of the aforementioned two factors and order processing costs.

Table 4 presents the mean and quartiles of three types of price impact and 5-minute realised variance across sample firms and days before and after the event. The permanent price impact, which measures the cumulative impact of one unit trade (innovation) on price, increases for all three groups at all quartiles, implying that trades contain more private information after the system upgrade. Interestingly, the magnitude of the permanent price impact is greater for the larger and more liquid group, suggesting that informed traders tend to use market orders for these stocks. This finding contradicts the conventional view that information asymmetry is stronger for smaller firms, leading to higher price impact of trades.
In contrast to the permanent price impact, the instantaneous price impact generally decreases slightly after the upgrade, resulting in a lower transitory price impact. Furthermore, Table 4 shows that the instantaneous price impact is lower than the permanent price impact for mid-cap stocks before the upgrade and for all groups after the upgrade. This is surprising as the transitory price impact, which is the exceeded value of the instantaneous impact over the permanent impact, is theoretically greater than zero, given that it reflects inventory management costs.

Comparing the three groups, the transitory price impact increases with market capitalization and liquidity before the event. However, after the event, the value of the transitory price impact for the most liquid group is lower than that for the F100 group. This implies that the upgrade had a greater impact on reducing the transitory price impact for the more liquid stocks.

In Yueshen (2021), two sources generating negative transitory price impact in a modern limit order market are discussed. One is computers' limited processing capacity. The second, supported by his theoretical model, is the lack of competition between liquidity providers, resulting in stale quotes in the market. Hence, the reduced transitory price impact implies a decline in competitiveness among liquidity suppliers. To test the change in transitory price impact, a stock fixed-effect panel regression with control variables is conducted. In particular, the permanent price impact is added to the right-hand side of the transitory price impact regression because Yueshen (2021)'s model suggests that the transitory price impact is negatively related to the

Table 4: Summary statistics of the three types of price impact parameters

This table reports the summary statistics of the permanent, instantaneous, and transitory price impacts (denoted by 'pi_perm','pi_inst', and 'pi_trans' respectively) before and after the system-upgrading event. The permanent and instantaneous price impacts are estimated over a trading day and are obtained via the Hasbrouck (1991a) method. The transitory price impact is the difference between the instantaneous and the permanent price impact. 'RV' is the 5-minute realised variance represented in basis point. 'p25', 'p50', and 'p75' are values at the 25%, 50% and 75% percentiles respectively. The pre-event period covers 6 weeks before 14/02/2022 and the post-event period covers 6 weeks since 14/02/2022.

		Pre-event				Post-event			
	Variable	Mean	p25	p50	p75	Mean	p25	p50	p75
F100acc	pi_perm	0.393	0.186	0.309	0.484	0.546	0.337	0.449	0.663
	pi_inst	0.470	0.295	0.401	0.599	0.442	0.289	0.384	0.573
	pi_trans	0.077	-0.040	0.069	0.166	-0.104	-0.158	-0.072	-0.005
F100	pi_perm	0.310	0.158	0.264	0.424	0.350	0.209	0.313	0.447
	pi_inst	0.318	0.190	0.295	0.411	0.275	0.173	0.261	0.365
	pi_trans	0.009	-0.089	0.008	0.111	-0.076	-0.135	-0.058	-0.004
F250	pi_perm	0.271	0.125	0.218	0.363	0.325	0.145	0.258	0.422
	pi_inst	0.194	0.108	0.165	0.254	0.192	0.106	0.169	0.244
	pi_trans	-0.077	-0.144	-0.054	0.009	-0.133	-0.188	-0.090	-0.026

permanent price impact. By fixing the permanent price impact, the change in competitiveness can be manifested by the coefficient of the event dummy variable. The regression estimate supports the reaction of the permanent price impact mentioned above. As for the transitory price impact, the coefficient of the event dummy variable is still significantly negative, indicating a reduction in competitiveness among liquidity providers.

Yueshen (2021)'s model also predicts that observed price volatility is positively correlated with competition, a relationship which is also supported by his empirical findings. Therefore, if the event indeed reduces the competitiveness of liquidity suppliers, it should have a negative impact on realised variance. To test this hypothesis, I use 5-minute realised variance as the dependent variable and include the same explanatory variables as in equation 1 (except 'RV') and permanent and transitory price impacts on the right-hand side of the equation.

However, the results show that the event does not have a significant impact on realised variance. There are a few possible explanations for this outcome. Firstly, the 5-minute realised variance is a good proxy for the *fundamental* return volatility, which is less related to market microstructure frictions, as demonstrated in previous studies such as Andersen et al. (2001) and Bandi and Russell (2006). The biases induced by competition thus may not be significant. Secondly, even if the 5-minute realised variance contains pricing errors, as specified by equation 23 in Yueshen

(2021), and the change in efficient price variance is offset by the change in monopolistic midquote variance, the variations of liquidity providers' private values (i.e., w_k in Yueshen (2021), reflecting inventory costs, sentiment, risk aversion, and/or disagreement) are not fully controlled. It is possible that the variance of w_k increases after the event, which could mitigate any impact on realised variance. Therefore, it is plausible that the Exchange system upgrade reduces the competitiveness of liquidity suppliers and results in the variance of liquidity providers' private values. To address this issue, one possible solution is to match the sample firms to similar firms that were not affected by the event. However, as the improvement in the trading system applies to all stocks on the LSE, it is impossible to find comparable firms in the UK market.

Table 5: The impact of the enhancement of the trading speed on the price impact parameters and realised variance

This table presents changes in the permanent and instantaneous price impacts after the system-upgrading event based on the equation 1. Dependent variables are the permanent and transitory price impacts (denoted by 'pi_perm' and 'pi_trans' respectively) over a trading day obtained via the Hasbrouck (1991a) method. The model includes stock-fixed effect dummies, event dummy and several control variables. The evaluation period covers 6 weeks prior to and 6 weeks after the event, which is from 04/01/2011 to 31/03/2011. 'TO', 'RV', 'InvPrice', 'lnMV', 'Intercept' respectively denote money-turnover, 5-minute realised variance, the inverse of the daily closing price, the natural log of market captilisation, and the intercept. *, **, and *** respectively denote 10%, 5% and 1% significance levels and standard errors are double-clustered by stock and day. Results are in basis points.

	F100acc			F100			F250		
	pi_perm	pi_trans	RV	pi_perm	pi_trans	RV	pi_perm	pi_trans	RV
EventDummy	0.135**	-0.068**	0.017	0.055***	-0.054***	0.019	0.067***	-0.016**	-0.348
	(2.810)	(-2.722)	(0.108)	(3.829)	(-6.756)	(0.201)	(3.011)	(-2.060)	(-0.743)
lnMV	0.230	0.056	-4.892***	0.157	-0.053	-3.278*	-0.014	0.016***	0.491
	(0.590)	(0.376)	(-12.526)	(0.906)	(-0.517)	(-2.000)	(-1.293)	(4.375)	(0.532)
RV	0.058***	0.026		0.031***	0.006*		0.006***	0.001**	
	(5.392)	(1.544)		(7.655)	(1.889)		(3.062)	(2.088)	
TO	-0.286***	-0.163*	1.911***	-0.175***	-0.039***	1.751***	-0.068***	-0.009**	4.135*
	(-5.441)	(-2.202)	(3.521)	(-8.690)	(-3.430)	(8.177)	(-3.095)	(-2.306)	(1.876)
InvPrice	52.634	58.141***	-569.664***	-0.673	4.930	184.753	-24.523	0.290	1093.733*
	(1.191)	(4.990)	(-8.491)	(-0.014)	(0.166)	(0.455)	(-0.946)	(0.029)	(1.712)
pi_perm		-0.834***	1.279*		-0.690***	2.009***		-0.714***	8.872***
		(-7.391)	(2.117)		(-24.511)	(4.514)		(-25.852)	(2.974)
pi_transi			0.521			0.901**			6.416***
			(1.632)			(2.530)			(2.834)
Intercept	-2.062	-0.227	54.020***	-0.938	0.702	27.829*	0.506***	0.016	-10.374
	(-0.472)	(-0.139)	(11.413)	(-0.599)	(0.748)	(1.899)	(3.284)	(0.754)	(-1.127)
N	472	472	472	1702	1702	1702	2292	2292	2292
R-sq	0.5142	0.5900	0.5755	0.3383	0.6928	0.5496	0.2822	0.8473	0.4383
adj. R-sq	0.5015	0.5783	0.5634	0.3252	0.6865	0.5405	0.2684	0.8443	0.4273

5.2 The impacts on the relative informativeness of quotes and trades

The permanent price impact measure used in the previous section reflects the ultimate impact of one unit trade innovation on price. This section further takes into account the *magnitude* of the trade innovations (i.e., trade intensity) and evaluates the relative informativeness between trades and quotes. The model is due to Hasbrouck (1991b).

Table 6 presents a summary of information shares for trades and quotes during the pre- and post-event periods. The results reveal that the average information share of trades after the event is 1.75, 1.24, and 1.33 times larger than the pre-event period for the F100acc, F100, and F250 groups, respectively. These results support previous findings indicating that the event increases the informativeness of trades. Additionally, the information share of trades for large-cap stocks increases from below 0.5 before the event to above 0.5 after the event, suggesting that trades dominate the price discovery process following the event.

Taken together, the evidence from the previous two subsections suggests that the event is likely to have a significant impact on the market. Informed traders appear to switch limit orders to market orders, and the competition among liquidity suppliers decreases as a result.

Table 6: Summary statistics of information shares of trades and quotes

This table reports the summary statistics of information shares of trades and quotes (denoted by 'IS_trades' and 'IS_quotes' respectively) before and after the system-upgrading event. The information shares are estimated over a trading day and are obtained via the Hasbrouck (1995) method. 'p25', 'p50', and 'p75' are values at the 25%, 50% and 75% percentiles respectively. The pre-event period covers 6 weeks before 14/02/2022 and the post-event period covers 6 weeks since 14/02/2022.

		Pre-event				Post-event			
	Variable	Mean	p25	p50	p75	Mean	p25	p50	p75
F100acc	IS_trades	0.300	0.168	0.303	0.420	0.526	0.480	0.532	0.584
	IS_qutoes	0.700	0.580	0.697	0.832	0.474	0.416	0.468	0.520
F100	IS_trades	0.440	0.323	0.459	0.567	0.559	0.509	0.574	0.628
	IS_qutoes	0.560	0.433	0.541	0.677	0.441	0.372	0.426	0.491
F250	IS_trades	0.392	0.267	0.394	0.520	0.435	0.327	0.448	0.561
	IS_qutoes	0.608	0.480	0.606	0.733	0.565	0.439	0.552	0.673

6 Incorporating the order book information beyond the best price level

The previous section examines the change in the relative informativeness of trades and quotes at the top of the book. This section focuses on the impact of the speed enhancement on the informativeness of liquidity providers. The informativeness of liquidity providers is inferred by the imbalance of the slopes between the buy and sell sides of the market. Hence, this section first introduces the measure of the slope of the LOB.

6.1 A theoretical model of the slope

The key structure of the theoretical model is based on the value trader profit function in Seppi (1997). Unlike Glosten (1994), who endogenized the demand side of liquidity, Sandås (2001) simplified the model by assuming exponentially distributed market order sizes. In addition, Sandås (2001) incorporated discrete prices and time priority rules discussed in Seppi (1997) into Glosten (1994)'s LOB model and derived the linear relationship between quotes and cumulative depth. Therefore, the coefficient of the cumulative depth in the linear function is the slope of the LOB, which has a crucial economic meaning, i.e., the permanent price impact.

However, the linear relationship greatly depends on two assumptions. The first assumption, as mentioned earlier, is that the market order size has an exponential distribution[15]

$$f(q) = \frac{1}{2}\theta e^{-\theta|q|}, \tag{2}$$

where θ is the expected market order quantity and q is the market order size.

The second assumption is that market makers update the expected value of the asset following the 'linear updating rule' proposed in Kyle (1985):[16]

$$E(\mu_{t+1}|\mu_t, q_t) = \mu_t + \lambda q_t \tag{3}$$

where μ_t is the efficient price of the asset and q_t is the market order size at time t.

Glosten (1994) and Sandås (2001) argued that the marginal share at each price level should earn zero profit, which ensures the 'no entry and no exit' condition.[17] Thus, based on this break-

[15] Gabaix et al. (2005) show that large trading volumes follow a power-law distribution. However, for normalized volumes, Farmer and Lillo (2004) could not find clear evidence for power-law tails. Additionally, Kyle and Obizhaeva (2016) found that bet size (not order size) follows a log-normal distribution. Nevertheless, as tested empirically by Frey and Grammig (2006), the distribution of market orders does not significantly affect the model specification. Therefore, I follow Sandås (2001) in assuming that the size of the market order is exponentially distributed.

[16] As is proved by Kyle (1985) and Back (1992), the unique linear pricing rule exists as long as the prior distribution of the fundamental value of the asset is Gaussian.

[17] Frey and Grammig (2006) imposed an 'average zero-profit condition' on the LOB instead of a marginal zero-profit condition. The 'average zero-profit condition' is reasonable when a liquidity overshooting event occurs (Yueshen, 2014). The overshooting event exists due to queuing uncertainty caused by low-latency technology. When reacting to information, liquidity providers are uncertain about their position and supply more shares than the stable level, resulting in negative profit for the marginal share. At the same time, FTSE 250 stocks are

even condition of the marginal order at each price level, the liquidity provider who submits the marginal unit order expects zero profit:

$$\Pi^k(Y_t^k) = P(Y_t^k)[A_t^k - E(\mu_{t+1}|q_t \geq Y_t^k)] \equiv 0, \tag{4}$$

where k is the price level, $\Pi^k(Y_t^k)$, A_t^k and Y_t^k respectively represent the expected profits, ask price at the k^{th} level, the cumulative depth at the ask price A_t^k and $P(Y_t^k)$ is the probability of execution of that marginal share which follows:

$$P(Y_t^k) \equiv Pr(q_t \geq Y_t^k) = 1 - F(Y_t^k) \tag{5}$$

If tick size is zero, using the law of iterated expectations and the linear updating rule, we have

$$\begin{aligned} A_t(Y_t) &= E(\mu_{t+1}|q_t \geq Y_t) \\ &= E(E(\mu_{t+1}|q_t = Y_t)|q_t \geq Y_t) \\ &= \mu_t + \lambda E(q_t|q_t \geq Y_t) \\ &= \mu_t + \lambda \frac{\frac{1}{2}\int_{Y_t}^{\infty} q_t \theta e^{-\theta q_t} \mathrm{d}q_t}{\frac{1}{2}\int_{Y_t}^{\infty} \theta e^{-\theta q_t} \mathrm{d}q_t} \\ &= \mu_t + \lambda \frac{e^{-\theta Y_t}[Y_t + \frac{1}{\theta}]}{e^{-\theta Y_t}} \\ &= \mu_t + \lambda Y_t + \frac{\lambda}{\theta}. \end{aligned} \tag{6}$$

In Equation 6, the efficient price μ_t is unobservable. I therefore use the midquote of the best bid and ask price immediately before the trade to proxy for the efficient price.[18] Thus, the equation becomes

$$\begin{aligned} A_t(Y_t) &= mq_t + \lambda Y_t + \frac{\lambda}{\theta} \\ S_t(Y_t) &= \lambda Y_t + \frac{\lambda}{\theta}, \end{aligned} \tag{7}$$

traded at a relatively lower market velocity (Kyle and Obizhaeva, 2016). It is reasonable to assume that liquidity providers are quick enough to react to the marginal zero-profit situation.

[18] Another way to eliminate μ is by calculating the difference of two price equations at different price levels. However, there are two drawbacks. The first is that, for each snapshot containing five price levels, there will be 10 permutations to calculate the difference. This will increase data size and, therefore, the computational burden. The second is that, in reality, price does not completely follow the model. In other words, there is an error term in the price equation. 10 permutations will lead the best price to be directly subtracted by four times and indirectly subtracted by six times. So the estimation will be highly sensitive to prices on the inside. If the best price on one side is greatly mispriced, then the error term is less likely to be IID distributed with zero means, while using the midquote to proxy for the efficient price has two benefits. The first is that, if one side of the best price is greatly mispriced, then the mispricing can be hedged by the price at the other side. The second benefit is that parameter θ can be identified.

where $S_t = A_t - mq_t$. The left-hand-side variable S_t is the difference between quotes and the midquote on one side of the book (the 'one-side spread'). A_t and mq_t are respectively the ask at a certain level and the midquote at time t. To evaluate the average slope in a trading day, it is important to subtract the midquote. While Kim et al. (2004), Dierker et al. (2016), and Amaya et al. (2018) also used regression to obtain the slopes of the LOB, they measure the slope at each point in time and therefore do not subtract the midquote. However, excluding the effect of the fundamental value of the asset, which may change throughout a day, is important in this paper.[19]

6.2 The estimation of the slope

Using the order-level data, the best five price levels of the LOB on each side are reconstructed. Five pairs of prices and the corresponding cumulative depth formed five pairs observations at each point in time on each side of the book. For two sides of the book, I conducted the following OLS regressions:

$$S^a_{i,t} = c^a_i + \lambda^a_i Y^a_{i,t} + \epsilon^a_{i,t}, \tag{8}$$

and

$$S^b_{i,t} = c^b_i + \lambda^b_i Y^b_{i,t} + \epsilon^b_{i,t}, \tag{9}$$

where i denotes the individual stock, t denotes intradaily market events (i.e. posting, modifying, and cancelling quotes and executions), the superscripts a and b respectively represent ask and bid side, c^a and c^b are constants, $Y_{i,t}$ is cumulative depth, rescaled by the exchange minimum size (EMS),[20] λ^a and λ^b are slopes for the ask- and bid-side of the market respectively, and ϵ^a and ϵ^b are residuals. In the estimation, I transformed quotes and midquote to the natural log value. Thus, $S^a_{i,t} = \ln(A_{i,t}) - \ln(midquote_{i,t})$. Please refer to Figure 1 for a diagram of the slopes.

Insert Figure 1 here.

[19] An advantage of subtracting the midquote instead of the true efficient price is removing the inventory effects. The inventory imbalance induces the midquote to deviate from the efficient price, which is called the price pressures. The inventory model also suggests that quotes symmetrically distribute around the midquote.

[20] EMS is defined by the Exchange as the minimum quote size for its registered market-makers. It is roughly 1% of the average daily traded value devided by the average price and is downloaded from the LSE website on 01/02/2016.

6.3 Summary statistics of the slope of the LOB

Table 7 presents the mean, standard deviation, and quartiles of the slope of the two sides of the book. Generally speaking, the magnitudes of the slope of the two sides of the market in each group-period are similar. Comparing the values in the two periods, it is noticeable that the mean, median, and standard deviations of the slopes for the three groups are much higher in the pre-event than the post-event period. If the slope measures the permanent price impact of trades, then the changes in the slope shown in this table contradict the changes in the permanent price impact analysed in Section 5.

Table 7: Summary statistics of the slope of the LOB

This table reports the summary statistics of the slopes of two sides of the LOB (denoted by 'BidSlope' and 'AskSlope') across stocks and days before and after the system-upgrading event. The slopes are estimated over a trading day and are obtained via equation 7. 'p25', 'p50', and 'p75' are values at the 25%, 50% and 75% percentiles respectively. The pre-event period covers 6 weeks before 14/02/2022 and the post-event period covers 6 weeks since 14/02/2022.

		Pre-event					Post-event				
		Mean	SD	p25	p50	p75	Mean	SD	p25	p50	p75
F100acc	BidSlope	0.666	2.826	0.014	0.137	0.471	0.090	0.071	0.060	0.083	0.118
	AskSlope	0.630	1.673	0.030	0.110	0.468	0.098	0.061	0.061	0.091	0.135
F100	BidSlope	0.175	0.764	0.033	0.055	0.091	0.042	0.033	0.031	0.044	0.058
	AskSlope	0.136	0.473	0.033	0.056	0.093	0.044	0.031	0.032	0.045	0.059
F250	BidSlope	0.144	0.248	0.055	0.092	0.156	0.095	0.081	0.043	0.077	0.122
	AskSlope	0.159	0.298	0.057	0.095	0.158	0.102	0.093	0.048	0.081	0.125

The the average slope of the LOB for the F100acc group in the pre-event period is more than three times as high as the average slope for other two groups in the same period. However, after the trading system being upgraded, the slope for the F100acc group drops sharply and the average value is almost the same as the value of the F250 group in the same period. The mean and median slope for the F100 group is the lowest among three groups. Naes and Skjeltorp (2006) argued that the slope of the LOB proxies for the disagreement among investors. The reduction in three groups indicates that the private value of investors are less heterogeneous. Comparing three groups in two periods, another pattern is that the higher the mean slope, the higher the standard deviation.

The mean slope of the LOB for the F100acc group during the pre-event period is more than three times higher than the average slope for the other two groups during the same period. However, following the upgrade of the trading system, the slope for the F100acc group experienced a sharp decline and the average value became almost equivalent to that of the F250 group during the same period. Notably, the mean and median slope for the F100 group is the lowest among the three groups. As suggested by Naes and Skjeltorp (2006), the slope of the LOB can be viewed as a proxy for the disagreement among investors. Thus, the reduction in slope values across the three groups implies that the private values of investors are now less heterogeneous. Furthermore, a comparison of the three groups between the two periods reveals a distinct pattern whereby the higher the mean slope, the higher the standard deviation of the slopes during the respective periods.

Table 8 reports the summary statistics of correlations between the slope and the permanent and instantaneous price impacts for three groups. Sandås (2001)'s model suggests that slope is the permanent price impact, which implies that the correlation coefficient between them is equal to 1. However, the empirical results do not suggest so. Specifically, for the F100acc and F100 groups, the slope and the permanent price impact are negatively related, contradicting to Sandås (2001) model. For the F250 group, the slopes are positively correlated with the permanent price impact, but the correlation coefficients are relatively low. Additionally, the slopes appear to be more closely related to the instantaneous price impact than the permanent price impact.[21] Therefore, it can be concluded that the slope does not accurately measure the permanent price impact, but it is relatively closer to measuring the instantaneous price impact.

Table 7 presents similar distributions for the bid-side and ask-side slopes, but their correlations for large-cap stocks, shown in Table 8, are negatively related, implying that a higher bid-side slope is associated with a lower ask-side slope. These findings align with Dierker et al. (2016)'s theory that the slope of the two sides of the market moves in opposite directions in the short run due to the 'switching effect' (i.e., switching between buy and sell) but in the same direction in the long run due to shifts in investors' information heterogeneity and risk aversions. Although the bid-side and ask-side slopes exhibit a positive relationship for the mid-cap group, the correlation coefficient is very small. Therefore, the following subsection of this paper discusses the order book imbalance.

[21] Weber and Rosenow (2005) and Rosu (2009) argued the slope of the LOB corresponds to to instantaneous price impact. However, the results presented in this paper do not support this argument either, as the correlation coefficients are still less than 0.5.

Table 8: Correlations between the slope of the LOB and permanent price impact

This table reports summary statistics of pair-wise correlations between the slope of the LOB and the permanent and instantaneous price impacts. The mean of the correlation is the average correlation across stocks and days for each group. The standard deviation and quartiles are computed analogously. ‘BidPerm’, ‘AskPerm’, ‘BidInstan’, ‘AskInstan’, ‘BidAsk’ and ‘PermInstan’ respectively represent correlations between bid slope and permanent price impact, bid slope and instantaneous price impact, ask slope and permanent price impact, ask slope and instantaneous price impact, bid slope and ask slopes, and permanent and instantaneous price impact. ‘p25’, ‘p50’, and ‘p75’ are values at the 25%, 50% and 75% percentiles respectively. The pre-event period covers 6 weeks before 14/02/2022 and the post-event period covers 6 weeks since 14/02/2022.

		Mean	SD	p25	p50	p75
F100acc	BidPerm	-0.163	0.117	-0.255	-0.185	-0.123
	AskPerm	-0.164	0.097	-0.219	-0.154	-0.119
	BidInstan	-0.098	0.094	-0.180	-0.085	-0.031
	AskInstan	-0.081	0.072	-0.151	-0.096	-0.011
	BidAsk	-0.086	0.071	-0.139	-0.086	-0.052
	PermInstan	0.264	0.262	0.041	0.285	0.456
F100	BidPerm	-0.059	0.141	-0.158	-0.069	0.006
	AskPerm	-0.090	0.157	-0.222	-0.122	-0.006
	BidInstan	0.069	0.177	-0.060	0.031	0.209
	AskInstan	0.097	0.156	-0.023	0.095	0.228
	BidAsk	-0.067	0.143	-0.183	-0.084	0.000
	PermInstan	0.554	0.158	0.404	0.567	0.684
F250	BidPerm	0.107	0.187	-0.024	0.098	0.280
	AskPerm	0.117	0.198	-0.011	0.157	0.263
	BidInstan	0.201	0.172	0.125	0.181	0.298
	AskInstan	0.222	0.169	0.149	0.234	0.288
	BidAsk	0.113	0.229	-0.052	0.050	0.233
	PermInstan	0.668	0.139	0.631	0.673	0.787

6.4 The imbalance between the ask-side and bid-side slopes

The impact parameter λ has traditionally been assumed to be identical for both buy and sell market orders, as suggested by Sandås (2001). This is based on the assumption that liquidity providers are uninformed and thus rely on liquidity demanders to acquire information. However, recent empirical studies such as those conducted by Kraus and Stoll (1972), Chan and Lakonishok (1993), Gemmill (1996), and Escribano and Pascual (2006) found evidence that challenges the symmetric price impact of the buyer- and seller-initiated trades. Specifically, these studies have shown that the price impact of a buy order is typically higher than that of a comparable sell order, contradicting the previously accepted notion. On the other hand, studies such as those carried out by Keim and Madhavan (1996) and Bikker et al. (2007) found that the price impact of a sell order is more significant. Therefore, it is reasonable to argue that the traditional assumption of identical λ for buy and sell market orders is not well-supported by empirical evidence.

Another possible interpretation of the LOB slope, as proposed by Dierker et al. (2016), emphasises the asymmetry between the bid and ask side slopes (Appendix A, the proof of proposition 1). They argue that the slope of the LOB reflects the private valuations of traders and determines the aggregate elasticities of supply and demand schedules. Their model shows that the bid-side and ask-side slopes would be unequal unless liquidity providers are uninformed and quotes are symmetrically distributed on both sides of the market. This asymmetry indicates the aggregate trading intention of liquidity providers and highlights the importance of considering their informational advantage.

To test whether liquidity providers are informed, the paper examines the order book imbalance and its link to daily returns. If the ask-side slope is greater than the bid-side slope, indicating that liquidity providers are demanding more, then an increase in price suggests that they possess superior information regarding price movements. Conversely, a decrease in price when the ask-side slope is greater implies that liquidity providers are less informed. The imbalance between the bid-side and ask-side slopes provides further evidence of liquidity providers' informational advantage. The imbalance between two slopes are specified below:

$$OBIB = \frac{AskSlope - BidSlope}{AskSlope + BidSlope}, \tag{10}$$

where $OBIB$, *AskSlope* and *BidSlope* respectively denote the order book imbalance, the slope of the ask-side market and the slope of the bid-side market. $OBIB$ lies between (-1,1). The positive (negative) value of the $OBIB$ indicates the bigger demand (supply) elasticity of liquidity providers relative to the supply (demand) elasticity. If $OBIB$ equals to zero, then the book is balanced (i.e. the demand elasticity of liquidity providers equals to the supply elasticity).

7 The impacts on the informativeness of liquidity providers in the LOB

The informativeness of liquidity providers can be evaluated by examining their information share relative to that of liquidity demanders. Section 5.2 demonstrates that liquidity providers have a lower information share, as reflected in the lower information share of quotes. However, this analysis does not account for the information content behind the best quotes in the LOB, which may be a limitation. To address this, previous literature has utilised multivariate time series models, such as structural vector autoregressive (SVAR) or vector error correction (VEC) systems, which incorporate the information behind the best quotes or all orders in the model. Some examples of such literature include Pascual and Veredas (2010), Hautsch and Huang (2012), Fleming et al. (2018), and Brogaard et al. (2018).

In this study, I depart from the multivariate time series approach and instead examine the relationship between $OBIB$ and contemporaneous price movements. The purpose of this approach is to assess the average likelihood of informed liquidity providers in the LOB. A balanced book indicates that liquidity providers are uninformed and act as traditional dealers by posting symmetric quotes on both sides of the market. However, an unbalanced book suggests that liquidity providers have private values that differ from the current price, indicating the likelihood of informed liquidity providers.

The dependent variable in this regression is the price movement, measured by the first difference of the natural log of daily closing price. The independent variables consist of a dummy variable identifying the post-event period, order book imbalance ($OBIB$), order imbalance measured in the number of shares (OIB) normalised by the $ADValue$ over the pre-event period, the interaction of the event dummy and $OBIB$, the interaction of the event dummy and OIB, and control variables used before. Additionally, control variables for liquidity (time-weighted quoted spread) and autocorrelations in returns (lagged log return) are included.

The order imbalance variable is the net demand of market orders, aiming to isolate the impact of aggressive orders on price from the impact of order book imbalance. The regression equation is specified as follows:

$$R_{i,t} = \alpha_i^{FE} + \beta_1 D_t + \beta_2 OBIB_{i,t} + \beta_3 OIB_{i,t} + \gamma_1 D_t \times OBIB_{i,t} + \gamma_2 D_t \times OIB_{i,t} + \delta' X_{i,t} + \epsilon_{i,t}, \quad (11)$$

where α_i^{FE} represents individual fixed effects on log returns, $R_{i,t}$ denotes the first difference of the natural log of the daily closing price without trimming, D_t is the event dummy variable, taking the value 0 in the first six weeks of the sample and value 1 from the 14^{th} of February onwards, $OBIB$ and OIB are order book imbalance and order imbalance, respectively, $X_{i,t}$ is a vector of control variables, and $\epsilon_{i,t}$ is the residual. As return is computed based on the price at the end of the day, the coefficients could be interpreted as the causal impacts.

The three β coefficients reflect the impacts of the new trading system, the order book imbalance, and the order imbalance on the daily price movement. The γs are the coefficients of the two interaction terms, reflecting the changes in the relationship between price movements and order book imbalance and the relationship between price movements and order imbalance. Standard errors are double-clustered by stock and day.

Table 9 reports the results of the regression. Columns 2-4 shows that $OBIB$, reflecting the buying pressures of liquidity providers, has a positive impact on daily return. The effects are significant even excluding the effects of liquidity demanders' buying pressure measured by OIB, suggesting liquidity providers in the book on average are informed about price movements. Moreover, the impact is larger for smaller stocks, signalling price movement is more sensitive to the order book imbalance for smaller stocks. Consistent with previous literature, OIB has a positive impact on price movement, implying liquidity demanders on average are also informed about price movements.

The impact of $OBIB$ on returns is significantly reduced by the speed-upgrading event for the F100 and F250 groups. The interaction between $OBIB$ and the event dummy has a negative

Table 9: The effects of book imbalance and slopes on price movements

This table shows the relationship between the book imbalance and price movements in columns 2-4 and the relationship between the slopes and price movements in columns 5-7 based on the regression model 11 and model 12. The dependent variable is the first difference of the natural log of daily closing price. For model 11, independent variables are $OBIB$, OIB, the interaction of $OBIB$ and the event dummy ('Event×$OBIB$'), the interaction of OIB and the event dummy ('Event×OIB'), the stock-fixed effect dummies, the event dummy, and several control variables. OIB is the imbalance of the daily trading shares normalised by the $ADVolume$ in the pre-event period. For model 12, independent variables are the bid-side slope ('$BidSlope$'), the ask-side slope ('$AskSlope$'), OIB, the interaction of the bid-side slope and the event dummy ('Event×$BidSlope$'), the interaction of the ask-side slope and the event dummy ('Event×$AskSlope$'), the interaction of OIB and the event dummy ('Event× OIB'), the stock-fixed effect dummies, the event dummy, and several control variables. The evaluation period covers 6 weeks prior to and 6 weeks after the event, which is from 04/01/2011 to 31/03/2011. 'L.Return', 'TO', 'RV', 'InvPrice', 'lnMV', 'Intercept' respectively denote the lagged log return, money-turnover, realised variance, the inverse of the daily closing price, the natural log of market captilisation, and the intercept. *, **, and *** respectively denote 10%, 5% and 1% significance levels and standard errors are double-clustered by stock and day.

	F100acc	F100	F250	F100acc	F100	F250
$OBIB$	0.003*	0.005***	0.008***			
	(2.080)	(2.946)	(6.454)			
$BidSlope$				-0.001	-0.003**	-0.008
				(-1.581)	(-2.154)	(-1.652)
$AskSlope$				0.002**	0.008***	0.011***
				(2.456)	(5.881)	(7.428)
OIB	0.032**	0.025***	0.013***	0.037***	0.026***	0.013***
	(2.621)	(5.911)	(5.328)	(3.614)	(4.775)	(5.139)
Event $\times OBIB$	-0.001	-0.014***	-0.008***			
	(-0.241)	(-5.808)	(-4.957)			
Event $\times BidSlope$				-0.007	0.003	-0.007
				(-0.564)	(0.064)	(-0.552)
Event $\times AskSlope$				-0.006	-0.069*	-0.028***
				(-0.436)	(-1.977)	(-3.447)
Event $\times OIB$	0.014	0.006	0.001	0.007	0.006	0.001
	(0.876)	(1.070)	(0.151)	(0.477)	(0.933)	(0.291)
EventDummy	0.002	-0.002	0.000	0.004	0.001	0.004
	(0.714)	(-0.889)	(0.152)	(1.357)	(0.539)	(1.530)
L.Return	-0.040	-0.048	-0.088**	-0.035	-0.063	-0.092***
	(-0.753)	(-1.092)	(-2.706)	(-0.654)	(-1.459)	(-2.984)
lnMV	0.064***	0.069***	0.003	0.065***	0.073***	0.002
	(4.261)	(4.540)	(1.356)	(4.034)	(4.587)	(1.329)
RV	-6.091	5.856	-16.929***	-7.393	5.052	-16.772***
	(-0.789)	(0.637)	(-7.310)	(-0.817)	(0.542)	(-7.291)
TO	-0.002	0.002	-0.001	-0.002	0.001	-0.001
	(-0.557)	(1.163)	(-0.630)	(-0.668)	(0.759)	(-0.993)
InvPrice	-0.408	0.760	-9.533***	-1.586	-0.427	-9.802***
	(-0.523)	(0.252)	(-3.780)	(-1.447)	(-0.174)	(-3.776)
QS	-0.084	0.024	0.024***	-0.053	0.025	0.024***
	(-0.919)	(0.435)	(4.099)	(-0.516)	(0.450)	(4.161)
Intercept	-0.688***	-0.608***	0.003	-0.700***	-0.642***	0.018
	(-4.284)	(-4.509)	(0.150)	(-4.004)	(-4.538)	(1.128)
N	376	1356	1872	376	1356	1872
R-sq	0.2596	0.2250	0.4442	0.2497	0.2208	0.4720
adj. R-sq	0.2222	0.2020	0.4290	0.2075	0.1965	0.4569

effect on the price movement for the F100 group. This indicates that the book imbalance has less power to move the price, and even has a negative impact on it, suggesting that liquidity providers are less informed about price movement for these groups. For the F250 group, the event drives down the impact of $OBIB$ to zero, indicating that the book imbalance is not likely to have an impact on price movement after the system update. For these two groups, the reduction in the impact of $OBIB$ does not contribute to the increase in the impact of OIB. Therefore, liquidity providers become less informed about the price movement, but liquidity demanders' price informativeness on average remains the same. For the most liquid group (i.e. F100acc), the effects of liquidity supply and demand sides are unaltered.

The reaction of $OBIB$ and OIB for F100acc may seem to be inconsistent with the analyses of price impact and information shares in Section 5. However, Geottler et al. (2009) have demonstrated that the depth at the best quotes and away from the best quotes provides opposite information. In particular, the depth at the best ask (bid) suggests that the current price is too high (low), while the depth away from the best ask (bid) suggests that the current price is too low (high). Consequently, quotes away from the best quotes for this group are more informative about the fundamental value of the asset, and hence the future price.

Table 13 displays supplementary regression analyses. Each stock group in the table contains three columns that correspond to the results obtained after removing different sets of explanatory variables. Specifically, the first column removes $OBIB$-related variables, the second column removes both $OBIB$- and OIB-related variables, while the third column removes the event dummy variable on top of the variables removed in the second column. Comparison of the R^2 and adjusted R^2 in Table 9 and Table 9 indicates that the $OBIB$-related variables account for nearly half of the variations in price movements among all independent variables in Equation 11 for the F100acc group. However, the explanatory power of $OBIB$-related variables decreases with decreasing size and liquidity. For instance, for the F100 group, the explanatory power drops to one-third, while for the F250 group, it is economically insignificant, with reductions in R^2 and adjusted R^2 of only about 1%. Consequently, the variation in price movements for the F250 group is primarily explained by firm characteristics, liquidity, and return autocorrelations. As such, liquidity providers for the largest and most liquid stock group remain more informed than those for smaller and less liquid stocks.

The possibility exists that the slopes of the two sides of the market may have different impacts on price movement. To investigate this further, I examined whether the relationship between price movement and order book imbalance is driven by one side of the market or both sides. To accomplish this, the equation is updated by replacing $OBIB$ with the bid-side slope ($BidSlope$) and the ask-side slope ($AskSlope$). The updated equation is as follows:

$$\begin{aligned} R_{i,t} = &\alpha_i^{FE} + \beta_1 D_t + \beta_4 BidSlope_{i,t} + \beta_5 AskSlope_{i,t} + \beta_3 OIB_{i,t} + \gamma_3 D_t \times BidSlope_{i,t} \\ &+ \gamma_4 D_t \times AskSlope_{i,t} + \gamma_2 D_t \times OIB_{i,t} + \delta' X_{it} + \epsilon_{i,t}, \end{aligned} \tag{12}$$

The β coefficients represent the impacts of the new trading system, the bid- and ask-side slopes, and the order imbalance on the daily price movement, while the γ coefficients reflect the changes in the relationships between price movements and the two slopes and the order imbalance. Standard errors are double-clustered by stock and day.

Column 5-7 in Table 9 show the regression estimates for Equation 12. The positive impact of book imbalance for the F100acc group is primarily driven by the ask-side slope. According to Saar (2001), buyers are more likely to be motivated by information because they can trade as much as they want, whereas sellers face more constraints. This suggests that informed traders tend to use market orders to buy and limit orders to sell in the most liquid stocks. This phenomenon also appears in the estimates for the other two groups, but to a lesser extent. In these groups, the significant impact of $OBIB$ is driven by both sides of the market, but the impact of the ask-side slope is stronger and more significant. Additionally, for these two groups, the event only reduces the impact of liquidity suppliers on price movements through the ask side of the book. This implies that the event likely encourages informed sellers to use more market orders.

Although the order imbalance in Kyle-style models is typically measured by the imbalance of the number of shares traded, Jones et al. (1994) found that the imbalance of the number of trades is more informative about price movements. Therefore, I used two other measures of order imbalance in the regression, and the results can be found in Table 12. These results do not qualitatively change the findings.

8 The determinants of the LOB imbalance

8.1 The baseline determinants of the LOB imbalance

In this section, I investigate under what condition the LOB is more balanced. In other words, what market factors affect liquidity providers act like traditional market makers who provide liquidity on both sides of the market symmetrically. The absolute value of the OBIB ($AbsOBIB$) is adopted to proxy for the degree of the order book imbalance. The lower value of the $AbsOBIB$ infers a more balanced book. Similar to the regression used in the previous sections, the assessment is built on the stock fixed effect panel regression with stock-day clustered standard errors to control for contemporaneous correlation across stocks and autocorrelation within stocks.

The imbalance of the LOB is likely to be affected by several factors, with volatility being the first one. Informed traders submitting orders contribute to the imbalance, and Geottler et al. (2009) argue that speculators who are more informed than others decrease liquidity provision when the volatility of the fundamental value is high. This results in liquidity mainly being supplied by market participants who have an intrinsic motive for trade (i.e., liquidity traders). Additionally, the volatility of the observed price tends to be higher when the fundamental volatility is high. Empirical evidence from Brogaard et al. (2018) supports this argument by showing that HFTs, who are not likely to have intrinsic motive for trade, reduce the use of limit orders when volatility is high. Consequently, it is expected that volatility has a positive impact on the imbalance of the LOB. However, Theissen and Westheide (2020) found that during call auctions, designated market makers, who do not have an information advantage, provide liquidity more actively when volatility is high.

Other studies relate volatility to limit order submission, but most do not show the impact of volatility on the order submission of informed investors. For instance, Foucault (1999) argued that when the fundamental value of an asset is more volatile, the proportion of limit orders and quoted spread increases due to the increased pick-off risk, leading to higher trading costs for liquidity demanders. However, their model assumes market participants are homogeneous, so information asymmetry is not reflected. Hoffmann (2014) separates fast and slow traders, and the model implies that both types submit more limit orders when the volatility of the fundamental value is high. However, the impact of volatility on the informativeness of liquidity providers remains unclear. Empirically, Ahn et al. (2001) and Ranaldo (2004) prove that limit order submission increases with transitory volatility, indicating that investors tend to submit limit orders when the noise in price is high, but it is unclear whether this increase is from informed or uninformed traders. Hasbrouck and Saar (2009) found that volatility increases limit order volume, but mostly they are fleeting orders. Although fleeting orders tend to be noises, they likely affect the informativeness at the top of the book. Therefore, the relationship between volatility and the order book imbalance is an empirical question.

To measure volatility empirically, several studies suggest that realised variance computed with observed high-frequency log return data is a reasonable proxy for the quadratic variation of the latent efficient price when the sampling frequency increases (Andersen et al., 2010). However, market microstructure noise increases with the sampling frequency and is included in realised variance, which contaminates the approximation. Most papers employ the 5-minute sampling frequency as a reasonable approximation to balance the trade-off between bias and efficiency.[22] Building on Bandi and Russell (2008), Bandi and Russell (2006) estimated that the optimal sampling frequency of the S&P100 stocks lies between 0.4 minutes to 13.8 minutes, and the commonly used 5 minutes is a reasonable approximation. Therefore, this study uses the 5-minute realised variance to proxy for the volatility of the asset's fundamental value. The study also examines the relationship between the order book imbalance and market-wide volatility by including the 5-minute realised variance of the FTSE 100 index.

In addition to volatility variables, this study considers two activity variables (turnover and order-to-trade ratio), three variables indicating the informativeness of trades and quotes (quoted spread, permanent price impact of trades, information shares of quotes, and the absolute value of the imbalance of the permanent price impact of buyer- and seller-initiated orders), two variables controlling for cross-sectional variations (the natural log of market capitalisation and the inverse of the daily closing price), and an event dummy variable controlling for the different behaviour resulting from the event, as explanatory variables. All variables have been explained in previous sections except for the absolute value of the imbalance of the permanent price impact of buyer- and seller-initiated orders ($AbsIBPI$). The permanent price impacts of buy- and sell-side market orders are also obtained via the Hasbrouck (1991a) framework. Compared to the estimations in 5.1, the trade series is separated into buy and sell series in the SVAR model. This imbalance

[22] As written by Andersen et al. (2001): 'The five-minute horizon is short enough that the accuracy of the continuous record asymptotic underlying our realised volatility measures work well, and long enough that the confounding influences from market microstructure frictions are not overwhelming.'

measure reflects the relative informativeness between the aggressive buyers and sellers, which is likely associated with the imbalance of the order book. The results are displayed in Table 10.

Table 10: Determinants of the absolute value of order book imbalance

This table presents the determinants of the absolute value of order book imbalance via the stock-fixed effects regression. The evaluation period covers 6 weeks prior to and 6 weeks after the event, which is from 04/01/2011 to 31/03/2011. 'EventDummy', 'TO', 'OTR', 'QS', 'PI_perm', 'IS_quotes', 'AbsIBPI', 'RV', 'F100_RV5', 'lnMV', 'InvPrice', and 'Intercept' respectively denote the event dummy variable, turnover, order-to-trade ratio, time-weighted quoted spread, the permanent price impact obtained via the Hasbrouck (1991a) model, the information shares of quotes obtained via the Hasbrouck (1991b) method, the absolute value of the differences between the permanent price impact of a buyer-initiated trade innovation and the seller-initiated trade innovation, 5-minute realised variance of the stock, the 5-minute realised variance of the FTSE 100 index, the natural log of market captilisation, the inverse of the daily closing price, and the intercept. Three columns are three regressions conducted separately for three groups. *, **, and *** respectively denote 10%, 5% and 1% significance levels.

	F100acc	F100	F250
EventDummy	-0.733**	-0.333***	-0.029
	(-3.108)	(-6.163)	(-0.738)
Activity			
TO	0.200	0.070	0.022***
	(0.944)	(0.942)	(3.005)
OTR	-0.140	3.291	0.053**
	(-0.074)	(1.397)	(2.126)
Informativeness			
QS	5.547	-1.800	-0.082
	(0.360)	(-1.550)	(-1.659)
PI_perm	-0.451	-0.446***	-0.135**
	(-0.907)	(-4.294)	(-2.587)
IS_quotes	0.526	0.901***	0.259**
	(0.819)	(7.357)	(2.693)
AbsIBPI	-0.077	-0.008	0.006
	(-1.015)	(-0.812)	(0.822)
Volatility			
RV	-417.603	192.819	-0.304
	(-0.725)	(1.682)	(-0.020)
FTSE_RV5	-86.067	268.286	-213.350**
	(-0.355)	(0.710)	(-2.423)
Cross-sectional variation			
lnMV	-0.903	0.559	0.019**
	(-0.667)	(1.576)	(2.567)
InvPrice	-681.836***	-3.162	-7.433
	(-3.521)	(-0.030)	(-0.230)
Intercept	12.110	-4.875	0.100
	(0.773)	(-1.522)	(0.732)
N	472	1702	2265
R-sq	0.2122	0.2711	0.0900
adj. R-sq	0.1809	0.2540	0.0699

Table 10 presents the results of the empirical analysis, where the second column displays the findings based on the full sample and the remaining columns correspond to the results of three subgroups. The second column indicates that the order book becomes more balanced after the speed-upgrading event, indicating that liquidity suppliers are more likely to provide symmetric liquidity on both sides of the market. This finding is consistent with the results reported in Amaya et al. (2018), which suggest that the LOB becomes more balanced. Moreover, controlling for the event, the order book imbalance is significantly positively associated with both market activity variables, implying that a more active market leads to a less balanced book. The coefficients of the three informativeness variables suggest that the book is more balanced when trades are more informed, indicating a trade-off between the informativeness of the supply and demand side of the liquidity. When liquidity demanders are more informed, liquidity suppliers tend to act like traditional market makers who provide liquidity on both sides of the book symmetrically. This overall suggests that if HFTs are informed, they tend to become more aggressive after the event, but on an active day, they tend to provide liquidity.

The imbalance of the informativeness of the aggressive buyers and sellers ($AbsIBPI$) does not have a significant relationship with the imbalance of the LOB. This further indicates that informed traders may switch between market and limit orders. When they use market orders to buy and sell, the book would be more balanced, whereas when they use a market buy order and limit sell order, the book would be less balanced.

Surprisingly, volatility, either the stock-specific or the market-wide volatility, does not exhibit any significant relationship with order book balance. This could be attributed to the fact that volatility tends to affect liquidity at the top of the book, as indicated by Table 2, but liquidity in the deeper levels of the book is more influenced by informativeness. This conclusion aligns with the findings reported in Beltran-Lopez et al. (2012).

Further decomposition of the full sample into three subgroups reveals that the book imbalance is more likely to be affected by the relative informativeness of liquidity providers and market conditions for the mid-cap group, as most variables demonstrate a significant relationship with the book imbalance. In contrast, market conditions have less impact on the book imbalance for large-cap groups. Specifically, the F100 group's imbalance is more likely to be influenced by the information advantage of liquidity providers. However, for the F100acc group, neither information advantage nor market conditions appear to significantly impact the imbalance.

8.2 The impact of the inventory risk on the LOB imbalance

Variables used in the previous subsection are mostly related to information and market conditions. The imbalance of the book may also be influenced by the inventory risks. In this section, I adopt the $HFOIV$ proposed by Bogousslavsky and Collin-Dufresne (2022) to proxy for the inventory risk. The $HFOIV$ is the standard deviation of the five-minute share imbalance. The results are presented in Table 11.[23]

The analysis demonstrates that for the F100acc group, the order book imbalance exhibits a significant and positive correlation with inventory risks, leading to an increased R^2. TThis implies that in the case of very large and liquid stocks, inventory risks are the primary drivers of the order book imbalance, rather than information advantage. In contrast, for the F100 group, the book imbalance is not significantly related to inventory risk but has a strong relationship with informativeness variables, suggesting that the order book imbalance in this group is primarily determined by the relative informativeness of liquidity suppliers. For the F250 group, the relationship between the book imbalance and inventory risk is negative, implying that the higher the inventory risk, the more balanced the book becomes. Furthermore, incorporating the effects of inventory risk for this subgroup strengthens the impact of other variables, further confirming that the book imbalance is more likely influenced by different types of risks in the market. When market, adverse selection, and inventory risks are higher, liquidity providers tend to post orders symmetrically on the market. Nevertheless, the supplementary findings presented in Tables 14, 15, and 16 show that inventory risks, as measured by two additional underlying variables with varying frequencies, exhibit either no significant relationship or a different relationship with the book imbalance as shown in this section. Hence, caution must be taken when interpreting the results of this section.

Despite the inclusion of several independent variables, our analysis suggests that the selected variables explain less than 30% of the variations in the absolute value of the order book imbalance, as indicated by the R^2 value. Additionally, although more variables exhibit explanatory power for the mid-cap group than for the large-cap groups, these variables explain the least variations in the absolute order book imbalance. Thus, other factors are likely to influence the book imbalance.

[23] The results of using different order imbalance measures (i.e. the imbalance of the number of trades and the imbalance of the money value with the interval) with different frequencies can be found in the Appendix Table 14, 15, and 16.

Table 11: The effects of book imbalance and slopes on price movements with different order imbalance measures

This table presents the determinants of the absolute value of order book imbalance via the stock-fixed effects regression with the inventory risk. The evaluation period covers 6 weeks prior to and 6 weeks after the event, which is from 04/01/2011 to 31/03/2011. 'EventDummy', 'TO', 'OTR', 'QS', 'PI_perm', 'IS_quotes', 'AbsPIperm', 'RV', 'F100_RV5', 'lnMV', 'InvPrice', and 'Intercept' respectively denote the event dummy variable, turnover, order-to-trade ratio, time-weighted quoted spread, the permanent price impact obtained via the Hasbrouck (1991a) model, the information shares of quotes obtained via the Hasbrouck (1991b) method, the absolute value of the differences between the permanent price impact of a buyer-initiated trade innovation and the seller-initiated trade innovation, 5-minute realised variance of the stock, the 5-minute realised variance of the FTSE 100 index, the natural log of market captilisation, the inverse of the daily closing price, and the intercept. 'HFOIV' is the standard deviation of the five-minute share imbalance. *, **, and *** respectively denote 10%, 5% and 1% significance levels.

	F100acc	F100	F250
EventDummy	-0.737**	-0.337***	-0.030
	(-3.048)	(-6.145)	(-0.719)
Inventory risk			
HFOIV	22.912*	-9.968	-1.073*
	(2.056)	(-1.288)	(-1.956)
Activity			
TO	0.100	0.131	0.032***
	(0.552)	(1.151)	(3.281)
OTR	-0.076	3.290	0.046*
	(-0.040)	(1.391)	(1.892)
Informativeness			
QS	5.513	-1.673	-0.073
	(0.361)	(-1.504)	(-1.406)
PI_perm	-0.435	-0.467***	-0.149**
	(-0.869)	(-3.999)	(-2.467)
IS_quotes	0.532	0.899***	0.262***
	(0.833)	(7.163)	(3.139)
AbsPI_perm	-0.075	-0.009	0.005
	(-0.973)	(-0.832)	(0.740)
Volatility			
RV	-344.703	168.809	5.949
	(-0.609)	(1.409)	(0.360)
FTSE_RV5	-113.557	244.411	-220.202**
	(-0.461)	(0.637)	(-2.546)
Cross-sectional variation			
lnMV	-0.761	0.512	0.003
	(-0.575)	(1.500)	(0.251)
InvPrice	-685.974**	8.796	-9.441
	(-3.474)	(0.085)	(-0.286)
Intercept	10.529	-4.464	0.230**
	(0.686)	(-1.449)	(2.251)
N	472	1702	2265
R-sq	0.2125	0.2722	0.0912
adj. R-sq	0.1794	0.2547	0.0707

9 Conclusion

This paper has investigate whether liquidity suppliers become more informed compared to liquidity demanders by focusing on the LSE system-upgrading event that took place in 2011. The study has found that the event has had a mixed effect on liquidity for different stock groups, with liquidity at the top of the book deteriorating for large-cap stocks but improving for mid-cap stocks. Moreover, the study has shown that the event has significantly increased adverse selection risks and made trades more informative than quotes, especially for large-cap stocks. The study has also introduced a novel indicator, the order book imbalance, which measures the trading intentions of liquidity suppliers in the LOB and has identified factors that influence the order book imbalance.

Additionally, the study has revealed that the event has suppressed the competition between liquidity suppliers, especially for the most liquid and largest stocks populated by HFTs. This has contributed to the change in transitory price impact from positive to negative for large-cap stocks. The study has also demonstrated that the link between the order book imbalance and daily return is influenced by the slope of the ask side of the market, implying that informed traders tend to utilize market orders for buying and limit orders for selling.

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Appendix A Liquidity variables

- Time-weighted quoted spread:

  The time-weighted quoted spread reflects the daily average trading costs of turning around one unit of share within a short period of time.

$$\begin{aligned} qspread_{i,d,t} &= 100 \times \frac{a_{i,d,t} - b_{i,d,t}}{m_{i,d,t}}, \\ TWqspread_{i,d} &= \sum_{t=1}^{T} qspread_{i,d,t} \frac{\delta_{i,d,t}}{\sum_{t=1}^{T} \delta_{i,d,t}}, \end{aligned} \tag{13}$$

  where δ is the duration between two market events for stock i on day d.

- Time-weighted depth:

  Empirical market microstructure researchers tend to measure market depth by the total number of shares available at the best price levels of two sides of the market. We follow this method and re-scale depth by the $ADVolume$.

$$\begin{aligned} depth_{i,d,t} &= bidsize_{i,d,t} + asksize_{i,d,t}, \\ TWdepth_{i,d} &= \sum_{t=1}^{T} depth_{i,d,t} \frac{\delta_{i,d,t}}{\sum_{t=1}^{T} \delta_{i,d,t}}, \end{aligned} \tag{14}$$

  where $bidsize_{i,d,t}$ and $asksize_{i,d,t}$ are re-scaled by the $ADVolume$.

- Value-weighted effective spread:

  The value-weighted effective spread reflects the real trading costs for liquidity demanders to turn around one unit of share within a short period of time. It captures the transactions of hidden orders. It is different from, and usually less than quoted spread.

$$\begin{aligned} espread_{i,d,t} &= 2 \times 100 \times q_{i,d,t} \frac{(p_{i,d,t} - m_{i,d,t})}{m_{i,d,t}}, \\ VWespread_{i,d} &= \sum_{t=1}^{n} espread_{i,d,t} \frac{\lambda_{i,d,t}}{\sum_{t=1}^{n} \lambda_{i,d,t}}, \end{aligned} \tag{15}$$

Appendix B The traditional measure of price impact – Hasbrouck (1991a) SVAR model

Hasbrouck (1991a) model is a structural VAR system. Two main variables are quote revisions and order flows. Order flows are treated as exogenous. Therefore, they have contemporaneous effects on quote revisions but not the other way around. Privately informed traders are assumed to use market orders, so any new private information is contained in the order flow innovation. Thus, the total price impact of new information can be quantified by the impulse response function (IRF) of the structural VAR model. As new private information moves price permanently, the total permanent price impact is the summation of the order flow innovation coefficients and its lags in the quote revision function. The instantaneous price impact caused by private information, inventory management, and order processing costs, is the coefficient of the order flow innovation in the quote revision function. The details of the model are described below:

The endogenous variables of the reduced-form VAR are order flows and returns, both of which follow zero mean covariance-stationary processes, denoted by x_t and r_t respectively. According to the Wold Theorem, the zero-mean covariance-stationary process can be decomposed into a stochastic process with MA representation and a deterministic process. The deterministic process, in this case, is zero, so two variables have a VMA representation. Hasbrouck argued that order flows have contemporaneous effects on price movements but not the other way around. Hence, two variables can be represented by a structural VMA (SVMA) model. If the SVMA is invertible, it has a structural VAR (SVAR) representation.

Hasbrouck (1991a) started with the SVAR representation. It is easier to estimate parameters than the SVMA. The SVAR is represented as:

$$\begin{bmatrix} 1 & 0 \\ b_0 & 1 \end{bmatrix} \begin{bmatrix} x_t \\ r_t \end{bmatrix} = \begin{bmatrix} B_x(L) & A_x(L) \\ B_r(L) & A_r(L) \end{bmatrix} \begin{bmatrix} x_t \\ r_t \end{bmatrix} + \begin{bmatrix} \epsilon_{x,t} \\ \epsilon_{r,t} \end{bmatrix}, \tag{16}$$

Then the SVMA representation is:

$$\begin{bmatrix} 1 & 0 \\ b_0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} 1 & 0 \\ b_0 & 1 \end{bmatrix} \begin{bmatrix} x_t \\ r_t \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ b_0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} B_x(L) & A_x(L) \\ B_r(L) & A_r(L) \end{bmatrix} \begin{bmatrix} x_t \\ r_t \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ b_0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} \epsilon_{x,t} \\ \epsilon_{r,t} \end{bmatrix}. \tag{17}$$

Equation 17 can be written as:

$$\begin{bmatrix} x_t \\ r_t \end{bmatrix} = \begin{bmatrix} C_x(L) & D_x(L) \\ C_r(L) & D_r(L) \end{bmatrix} \begin{bmatrix} x_t \\ r_t \end{bmatrix} + \begin{bmatrix} u_{x,t} \\ u_{r,t} \end{bmatrix}. \tag{18}$$

This is the reduced-form VAR which can then be transformed into a VMA format:

$$\begin{bmatrix} x_t \\ r_t \end{bmatrix} = \begin{bmatrix} \beta_x(L) & \alpha_x(L) \\ \beta_r(L) & \alpha_r(L) \end{bmatrix} \begin{bmatrix} u_{x,t} \\ u_{r,t} \end{bmatrix}, \tag{19}$$

Replacing $\begin{bmatrix} u_{x,t} \\ u_{r,t} \end{bmatrix}$ by $\begin{bmatrix} \epsilon_{x,t} \\ \epsilon_{r,t} \end{bmatrix}$, then Equation 19 can be represented by

$$\begin{bmatrix} x_t \\ r_t \end{bmatrix} = \begin{bmatrix} \beta_x(L) - b_0\alpha_x(L) & \alpha_x(L) \\ \beta_r(L) - b_0\alpha_r(L) & \alpha_r(L) \end{bmatrix} \begin{bmatrix} \epsilon_{x,t} \\ \epsilon_{r,t} \end{bmatrix}. \tag{20}$$

This is the impulse response function of the SVAR. And the long-term effects of one unit $\epsilon_{x,t}$ is the summation of all $\beta_r(L) - b_0\alpha_r(L)$.

The future price p_∞ proxies for the expected price at time t. Hence, the difference between p_∞ and p_t is due to the new information. This is measured by the long-run effects of one unit $\epsilon_{x,t}$, which is the permanent price impact. By the same token, the instantaneous price impact is measured by $\beta_r(0) - b_0\alpha_r(0)$.

Transitory price impact is the difference between the instantaneous price impact and permanent price impact. Order flows are re-scaled by the EMS to be consistent with the measure of cumulative depth.

Appendix C Change order imbalance measures

Table 12: The effects of book imbalance and slopes on price movements with different order imbalance measures

This table shows the relationship between the book imbalance and price movements in columns 2, 3, 6, 7, 10, 11 and the relationship between the slopes and price movements in columns 4, 5, 8, 9, 12, 13 respectively based on the regression model 11 and model 12 with different order imbalance measures. The dependent variable is the first difference of the natural log of daily closing price. For model 11, independent variables are $OBIB$, $OIBnum$ or $OIBdol$, the interaction of $OBIB$ and the event dummy ('Event×$OBIB$'), the interaction of $OIBnum$ or $OIBdol$ and the event dummy ('Event×$OIBnum$' or 'Event×$OIBdol$'), the stock-fixed effect dummies, the event dummy, and several control variables. $OIBnum$ is the imbalance of the number of daily trades normalised by the total number of trades on that day and $OIBdol$ is the imbalance of the daily trading value normalised by the $ADValue$ in the pre-event period. For model 12, independent variables are the bid-side slope ('$BidSlope$'), the ask-side slope ('$AskSlope$'), $OIBnum$ or $OIBdol$, the interaction of the bid-side slope and the event dummy ('Event×$BidSlope$'), the interaction of the ask-side slope and the event dummy ('Event×$AskSlope$'), the interaction of $OIBnum$ or $OIBdol$ and the event dummy ('Event× $OIBnum$' or 'Event×$OIBdol$'), the stock-fixed effect dummies, the event dummy, and several control variables. The evaluation period covers 6 weeks prior to and 6 weeks after the event, which is from 04/01/2011 to 31/03/2011. 'L.Return', 'TO', 'RV', 'InvPrice', 'lnMV', 'Intercept' respectively denote the lagged log return, money-turnover, realised variance, the inverse of the daily closing price, the natural log of market captilisation, and the intercept. *, **, and *** respectively denote 10%, 5% and 1% significance levels and standard errors are double-clustered by stock and day.

	F100acc				F100				F250			
$OBIB$	0.003** (3.274)	0.003* (2.092)			0.005*** (2.846)	0.005*** (2.938)			0.007*** (6.575)	0.008*** (6.485)		
$BidSlope$			-0.001 (-1.405)	-0.001 (-1.580)			-0.003** (-2.184)	-0.003** (-2.143)			-0.008* (-1.722)	-0.008 (-1.666)
$AskSlope$			0.002** (3.468)	0.002** (2.473)			0.009*** (6.789)	0.008*** (5.827)			0.011*** (6.861)	0.011*** (7.332)
$OIBnum$	0.012 (0.677)		0.015 (0.954)		0.024*** (4.955)		0.027*** (4.679)		0.016*** (4.878)		0.016*** (5.014)	
$OIBdol$		0.031** (2.613)		0.036*** (3.595)		0.025*** (5.988)		0.026*** (4.858)		0.013*** (5.402)		0.013*** (5.219)
Event ×$OBIB$	-0.009 (-1.186)	-0.001 (-0.271)			-0.017*** (-4.753)	-0.014*** (-5.832)			-0.008*** (-5.087)	-0.008*** (-4.933)		
Event ×$BidSlope$			0.002 (0.170)	-0.007 (-0.564)			0.017 (0.350)	0.001 (0.038)			-0.006 (-0.501)	-0.008 (-0.646)
Event ×$AskSlope$			-0.028 (-1.713)	-0.007 (-0.472)			-0.085* (-1.855)	-0.068* (-1.955)			-0.027*** (-3.363)	-0.027*** (-3.345)
Event ×$OIBnum$	0.016 (1.143)		0.013 (0.904)		0.014* (1.913)		0.011 (1.399)		0.004 (0.802)		0.004 (0.889)	
Event ×$OIBdol$		0.015 (0.930)		0.009 (0.565)		0.007 (1.245)		0.007 (1.060)		0.000 (0.117)		0.001 (0.259)
EventDummy	0.001 (0.278)	0.002 (0.699)	0.004 (1.300)	0.004 (1.365)	-0.002 (-1.023)	-0.002 (-0.882)	0.001 (0.444)	0.001 (0.538)	0.000 (0.025)	0.000 (0.157)	0.004 (1.368)	0.004 (1.566)
L.Return	-0.055 (-0.993)	-0.040 (-0.747)	-0.053 (-0.859)	-0.035 (-0.658)	-0.067 (-1.427)	-0.049 (-1.100)	-0.083* (-1.818)	-0.063 (-1.465)	-0.114** (-2.336)	-0.103** (-2.533)	-0.117** (-2.462)	-0.107*** (-2.739)
lnMV	0.087*** (7.327)	0.064*** (4.184)	0.091*** (7.991)	0.065*** (3.991)	0.082*** (4.887)	0.069*** (4.509)	0.087*** (4.984)	0.073*** (4.555)	0.005** (2.264)	0.002 (1.224)	0.005** (2.254)	0.002 (1.203)
RV	-4.405 (-0.567)	-6.310 (-0.806)	-4.776 (-0.496)	-7.566 (-0.830)	5.399 (0.552)	5.731 (0.625)	4.568 (0.460)	4.920 (0.529)	-17.038*** (-8.182)	-16.553*** (-7.601)	-16.881*** (-8.212)	-16.383*** (-7.589)
TO	-0.004 (-1.085)	-0.002 (-0.590)	-0.004 (-1.276)	-0.002 (-0.710)	0.002 (1.157)	0.002 (1.144)	0.001 (0.796)	0.001 (0.742)	-0.000 (-0.309)	-0.001 (-0.769)	-0.001 (-0.549)	-0.001 (-1.121)
InvPrice	-0.469 (-0.379)	-0.389 (-0.498)	-1.656 (-1.252)	-1.556 (-1.405)	2.035 (0.698)	0.760 (0.256)	0.811 (0.304)	-0.420 (-0.173)	-10.083*** (-3.902)	-9.888*** (-3.881)	-10.340*** (-3.881)	-10.160*** (-3.885)
QS	-0.086 (-0.720)	-0.084 (-0.924)	-0.058 (-0.532)	-0.053 (-0.522)	0.030 (0.560)	0.025 (0.450)	0.033 (0.605)	0.026 (0.465)	0.022*** (3.522)	0.023*** (3.955)	0.022*** (3.566)	0.023*** (4.000)
Intercept	-0.936*** (-7.683)	-0.692*** (-4.204)	-0.977*** (-8.199)	-0.705*** (-3.958)	-0.721*** (-4.865)	-0.608*** (-4.478)	-0.760*** (-4.937)	-0.641*** (-4.506)	0.003 (0.150)	0.019 (1.128)	0.004 (0.203)	0.021 (1.184)
N	376	376	376	376	1356	1356	1356	1356	1872	1872	1872	1872
R-sq	0.2001	0.2600	0.1842	0.2502	0.1839	0.2261	0.1799	0.2221	0.4442	0.4625	0.4506	0.4683
adj. R-sq	0.1598	0.2227	0.1382	0.2080	0.1597	0.2031	0.1543	0.1978	0.4290	0.4478	0.4349	0.4532

Appendix D Additional panel regressions

Table 13: The relationship between control variables and price movements

This table presents additional tests for the explanatory power of control variables to price movements for three groups based on the regression model 11. The dependent variable is the first difference of the natural log of daily closing price. Independent variables for columns 2,5, and 8 areOIB, the interaction of OIB and the event dummy (‘Event$\times OIB$’), the stock-fixed effect dummies, the event dummy, and several control variables. The evaluation period covers 6 weeks prior to and 6 weeks after the event, which is from 04/01/2011 to 31/03/2011. ‘L.Return’, ‘TO’, ‘RV’, ‘InvPrice’, ‘lnMV’, ‘Intercept’ respectively denote the lagged log return, money-turnover, realised variance, the inverse of the daily closing price, the natural log of market captilisation, and the intercept. *, **, and *** respectively denote 10%, 5% and 1% significance levels and standard errors are double-clustered by stock and day.

	F100acc			F100			F250		
OIB	0.045***			0.027***			0.013***		
	(4.274)			(5.091)			(5.409)		
EventDummy	0.002	0.002		-0.002	-0.002		0.000	0.001	
	(0.869)	(0.512)		(-0.907)	(-0.770)		(0.181)	(0.343)	
1.eventdummy#c.ofnum	-0.001			0.005			0.001		
	(-0.066)			(0.843)			(0.236)		
L.Return	-0.025	-0.016	-0.017	-0.048	-0.009	-0.009	-0.090***	-0.104*	-0.104*
	(-0.514)	(-0.327)	(-0.358)	(-0.993)	(-0.173)	(-0.173)	(-2.892)	(-1.909)	(-1.903)
lnMV	0.068***	0.098***	0.097***	0.075***	0.078***	0.076***	0.003	0.004	0.004
	(3.689)	(5.900)	(6.031)	(4.418)	(4.109)	(3.955)	(1.425)	(1.528)	(1.678)
RV	-8.576	-5.043	-4.953	6.062	7.084	7.138	-16.891***	-17.083***	-17.081***
	(-1.087)	(-0.649)	(-0.627)	(0.669)	(0.735)	(0.747)	(-7.392)	(-8.105)	(-8.047)
TO	-0.002	-0.004	-0.004	0.002	0.001	0.001	-0.001	-0.000	-0.000
	(-0.649)	(-1.458)	(-1.418)	(1.255)	(0.781)	(0.583)	(-0.649)	(-0.201)	(-0.179)
InvPrice	-1.993**	-3.190***	-2.608***	0.764	3.066	1.854	-9.456***	-10.661***	-10.499***
	(-2.376)	(-4.119)	(-4.203)	(0.222)	(0.890)	(0.382)	(-3.664)	(-3.812)	(-3.805)
QS	-0.012	-0.007	0.007	0.042	-0.012	-0.022	0.024***	0.022***	0.022***
	(-0.123)	(-0.074)	(0.068)	(0.706)	(-0.256)	(-0.483)	(4.165)	(3.986)	(3.892)
Intercept	-0.737***	-1.051***	-1.043***	-0.662***	-0.686***	-0.662***	0.015	0.014	0.012
	(-3.678)	(-5.923)	(-6.016)	(-4.382)	(-4.040)	(-3.835)	(0.948)	(0.655)	(0.620)
N	376	376	376	1356	1363	1363	1873	1880	1880
R-sq	0.2018	0.0958	0.0928	0.1673	0.0542	0.0502	0.4573	0.4064	0.4061
adj. R-sq	0.1662	0.0607	0.0602	0.1439	0.0293	0.0259	0.4430	0.3915	0.3915

Appendix E The impact of the inventory risk on the LOB imbalance

Table 14: Determinants further with inventory risk for F100acc

This table presents the determinants of the absolute value of order book imbalance via the stock-fixed effects regression for the F100acc group. The evaluation period covers 6 weeks prior to and 6 weeks after the event, which is from 04/01/2011 to 31/03/2011. 'EventDummy', 'TO', 'OTR', 'QS', 'PI_perm', 'IS_quotes', 'AbsPIperm', 'RV', 'F100_RV5', 'lnMV', 'InvPrice', and 'Intercept' respectively denote the event dummy variable, turnover, order-to-trade ratio, time-weighted quoted spread, the permanent price impact obtained via the Hasbrouck (1991a) model, the information shares of quotes obtained via the Hasbrouck (1991b) method, the absolute value of the differences between the permanent price impact of a buyer-initiated trade innovation and the seller-initiated trade innovation, 5-minute realised variance of the stock, the 5-minute realised variance of the FTSE 100 index, the natural log of market captilisation, the inverse of the daily closing price, and the intercept. 'HFOIV' is the standard deviation of the high-frequency order imbalance. Five frequencies, 30s, 60s, 300s, 600s, and 1800s, are adopted and are specified in the first row. *, **, and *** respectively denote 10%, 5% and 1% significance levels.

	HFOIV_num30s	HFOIV_num60s	HFOIV_num300s	HFOIV_num600s	HFOIV_num1800s	HFOIV_numraw30s	HFOIV_numraw60s	HFOIV_numraw300s	HFOIV_numraw600s	HFOIV_numraw1800s	HFOIV_shares30s	HFOIV_shares60s	HFOIV_shares300s	HFOIV_shares600s	HFOIV_shares1800s
EventDummy	-0.731**	-0.731**	-0.742**	-0.748**	-0.736**	-0.730**	-0.724**	-0.714**	-0.714**	-0.717**	-0.733**	-0.733**	-0.737**	-0.735**	-0.736**
	(-3.112)	(-3.196)	(-3.073)	(-3.120)	(-2.967)	(-3.125)	(-3.131)	(-2.957)	(-2.931)	(-3.064)	(-3.325)	(-3.277)	(-3.048)	(-3.065)	(-3.079)
Activity															
TO	0.134	0.157	0.251	0.239	0.204	0.413	0.406	0.326	0.315	0.311	0.249	0.156	0.100	0.169	0.142
	(0.648)	(1.007)	(0.937)	(1.032)	(0.928)	(1.421)	(1.389)	(1.328)	(1.242)	(1.153)	(0.877)	(0.600)	(0.552)	(0.797)	(0.861)
OTR	-0.264	-0.245	-0.005	0.007	-0.100	-0.621	-0.557	-0.430	-0.329	-0.394	-0.158	-0.126	-0.076	-0.115	-0.104
	(-0.164)	(-0.145)	(-0.003)	(0.004)	(-0.053)	(-0.294)	(-0.265)	(-0.210)	(-0.161)	(-0.179)	(-0.083)	(-0.067)	(-0.040)	(-0.061)	(-0.057)
Informativeness															
QS	6.697	6.330	4.679	4.559	5.304	5.606	5.387	5.124	5.118	5.584	5.831	5.404	5.513	5.552	5.640
	(0.434)	(0.415)	(0.294)	(0.279)	(0.319)	(0.365)	(0.350)	(0.339)	(0.341)	(0.362)	(0.385)	(0.349)	(0.361)	(0.360)	(0.371)
PI_perm	-0.470	-0.464	-0.435	-0.437	-0.449	-0.466	-0.463	-0.456	-0.461	-0.464	-0.462	-0.442	-0.435	-0.446	-0.443
	(-0.973)	(-0.986)	(-1.067)	(-1.167)	(-0.979)	(-0.960)	(-0.976)	(-0.991)	(-1.022)	(-0.950)	(-0.920)	(-0.836)	(-0.869)	(-0.885)	(-0.989)
IS_quotes	0.515	0.519	0.535	0.530	0.530	0.516	0.531	0.555	0.553	0.551	0.521	0.530	0.532	0.528	0.533
	(0.840)	(0.812)	(0.840)	(0.827)	(0.846)	(0.805)	(0.829)	(0.871)	(0.867)	(0.882)	(0.802)	(0.837)	(0.833)	(0.838)	(0.834)
AbsPI_perm	-0.079	-0.078	-0.077	-0.078	-0.077	-0.070	-0.069	-0.070	-0.069	-0.068	-0.078	-0.076	-0.075	-0.076	-0.076
	(-1.097)	(-1.024)	(-1.177)	(-1.175)	(-1.036)	(-0.892)	(-0.889)	(-0.858)	(-0.845)	(-0.827)	(-1.036)	(-1.005)	(-0.973)	(-0.971)	(-1.009)
Volatility															
RV	-460.860	-436.413	-424.586	-395.529	-410.444	-509.834	-496.040	-482.399	-476.591	-459.210	-454.459	-386.724	-344.703	-392.939	-394.897
	(-0.796)	(-0.744)	(-0.740)	(-0.684)	(-0.691)	(-0.865)	(-0.844)	(-0.810)	(-0.801)	(-0.767)	(-0.813)	(-0.669)	(-0.609)	(-0.688)	(-0.686)
FTSE_RV5	-154.021	-143.728	-2.256	-3.718	-77.376	-103.060	-82.830	-26.065	-33.769	-30.974	-95.834	-79.604	-113.557	-100.611	-99.069
	(-0.486)	(-0.416)	(-0.009)	(-0.013)	(-0.287)	(-0.403)	(-0.330)	(-0.104)	(-0.137)	(-0.132)	(-0.412)	(-0.312)	(-0.461)	(-0.411)	(-0.387)
Cross-sectional variation															
lnMV	-0.759	-0.830	-0.893	-0.849	-0.886	-1.107	-1.161	-1.170	-1.184	-1.096	-0.947	-0.857	-0.761	-0.850	-0.844
	(-0.570)	(-0.646)	(-0.660)	(-0.641)	(-0.672)	(-0.776)	(-0.804)	(-0.824)	(-0.820)	(-0.789)	(-0.678)	(-0.632)	(-0.575)	(-0.634)	(-0.633)
InvPrice	-655.709**	-668.281***	-693.952**	-694.841**	-680.703**	-687.345***	-686.407***	-690.806***	-689.765***	-695.383***	-678.953***	-684.563***	-685.974**	-681.639**	-685.132**
	(-3.458)	(-3.524)	(-3.482)	(-3.337)	(-3.461)	(-3.596)	(-3.618)	(-3.582)	(-3.591)	(-3.560)	(-3.550)	(-3.547)	(-3.474)	(-3.499)	(-3.444)
Inventory risk															
HFOIV	-0.995	-0.502	0.748	1.145	0.291	-0.067	-0.041	-0.008	-0.005	-0.002	-45.175	27.546	22.912*	4.420	3.858
	(-0.628)	(-0.341)	(0.538)	(0.609)	(0.120)	(-1.810)	(-1.682)	(-1.263)	(-1.170)	(-1.038)	(-0.326)	(0.338)	(2.056)	(0.887)	(0.566)
Intercept	11.269	11.635	11.737	11.247	11.875	14.756	15.245	15.176	15.294	14.334	12.599	11.598	10.529	11.522	11.453
	(0.721)	(0.763)	(0.753)	(0.736)	(0.782)	(0.893)	(0.914)	(0.928)	(0.921)	(0.895)	(0.781)	(0.739)	(0.686)	(0.742)	(0.741)
N	472	472	472	472	472	472	472	472	472	472	472	472	472	472	472
R-sq	0.2126	0.2124	0.2128	0.2133	0.2122	0.2155	0.2153	0.2140	0.2141	0.2155	0.2122	0.2122	0.2125	0.2122	0.2124
adj. R-sq	0.1795	0.1792	0.1797	0.1802	0.1791	0.1826	0.1823	0.1810	0.1811	0.1825	0.1791	0.1791	0.1794	0.1791	0.1793

	HFOIV_sharesraw30s	HFOIV_sharesraw60s	HFOIV_sharesraw300s	HFOIV_sharesraw600s	HFOIV_sharesraw1800s	HFOIV_dol30s	HFOIV_dol60s	HFOIV_dol300s	HFOIV_dol600s	HFOIV_dol1800s	HFOIV_dolraw30s	HFOIV_dolraw60s	HFOIV_dolraw300s	HFOIV_dolraw600s	HFOIV_dolraw1800s
EventDummy	-0.733**	-0.733**	-0.735**	-0.734**	-0.732**	-0.733**	-0.733**	-0.737**	-0.735**	-0.736**	-0.729***	-0.727***	-0.725***	-0.723**	-0.728**
	(-3.275)	(-3.248)	(-3.224)	(-3.196)	(-3.190)	(-3.220)	(-3.119)	(-3.053)	(-3.081)	(-3.046)	(-3.643)	(-3.627)	(-3.501)	(-3.474)	(-3.281)
Activity															
TO	0.211	0.212	0.231	0.234	0.241	0.264	0.174	0.108	0.174	0.144	0.440	0.399	0.321	0.316	0.256
	(0.906)	(0.908)	(0.941)	(0.951)	(0.975)	(0.947)	(0.682)	(0.591)	(0.820)	(0.867)	(1.070)	(0.969)	(0.912)	(0.938)	(0.939)
OTR	-0.116	-0.111	-0.067	-0.081	-0.086	-0.163	-0.131	-0.079	-0.118	-0.104	-0.094	-0.087	-0.160	-0.185	-0.152
	(-0.061)	(-0.059)	(-0.035)	(-0.042)	(-0.044)	(-0.086)	(-0.070)	(-0.042)	(-0.063)	(-0.057)	(-0.048)	(-0.046)	(-0.085)	(-0.098)	(-0.080)
Informativeness															
QS	5.444	5.417	5.284	5.304	5.149	5.886	5.473	5.549	5.562	5.664	6.913	6.220	5.742	5.678	5.474
	(0.351)	(0.349)	(0.342)	(0.344)	(0.336)	(0.385)	(0.354)	(0.364)	(0.361)	(0.374)	(0.484)	(0.422)	(0.375)	(0.369)	(0.353)
PI_perm	-0.461	-0.461	-0.469	-0.473	-0.475	-0.466	-0.446	-0.437	-0.447	-0.443	-0.511	-0.497	-0.474	-0.474	-0.461
	(-0.942)	(-0.935)	(-0.943)	(-0.931)	(-0.937)	(-0.929)	(-0.870)	(-0.875)	(-0.890)	(-0.957)	(-1.031)	(-1.016)	(-0.958)	(-0.945)	(-0.928)
IS_quotes	0.520	0.519	0.504	0.500	0.497	0.520	0.528	0.531	0.528	0.532	0.501	0.508	0.514	0.513	0.519
	(0.805)	(0.804)	(0.784)	(0.778)	(0.775)	(0.800)	(0.826)	(0.826)	(0.832)	(0.827)	(0.777)	(0.795)	(0.815)	(0.822)	(0.826)
AbsPI_perm	-0.075	-0.074	-0.070	-0.069	-0.067	-0.079	-0.076	-0.075	-0.077	-0.076	-0.084	-0.082	-0.079	-0.079	-0.078
	(-1.013)	(-1.000)	(-0.913)	(-0.901)	(-0.851)	(-1.060)	(-1.002)	(-0.971)	(-0.970)	(-0.999)	(-1.079)	(-1.054)	(-0.977)	(-0.969)	(-0.995)
Volatility															
RV	-418.327	-418.213	-438.791	-451.070	-441.069	-466.166	-399.053	-350.334	-396.618	-395.311	-524.839	-493.595	-463.473	-470.727	-405.398
	(-0.724)	(-0.722)	(-0.743)	(-0.754)	(-0.722)	(-0.837)	(-0.693)	(-0.622)	(-0.696)	(-0.688)	(-0.996)	(-0.926)	(-0.835)	(-0.838)	(-0.690)
FTSE_RV5	-95.467	-97.096	-87.303	-72.979	-82.872	-101.551	-81.104	-106.199	-96.908	-95.725	-185.301	-163.502	-89.095	-68.001	-99.145
	(-0.370)	(-0.372)	(-0.356)	(-0.315)	(-0.359)	(-0.432)	(-0.321)	(-0.431)	(-0.397)	(-0.372)	(-0.702)	(-0.587)	(-0.371)	(-0.293)	(-0.417)
Cross-sectional variation															
lnMV	-0.909	-0.909	-0.918	-0.923	-0.920	-0.872	-0.909	-0.876	-0.886	-0.899	-0.812	-0.885	-0.967	-1.005	-0.916
	(-0.665)	(-0.666)	(-0.672)	(-0.676)	(-0.678)	(-0.649)	(-0.670)	(-0.649)	(-0.657)	(-0.657)	(-0.634)	(-0.670)	(-0.696)	(-0.712)	(-0.682)
InvPrice	-682.460**	-680.367***	-671.400***	-674.608***	-674.468**	-676.305**	-684.034**	-687.214***	-682.037***	-685.581***	-657.685**	-662.719**	-674.193***	-680.299***	-677.057**
	(-3.494)	(-3.515)	(-3.504)	(-3.508)	(-3.477)	(-3.459)	(-3.494)	(-3.500)	(-3.508)	(-3.520)	(-3.340)	(-3.441)	(-3.549)	(-3.566)	(-3.482)
Inventory risk															
HFOIV	-0.816	-0.588	-0.451	-0.295	-0.154	-59.336	16.460	21.152	3.750	3.755	-0.029	-0.016	-0.004	-0.002	-0.000
	(-0.211)	(-0.251)	(-0.574)	(-0.694)	(-1.078)	(-0.468)	(0.219)	(1.858)	(0.721)	(0.531)	(-0.755)	(-0.618)	(-0.525)	(-0.574)	(-0.503)
Intercept	12.195	12.187	12.280	12.349	12.314	11.789	12.167	11.789	11.915	12.050	11.121	11.916	12.804	13.242	12.245
	(0.770)	(0.771)	(0.777)	(0.781)	(0.784)	(0.757)	(0.776)	(0.754)	(0.763)	(0.762)	(0.748)	(0.779)	(0.798)	(0.812)	(0.787)
N	472	472	472	472	472	472	472	472	472	472	472	472	472	472	472
R-sq	0.2122	0.2123	0.2127	0.2129	0.2135	0.2123	0.2122	0.2125	0.2122	0.2124	0.2141	0.2135	0.2128	0.2130	0.2125
adj. R-sq	0.1791	0.1792	0.1796	0.1798	0.1805	0.1792	0.1791	0.1794	0.1791	0.1793	0.1811	0.1805	0.1797	0.1799	0.1794

Table 15: Determinants further with inventory risk for F100

This table presents the determinants of the absolute value of order book imbalance via the stock-fixed effects regression for the F100 group. The evaluation period covers 6 weeks prior to and 6 weeks after the event, which is from 04/01/2011 to 31/03/2011. ‘EventDummy’, ‘TO’, ‘OTR’, ‘QS’, ‘PI_perm’, ‘IS_quotes’, ‘AbsPIperm’, ‘RV’, ‘F100_RV5’, ‘lnMV’, ‘InvPrice’, and ‘Intercept’ respectively denote the event dummy variable, turnover, order-to-trade ratio, time-weighted quoted spread, the permanent price impact obtained via the Hasbrouck (1991a) model, the information shares of quotes obtained via the Hasbrouck (1991b) method, the absolute value of the differences between the permanent price impact of a buyer-initiated trade innovation and the seller-initiated trade innovation, 5-minute realised variance of the stock, the 5-minute realised variance of the FTSE 100 index, the natural log of market captilisation, the inverse of the daily closing price, and the intercept. ‘HFOIV’ is the standard deviation of the high-frequency order imbalance. Five frequencies, 30s, 60s, 300s, 600s, and 1800s, are adopted and are specified in the first row. *, **, and *** respectively denote 10%, 5% and 1% significance levels.

	HFOIV_num30s	HFOIV_num60s	HFOIV_num300s	HFOIV_num600s	HFOIV_num1800s	HFOIV_numraw30s	HFOIV_numraw60s	HFOIV_numraw300s	HFOIV_numraw600s	HFOIV_numraw1800s	HFOIV_shares30s	HFOIV_shares60s	HFOIV_shares300s	HFOIV_shares600s	HFOIV_shares1800s
EventDummy	-0.332***	-0.334***	-0.333***	-0.333***	-0.330***	-0.332***	-0.332***	-0.329***	-0.331***	-0.332***	-0.333***	-0.333***	-0.337***	-0.337***	-0.335***
	(-6.205)	(-6.162)	(-6.095)	(-6.054)	(-6.096)	(-6.154)	(-6.168)	(-6.137)	(-6.144)	(-6.158)	(-6.273)	(-6.301)	(-6.145)	(-6.212)	(-6.183)
Activity															
TO	0.065	0.075	0.081	0.070	0.078	0.049	0.041	0.036	0.042	0.059	0.113	0.117	0.131	0.128	0.111
	(0.932)	(1.045)	(1.419)	(1.086)	(1.036)	(0.674)	(0.578)	(0.499)	(0.585)	(0.875)	(1.046)	(1.057)	(1.151)	(1.248)	(1.176)
OTR	3.319	3.276	3.263	3.291	3.278	3.428	3.466	3.522	3.462	3.366	3.336	3.336	3.290	3.291	3.272
	(1.387)	(1.381)	(1.351)	(1.374)	(1.398)	(1.446)	(1.461)	(1.481)	(1.453)	(1.399)	(1.390)	(1.388)	(1.391)	(1.390)	(1.390)
Informativeness															
QS	-1.804	-1.806	-1.869	-1.799	-1.920	-1.870	-1.878	-1.829	-1.834	-1.809	-1.617	-1.616	-1.673	-1.691	-1.720
	(-1.543)	(-1.547)	(-1.643)	(-1.598)	(-1.618)	(-1.577)	(-1.585)	(-1.562)	(-1.556)	(-1.556)	(-1.447)	(-1.453)	(-1.504)	(-1.514)	(-1.505)
PI_perm	-0.447***	-0.444***	-0.439***	-0.446***	-0.439***	-0.448***	-0.447***	-0.447***	-0.447***	-0.444***	-0.466***	-0.468***	-0.467***	-0.464***	-0.458***
	(-4.238)	(-4.257)	(-3.935)	(-4.057)	(-4.260)	(-4.295)	(-4.292)	(-4.274)	(-4.273)	(-4.299)	(-3.957)	(-3.936)	(-3.999)	(-4.141)	(-4.141)
IS_quotes	0.895***	0.904***	0.907***	0.901***	0.902***	0.904***	0.903***	0.895***	0.890***	0.897***	0.897***	0.897***	0.899***	0.902***	0.904***
	(7.769)	(7.542)	(7.594)	(7.440)	(7.441)	(7.464)	(7.518)	(7.599)	(7.642)	(7.534)	(7.236)	(7.203)	(7.163)	(7.115)	(7.279)
AbsPI_perm	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008	-0.009	-0.009	-0.009	-0.009	-0.009
	(-0.776)	(-0.781)	(-0.753)	(-0.783)	(-0.768)	(-0.781)	(-0.780)	(-0.798)	(-0.807)	(-0.796)	(-0.812)	(-0.822)	(-0.832)	(-0.833)	(-0.834)
Volatility															
RV	190.922*	194.857*	199.156*	192.778	201.077*	208.298*	206.484*	194.911*	194.769	194.793	159.059	161.080	168.809	172.045	176.621
	(1.702)	(1.723)	(1.712)	(1.675)	(1.730)	(1.785)	(1.777)	(1.713)	(1.692)	(1.697)	(1.292)	(1.331)	(1.409)	(1.468)	(1.499)
FTSE_RV5	263.802	273.331	290.166	268.165	278.531	286.761	284.584	276.802	275.341	266.643	235.776	238.193	244.411	249.709	264.052
	(0.690)	(0.707)	(0.713)	(0.677)	(0.750)	(0.767)	(0.758)	(0.731)	(0.727)	(0.702)	(0.600)	(0.609)	(0.637)	(0.653)	(0.693)
Cross-sectional variation															
lnMV	0.572	0.550	0.537	0.559	0.538	0.527	0.524	0.540	0.545	0.553	0.527	0.531	0.512	0.522	0.531
	(1.619)	(1.590)	(1.537)	(1.554)	(1.567)	(1.517)	(1.513)	(1.536)	(1.552)	(1.564)	(1.513)	(1.527)	(1.500)	(1.488)	(1.491)
InvPrice	-2.335	-4.475	-7.899	-3.142	-6.718	-15.505	-16.935	-20.310	-18.214	-8.475	3.421	5.154	8.796	8.894	5.220
	(-0.022)	(-0.043)	(-0.080)	(-0.030)	(-0.066)	(-0.150)	(-0.164)	(-0.198)	(-0.178)	(-0.081)	(0.033)	(0.050)	(0.085)	(0.084)	(0.049)
Inventory risk															
HFOIV	-0.216	0.117	0.162	-0.001	0.266	0.016**	0.015**	0.007**	0.004**	0.001	-18.520	-16.148	-9.968	-6.328*	-2.224
	(-0.497)	(0.349)	(0.377)	(-0.003)	(1.659)	(2.438)	(2.587)	(2.632)	(2.210)	(0.998)	(-1.079)	(-1.099)	(-1.288)	(-1.765)	(-1.503)
Intercept	-4.792	-4.897	-4.781	-4.876	-4.752	-4.654	-4.635	-4.755	-4.771	-4.834	-4.590	-4.633	-4.464	-4.567	-4.645
	(-1.480)	(-1.523)	(-1.515)	(-1.509)	(-1.530)	(-1.484)	(-1.482)	(-1.497)	(-1.506)	(-1.515)	(-1.460)	(-1.474)	(-1.449)	(-1.440)	(-1.441)
N	1702	1702	1702	1702	1702	1702	1702	1702	1702	1702	1702	1702	1702	1702	1702
R-sq	0.2712	0.2711	0.2713	0.2711	0.2717	0.2721	0.2723	0.2724	0.2720	0.2713	0.2718	0.2719	0.2722	0.2722	0.2719
adj. R-sq	0.2536	0.2536	0.2537	0.2536	0.2541	0.2546	0.2548	0.2548	0.2545	0.2538	0.2543	0.2544	0.2547	0.2547	0.2544

	HFOIV_sharesraw30s	HFOIV_sharesraw60s	HFOIV_sharesraw300s	HFOIV_sharesraw600s	HFOIV_sharesraw1800s	HFOIV_dol30s	HFOIV_dol60s	HFOIV_dol300s	HFOIV_dol600s	HFOIV_dol1800s	HFOIV_dolraw30s	HFOIV_dolraw60s	HFOIV_dolraw300s	HFOIV_dolraw600s	HFOIV_dolraw1800s
EventDummy	-0.336***	-0.336***	-0.337***	-0.337***	-0.335***	-0.333***	-0.333***	-0.337***	-0.337***	-0.335***	-0.334***	-0.334***	-0.335***	-0.335***	-0.333***
	(-6.302)	(-6.288)	(-6.271)	(-6.285)	(-6.225)	(-6.281)	(-6.310)	(-6.153)	(-6.222)	(-6.192)	(-6.167)	(-6.161)	(-6.075)	(-6.118)	(-6.076)
Activity															
TO	0.102	0.103	0.098	0.097	0.084	0.113	0.117	0.132	0.129	0.111	0.093	0.095	0.085	0.086	0.073
	(1.208)	(1.219)	(1.190)	(1.196)	(1.062)	(1.047)	(1.059)	(1.156)	(1.248)	(1.181)	(0.981)	(0.991)	(0.921)	(0.959)	(0.855)
OTR	3.310	3.307	3.281	3.282	3.280	3.340	3.339	3.292	3.292	3.272	3.300	3.300	3.283	3.285	3.290
	(1.394)	(1.394)	(1.390)	(1.391)	(1.393)	(1.389)	(1.388)	(1.390)	(1.390)	(1.390)	(1.392)	(1.393)	(1.397)	(1.395)	(1.399)
Informativeness															
QS	-1.667	-1.684	-1.731	-1.736	-1.767	-1.627	-1.629	-1.685	-1.703	-1.729	-1.710	-1.707	-1.762	-1.761	-1.793
	(-1.497)	(-1.501)	(-1.529)	(-1.536)	(-1.547)	(-1.455)	(-1.459)	(-1.508)	(-1.518)	(-1.512)	(-1.504)	(-1.508)	(-1.550)	(-1.547)	(-1.554)
PI_perm	-0.474***	-0.473***	-0.463***	-0.461***	-0.454***	-0.467***	-0.469***	-0.469***	-0.464***	-0.459***	-0.464***	-0.465***	-0.455***	-0.454***	-0.447***
	(-4.142)	(-4.172)	(-4.236)	(-4.264)	(-4.223)	(-3.956)	(-3.936)	(-3.994)	(-4.142)	(-4.139)	(-3.893)	(-3.891)	(-3.970)	(-4.060)	(-4.085)
IS_quotes	0.897***	0.898***	0.900***	0.901***	0.902***	0.897***	0.897***	0.899***	0.902***	0.905***	0.898***	0.899***	0.900***	0.901***	0.901***
	(7.203)	(7.233)	(7.238)	(7.295)	(7.363)	(7.233)	(7.193)	(7.163)	(7.106)	(7.286)	(7.322)	(7.309)	(7.362)	(7.314)	(7.374)
AbsPI_perm	-0.009	-0.009	-0.009	-0.009	-0.009	-0.009	-0.009	-0.009	-0.009	-0.009	-0.009	-0.009	-0.009	-0.009	-0.008
	(-0.876)	(-0.878)	(-0.856)	(-0.859)	(-0.829)	(-0.809)	(-0.819)	(-0.833)	(-0.838)	(-0.834)	(-0.843)	(-0.846)	(-0.797)	(-0.792)	(-0.790)
Volatility															
RV	176.068	177.796	184.815	186.145	187.670	159.795	162.050	170.318	173.587	177.642	177.212	177.938	187.049	187.277	191.565
	(1.501)	(1.528)	(1.590)	(1.609)	(1.626)	(1.303)	(1.344)	(1.425)	(1.483)	(1.510)	(1.514)	(1.532)	(1.633)	(1.636)	(1.678)
FTSE_RV5	241.847	247.626	259.579	262.999	269.602	232.792	235.152	239.987	246.066	262.019	247.011	248.320	259.443	260.229	267.414
	(0.641)	(0.659)	(0.696)	(0.706)	(0.718)	(0.590)	(0.600)	(0.623)	(0.642)	(0.687)	(0.635)	(0.642)	(0.681)	(0.686)	(0.706)
Cross-sectional variation															
lnMV	0.538	0.539	0.550	0.560	0.567	0.598	0.604	0.589	0.592	0.574	0.568	0.571	0.563	0.565	0.560
	(1.526)	(1.525)	(1.552)	(1.573)	(1.591)	(1.648)	(1.650)	(1.624)	(1.626)	(1.577)	(1.594)	(1.597)	(1.576)	(1.576)	(1.572)
InvPrice	1.105	-0.528	5.021	8.899	8.373	3.431	4.948	7.343	7.223	3.542	-3.924	-2.914	-1.757	-1.030	-2.838
	(0.011)	(-0.005)	(0.048)	(0.083)	(0.077)	(0.033)	(0.047)	(0.070)	(0.067)	(0.033)	(-0.037)	(-0.027)	(-0.017)	(-0.010)	(-0.027)
Inventory															
HFOIV	-10.239**	-7.704**	-2.645*	-1.614*	-0.418	-18.720	-16.225	-10.252	-6.434*	-2.298	-0.011	-0.009	-0.002	-0.002	-0.000
	(-2.165)	(-2.254)	(-2.029)	(-1.914)	(-1.341)	(-1.088)	(-1.105)	(-1.290)	(-1.737)	(-1.514)	(-0.819)	(-0.837)	(-0.529)	(-0.652)	(-0.142)
Intercept	-4.665	-4.673	-4.796	-4.896	-4.960	-5.203	-5.261	-5.134	-5.162	-5.013	-4.926	-4.962	-4.900	-4.928	-4.881
	(-1.467)	(-1.467)	(-1.500)	(-1.523)	(-1.540)	(-1.587)	(-1.591)	(-1.566)	(-1.568)	(-1.522)	(-1.531)	(-1.536)	(-1.521)	(-1.521)	(-1.518)
N	1702	1702	1702	1702	1702	1702	1702	1702	1702	1702	1702	1702	1702	1702	1702
R-sq	0.2726	0.2725	0.2722	0.2721	0.2715	0.2719	0.2719	0.2723	0.2722	0.2720	0.2714	0.2714	0.2712	0.2713	0.2711
adj. R-sq	0.2550	0.2550	0.2547	0.2546	0.2539	0.2543	0.2544	0.2548	0.2547	0.2544	0.2539	0.2539	0.2537	0.2537	0.2536

Table 16: Determinants further with inventory risk for F250

This table presents the determinants of the absolute value of order book imbalance via the stock-fixed effects regression for the F250 group. The evaluation period covers 6 weeks prior to and 6 weeks after the event, which is from 04/01/2011 to 31/03/2011. 'EventDummy', 'TO', 'OTR', 'QS', 'PI_perm', 'IS_quotes', 'AbsPIperm', 'RV', 'F100_RV5', 'lnMV', 'InvPrice', and 'Intercept' respectively denote the event dummy variable, turnover, order-to-trade ratio, time-weighted quoted spread, the permanent price impact obtained via the Hasbrouck (1991a) model, the information shares of quotes obtained via the Hasbrouck (1991b) method, the absolute value of the differences between the permanent price impact of a buyer-initiated trade innovation and the seller-initiated trade innovation, 5-minute realised variance of the stock, the 5-minute realised variance of the FTSE 100 index, the natural log of market captilisation, the inverse of the daily closing price, and the intercept. 'HFOIV' is the standard deviation of the high-frequency order imbalance. Five frequencies, 30s, 60s, 300s, 600s, and 1800s, are adopted and are specified in the first row. *, **, and *** respectively denote 10%, 5% and 1% significance levels.

	HFOIV_num30s	HFOIV_num60s	HFOIV_num300s	HFOIV_num600s	HFOIV_num1800s	HFOIV_numraw30s	HFOIV_numraw60s	HFOIV_numraw300s	HFOIV_numraw600s	HFOIV_numraw1800s	HFOIV_shares30s	HFOIV_shares60s	HFOIV_shares300s	HFOIV_shares600s	HFOIV_shares1800s
EventDummy	-0.029	-0.029	-0.029	-0.029	-0.029	-0.030	-0.030	-0.029	-0.029	-0.029	-0.030	-0.030	-0.030	-0.030	-0.029
	(-0.658)	(-0.675)	(-0.713)	(-0.735)	(-0.743)	(-0.769)	(-0.764)	(-0.746)	(-0.746)	(-0.745)	(-0.751)	(-0.741)	(-0.719)	(-0.690)	(-0.684)
Activity															
TO	0.021**	0.021***	0.019***	0.019**	0.020**	0.013*	0.012*	0.015**	0.017***	0.018***	0.027***	0.028***	0.032***	0.033***	0.034***
	(2.616)	(2.742)	(2.824)	(2.490)	(2.531)	(1.952)	(1.859)	(2.510)	(2.783)	(3.178)	(3.203)	(3.246)	(3.281)	(3.185)	(3.193)
OTR	0.054**	0.054**	0.055**	0.054**	0.053**	0.059**	0.059**	0.056**	0.055**	0.054**	0.049*	0.048*	0.046*	0.046*	0.046*
	(2.059)	(2.089)	(2.122)	(2.153)	(2.161)	(2.222)	(2.253)	(2.258)	(2.237)	(2.209)	(2.006)	(1.983)	(1.892)	(1.938)	(2.014)
Informativeness															
QS	-0.082	-0.082	-0.083	-0.081	-0.078*	-0.091*	-0.094*	-0.090*	-0.088*	-0.085*	-0.075	-0.073	-0.073	-0.074	-0.079
	(-1.542)	(-1.560)	(-1.579)	(-1.557)	(-1.739)	(-1.880)	(-1.988)	(-2.019)	(-2.008)	(-1.927)	(-1.525)	(-1.478)	(-1.406)	(-1.393)	(-1.461)
PI_perm	-0.135**	-0.135**	-0.136**	-0.136**	-0.136**	-0.125**	-0.124**	-0.130**	-0.131**	-0.133**	-0.145**	-0.147**	-0.149**	-0.148**	-0.146**
	(-2.432)	(-2.417)	(-2.277)	(-2.329)	(-2.522)	(-2.393)	(-2.351)	(-2.422)	(-2.435)	(-2.433)	(-2.688)	(-2.631)	(-2.467)	(-2.281)	(-2.287)
IS_quotes	0.258***	0.258***	0.258***	0.258***	0.256***	0.257***	0.257***	0.257***	0.257***	0.257***	0.261***	0.261***	0.262***	0.261***	0.260***
	(3.192)	(3.154)	(2.913)	(2.755)	(2.888)	(2.915)	(2.908)	(2.810)	(2.775)	(2.716)	(2.944)	(3.037)	(3.139)	(3.022)	(2.996)
AbsPI_perm	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.005	0.005	0.005	0.005	0.005
	(0.821)	(0.824)	(0.797)	(0.784)	(0.792)	(0.913)	(0.923)	(0.881)	(0.868)	(0.851)	(0.705)	(0.715)	(0.740)	(0.786)	(0.821)
Volatility															
RV	-0.035	-0.091	0.530	0.516	0.037	3.136	3.580	2.024	1.546	0.768	0.234	1.354	5.949	6.684	7.286
	(-0.002)	(-0.006)	(0.035)	(0.034)	(0.003)	(0.230)	(0.269)	(0.150)	(0.113)	(0.056)	(0.015)	(0.090)	(0.360)	(0.373)	(0.372)
FTSE_RV5	-210.675**	-212.265**	-217.864**	-221.475**	-219.379**	-210.412**	-212.250**	-218.490**	-220.068**	-218.084**	-212.818**	-214.702**	-220.202**	-217.163**	-217.391**
	(-2.371)	(-2.408)	(-2.472)	(-2.577)	(-2.570)	(-2.323)	(-2.356)	(-2.466)	(-2.502)	(-2.436)	(-2.428)	(-2.456)	(-2.546)	(-2.518)	(-2.536)
Cross-sectional variation															
lnMV	0.019	0.019	0.019*	0.019**	0.020***	0.019**	0.020**	0.020**	0.020**	0.020**	0.007	0.006	0.003	0.005	0.006
	(1.379)	(1.550)	(2.012)	(2.052)	(2.845)	(2.422)	(2.382)	(2.398)	(2.345)	(2.317)	(0.793)	(0.604)	(0.251)	(0.397)	(0.468)
InvPrice	-7.820	-7.895	-9.224	-8.884	-7.982	-5.758	-6.301	-8.107	-8.461	-8.065	-9.441	-9.776	-9.441	-8.348	-8.594
	(-0.243)	(-0.245)	(-0.287)	(-0.273)	(-0.247)	(-0.176)	(-0.193)	(-0.251)	(-0.261)	(-0.248)	(-0.283)	(-0.294)	(-0.286)	(-0.257)	(-0.267)
Inventory risk															
HFOIV	-0.062	-0.046	-0.097	-0.071	-0.055	0.023	0.019	0.005	0.002	0.001	-1.205*	-1.187*	-1.073*	-0.829	-0.445
	(-0.344)	(-0.349)	(-1.254)	(-1.048)	(-0.503)	(1.504)	(1.602)	(0.996)	(0.695)	(0.444)	(-1.850)	(-1.885)	(-1.956)	(-1.597)	(-1.259)
Intercept	0.157	0.142	0.181	0.152	0.123	0.026	0.033	0.077	0.088	0.093	0.197*	0.209*	0.230**	0.209*	0.197
	(1.150)	(1.159)	(1.419)	(1.101)	(0.893)	(0.160)	(0.208)	(0.524)	(0.611)	(0.663)	(1.769)	(1.947)	(2.251)	(1.824)	(1.593)
N	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265
R-sq	0.0901	0.0900	0.0902	0.0902	0.0902	0.0911	0.0911	0.0904	0.0903	0.0901	0.0907	0.0908	0.0912	0.0912	0.0910
adj. R-sq	0.0695	0.0695	0.0697	0.0696	0.0696	0.0705	0.0706	0.0699	0.0697	0.0696	0.0702	0.0703	0.0707	0.0707	0.0704

	HFOIV_sharesraw30s	HFOIV_sharesraw60s	HFOIV_sharesraw300s	HFOIV_sharesraw600s	HFOIV_sharesraw1800s	HFOIV_dol30s	HFOIV_dol60s	HFOIV_dol300s	HFOIV_dol600s	HFOIV_dol1800s	HFOIV_dolraw30s	HFOIV_dolraw60s	HFOIV_dolraw300s	HFOIV_dolraw600s	HFOIV_dolraw1800s
EventDummy	-0.029	-0.029	-0.029	-0.029	-0.029	-0.030	-0.030	-0.030	-0.030	-0.029	-0.030	-0.030	-0.030	-0.030	-0.029
	(-0.746)	(-0.747)	(-0.749)	(-0.748)	(-0.744)	(-0.757)	(-0.754)	(-0.747)	(-0.710)	(-0.684)	(-0.773)	(-0.771)	(-0.771)	(-0.760)	(-0.752)
Activity															
TO	0.022***	0.022***	0.023***	0.022***	0.021***	0.026***	0.027***	0.030***	0.032***	0.033***	0.026***	0.026***	0.027***	0.025***	0.024***
	(2.847)	(2.957)	(3.351)	(3.985)	(3.841)	(3.024)	(3.073)	(3.111)	(3.099)	(3.182)	(3.012)	(3.113)	(3.648)	(4.417)	(4.219)
OTR	0.053**	0.053**	0.053**	0.053**	0.053**	0.051**	0.050**	0.048*	0.048**	0.049**	0.053**	0.053**	0.053**	0.053**	0.053**
	(2.131)	(2.136)	(2.112)	(2.130)	(2.131)	(2.064)	(2.050)	(2.013)	(2.031)	(2.074)	(2.151)	(2.144)	(2.151)	(2.135)	(2.125)
Informativeness															
QS	-0.081	-0.081	-0.080	-0.081*	-0.082*	-0.074	-0.072	-0.069	-0.069	-0.073	-0.075	-0.075	-0.075	-0.077*	-0.079*
	(-1.635)	(-1.653)	(-1.683)	(-1.840)	(-1.862)	(-1.504)	(-1.460)	(-1.376)	(-1.363)	(-1.426)	(-1.589)	(-1.640)	(-1.666)	(-1.825)	(-1.872)
PI_perm	-0.136**	-0.136**	-0.137**	-0.136**	-0.135**	-0.144**	-0.145**	-0.147**	-0.146**	-0.145**	-0.146**	-0.144**	-0.144**	-0.140**	-0.138**
	(-2.366)	(-2.321)	(-2.325)	(-2.286)	(-2.301)	(-2.710)	(-2.677)	(-2.596)	(-2.402)	(-2.351)	(-2.424)	(-2.389)	(-2.415)	(-2.355)	(-2.352)
IS_quotes	0.259***	0.259***	0.259***	0.259***	0.259***	0.262***	0.261***	0.263***	0.262***	0.262***	0.260***	0.260***	0.261***	0.260***	0.260***
	(2.736)	(2.764)	(2.766)	(2.767)	(2.750)	(2.768)	(2.862)	(2.984)	(2.918)	(2.952)	(2.766)	(2.784)	(2.769)	(2.742)	(2.719)
AbsPI_perm	0.006	0.006	0.006	0.006	0.006	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.006	0.006
	(0.756)	(0.772)	(0.831)	(0.851)	(0.851)	(0.713)	(0.720)	(0.736)	(0.778)	(0.810)	(0.763)	(0.775)	(0.800)	(0.837)	(0.848)
Volatility															
RV	-0.503	-0.519	-0.674	-0.522	-0.277	-2.552	-2.473	-2.227	-2.462	-2.065	-3.286	-2.763	-2.881	-2.037	-1.211
	(-0.035)	(-0.037)	(-0.047)	(-0.036)	(-0.020)	(-0.167)	(-0.165)	(-0.149)	(-0.164)	(-0.133)	(-0.232)	(-0.197)	(-0.200)	(-0.142)	(-0.086)
FTSE_RV5	-213.992**	-214.085**	-214.564**	-213.753**	-213.313**	-211.371**	-212.412**	-214.564**	-210.963**	-210.436**	-214.254**	-213.942**	-212.560**	-211.055**	-211.476**
	(-2.433)	(-2.441)	(-2.453)	(-2.441)	(-2.447)	(-2.410)	(-2.425)	(-2.466)	(-2.421)	(-2.418)	(-2.396)	(-2.398)	(-2.381)	(-2.348)	(-2.343)
Cross-sectional variation															
lnMV	0.019**	0.019**	0.018**	0.019**	0.019**	0.010	0.009	0.006	0.007	0.008	0.017**	0.017**	0.018**	0.018**	0.019**
	(2.266)	(2.246)	(2.242)	(2.228)	(2.262)	(1.174)	(0.975)	(0.614)	(0.684)	(0.746)	(2.131)	(2.210)	(2.239)	(2.295)	(2.322)
InvPrice	-7.246	-7.253	-6.986	-7.105	-7.458	-10.838	-11.350	-11.957	-11.368	-11.581	-8.699	-8.471	-7.697	-7.270	-7.398
	(-0.222)	(-0.223)	(-0.215)	(-0.216)	(-0.228)	(-0.327)	(-0.343)	(-0.363)	(-0.354)	(-0.366)	(-0.273)	(-0.266)	(-0.239)	(-0.225)	(-0.229)
Inventory															
HFOIV	-0.588	-0.582	-0.643	-0.266	0.016	-1.032	-1.012*	-0.921*	-0.743*	-0.423	-0.019	-0.013	-0.008	-0.004	-0.001
	(-0.167)	(-0.179)	(-0.318)	(-0.140)	(0.017)	(-1.654)	(-1.744)	(-2.022)	(-1.924)	(-1.602)	(-0.966)	(-0.791)	(-1.025)	(-0.567)	(-0.324)
Intercept	0.103	0.104	0.105	0.102	0.100	0.180	0.192*	0.215*	0.204*	0.195	0.133	0.126	0.119	0.109	0.104
	(0.784)	(0.785)	(0.778)	(0.747)	(0.728)	(1.536)	(1.706)	(2.023)	(1.779)	(1.620)	(1.040)	(0.976)	(0.892)	(0.802)	(0.765)
N	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265	2265
R-sq	0.0900	0.0900	0.0900	0.0900	0.0900	0.0905	0.0906	0.0909	0.0909	0.0908	0.0903	0.0902	0.0903	0.0902	0.0901
adj. R-sq	0.0695	0.0695	0.0695	0.0695	0.0695	0.0699	0.0700	0.0703	0.0704	0.0702	0.0698	0.0697	0.0698	0.0696	0.0695

Appendix F The visualisation of the slope of the LOB

Figure 1: Slopes

This figure illustrates the ask side of the slope. Each dot represents the last share of the queue at each price level at one point in time. The value of the horizontal axis is the cumulative depth and the value of the vertical axis is the price level in the book minus the mid-quote at a point in time. All blue dots form a snapshot at one point in time. Likewise, each red dot represents the last share of the queue at each price level at another point in time and all red dots form another snapshot. Layering up all snapshots over a trading day, a straight line can be found for each side of the book. The slope of the line is the variable of interest. Cumulative depth is the number of shares re-scaled by the EMS.