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Informed trading and the price impact of block trades: A high frequency trading analysis☆

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ABSTRACT

Using high frequency data from the London Stock Exchange (LSE), we investigate the relationship between informed trading and the price impact of block trades on intraday and inter-day basis. Price impact of block trades is stronger during the first hour of trading; this is consistent with the hypothesis that information accumulates overnight during non-trading hours. Furthermore, private information is gradually incorporated into prices despite heightened trading frequency. Evidence suggests that informed traders exploit superior information across trading days, and stocks with lower transparency exhibit stronger information diffusion effects when traded in blocks, thus informed block trading facilitates price discovery.

1. Introduction

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

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

This paper contributes to the literature on the informativeness of block trades by testing the competing information diffusion hypotheses stated above. Our contributions are three-fold: firstly, the models employed in this paper present new empirical evidence on the diffusion process of private information in a high frequency trading environment. Instead of focusing trades around short term corporate events and insider trading sample, we expand observations of block trades to

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normal trading periods. This is because informed trading activities occur not only around corporate events but also across regular trading hours.

Secondly, we find intraday and inter-day patterns within this information diffusion process. The results suggest that the impounding of information into stock prices is stronger in the first trading hour than at other time periods during the normal trading day. Further, informed trading at day t_{-1} could still affect informed traders' block transaction at day *t*. These results support the theoretical frameworks of Kyle (1985), Holden and Subrahmanyam (1992), Foster and Viswanathan (1994) and Hong and Stein (1999) that suggest that private information is gradually impounded into instrument prices because informed traders slowly exploit the private information across trading days. The results, however, run contrary to the expectation that informed traders quickly take advantage of their private information by trading quickly and aggressively, as suggested by Easley and O'Hara (1987) and Karpoff (1987). It is interesting that high frequency data from an era that is characterised by short-termism in trading terms could validate theoretical propositions (such as that of Kyle, 1985) from an era in which buy and hold strategies were more orthodox.

Thirdly, since the probability of the occurrence of an informed trade (PIN) also reflects the level of firms' financial transparency (Vega, 2006), we stratify our sample stocks into four portfolios according to the mean value of their daily PINs, and show that the information incorporation process can vary across stocks with different levels of financial transparency. The results imply that the larger the levels of informed trading in a stock, the higher the permanent price impact of block trades. There are several implications of this, including that informed trading aids the price discovery process for less transparent stocks.

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

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

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

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

This paper employs probability of information-based trading (PIN) to proxy the proportion of the unobservable informed trades across normal trading hours. PIN has been elaborated in previous work (see for example Easley, Kiefer, & O'hara, 1996, 1997a; Easley, Kiefer, O'hara, & Paperman, 1996). Easley, Hvidkjaer, and O'hara (2002) find that a difference of 10% in PIN between two stocks leads to a difference in the excessive returns of 2.5% per annum. This implies that uninformed investors demand a premium to hold stocks with higher information risk. PIN has been extensively used to capture information asymmetry. Easley, Hvidkjaer, and O'hara (2010) use the returns of high and low-PIN portfolios to construct a risk factor which explains portfolio returns. Vega (2006) constructs PIN to test market efficiency, suggesting that the more information investors have about the true value of an asset, the smaller the abnormal return drift. Chung, Li, and Mcinish (2005), using a sample of NYSE stocks, examine the relationship between price impacts of all trades, serial correlation in trade direction, and PIN. They find that there is a positive relationship between PIN and permanent price impacts of all trades, and stocks with higher PIN exhibit higher correlations in the trade direction. Their result is consistent with information hypothesis that strategic trading of informed trades results in serially correlated trades. Based on three months-worth of NYSE and NASDAQ transactions data, Lee and Chung (2009) find a negative relationship between price improvement in NYSE stocks and PIN. This suggests that liquidity providers on the NYSE offer greater price improvements for stocks with a lower PIN. However, Lai, Ng, and Zhang (2014) deconstruct PIN into risk and liquidity components and they find that only the liquidity component is priced. Lai et al. (2014) also construct stock-level PINs over a 15-year period in 47 stock markets worldwide. Their results show the variations of PIN between emerging

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and developed markets. However, they do not find that PIN exhibits explanatory power to expected stock returns in global stock markets.

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

2. Data and methodology

2.1. Data

2.1.1. Sample selection

Our data consists of FTSE 100 stocks, which account for about 80% of total market capitalisation on the LSE. The LSE is a hybrid trading platform, hosting the upstairs dealer market and the downstairs order-driven, i.e. the transparent order book named the Stock Exchange Electronic Trading System (SETS). By design the dealer market hosts large liquidity-driven institutional trades with little, but not negligible, price impact in the market since the trades are bilateral and are based on reference prices from the downstairs market (see Armitage & Ibikunle, 2015; Jain, Jiang, Mcinish, & Taechapiroontong, 2003). Hence, in order to adequately examine the price impact of block trades on the LSE one needs to examine the downstairs market data. Furthermore, according to Armitage and Ibikunle (2015), the downstairs market routinely accounts for roughly about 82.1% of all transactions in the FTSE 100. The intraday SETS transactions data for this research comes from the Thomson Reuters Tick History (TRTH) Database. Our dataset contains 253 trading days from 1st October 2012 to 30th September 2013[2] and includes variables such as Reuters Identification Code (RIC), date, timestamp, price, volume, bid price, ask price, bid volume and ask volume. Each trade has been allocated corresponding prevailing best bid and ask quotes. Since we only focus on normal trading hours, we delete the opening auction period (7:50 h–8:00 h) and the closing auction period (16:30 h–16:35 h).

Following data cleaning, the dataset comprises of 44,742,693 transactions, which are restricted to regular trades with eligible best bid and ask prices. We define block trades in line with Frino et al. (2007) as the largest 1% of the trades in each stock. There are two main reasons why we have not defined block trades in terms of absolute size. The first is the potential for noise. The LSE is the fourth largest exchange in the world and one of the most liquid, simply setting 10,000 shares as a block trade threshold across the entire sample period in the London high frequency trading environment could lead to the inclusion of trades based on noise and liquidity demand. Secondly, there is a distinctively large variation in the liquidity properties of FTSE 100 stocks. Ibikunle (2015a) show that the largest trading volume quintile FTSE 100 stocks have average trade sizes that are on average more than 33 times the size of the lowest volume quintile stocks in the same index. Thus, a 10,000-share trade in one stock could be its median while such trade could sit in above the 95th percentile in a less liquid stock. Furthermore, we bunch trades occurring during the same millisecond by aggregating their volume and price Huang and Stoll (1997); the price used is the weighted average of all the trades during that millisecond weighed by the volume of each transaction. Millisecond rather than second is chosen as the relevant time interval, in contrast with the second interval used by Spierdijk (2004) and Engle and Russell (1998), due to the ultrahigh frequency nature of the data we employ. Finally, we also classify trades into purchase or sale by using the established Lee and Ready (1991) tick rule algorithm. Specifically, when the transaction price is higher than the prevailing quote mid-point, we classify the transaction as a buyer-initiated (purchase) trade. If price is the execution price lower than quote mid-point, then we classify it as seller-initiated (sale) trade. If the current and the previous trades are the same price, we classify using the next previous trade. Aitken and Frino (1996) and Lee and Ready (1991) suggest that the tick rule has an accuracy in excess of 90%. These two classification conditions yield 206,002 block purchases and 246,867 block sales in our final sample.

2.1.2. Sample description

Table 1 shows the descriptive data of block trades based on midpoint classification. The average number of shares and average traded values of block sales are greater than those of block purchases. However, the average value of price impact of block purchases is 0.020%, which is more pronounced than the absolute value of the permanent price impact of block sales, at −0.011%. This is significant given that the average price impact is computed from trades occurring at very short intervals of less than 50 s in all cases. The impact asymmetry is expected given that prices usually fall after a seller-initiated trade and appreciate after a buyer-initiated trade (see Kraus & Stoll, 1972). The phenomenon is also attributable to the fact that block sales are usually initiated on the basis of a number of factors, one of which is the search for liquidity, while block purchases are more likely to contain firm specific information. This price impact asymmetry is also documented in Keim and Madhavan (1996) and Saar (2001). The BAS average for block sales is larger than that for block purchases. This is surprising given that the literature suggests that spreads are larger for informed trades. It is important to point out, however, that the difference between both estimates is small and is not statistically significant at any conventional level. Table 2 shows the correlation matrix of the explanatory variables. We observe that there are no multicollinearity issues within the secondary model for the price impact of block trades.

2.2. Methodology

2.2.1. The price impact model

We start by constructing three types of price impact that are generally accepted in the literature. These include temporary, permanent and total price impact measures. In the microstructure literature, the permanent price impacts as trading effects on price caused by informed

Table 1
Summary statistics for block trades.
This table shows the descriptive statistics for purchase block, sale block and all block trades. The sample includes FTSE 100 stocks trading on the London Stock Exchange between 1st October 2012 and 30th September 2013.

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

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

[2] Although our data range is one year, the sample size is the large ever examined in the price impact of block trades literature. The overall cleaned sample of all buy and sell trades contains 44,742,693 transactions in FTSE 100 stocks across 253 trading days. By contrast, Alzahrani, Gregoriou, and Hudson (2013), the paper with the next largest base dataset has only 20,297,452 transactions in their base dataset, and other papers even have much less. Furthermore, our final sample of block trades (based on our selection criteria) consists of 453,012 LSE block trades in total. By comparison, this is a much larger block trades sample than the 166,976 ASX block trades employed by Frino, Jarnecic, and Lepone (2007) and the16,951 NYSE block trades employed by Madhavan and Cheng (1997).

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Table 2
Correlation matrix of the explanatory variables.
This table plots the correlation matrix of the explanatory variables employed in the price impact model in Table 4. PIN is the probability of an informed trade, *lnSize* is the natural logarithm of the number of shares per trade, *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place, *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade and *OIB* represents the order imbalance. *BAS* corresponds to the bid-ask spread at the time of the block trade, *Market return* is the daily FTSE100 index return on the day of the block trade, while *Momentum* is the cumulative return of the stock in the five days preceding the block trade. The sample includes FTSE 100 stocks trading on the London Stock Exchange between 1st October 2012 and 30th September 2013.

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

trading, while temporary price impacts usually result from noise or liquidity trading, thus leading to price reversal (see for example Glosten & Harris, 1988; Chan & Lakonishok, 1995; Easley et al., 2002). Block trades demand more liquidity than is likely to be available at current quoted prices. Therefore in order to ensure the execution of such trades against the expressed level of liquidity, it will have to 'walk' through the order book. This will result in the move of prices in the trade direction; specifically, purchase trades will force an upward swing and sales will force a downward swing. The temporary impact on the other hand captures the market's frictional price reaction to the execution of a block trade, which should be reversed soon after the block trade. Eq. (1) expresses how we measure the temporary price impact as the liquidity effect of executing a block trade. The price deviation on account of an un-informed block trade execution occurs because counterparties at the best expressed corresponding quote are not readily available. The temporary effect is therefore compensation to the counterparties providing the liquidity needed for an un-informed block trade execution. Block purchasers (sellers) offer a price premium (discount) as compensation in order to ensure trade execution.

The permanent impact captures the lasting impact of a block trade execution, that is, the price change that is not reversed within a reasonable timeframe after the block trade execution. The information element of a block trade execution is therefore captured by the permanent impact. The lack of price reversal in this case suggests a learning event in the market, which ultimately results in the discovery of a new price for the traded instrument. Consistent with Holthausen, Leftwich, and Mayers (1990), Gemmill (1996), Frino et al. (2007) and Alzahrani et al. (2013), we employ the five-trade benchmark to calculate the price impact measures. Thus, for temporary price impact (Eq. (1)), we measure the percentage of price reversal after five trades after a block trade execution, and for permanent price impact Eq. (2) captures the percentage change in price from five trades *before* the block trade to five trades *following* the block trade. The third price impact measure, total impact, captures the total percentage price impact, which includes both the liquidity and the information component. Computing all three measures as percentage returns ensures comparability with existing studies:

$$Temporary\ \ impact = \frac{P_{t+5} - P_t}{P_t} \tag{1}$$

$$Permanent\ \ impact = \frac{P_{t+5} - P_{t-5}}{P_{t-5}} \tag{2}$$

$$Total\ \ impact = \frac{P_t - P_{t-5}}{P_{t-5}} \tag{3}$$

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

$$\begin{aligned} Price\ \ impact = {} & \alpha + \beta_1 PIN + \beta_2 \ln Size + \beta_3 Volatility + \beta_4 \ln Turnover \\ & + \beta_5 Market\ \ return + \beta_6 Momentum + \beta_7 BAS + \beta_8 |OIB| \\ & + \beta_9 DUM_1 + \beta_{10} DUM_2 + \beta_{11} DUM_3 + \varepsilon \end{aligned} \tag{4}$$

where *Price impact* refers to one of three measures: temporary, permanent and total price impacts. *PIN* is a daily approximation of informed trading in every stock obtained through the maximum likelihood estimation of Eq. (6) and as discussed in Section 2.2.2. This is the most important variable we study in this paper. We expect to see a positive (negative) relation between PIN and the permanent price impact of purchase (sale) block trades. This is because price shifts should follow the direction of an informed trade; hence we expect that an informed block purchase (sale) will lead to appreciation (depreciation). *lnSize* is the natural logarithm of the number of shares traded and reported to the nearest millisecond. Based on the established premise that size is related to the information content of a trade (see for example Kraus & Stoll, 1972; Chan & Lakonishok, 1997), we also proxy information content using block trade size.

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

Market return is the daily return on the FTSE 100 index. It is included in the regression model because literature has found that most stocks have positive beta (Aitken & Frino, 1996; Chiyachantana, Jain, Jiang, & Wood, 2004; Frino et al., 2007). Thus, a positive relationship is expected to exist between market return and price impact. *Momentum* is calculated as the lagged cumulative daily return for each stock on the five trading days prior to the block trades. Momentum captures the trading trend for each stock. Thus, higher returns indicate a purchasing trend, and lower returns indicate a selling trend. Saar (2001) argues that the historical performance of stocks is related to their expected price impact asymmetry. Specifically, block trades that are executed following a depreciating price trend will exhibit higher positive asymmetry, and block trades executed following a run of price appreciation should display less price impact, or perhaps negative asymmetry. Specifically, historical cumulative lagged returns correspond to the magnitude of price impact. A positive relationship is therefore expected between momentum and price impact due to the herding effect. *BAS* is the relative bid-ask spread prior to the block trades. We calculate relative bid-ask spread as the ask price prior to the block trade minus the bid price before the block trade, divided by the midpoint of both prices. This measure is a proxy for liquidity, and when liquidity is high, BAS tends to be narrow. Hence, we expect lower price impact when spreads are narrow and larger price impact when they are wide.[3]

OIB corresponds to daily order imbalance. This variable and PIN are new additions to the Frino et al. (2007) price impact model. We compute OIB as shown in Eq. (5) for each day.[4] According to Chordia, Roll, and Subrahmanyam (2008), the extent of the predictability of returns by lagged OIB is an inverse measure of market efficiency. *OIB* in the model is therefore a proxy for how efficiently each stock is being traded.

$$OIB = \left|\frac{\#Buy\ \ trades\text{-}\#Sell\ \ trades}{\#Buy\ \ trades + \#Sell\ \ trades}\right| \tag{5}$$

Time dummy variables are used to capture intraday effects of the private information diffusion process. Frino et al. (2007) and Alzahrani et al. (2013) document intraday patterns in the price impact of block trades. In this paper, we employ dummy variables to capture intraday patterns of price effects. DUM_1 equals to one if block trade occurs between 8:00 and 9:00, and is otherwise zero. DUM_2 equals to one if the block trade occurs during 9:00 to 15:30, and is otherwise zero. DUM_3 equals to one if block trade occurs during 15:30 to 16:00, and is otherwise zero. The last trading period (16:00–16:30) is not in the regression, as it is the reference group of block trades.

2.2.2. The PIN model

In order to capture the informed trading elements of stock for each day, we compute the daily probabilities of informed trading (PINs) based on the PIN model of Easley, Kiefer, and O'hara (1996) and Easley, Kiefer, and O'hara (1997b). The model as specified is based on the expectation that trading between informed traders, liquidity traders and market makers occurs repeatedly over numerous trading intervals. As presented in Fig. 1, trading intervals begin with the informed traders acquiring a private signal on a stock's value with a probability of α. Dependent on the arrival of a private signal, bad news will arrive with a probability of δ, and good news arrives with a probability of $(1-\delta)$. The market makers determine their bid and ask prices, with orders arriving from liquidity traders at the arrival rate ε. If there is a new piece of private information, informed traders will also trade and their orders will arrive at the rate μ. Hence, informed traders will execute a purchase trade should they receive a good news signal and sell if they receive a bad news signal. It is important to point out that the setting of different arrival rates for uninformed buyers and sellers does not qualitatively alter estimations of the probability that an informed trade has been executed (see Easley et al., 2002).

The PIN model allows us to approximate the unobservable distribution of trades between informed and uninformed traders through the modelling of purchases and sales.[5] Thus, the 'normal level' of sales and purchases executed within a stock on a given day over several intervals is interpreted as an uninformed trade by the model, and this information is employed when estimating ε. An unusual volume of purchase or sale transactions is interpreted as an information-based trade and employed when computing μ. In addition, the frequency of intervals during which 'abnormal' levels of purchase and sale transactions are executed is used when calculating the values of α and δ. These calculations are conducted in a simultaneous fashion by the use of the maximum likelihood estimation method. Supposing that the uninformed and informed trades arrive as a Poisson distribution, the likelihood function for the PIN model for each interval estimated can be expressed as:

$$L((B,S)|\theta) = (1-\alpha)\ e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}\ e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!} + \alpha\delta e^{-e_b}\frac{\varepsilon_b^B}{B!}\ e^{-(\mu+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^S}{S!} + \alpha(1-\delta)\ e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!}\ e^{-(\mu+\varepsilon_b)}\frac{(\mu+\varepsilon_b)^B}{B!} \tag{6}$$

where *B* and *S* respectively represent the total number of purchase and sale transactions for each 1 h trading period within each trading day. $\theta = (\alpha, \delta, \mu, \varepsilon)$ is the parameter vector for the structural model. Eq. (6) corresponds to a mix of distributions in which the possible trades are weighted by the probability of a 1 h trading period with no news $(1-\alpha)$, a 1h trading period with good news $(\alpha(1-\delta))$ or a 1 h trading period with bad news $(\alpha\delta)$. Based on the assumption that this process ensues independently across the different trading periods, Easley, Kiefer, and O'hara (1996) and Easley et al. (1997b) compute the parameter vector estimates using maximum likelihood estimation. Hence we obtain the parameters for each trading day and for each stock in the sample by maximum likelihood estimation. We follow Easley, Kiefer, and O'hara (1996) and Easley et al. (1997b) to compute PIN as:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \tag{7}$$

We include the daily stock-dependent PIN variable into the regression model (4).

3. Regression results and discussion

3.1. Preliminary predictive analysis

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

$$\ln(\#Block\ \ trades_t) = \alpha + \beta\ln(\#Informed\ \ trades_t) + \varepsilon \tag{8}$$

Table 3 shows the statistical results. As expected, the positive and significant coefficient of informed trades indicates that with a 1% increase in the number of informed trades the number of block trades correspondingly increases 1.11% on the same trading day. The adjusted R^2 is about 52.18%, which is high for a univariate estimation. This is an indication that variation in the estimated number of informed trades can be explained by the quantity of block trades. This result is consistent with Easley and O'Hara (1987) and Blau et al. (2009), who suggest that informed traders prefer block trades to exploit private information. However, this result may be viewed to some extent as a contradiction of Barclay and Warner (1993) stealth trading hypothesis, which implies that most of cumulative price changes are due to mid-size trades. One

[3] For robustness, we also estimate Eq. (4) using the effective bid-ask spread measure, defined as twice the absolute value of the difference between the execution price for a block transaction and the prevailing quote mid-point at the time of the transaction, as the liquidity proxy. The results, which are available on request, are qualitatively unaffected by the substitution of a liquidity proxy.

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

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

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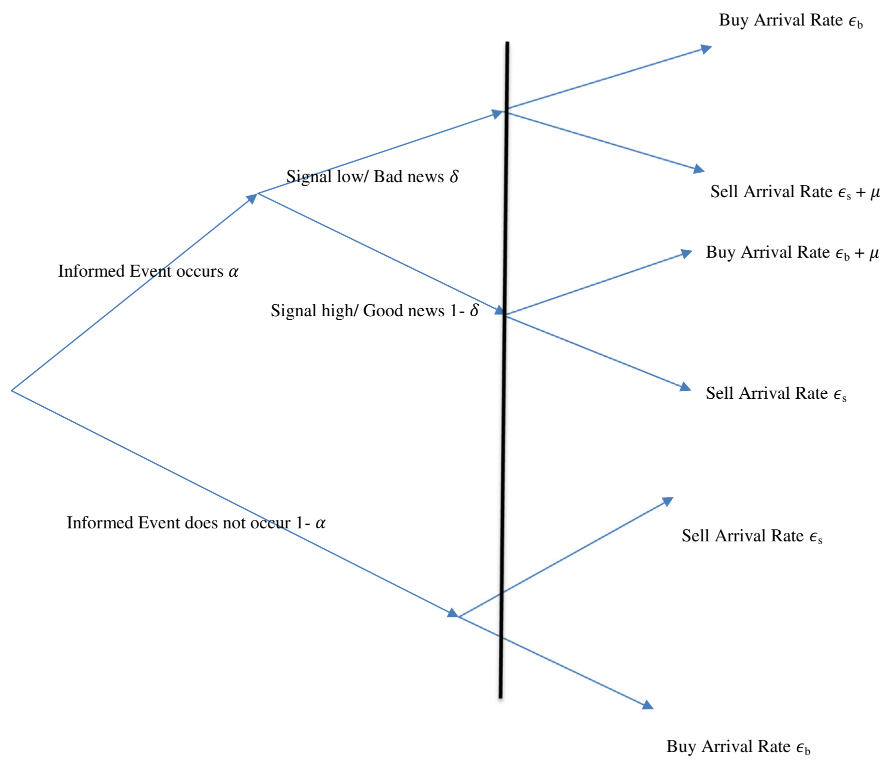

Fig. 1. Tree diagram of the trading process. A corresponds to the probability of an information event, δ represents the probability that a low signal ensues, μ is the arrival rate of informed orders, and ε is the arrival rate of uninformed orders. The nodes to the left of the thick vertical line occur only once a day.

of the explanations could be that Barclay and Warner (1993) focus on trades prior to tender offer events, during which any larger order could easily attract other investors' *unwanted* attention. Informed traders might therefore be more discrete in their exploitation of private information by splitting up large orders. In contrast, during uneventful trading periods informed traders might prefer block trades because they believe the market can absorb large orders without attracting undue attention. The view that stealth trading is mainly prevalent during eventful periods is further emphasised by Yang (2009). Yang (2009) reports that there is an increase in the implementation of stealth trading from around six to ten days prior to the release of quarterly earnings. However, informed traders are likely to aggressively exploit private information through the use of larger trades from about five days prior to the earnings announcements. Despite the inconsistency in the evidence, theoretical and empirical studies generally agree that informed traders are more likely to exploit private information by trading block sizes.

Table 3
Predictive analysis test.
This table shows the results of regressing the natural logarithm of the daily number of block trades against the natural logarithm of estimated number of daily informed trades. We use the following model:

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

The coefficients and standard errors (in parentheses) are reported. The sample includes FTSE 100 stocks trading on the London Stock Exchange between 1st October 2012 and 30th September 2013.

	$\ln(\#Informed\ \ trades_t)$	
	Coefficient	S.E.
$\ln(\#Block\ \ trades_t)$	1.11***	2.83×10^{-2}
Constant	2.47***	4.98×10^{-2}
Observations	2007	
R-squared	52.20%	
Adj R-squared	52.18%	

*** Statistical significance at the 0.01 level.

3.2. Trading on information with block trades

Following the establishment of a predictive relationship between informed trading and block trades, we now examine the process by which information is compounded in instrument prices via block trading. Panels A, B and C of Table 4 present the estimated parameters from Eq. (4) for all three price impact measures and for block purchases, block sales and all block trades in the sample. For block purchases, PIN shows a positive and statistically significant relationship with both permanent and temporary price impacts. The PIN Permanent price impact of block purchases is 0.000294, while the corresponding temporary price impact is 0.000386. The lesser permanent price impact coefficient estimate implies that the FTSE 100 stocks are less sensitive to informed trades than they are to liquidity trades. Consistent with our expectations, the PIN coefficient estimates for block sales are negative and statistically significant for both the temporary and permanent price impact regressions. As with the block purchases, there is a stronger level of temporary price impact than there is for permanent price impact. The negative (positive) statistically significant coefficient estimates of the PIN coefficients for the block sales (purchases) appear to confirm the information diffusion hypothesis via block trading.

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

Table 4
Incorporation of private information via block trading in FTSE 100 stocks.
The relationship between informed trading and block trading is estimated using the following model:

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

Price impact corresponds to *permanent, temporary* or *total price impact*, and is as defined in Table 5. *PIN* is the probability of an informed trade. *LnSize* is the natural logarithm of the number of shares per trade; *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place; *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade; *OIB* represents the order imbalance; *BAS* is the bid-ask spread at the time of the block trade; *Market return* is the daily FTSE100 return on the day of the block trade. *Momentum* is the cumulative return of the stock in the five days preceding the block trade. DUM_1 takes the value of 1 if the trade occurs between 8:00 and 9:00; DUM_2 takes the value of 1 if the trade occurs between 9:00 and 15:30; DUM_3 takes the value of 1 if the trade occurs between 15:30 and 16:00. Standard errors are presented in parentheses. Panels A, B and C present results for when permanent price impact, temporary price impact and total price impact are employed as dependent variables respectively. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively. The sample includes FTSE 100 stocks trading on the London Stock Exchange between 1st October 2012 and 30th September 2013.

	Panel A. Permanent price impact			Panel B. Temporary price impact			Panel C. Total price impact		
	Purchases	*Sales*	*All Trades*	*Purchases*	*Sales*	*All Trades*	*Purchases*	*Sales*	*All Trades*
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
PIN	2.94×10^{-4}***	-2.00×10^{-4}**	6.81×10^{-7}	3.86×10^{-4}***	-8.33×10^{-4}***	-1.43×10^{-4}	1.13×10^{-3}	6.22×10^{-4}***	1.99×10^{-4}*
	(7.74×10^{-5})	(9.01×10^{-5})	(1.00×10^{-4})	(4.64×10^{-5})	(7.38×10^{-5})	(1.40×10^{-4})	(1.14×10^{-3})	(1.01×10^{-4})	(1.19×10^{-4})
Ln(size)	-1.01×10^{-6}	1.13×10^{-5}***	3.94×10^{-6}**	2.31×10^{-6}**	5.88×10^{-6}*	-7.07×10^{-7}	3.89×10^{-5}	4.81×10^{-6}	9.41×10^{-8}
	(1.96×10^{-6})	(2.1×10^{-6})	(1.57×10^{-6})	(1.00×10^{-6})	(3.06×10^{-6})	(6.25×10^{-6})	(4.24×10^{-5})	(3.38×10^{-6})	(3.05×10^{-6})
Volatility	3.02×10^{-5}	1.78×10^{-4}	5.47×10^{-6}	3.26×10^{-4}*	2.41×10^{-3}***	0.01	0.02	-2.17×10^{-3}***	-8.66×10^{-3}***
	(3.33×10^{-4})	(2.92×10^{-4})	(2.50×10^{-4})	(1.93×10^{-4})	(7.55×10^{-4})	(3.57×10^{-3})	(0.02)	(7.24×10^{-4})	(1.79×10^{-3})
Ln(turnover)	1.31×10^{-5}***	-1.52×10^{-5}***	-1.54×10^{-6}	1.54×10^{-5}***	2.21×10^{-5}***	-3.8×10^{-8}	5.83×10^{-5}	-3.60×10^{-5}***	-7.93×10^{-6}
	(6.25×10^{-6})	(4.13×10^{-6})	(4.55×10^{-6})	(2.31×10^{-6})	(5.95×10^{-6})	(1.11×10^{-5})	(6.28×10^{-5})	(6.43×10^{-6})	(7.62×10^{-6})
Market Return	-8.22×10^{-4}***	-1.16×10^{-4}	-4.72×10^{-4}*	-9.71×10^{-4}***	5.42×10^{-3}***	1.30×10^{-3}	7.37×10^{-3}	-5.38×10^{-3}***	-2.49×10^{-3}***
	(3.86×10^{-4})	(3.22×10^{-4})	(2.55×10^{-4})	(2.01×10^{-4})	(6.57×10^{-4})	(1.58×10^{-3})	(7.27×10^{-3})	(6.51×10^{-4})	(8.40×10^{-4})
Momentum	1.14×10^{-5}	6.10×10^{-5}***	2.39×10^{-5}	-5.03×10^{-5}***	7.71×10^{-5}***	-1.71×10^{-4}	6.38×10^{-5}	-1.51×10^{-5}	6.77×10^{-5}
	(2.11×10^{-5})	(1.65×10^{-5})	(1.74×10^{-5})	(1.18×10^{-5})	(2.48×10^{-5})	(2.09×10^{-4})	(1.74×10^{-5})	(2.50×10^{-5})	(8.10×10^{-5})
OIB	-1.03×10^{-5}	6.12×10^{-5}	6.81×10^{-5}*	-7.47×10^{-5}***	-2.82×10^{-4}***	-4.05×10^{-4}	3.79×10^{-4}	3.38×10^{-4}***	3.87×10^{-4}***
	(7.00×10^{-5})	(4.12×10^{-5})	(3.89×10^{-5})	(2.40×10^{-5})	(6.96×10^{-5})	(1.41×10^{-4})	(3.40×10^{-4})	(7.18×10^{-5})	(8.86×10^{-5})
BAS	0.42 ***	−0.199***	0.12**	−0.42***	0.96***	0.41***	0.76***	−1.16***	−0.23***
	(0.05)	(0.07)	(0.046)	(0.03)	(0.03)	(0.04)	(0.09)	(0.07)	(0.08)
DUM_1	9.66×10^{-5}***	-7.92×10^{-5}***	7.20×10^{-6}	5.44×10^{-5}***	-2.46×10^{-4}***	-1.46×10^{-4}***	7.59×10^{-5}**	1.66×10^{-4}***	1.36×10^{-4}***
(8:00–9:00)	(1.94×10^{-5})	(1.63×10^{-5})	(1.21×10^{-5})	(9.29×10^{-6})	(1.71×10^{-5})	(2.96×10^{-5})	(3.60×10^{-5})	(2.10×10^{-5})	(2.13×10^{-5})
DUM_2	2.10×10^{-5}***	-3.13×10^{-5}***	-1.10×10^{-5}**	1.20×10^{-5}*	-9.09×10^{-5}***	-1.49×10^{-5}	8.52×10^{-5}	5.99×10^{-5}***	1.19×10^{-5}
(9:00–15:30)	(7.78×10^{-6})	(6.07×10^{-6})	(4.85×10^{-6})	(7.31×10^{-6})	(1.41×10^{-5})	(3.06×10^{-5})	(7.50×10^{-5})	($1.37 \times 10^{-5)}$	(1.65×10^{-5})
DUM_3	1.22×10^{-5}	-3.01×10^{-5}***	-1.19×10^{-5}**	3.42×10^{-7}	-1.44×10^{-4}***	-1.11×10^{-4}***	8.56×10^{-6}	1.13×10^{-4}***	8.22×10^{-5}***
(15:30–16:00)	(8.96×10^{-6})	(6.33×10^{-6})	(5.50×10^{-6})	(8.33×10^{-6})	(1.88×10^{-5})	(2.84×10^{-5})	(5.39×10^{-6})	(1.79×10^{-5})	(1.69×10^{-5})
Constant	5.96×10^{-5}	-1.99×10^{-4}***	-6.77×10^{-5}**	1.03×10^{-4}***	6.59×10^{-4}***	2.36×10^{-4}	-1.78×10^{-4}	-8.45×10^{-4}***	-3.55×10^{-4}***
	(5.56×10^{-5})	(3.93×10^{-5})	(3.42×10^{-5})	(2.28×10^{-5})	(6.75×10^{-5})	(1.26×10^{-4})	(1.04×10^{-4})	(6.99×10^{-5})	(8.33×10^{-5})
Observations	206,002	246,867	453,012	206,002	246,867	453,012	206,002	246,867	453,012
R-squared	0.77%	0.34%	0.07%	2.14%	1.40%	0.05%	2.92%	1.89%	0.06%
Adj R-squared	0.76%	0.34%	0.06%	2.14%	1.39%	0.05%	2.92%	1.89%	0.06%

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

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

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

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

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

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

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

3.3. Intraday patterns

The dummy variables in the full sample regression imply intraday patterns of price impact; we therefore examine this trend in more detail. First, we compute the average price impact measures for every half-hour as presented in Table 5. As expected, there is an emerging pattern in the price impact of block trades. For example, the permanent price impact estimates for both block purchases and sales are largest during early trading. This is consistent with Ibikunle (2015a) who argues that roughly 40% of close-close price discovery for FTSE 100 stocks occur within the first 30 min of continuous trading on an average day, the remaining 60% is distributed across the day. This uneven pattern is due to the large amount of information accumulated overnight and is being released into the market through new orders during the early continuous trading period.

In order to explore this intraday effect of the information diffusion process more keenly, we exogenously split the sample into four time intervals: the first trading hour (8:00 h–9:00 h), middle of the day (9:00 h–15:30 h), the penultimate 30 min of trading (15:30 h–16:00 h) and the final 30 min of trading (16:00 h–16:30 h). Tables 6 and 7 show the regression results for block purchases and sales. Panel A in Table 6 shows the regression coefficients of the permanent price impact of block purchase. It can be seen that the coefficient of PIN in the first trading hour is 0.000599, which is larger than that of the middle of day trading hours' estimate at 0.000396; both estimates are statistically significant at the 0.05 and 0.01 levels respectively. This indicates that the information diffusion process is strongest during the opening hour, despite the fact that the middle trading period includes six and half hours of the largest volume trading. The observation is also consistent for temporary price impact estimates. These results are in line with Ibikunle (2015a), who argues that a substantial fraction of price discovery occurs during the first trading hour because large amount of new information, held back during the opening auction, is released into the market early on during the continuous trading session of the day. The PIN coefficients for the other trading sub-periods of the day are not statistically significant since, as shown by Ibikunle (2015a), more than 97% of the efficient price discovery occurs prior to the last half hour of trading for FTSE 100 stocks trading on the LSE.

Results in Table 7 are very intriguing because they suggest that, while information diffusion behaviour is strongest during the opening hour for block purchases, block sales do not register statistically significant information diffusion effects until the trading day is truly well under way. The PIN coefficients are only statistically significant for the final two half-hour trading periods of the day. The permanent price impact coefficient for the half-hour period between 15:30–16:00 h is −0.00024 and is statistically significant at the 0.01 level. For the temporary price impact, the coefficients for the final two half-hour trading periods are −0.0014 and −0.0018 respectively and both are statistically significant at the 0.01 level. The results imply that when informed trading activity is highest in the market, arbitrage traders operate from neutral positions from where they bid for profit opportunities. According to Ibikunle (2015b), informed trading is high on the LSE during early trading, and decreases as the continuous trading session progresses. Thus, with the reduction in the arbitrage seeking activities of informed traders comes a reduction in purchase trades. The decreases in purchases will allow for increased price impact for block sales, hence the larger information diffusion activity of block sales during the latter end of the continuous trading day. Overall, this section provides evidence that the diffusion process is strong during the opening of the trading session, when trading is most vigorous and there is an increased presence of informed traders (Dufour and Engle (2000). These results also indicate that a liquid and deep market could well facilitate the information diffusion process.

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

We now explore the systematic inter-day variations of the information diffusion process. Kyle (1985)'s theoretical model suggests that informed traders do not immediately execute trades with all of the information at their disposal; rather, they do so in a gradual manner. This implies that information could be slowly incorporated into prices of instruments over a time frame longer than the length of the trading day. This theoretical position is bolstered by the empirical analysis of Hong et al. (2000). Using analyst coverage as a proxy for firm-specific information inflow, Hong et al. (2000) find that the momentum trend

Table 5
Intraday mean price impact for purchase and sale block trades.
This table shows the average permanent, total and temporary price impact estimates for FTSE 100 stocks trading on the London Stock Exchange. The five-trade benchmark is used to calculate the price impact measures. Thus, for temporary price impact (Eq. (1)), we measure the percentage of price reversal after five trades after a block trade execution, and for permanent price impact Eq. (2) captures the percentage change in price from five trades before the block trade to five trades following the block trade. The third price impact measure, total impact, captures the total percentage price impact, which includes both the liquidity and the information component:

$$Temporary\ \ impact = \frac{P_{t+5} - P_t}{P_t}$$
$$Permanent\ \ impact = \frac{P_{t+5} - P_{t-5}}{P_{t-5}}$$
$$Total\ \ impact = \frac{P_t - P_{t-5}}{P_{t-5}}$$

The sample includes FTSE 100 stocks trading on the London Stock Exchange between 1st October 2012 and 30th September 2013.

	Purchase block trades			Sale block trades		
Time of the day	Permanent price impact	Total price impact	Temporary price impact	Permanent price impact	Total price impact	Temporary price impact
8:00–8:29	0.0420%	0.2003%	−0.0024%	−0.0276%	−0.0683%	0.0316%
8:30–8:59	0.0183%	0.0170%	0.0012%	−0.0152%	−0.0484%	0.0337%
9:00–9:29	0.0183%	0.0178%	0.0005%	−0.0160%	−0.0554%	0.0400%
9:30–9:59	0.0165%	0.0173%	−0.0008%	−0.0155%	−0.0431%	0.0280%
10:00–10:29	0.0172%	0.0192%	−0.0021%	−0.0125%	−0.0439%	0.0317%
10:30–10:59	0.0179%	0.0178%	0.0001%	−0.0151%	−0.0489%	0.0343%
11:00–11:29	0.0162%	0.0177%	−0.0015%	−0.0182%	−0.0518%	0.0341%
11:30–11:59	0.0173%	0.1228%	−0.0005%	−0.0153%	−0.0493%	0.0345%
12:00–12:29	0.0169%	0.0176%	−0.0007%	−0.0130%	−0.0555%	0.0431%
12:30–12:59	0.0247%	0.0190%	0.0057%	−0.0093%	−0.0458%	0.0369%
13:00–13:29	0.0164%	0.0158%	0.0007%	−0.0119%	−0.0477%	0.0362%
13:30–13:59	0.0195%	0.0173%	0.0021%	−0.0158%	−0.0457%	0.0303%
14:00–14:29	0.0148%	0.0154%	−0.0006%	−0.0145%	−0.0513%	0.0373%
14:30–14:59	0.0179%	0.0158%	0.0020%	−0.0156%	−0.0418%	0.0266%
15:00–15:29	0.0156%	0.0149%	0.0007%	−0.0147%	−0.0454%	0.0310%
15:30–15:59	0.0150%	0.0149%	0.0001%	−0.0140%	−0.0389%	0.0252%
16:00–16:30	0.0134%	0.0126%	0.0008%	−0.0107%	−0.0489%	0.0386%

Table 6

Incorporation of private information via purchase block trading in FTSE 100 stocks across trading hours.

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

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

Price impact corresponds to *permanent*, *temporary* or *total price impact*, and are as defined in Table 5. *PIN* is the probability of an informed trade. *LnSize* is the natural logarithm of the number of shares per trade; *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place; *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade; *OIB* represents the order imbalance; *BAS* is the bid-ask spread at the time of the block trade; *Market return* is the daily FTSE100 return on the day of the block trade. *Momentum* is the cumulative return of the stock in the five days preceding the block trade. Standard errors are presented in parentheses. Panels A, B and C present results for when permanent price impact, temporary price impact and total price impact are employed as dependent variables respectively. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively. The sample includes FTSE 100 stocks trading on the London Stock Exchange between 1st October 2012 and 30th September 2013.

	Panel A. Permanent price impact			
	8:00–9:00	*9:00–15: 30*	*15:30–16:00*	*16:00–16:30*
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*
PIN	$5.99 \times 10^{-4**}$	$3.96 \times 10^{-4***}$	9.42×10^{-5}	2.37×10^{-4}
	(2.58×10^{-4})	(3.98×10^{-5})	(1.03×10^{-4})	(2.79×10^{-4})
Ln(size)	-9.95×10^{-7}	8.7×10^{-7}	$-5.09 \times 10^{-6*}$	4.00×10^{-6}
	(1.02×10^{-5})	(1.70×10^{-6})	(2.98×10^{-6})	(3.96×10^{-6})
Volatility	1.14×10^{-3}	5.48×10^{-5}	4.65×10^{-4}	6.96×10^{-4}
	(1.93×10^{-3})	(2.75×10^{-4})	(6.74×10^{-4})	(5.61×10^{-4})
Ln(turnover)	4.52×10^{-5}	$5.68 \times 10^{-6**}$	1.05×10^{-5}	$2.01 \times 10^{-5*}$
	(3.04×10^{-5})	(2.91×10^{-6})	(7.97×10^{-6})	(1.18×10^{-5})
Market Return	$-3.41 \times 10^{-3*}$	6.22×10^{-5}	-1.40×10^{-3}	$-2.19 \times 10^{-3***}$
	(1.93×10^{-3})	(2.58×10^{-4})	(1.25×10^{-3})	(6.21×10^{-4})
Momentum	1.66×10^{-4}	$-4.31 \times 10^{-5***}$	1.86×10^{-5}	1.95×10^{-5}
	(1.13×10^{-4})	(1.62×10^{-5})	(2.57×10^{-5})	(2.47×10^{-5})
OIB	$7.73 \times 10^{-4*}$	$-1.44 \times 10^{-4***}$	-4.91×10^{-5}	$-1.55 \times 10^{-4**}$
	(4.22×10^{-4})	(3.40×10^{-5})	(2.54×10^{-5})	(6.68×10^{-5})
BAS	0.54^{***}	0.24^{***}	0.368^{***}	0.24
	(0.09)	(0.02)	(0.06)	(0.18)
Constant	2.66×10^{-4}	2.52×10^{-5}	$1.65 \times 10^{-4*}$	$1.74 \times 10^{-4***}$
	(3.02×10^{-4})	(2.81×10^{-5})	(9.17×10^{-5})	(6.74×10^{-5})
Observations	35,490	129,411	15,262	25,839
R-squared	0.80%	1.00%	1.09%	0.25%
Adj R-squared	0.78%	1.00%	1.03%	0.22%

	Panel B. Temporary price impact			
	8:00–9:00	*9:00–15: 30*	*15:30–16:00*	*16:00–16:30*
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*
PIN	$3.45 \times 10^{-4***}$	$3.03 \times 10^{-4***}$	1.34×10^{-4}	4.25×10^{-4}
	(1.15×10^{-4})	(3.08×10^{-5})	(8.43×10^{-5})	(2.97×10^{-4})
Ln(size)	5.23×10^{-6}	7.45×10^{-7}	-2.81×10^{-6}	4.00×10^{-6}
	(3.68×10^{-6})	(1.49×10^{-6})	(2.44×10^{-6})	(3.92×10^{-6})
Volatility	1.85×10^{-4}	3.05×10^{-4}	$5.43 \times 10^{-4***}$	4.11×10^{-4}
	(8.81×10^{-4})	(2.01×10^{-4})	(4.41×10^{-5})	(4.57×10^{-4})
Ln(turnover)	$4.03 \times 10^{-5***}$	$8.39 \times 10^{-6***}$	8.15×10^{-6}	1.51×10^{-5}
	(6.99×10^{-6})	(1.88×10^{-6})	(5.97×10^{-6})	(1.12×10^{-5})
Market Return	$-2.40 \times 10^{-3***}$	$-3.41 \times 10^{-4*}$	1.91×10^{-3}	$-1.61 \times 10^{--3***}$
	(7.17×10^{-4})	(1.88×10^{-4})	(1.18×10^{-3})	(5.45×10^{-4})
Momentum	$-1.24 \times 10^{-4**}$	$-4.52 \times 10^{-5***}$	-3.44×10^{-6}	1.25×10^{-6}
	(5.12×10^{-5})	(1.16×10^{-5})	(1.58×10^{-3})	(1.67×10^{-5})
OIB	5.22×10^{-5}	$-9.76 \times 10^{-5***}$	-2.14×10^{-5}	$-1.25 \times 10^{-4**}$
	(1.11×10^{-3})	(2.41×10^{-5})	(5.25×10^{-5})	(6.04×10^{-5})
BAS	-0.474^{***}	-0.348^{***}	-0.17^{***}	-0.38^{*}
	(0.05)	(0.02)	(0.06)	(0.20)
Constant	$4.12 \times 10^{-4***}$	$6.94 \times 10^{-5***}$	9.23×10^{-5}	7.32×10^{-5}
	(7.91×10^{-5})	$(2.85 \times 10^{-5)}$	(7.18×10^{-5})	(6.08×10^{-5})
Observations	35,490	129,411	15,262	25,839
R-squared	4.42%	1.88%	0.32%	0.31%
Adj R-squared	4.40%	1.88%	0.27%	0.28%

	Panel C. Total price impact			
	8:00–9:00	*9:00–15: 30*	*15:30–16:00*	*16:00–16:30*
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*
PIN	2.50×10^{-4}	$9.23 \times 10^{-5***}$	-4.04×10^{-5}	-1.90×10^{-4}
	(2.45×10^{-4})	(3.16×10^{-5})	(7.14×10^{-5})	(1.06×10^{-4})
Ln(size)	-6.30×10^{-6}	1.2×10^{-7}	-2.28×10^{-6}	-1.01×10^{-7}
	(9.09×10^{-6})	(3.84×10^{-6})	(2.13×10^{-6})	(6.30×10^{-6})
Volatility	-1.32×10^{-3}	-2.51×10^{-4}	-7.87×10^{-5}	2.84×10^{-4}
	(1.67×10^{-3})	(1.93×10^{-4})	(4.03×10^{-5})	(3.19×10^{-4})
Ln(turnover)	5.30×10^{-6}	-2.72×10^{-6}	2.38×10^{-6}	4.60×10^{-6}
	(2.94×10^{-5})	(2.11×10^{-6})	(4.00×10^{-6})	(3.70×10^{-6})
Market Return	-1.02×10^{-3}	4.03×10^{-4}	5.15×10^{-4}	$-5.76 \times 10^{-4*}$
	(1.79×10^{-3})	(1.74×10^{-4})	(3.65×10^{-4})	(3.02×10^{-4})
Momentum	$2.91 \times 10^{-4***}$	2.4×10^{-6}	2.23×10^{-5}	1.83×10^{-5}
	(3.93×10^{-5})	(9.09×10^{-6})	(1.76×10^{-5})	(1.23×10^{-5})
OIB	$7.21 \times 10^{-4*}$	$-4.62 \times 10^{-5**}$	-2.77×10^{-5}	-3.03×10^{-5}
	(4.07×10^{-4})	(2.35×10^{-5})	(5.38×10^{-5})	(3.26×10^{-5})
BAS	1.02^{***}	0.59^{***}	0.54^{***}	0.63^{***}
	(0.09)	(0.02)	(0.04)	(0.09)
Constant	-1.46×10^{-4}	$-4.4 \times 10^{-5**}$	7.29×10^{-5}	$1.01 \times 10^{-4***}$
	(2.98×10^{-4})	$(1.90 \times 10^{-5)}$	(5.62×10^{-5})	(3.42×10^{-5})
Observations	35,490	129,411	15,262	25,839
R-squared	2.56%	7.10%	5.53%	10.06%
Adj R-squared	2.54%	7.10%	5.48%	10.04%

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Table 7
Incorporation of private information via sale block trading in FTSE 100 stocks across trading hours.
The relationship between informed trading and sale block trading across intraday trading intervals is estimated using the following model:

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

Price impact corresponds to *permanent, temporary* or *total price impact*, and is as defined in Table 5. *PIN* is the probability of an informed trade. *LnSize* is the natural logarithm of the number of shares per trade; *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place; *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade; *OIB* represents the order imbalance; *BAS* is the bid-ask spread at the time of the block trade; *Market return* is the daily FTSE100 return on the day of the block trade. *Momentum* is the cumulative return of the stock in the five days preceding the block trade. Standard errors are presented in parentheses. Panels A, B and C present results for when permanent price impact, temporary price impact and total price impact are employed as dependent variables respectively. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively. The sample includes FTSE 100 stocks trading on the London Stock Exchange between 1st October 2012 and 30th September 2013.

	Panel A. Permanent price impact				Panel B. Temporary price impact				Panel C. Total price impact			
	8:00–9:00	*9:00–15: 30*	*15:30–16:00*	*16:00–16:30*	*8:00–9:00*	*9:00–15: 30*	*15:30–16:00*	*16:00–16:30*	*8:00–9:00*	*9:00–15: 30*	*15:30–16:00*	*16:00–16:30*
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
PIN	-1.15×10^{-4}	2.91×10^{-3}	$-2.44 \times 10^{-4***}$	-1.09×10^{-4}	-2.00×10^{-4}	5.46×10^{-3}	$-1.44 \times 10^{-3***}$	$-1.78 \times 10^{-3***}$	3.12×10^{-4}	3.74×10^{-3}	$1.17 \times 10^{-3***}$	$1.70 \times 10^{-3***}$
	(2.87×10^{-4})	(2.44×10^{-3})	(8.41×10^{-5})	(1.28×10^{-4})	(1.75×10^{-4})	(0.02)	(3.83×10^{-4})	(2.97×10^{-4})	(2.85×10^{-4})	(2.46×10^{-3})	(3.50×10^{-4})	(2.60×10^{-4})
Ln(size)	$3.18 \times 10^{-5***}$	2.72×10^{-5}	-5.29×10^{-7}	3.8×10^{-6}	$1.39 \times 10^{-5**}$	$-1.55 \times 10^{-3*}$	$2.47 \times 10^{-5**}$	$-5.96 \times 10^{-5*}$	$1.80 \times 10^{-5*}$	$8.11 \times 10^{-5*}$	$-2.50 \times 10^{-5**}$	$4.58 \times 10^{-5***}$
	(8.69×10^{-6})	(3.79×10^{-5})	(1.00×10^{-5})	(3.57×10^{-6})	(6.07×10^{-6})	(8.59×10^{-4})	(1.14×10^{-5})	(3.06×10^{-5})	(9.90×10^{-6})	(4.29×10^{-5})	(1.07×10^{-5})	(1.53×10^{-5})
Volatility	$3.52 \times 10^{-3**}$	3.56	-1.67×10^{-4}	-1.14×10^{-3}	$3.13 \times 10^{-3*}$	6.78^{***}	-4.16×10^{-4}	1.12×10^{-2}	4.23×10^{-4}	3.43	1.97×10^{-4}	-6.51×10^{-3}
	(1.47×10^{-3})	(2.51)	(7.26×10^{-4})	(9.87×10^{-4})	(1.84×10^{-3})	(2.24)	(1.43×10^{-3})	(0.01)	(1.97×10^{-3})	(2.51)	(1.52×10^{-3})	(4.68×10^{-3})
Ln(turnover)	$-3.81 \times 10^{-5**}$	1.29×10^{-3}	-4.93×10^{-6}	-8.93×10^{-6}	$3.00 \times 10^{-5**}$	$3.82 \times 10^{-3*}$	3.39×10^{-5}	1.38×10^{-5}	-7.60×10^{-6}	1.23×10^{-3}	$-3.76 \times 10^{-5*}$	-2.81×10^{-5}
	(1.75×10^{-5})	(9.19×10^{-4})	(6.33×10^{-6})	(6.16×10^{-6})	(1.18×10^{-5})	(2.21×10^{-3})	(2.19×10^{-5})	(3.59×10^{-5})	(1.88×10^{-5})	(9.22×10^{-4})	(2.03×10^{-5})	(2.92×10^{-5})
Market	$-4.67 \times 10^{-3***}$	-9.78×10^{-2}	-1.12×10^{-4}	$-1.19 \times 10^{-3***}$	$3.93 \times 10^{-3**}$	0.13	-1.07×10^{-3}	2.26×10^{-3}	$-8.47 \times 10^{-3***}$	-0.107	8.20×10^{-4}	-1.53×10^{-3}
Return	(1.62×10^{-3})	(0.07)	(4.87×10^{-4})	(5.44×10^{-4})	(1.39×10^{-3})	(0.17)	(2.24×10^{-3})	(3.71×10^{-3})	(1.85×10^{-3})	(0.07)	(2.10×10^{-3})	(2.24×10^{-3})
Momentum	$2.44 \times 10^{-4***}$	-2.88×10^{-3}	2.08×10^{-5}	2.99×10^{-5}	$1.13 \times 10^{-4**}$	6.5×10^{-3}	6.47×10^{-5}	-6.18×10^{-5}	1.32×10^{-4}	-2.87×10^{-3}	-4.19×10^{-5}	7.38×10^{-5}
	(8.18×10^{-5})	(2.06×10^{-3})	(2.80×10^{-5})	(2.68×10^{-5})	(4.72×10^{-5})	(5.56×10^{-3})	(6.48×10^{-5})	(8.26×10^{-5})	(6.95×10^{-4})	(2.08×10^{-3})	(6.18×10^{-5})	(4.56×10^{-5})
OIB	1.63×10^{-4}	1.08×10^{-3}	$1.39 \times 10^{-4*}$	$-1.38 \times 10^{-4*}$	2.15×10^{-4}	-0.04^{**}	-2.98×10^{-4}	$-1.07 \times 10^{-3**}$	-4.26×10^{-5}	1.16×10^{-2}	4.17×10^{-4}	$6.27 \times 10^{-4**}$
	(2.24×10^{-4})	(7.61×10^{-3})	(7.16×10^{-5})	(7.67×10^{-5})	(2.11×10^{-4})	(0.02)	(2.89×10^{-4})	(5.39×10^{-4})	(2.70×10^{-4})	(7.60×10^{-3})	(2.66×10^{-4})	(3.03×10^{-4})
BAS	-0.29^{**}	-3.77	-0.24^{***}	-0.144	0.89^{***}	5.66	1.035^{***}	1.16^{***}	-1.18^{***}	-5.15^{**}	-1.24^{***}	-1.33^{***}
	(0.14)	(2.62)	(0.05)	(0.12)	(0.05)	(5.34)	(0.22)	(0.16)	(0.13)	(2.61)	(0.20)	(0.15)
Constant	$-7.14 \times 10^{-4***}$	8.59×10^{-3}	-5.05×10^{-5}	$-1.31 \times 10^{-4**}$	$-3.70 \times 10^{-4***}$	0.05^{*}	$7.63 \times 10^{-4***}$	$1.40 \times 10^{-3***}$	-3.38×10^{-4}	7.38×10^{-3}	$-7.97 \times 10^{-4***}$	$-1.44 \times 10^{-3***}$
	(1.99×10^{-4})	(6.23×10^{-3})	(6.67×10^{-5})	(6.58×10^{-5})	1.38×10^{-4}	(0.02)	(2.33×10^{-4})	(4.17×10^{-4})	(2.15×10^{-4})	(6.26×10^{-3})	(2.22×10^{-4})	(3.07×10^{-4})
Observations	41,492	156,625	18,224	30,476	41,492	156,625	18,224	30,476	41,492	156,625	18,224	30,476
R-squared	0.40%	0.37%	0.79%	0.22%	4.01%	0.30%	0.47%	0.08%	3.58%	0.34%	0.77%	0.29%
Adj R-squared	0.39%	0.36%	0.74%	0.19%	4.00%	0.29%	0.42%	0.05%	3.56%	0.34%	0.73%	0.26%

of stocks is caused by the slow impounding of firm-specific information into stock prices. The use of analyst following as a proxy for firm-specific (private) information has been criticised by Vega (2006); in this section, we employ a more generally accepted proxy for private information to examine the hypothesis that private information in trading could be long-lived. Foster and Viswanathan (1993) also propose a theoretical optimal trading strategy, in which informed traders prefer to trade intensively on common information, and trade less on their private information. Once common information is fully reflected in the stock prices, informed traders then start trading based on private information. This also supports the hypothesis that private information is incorporated into stock prices in a gradual manner. Based on the foregoing submissions, we hypothesise that informed traders will not fully exploit their superior information by the end of an average trading day; they will hold on to it and exploit it during the next trading opportunity (day). According to Holden and Subrahmanyam (1992), informed traders might also try to obtain updated private information during non-trading hours. Then, once the market opens, they may trade aggressively based on yesterday's (re-evaluated) private information. We test this hypothesis by employing the following regression model:

$$\ln\left(\frac{\#Block\ \ trades_t}{\#Block\ \ trades_{t-1}}\right) = \alpha + \beta_1 PIN_{t-1} + \beta_2 Volatility_{t-1} + \beta_3 \ln Turnover_{t-1} + \beta_4 Market\ \ return_{t-1} + \beta_5 Momentum + \beta_6 |OIB|_{t-1} + \varepsilon \quad (9)$$

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

Table 8 presents the regression results from Eq. (9). Panel A shows the regression results for the entire trading day's block trades, while Panel B is focused only on the first hour of the trading day. The focus on the first hour of trading as an extension of the analysis is based on the expectation that overnight private information is more likely to be traded upon within the first hour of trading. Most of the PIN_{t-1} coefficients in Panels A and B are positive and statistically significant. This indicates that informed traders adjust their block trade positions on day t relative to day$_{t-1}$ based on private information gleaned during day t_{-1}. In Panel B, the coefficients of PIN_{t-1} of block purchases and sales are larger than the corresponding coefficients of PIN_{t-1} in Panel A. This confirms our expectations that informed traders holding long-lived private information will aim to utilise it by aggressively adjusting their positions during the first trading hour. This is because the longer they hold on to a set of privately acquired information, the more likely it is that they become public before the informed traders could benefit from them (see Foster & Viswanathan, 1993). Further, the market is at one of its most liquid (in terms of depth) and volatile intervals during the opening period, and therefore informed traders aim to take advantage of this natural camouflage to execute informed block trades. All turnover coefficients in both panels of Table 8 are, statistically, highly significant and positive. This implies that informed traders are more willing to adjust their block positions if the stock is very liquid during the previous trading day. This is because a liquid market can easily absorb block trades without causing large price fluctuations. We also observe that in Panel A, market return has statistically significant negative coefficients for purchase and sale block trades. A possible explanation for this could be that when the market is on the rise, informed traders do not adjust their positions by block trades the following day because they may expect a price run-up in their portfolio holdings. Informed

Table 8
Inter-day relationship between PIN and block trades.
This table shows the regression results of the relationship between the inter-day percentage change of number of block trades and the probability of an informed trade. Panel A reports the regression coefficient estimates for block trades sample during the entire continuous trading day, while Panel B reports the regression coefficient estimates for the one-hour period between 08:00 and 09:00 h. We use the following model:

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

$\ln(\frac{\#Block\ \ trades_t}{\#Block\ \ trades_{t-1}})$ corresponds to the natural logarithm of number of block trades at day t divided by the number of block trades at day t_{-1}, it depicts the change of number of block trades based on the previous trading day. *PIN* is the probability of an informed trade. *LnSize* is the natural logarithm of the number of shares per trade; *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place; *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade; *OIB* represents the order imbalance; *BAS* is the bid-ask spread at the time of the block trade; *Market return* is the daily FTSE100 return on the day of the block trade. *Momentum* is the cumulative return of the stock in the five days preceding the block trade. Standard errors are presented in parentheses. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively. The sample includes FTSE 100 stocks trading on the London Stock Exchange between 1st October 2012 and 30th September 2013.

	Panel A. Block trades during the day			Panel B. Block trades during the first trading hour (8:00–9:00)		
	Block purchases	Block sales	All block trades	Block purchases	Block sales	All block trades
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
PIN_{t-1}	0.25*	0.23*	0.44***	0.41**	0.25	0.35**
	(0.14)	(0.13)	(0.10)	(0.19)	(0.21)	(0.16)
$Turnover_{t-1}$	0.07***	0.07***	0.06***	0.07***	0.04**	0.07***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Momentum	−0.05	−0.05	−0.06	0.01	0.02	−0.04
	(0.05)	(0.06)	(0.04)	(0.07)	(0.07)	(−0.06)
$Volatility_{t-1}$	0.92	0.36	2.51	0.45	−1.77	−1.16
	(2.04)	(1.98)	(1.67)	(0.28)	(3.21)	(2.51)
OIB_{t-1}	0.08	0.06	−0.11	−0.23	−0.45**	−0.22
	(0.14)	(0.15)	(0.11)	(0.19)	(0.21)	(0.16)
$Market\ Return_{t-1}$	−4.84***	−5.15***	0.28	−0.37	2.31	−0.12
	(1.25)	(1.27)	(1.00)	(1.62)	(1.86)	(1.48)
Constant	0.54***	0.58***	0.38***	0.55***	0.35	0.60***
	(0.15)	(0.15)	(0.10)	(0.21)	(0.23)	(0.19)
Observations	9555	9224	10,071	6598	5360	8306
R-squared	0.49%	0.51%	0.62%	0.36%	0.23%	0.35%
Adj R-squared	0.47%	0.44%	0.55%	0.28%	0.14%	0.29%

Table 9
Stock transparency and incorporation of private information via purchase block trading in FTSE 100 stocks.
The relationship between informed trading and purchase block trading in FTSE 100 stocks with varying levels of stock transparency is estimated using the following model:

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

Price impact corresponds to *permanent*, *temporary* or *total price impact*, and is as defined in Table 5. *PIN* is the probability of an informed trade. *LnSize* is the natural logarithm of the number of shares per trade; *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place; *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade; *OIB* represents the order imbalance; *BAS* is the bid-ask spread at the time of the block trade; *Market return* is the daily FTSE100 return on the day of the block trade. *Momentum* is the cumulative return of the stock in the five days preceding the block trade. DUM_1 takes the value of 1 if the trade occurs between 8:00 and 9:00; DUM_2 takes the value of 1 if the trade occurs between 9:00 and 15:30; DUM_3 takes the value of 1 if the trade occurs between 15:30 and 16:00. Standard errors are presented in parentheses. PIN estimates are used as proxies for stocks' levels of transparency; on this basis, stocks are partitioned into transparency quartiles/portfolios. The highest (lowest) PIN stocks are designated as Portfolio 1 (4) stocks. Panels A, B and C present results for when permanent price impact, temporary price impact and total price impact are employed as dependent variables respectively. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively. The sample includes FTSE 100 stocks trading on the London Stock Exchange between 1st October 2012 and 30th September 2013.

	Panel A. Permanent price impact				Panel B. Temporary price impact				Panel C. Total price impact			
	Portfolio 1 (High-PIN)	Portfolio 2	Portfolio 3	Portfolio 4 (Low-PIN)	Portfolio 1 (High-PIN)	Portfolio 2	Portfolio 3	Portfolio 4 (Low-PIN)	Portfolio 1 (High-PIN)	Portfolio 2	Portfolio 3	Portfolio 4 (Low-PIN)
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
PIN	$5.46 \times 10^{-4***}$	$3.65 \times 10^{-4**}$	$1.84 \times 10^{-4***}$	$1.84 \times 10^{-4*}$	2.15×10^{-5}	-9.21×10^{-5}	$1.95 \times 10^{-4***}$	8.27×10^{-5}	3.32×10^{-4}	$4.56 \times 10^{-4***}$	1.13×10^{-5}	4.85×10^{-5}
	(-2.64×10^{-4})	(1.51×10^{-4})	(6.81×10^{-5})	(1.08×10^{-4})	(1.52×10^{-4})	(7.08×10^{-5})	(3.07×10^{-5})	(6.43×10^{-5})	(2.08×10^{-4})	(1.38×10^{-4})	(5.56×10^{-5})	(8.31×10^{-5})
Ln(size)	1.43×10^{-5}	$8.46 \times 10^{-6*}$	$-6.16 \times 10^{-6***}$	$-7.63 \times 10^{-6*}$	3.59×10^{-6}	$9.99 \times 10^{-6***}$	$-3.78 \times 10^{-6***}$	$6.23 \times 10^{-6*}$	1.07×10^{-5}	-1.56×10^{-6}	-2.38×10^{-6}	$-1.53 \times 10^{-5***}$
	(1.27×10^{-5})	(4.74×10^{-6})	(2.13×10^{-6})	(4.34×10^{-6})	(6.35×10^{-6})	(2.34×10^{-6})	(1.29×10^{-6})	(3.39×10^{-7})	(1.17×10^{-5})	(5.71×10^{-6})	(1.59×10^{-6})	(4.18×10^{-6})
Volatility	$-5.62 \times 10^{-3*}$	8.82×10^{-6}	1.46×10^{-4}	5.68×10^{-4}	2.28×10^{-4}	2.34×10^{-4}	2.50×10^{-4}	$6.67 \times 10^{-4*}$	$-5.89 \times 10^{-3**}$	-2.25×10^{-4}	-1.04×10^{-4}	1.18×10^{-4}
	(3.39×10^{-3})	(9.01×10^{-4})	(4.29×10^{-4})	(6.84×10^{-4})	(1.34×10^{-3})	(5.09×10^{-4})	(2.25×10^{-4})	(4.04×10^{-4})	(2.82×10^{-3})	(4.69×10^{-4})	(3.71×10^{-4})	(5.36×10^{-4})
Ln(turnover)	-1.68×10^{-5}	$-3.72 \times 10^{-5***}$	2.61×10^{-6}	$2.11 \times 10^{-5**}$	-9.5×10^{-6}	$-1.59 \times 10^{-5***}$	$1.32 \times 10^{-5***}$	$2.16 \times 10^{-5***}$	-7.35×10^{-6}	$-2.07 \times 10^{-5*}$	$-1.05 \times 10^{-5***}$	-3.23×10^{-6}
	(3.47×10^{-5})	(1.27×10^{-5})	(4.76×10^{-6})	(9.50×10^{-6})	(1.82×10^{-5})	(6.11×10^{-6})	(1.97×10^{-6})	(6.47×10^{-6})	(2.69×10^{-5})	(1.17×10^{-5})	(4.10×10^{-6})	(9.97×10^{-6})
Market Return	$-3.80 \times 10^{-3*}$	4.45×10^{-4}	$-1.08 \times 10^{-3***}$	-5.93×10^{-4}	-2.00×10^{-3}	$-7.50 \times 10^{-4***}$	$-9.32 \times 10^{-4***}$	$-7.18 \times 10^{-4*}$	-1.82×10^{-3}	1.20×10^{-3}	-1.42×10^{-4}	-7.15×10^{-4}
	(2.29×10^{-3})	(1.03×10^{-3})	(3.76×10^{-4})	(6.45×10^{-4})	(1.25×10^{-3})	(1.87×10^{-4})	(2.09×10^{-4})	(4.35×10^{-4})	(1.82×10^{-3})	(9.26×10^{-4})	(3.16×10^{-4})	(6.06×10^{-4})
Momentum	-4.46×10^{-6}	$1.08 \times 10^{-4***}$	2.45×10^{-5}	-2.11×10^{-5}	$-6.30 \times 10^{-5**}$	6.07×10^{-6}	3.75×10^{-6}	$-6.76 \times 10^{-5***}$	5.86×10^{-5}	$1.01 \times 10^{-4***}$	2.07×10^{-5}	$4.88 \times 10^{-5***}$
	(5.00×10^{-5})	(4.08×10^{-5})	(1.98×10^{-5})	(3.09×10^{-5})	(2.64×10^{-5})	(2.02×10^{-5})	(1.05×10^{-5})	(2.30×10^{-5})	(4.18×10^{-5})	(3.36×10^{-5})	(1.61×10^{-5})	(2.46×10^{-5})
OIB	$-8.10 \times 10^{-4***}$	$2.37 \times 10^{-4**}$	-1.09×10^{-5}	$-1.77 \times 10^{-4*}$	$-1.85 \times 10^{-4*}$	-3.21×10^{-5}	$-6.38 \times 10^{-5**}$	$-8.37 \times 10^{-5*}$	$-6.24 \times 10^{-4***}$	$2.69 \times 10^{-4***}$	5.16×10^{-5}	-8.47×10^{-5}
	(2.16×10^{-4})	(1.07×10^{-4})	(5.01×10^{-5})	(7.73×10^{-5})	(9.64×10^{-5})	(5.52×10^{-5})	(2.79×10^{-5})	(4.44×10^{-5})	(1.87×10^{-4})	(9.41×10^{-5})	(4.48×10^{-5})	(6.85×10^{-5})
BAS	0.45**	0.24**	0.49***	0.488***	−0.39***	−0.55***	−0.54***	−0.38***	0.84***	0.79***	1.03***	0.86***
	(0.19)	(0.12)	(0.09)	(0.07)	(0.08)	(0.05)	(0.04)	(0.07)	(0.15)	(0.13)	(0.09)	(0.09)
DUM_1	$4.65 \times 10^{-4***}$	$1.08 \times 10^{-4**}$	$3.45 \times 10^{-5**}$	$8.34 \times 10^{-5***}$	$1.56 \times 10^{-4***}$	$7.58 \times 10^{-5***}$	$7.13 \times 10^{-5***}$	$4.32 \times 10^{-5**}$	$3.08 \times 10^{-4***}$	3.26×10^{-5}	$-3.63 \times 10^{-5***}$	1.47×10^{-5}
	(1.15×10^{-4})	(4.48×10^{-5})	(1.70×10^{-5})	(2.69×10^{-5})	(4.88×10^{-5})	(1.96×10^{-5})	(7.04×10^{-6})	(1.82×10^{-5})	(1.04×10^{-4})	(4.78×10^{-5})	(1.55×10^{-5})	(2.73×10^{-5})
DUM_2	$7.12 \times 10^{-5**}$	$6.33 \times 10^{-5***}$	4.58×10^{-6}	$2.49 \times 10^{-5***}$	$4.87 \times 10^{-5**}$	$1.91 \times 10^{-5**}$	$1.7 \times 10^{-5***}$	$1.81 \times 10^{-5**}$	2.20×10^{-5}	$4.41 \times 10^{-5***}$	$-1.18 \times 10^{-5***}$	5.89×10^{-6}
	(2.87×10^{-5})	(1.12×10^{-5})	(6.41×10^{-6})	(9.30×10^{-6})	(2.25×10^{-5})	(8.12×10^{-6})	(5.03×10^{-6})	(8.22×10^{-6})	(1.68×10^{-5})	(8.63×10^{-6})	(3.91×10^{-6})	(6.12×10^{-6})
DUM_3	$1.06 \times 10^{-4***}$	$2.84 \times 10^{-5**}$	1.16×10^{-5}	9.87×10^{-6}	$6.88 \times 10^{-5***}$	1.14×10^{-5}	3.68×10^{-6}	-1.12×10^{-5}	$3.71 \times 10^{-5**}$	$1.72 \times 10^{-5*}$	7.89×10^{-6}	4.32×10^{-6}
	(3.05×10^{-5})	(1.37×10^{-5})	(7.84×10^{-6})	(1.11×10^{-5})	(2.58×10^{-5})	(1.02×10^{-5})	(6.25×10^{-6})	(1.44×10^{-5})	(1.72×10^{-5})	(9.77×10^{-6})	(5.16×10^{-6})	(5.08×10^{-6})
Constant	-3.76×10^{-4}	$-5.08 \times 10^{-4***}$	4.33×10^{-5}	$2.07 \times 10^{-4**}$	-4.89×10^{-5}	1.07×10^{-5}	1.84×10^{-4}	$2.36 \times 10^{-4***}$	-3.26×10^{-4}	$-5.19 \times 10^{-4***}$	$-1.54 \times 10^{-4***}$	-1.89×10^{-5}
	(3.27×10^{-4})	(1.46×10^{-4})	(5.44×10^{-5})	(9.81×10^{-5})	(1.61×10^{-4})	(6.47×10^{-5})	(2.23×10^{-4})	(6.50×10^{-5})	(2.83×10^{-4})	(1.37×10^{-4})	(5.00×10^{-5})	(9.95×10^{-5})
Observations	15,605	35,665	100,467	54,251	15,605	35,665	100,467	54,251	15,605	35,665	100,467	54,251
R-squared	1.26%	0.31%	0.70%	2.32%	1.53%	3.83%	3.12%	3.75%	3.26%	2.11%	3.24%	8.41%
Adj R-squared	1.19%	0.28%	0.69%	2.30%	1.46%	3.80%	3.11%	3.72%	3.19%	2.08%	3.23%	8.39%

***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

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Table 10

Stock transparency and incorporation of private information via sale block trading in FTSE 100 stocks.

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

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

Price impact corresponds to *permanent, temporary* or *total price impact*, and is as defined in Table 5. *PIN* is the probability of an informed trade. *LnSize* is the natural logarithm of the number of shares per trade; *volatility* is the standard deviation of stock returns on the trading day before the block trade takes place; *lnTurnover* is the natural logarithm of the total stock turnover on the trading day prior to the block trade; *OIB* represents the order imbalance; *BAS* is the bid-ask spread at the time of the block trade; *Market return* is the daily FTSE100 return on the day of the block trade. *Momentum* is the cumulative return of the stock in the five days preceding the block trade. *DUM_1* takes the value of 1 if the trade occurs between 8:00 and 9:00; *DUM_2* takes the value of 1 if the trade occurs between 9:00 and 15:30; *DUM_3* takes the value of 1 if the trade occurs between 15:30 and 16:00. Standard errors are presented in parentheses. PIN estimates are used as proxies for stocks' levels of transparency; on this basis, stocks are partitioned into transparency quartiles/portfolios. The highest (lowest) PIN stocks are designated as Portfolio 1 (4) stocks. Panels A, B and C present results for when permanent price impact, temporary price impact and total price impact are employed as dependent variables respectively. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively. The sample includes FTSE 100 stocks trading on the London Stock Exchange between 1st October 2012 and 30th September 2013.

	Panel A. Permanent price impact			
	Portfolio 1 (High-PIN)	Portfolio 2	Portfolio 3	Portfolio 4 (Low-PIN)
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*
PIN	-4.04×10^{-5}	8.14×10^{-5}	2.71×10^{-5}	9.52×10^{-5}
	(1.97×10^{-4})	(1.42×10^{-4})	(7.45×10^{-5})	(1.01×10^{-4})
Ln(size)	$1.74 \times 10^{-5**}$	2.93×10^{-6}	$1.31 \times 10^{-5***}$	-1.33×10^{-6}
	(7.70×10^{-6})	(5.09×10^{-6})	(2.28×10^{-6})	(4.94×10^{-6})
Volatility	8.36×10^{-4}	7.96×10^{-5}	-1.13×10^{-4}	$1.12 \times 10^{-3*}$
	(2.45×10^{-3})	(6.74×10^{-4})	(3.62×10^{-4})	(6.64×10^{-4})
Ln(turnover)	$-4.38 \times 10^{-5**}$	1.36×10^{-5}	$-2.27 \times 10^{-5***}$	-5.34×10^{-6}
	(2.05×10^{-5})	(1.51×10^{-5})	(4.01×10^{-6})	(1.27×10^{-5})
Market Return	1.57×10^{-3}	-1.24×10^{-3}	1.56×10^{-5}	-1.93×10^{-4}
	(1.62×10^{-3})	(9.86×10^{-4})	(4.06×10^{-4})	(6.09×10^{-4})
Momentum	5.76×10^{-5}	4.45×10^{-5}	2.23×10^{-5}	$9.19 \times 10^{-5***}$
	(3.93×10^{-4})	(3.71×10^{-5})	(2.12×10^{-5})	(2.85×10^{-5})
OIB	$2.70 \times 10^{-3**}$	-7.80×10^{-5}	$1.05 \times 10^{-4**}$	-6.49×10^{-5}
	(1.54×10^{-4})	(9.52×10^{-5})	(5.26×10^{-5})	(8.44×10^{-5})
BAS	-0.56^{***}	-0.24^{***}	-0.45^{***}	0.06
	(0.04)	(0.10)	(0.11)	(0.13)
DUM_1	8.07×10^{-6}	$-1.75 \times 10^{-4***}$	$-3.67 \times 10^{-5***}$	$-1.00 \times 10^{-4***}$
	(5.66×10^{-5})	(3.84×10^{-5})	(1.71×10^{-5})	(3.53×10^{-5})
DUM_2	2.32×10^{-5}	$-4.43 \times 10^{-5***}$	$-1.68 \times 10^{-4***}$	$-4.65 \times 10^{-5***}$
	(4.45×10^{-5})	(1.38×10^{-5})	(6.65×10^{-6})	(1.26×10^{-5})
DUM_3	-1.13×10^{-5}	$-3.41 \times 10^{-5***}$	$-2.38 \times 10^{-5***}$	$-3.69 \times 10^{-5***}$
	(2.89×10^{-5})	(1.54×10^{-5})	(8.27×10^{-6})	(1.24×10^{-5})
Constant	$5.24 \times 10^{-4**}$	-3.14×10^{-5}	$-3.30 \times 10^{-4***}$	-1.85×10^{-4}
	(2.12×10^{-4})	(1.57×10^{-4})	(5.53×10^{-5})	(1.25×10^{-4})
Observations	17,375	38,831	118,872	71,789
R-squared	1.50%	0.43%	0.59%	0.08%
Adj R-squared	1.44%	0.42%	0.58%	0.08%

	Panel B. Temporary price impact			
	Portfolio 1 (High-PIN)	Portfolio 2	Portfolio 3	Portfolio 4 (Low-PIN)
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*
PIN	3.48×10^{-4}	$-7.24 \times 10^{-4***}$	$-7.84 \times 10^{-4***}$	$8.60 \times 10^{-4***}$
	(2.74×10^{-4})	(2.19×10^{-4})	(1.18×10^{-4})	(1.73×10^{-4})
Ln(size)	$1.97 \times 10^{-5*}$	-1.69×10^{-6}	-6.64×10^{-8}	1.47×10^{-6}
	(1.07×10^{-5})	(7.30×10^{-6})	(4.37×10^{-6})	(6.15×10^{-6})
Volatility	2.20×10^{-3}	$-1.54 \times 10^{-3*}$	$3.14 \times 10^{-3***}$	$3.96 \times 10^{-3***}$
	(4.90×10^{-3})	(8.30×10^{-4})	(1.09×10^{-3})	(1.79×10^{-3})
Ln(turnover)	9.52×10^{-6}	$4.01 \times 10^{-5**}$	$-1.32 \times 10^{-5*}$	$1.53 \times 10^{-4***}$
	(2.85×10^{-5})	(1.83×10^{-4})	(7.49×10^{-6})	(1.44×10^{-5})
Market Return	$6.84 \times 10^{-3***}$	$8.30 \times 10^{-3***}$	$5.41 \times 10^{-3***}$	$2.76 \times 10^{-3**}$
	(2.25×10^{-3})	(1.63×10^{-3})	(9.43×10^{-4})	(1.26×10^{-3})
Momentum	6.25×10^{-6}	$1.04 \times 10^{-4**}$	1.88×10^{-5}	$1.12 \times 10^{-4**}$
	(5.47×10^{-5})	(5.17×10^{-5})	(1.94×10^{-5})	(4.93×10^{-5})
OIB	-4.37×10^{-5}	1.71×10^{-4}	$-2.58 \times 10^{-4***}$	$-8.69 \times 10^{-4***}$
	(2.03×10^{-4})	(1.56×10^{-4})	(1.11×10^{-4})	(1.27×10^{-4})
BAS	0.81^{***}	1.03^{***}	1.27^{***}	0.93^{***}
	(0.05)	(0.06)	(0.05)	(0.06)
DUM_1	1.34×10^{-5}	-4.65×10^{-5}	$-4.08 \times 10^{-4***}$	$-1.32 \times 10^{-4***}$
	(7.89×10^{-5})	(4.44×10^{-5})	(2.36×10^{-5})	(3.47×10^{-5})
DUM_2	$1.53 \times 10^{-6***}$	2.31×10^{-5}	$-1.81 \times 10^{-4***}$	$4.83 \times 10^{-5*}$
	(5.04×10^{-5})	(3.06×10^{-5})	(2.12×10^{-5})	(2.64×10^{-5})
DUM_3	-1.52×10^{-4}	-1.10×10^{-6}	$-2.20 \times 10^{-4***}$	$-9.66 \times 10^{-5***}$
	(6.25×10^{-5})	(4.25×10^{-5})	(2.77×10^{-5})	(3.68×10^{-5})
Constant	-3.56×10^{-4}	$5.72 \times 10^{-4***}$	$3.79 \times 10^{-4***}$	$1.38 \times 10^{-3***}$
	(3.01×10^{-4})	(1.96×10^{-4})	(8.87×10^{-5})	(1.62×10^{-4})
Observations	17,375	38,831	118,872	71,789
R-squared	1.64%	1.34%	1.06%	2.46%
Adj R-squared	1.58%	1.33%	1.05%	2.44%

	Panel C. Total price impact			
	Portfolio 1 (High-PIN)	Portfolio 2	Portfolio 3	Portfolio 4 (Low-PIN)
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*
PIN	3.87×10^{-4}	7.89×10^{-4}	$7.96 \times 10^{-4***}$	$-7.60 \times 10^{-4***}$
	(2.84×10^{-4})	$(2.30 \times 10^{-4)}$	(1.28×10^{-4})	(1.71×10^{-4})
Ln(size)	2.07×10^{-6}	4.56×10^{-6}	$1.31 \times 10^{--4***}$	-2.74×10^{-6}
	(1.11×10^{-5})	$(8.00 \times 10^{-6)}$	(4.62×10^{-6})	(6.86×10^{-6})
Volatility	-1.32×10^{-3}	$1.59 \times 10^{-3**}$	$-3.20 \times 10^{-3***}$	-2.74×10^{-3}
	(5.06×10^{-3})	$(7.08 \times 10^{-4)}$	(1.04×10^{-3})	(1.77×10^{-3})
Ln(turnover)	-3.45×10^{-5}	-2.60×10^{-5}	-9.32×10^{-6}	$-1.55 \times 10^{-4***}$
	(2.95×10^{-5})	$(2.17 \times 10^{-5)}$	(7.59×10^{-6})	(1.70×10^{-5})
Market Return	5.14×10^{-3}	$-9.35 \times 10^{-2***}$	$-5.23 \times 10^{-3***}$	$-2.79 \times 10^{-3**}$
	(2.33×10^{-3})	$(1.70 \times 10^{-3)}$	(9.12×10^{-4})	(1.26×10^{-3})
Momentum	5.03×10^{-5}	-5.72×10^{-5}	4.36×10^{-6}	-1.98×10^{-5}
	(5.66×10^{-5})	$(5.21 \times 10^{-5)}$	(2.42×10^{-5})	(5.02×10^{-5})
OIB	3.13×10^{-4}	-2.48×10^{-4}	$3.58 \times 10^{-4***}$	$7.93 \times 10^{-4***}$
	(2.10×10^{-4})	$(1.65 \times 10^{-4)}$	(1.14×10^{-4})	(1.33×10^{-5})
BAS	-1.36^{***}	-1.27^{***}	-1.71^{***}	-0.86^{***}
	(0.05)	(0.10)	(0.10)	(0.11)
DUM_1	1.34×10^{-5}	$-1.29 \times 10^{-4**}$	$3.67 \times 10^{-4***}$	$7.10 \times 10^{-5*}$
	(7.41×10^{-5})	(5.04×10^{-5})	(2.65×10^{-5})	(4.23×10^{-5})
DUM_2	1.21×10^{-5}	$-6.66 \times 10^{-4**}$	$1.64 \times 10^{-4***}$	1.81×10^{-6}
	(4.98×10^{-5})	(2.85×10^{-5})	(2.06×10^{-5})	(2.48×10^{-5})
DUM_3	$1.40 \times 10^{-4***}$	-3.32×10^{-5}	$1.93 \times 10^{-4***}$	$5.95 \times 10^{-5*}$
	(6.03×10^{-5})	(3.69×10^{-5})	(2.62×10^{-5})	(3.46×10^{-5})
Constant	$5.33 \times 10^{-4**}$	$-5.29 \times 10^{-4**}$	$-6.98 \times 10^{-4***}$	$-1.53 \times 10^{-3***}$
	(2.12×10^{-4})	(2.27×10^{-4})	(8.74×10^{-5})	(1.80×10^{-4})
Observations	17,375	38,831	118,872	71,789
R-squared	3.98%	1.97%	1.62%	2.09%
Adj R-squared	3.91%	1.96%	1.61%	2.07%

traders also may not adjust positions by block sales if they have no liquidity motives to do so.

3.5. Stock opacity and the incorporation of information

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

Based on the foregoing, we hypothesise that the information diffusion process of high-PIN stocks is stronger than that of low-PIN stocks, since firms with low financial transparency might have more firm-specific information to reveal, and informed trade can facilitate more information into price discovery. We split the sample of FTSE 100 stocks into four portfolios according to the mean value of intraday PIN and estimate Eq. (4) for each portfolio.

In Table 9, Panels A, B and C show the regression results for permanent, temporary and total price impacts of purchase block trades across portfolios. Clearly, PIN coefficients on permanent price impacts increase with the average PIN value in each portfolio. This confirms our expectation that the information diffusion effect is strongest for stocks with lower levels of transparency. However, in the case of block sales, as shown in Table 10, there is little evidence to support our hypothesis. It is also related to the fact that block sales are less informative than block purchases, since block sales are more likely to be liquidity-induced rather than information-based when compared to purchase trades. In this section we find that for those firms with relatively low financial transparency, investors and agents who are particularly skilful in analysing public news play an important role in revealing information via block purchases. This result is in line with Vega (2006)'s finding that return of high PIN firms is less sensitive to the same size of surprise news than low PIN firms, because the private information should have already been revealed to the market by informed investors across trading periods. Hence, on balance, informed trading plays a positive role in facilitating more information into the price discovery process.

4. Conclusion

We examine intraday price impact of block trades in the presence of informed trading. While, previous studies mainly focus on trading around corporate events and insider trading activities, we expand our investigations to encompass the entire regular trading hours on the LSE. Our results show that the number of informed trades is positively related with the number of block trades. The positive (negative) relationship between informed trading, using PIN as a proxy, and the permanent price impact of block purchases (sales) suggests that there exists an impounding of private information via block trading on the LSE.

We also find that firms with low trading transparency exhibit stronger effects for private information incorporation when compared with those with a high level of trading transparency. Informed trading plays a positive role in facilitating the price discovery process through trading in the direction of permanent price impact for both purchase and sale block trades. This finding is consistent with two streams of existing literature: insider trading (see for example John & Lang, 1991) and high frequency trading (see for example Brogaard, Hendershott, & Riordan, 2014).

Further contributions made in this paper include new insights on the intraday and inter-day dynamics of the private information incorporation process. Firstly, we show that impounding of private information into stock prices on the LSE is mostly aggressively propagated during the first hour of trading. This pattern is consistent with recent evidence from the LSE (see Ibikunle, 2015a). Secondly however, despite the seemingly rapid private information usage during the trading day, traders also appear to withhold private information longer than a trading day window, such that trading positions are adjusted based on the previous day's private information. We document a linear relationship between the lag PIN variable and the logarithmic of change of number of block trades, which indicates that informed traders adjust their block positions based on historical private information. The combination of intraday and inter-day patterns provides empirical support to previous theoretical contributions (see for example Foster & Viswanathan, 1994; Holden & Subrahmanyam, 1992; Hong & Stein, 1999; Hong et al., 2000; Kyle, 1985; Lin & Rozeff, 1995) suggesting that informed traders gradually exploit private information.

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