Opening and Closing Price Efficiency in Hybrid Markets: Does the London Stock Exchange need the Call Auction?

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Abstract

We model 73.62 million London Stock Exchange (LSE) trades with a combined transaction value of £5.45 ($8.96) trillion. We show that the LSE's high failure rate to open at the opening call auction only relates to low volume stocks. Evidence suggests that traders opt to hold off trading until the floor opens at 08:00hrs; this decision seems connected to the need to avoid the informed traders who dominate the opening auction. For the largest volume stocks, the opening call auction provides highly efficient opening prices, while the lower volume stocks attain similar levels of price efficiency only after the start of the normal trading hours (NTH). At the close however, all stocks only lose small fractions of informational efficiency achieved during the NTH. Opening prices may influence trader sentiment throughout the trading day, and opening/closing prices may be the basis for settling derivative contracts, they are therefore of great importance.

JEL classification: G12; G14

Keywords: Market efficiency; Price discovery; Trading activity; Call auction; London Stock Exchange

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1. Introduction

The question of how financial instruments' prices develop on financial platforms has fascinated both academic researchers and practitioners for decades. The introduction of computer-aided trading, and relatively more recently, algorithmic trading, has only increased this interest. The process of generating a fair price for an instrument can be quite complicated given the reasonable probability of informed trading. However, decades of relentless technological advancement has led to the development of ultra-quick information dissemination processes, which now feed directly into platform trades. The proliferation of information dissemination structures such as bespoke real-time trading information providers and 24-hour financial markets news channels such as CNBC and Bloomberg, has now led to an unprecedented timely release of information to the market place. These streams of data feed directly into trading algorithmic trading strategies, which have been shown to improve trading quality by narrowing spreads, reducing adverse selection and enhancing the informativeness of quotes (see Hendershott et al., 2011). Even with these advancements, establishing an opening reference price after a market closure can still be a challenging process. Market closure may be due to the close of regular trading, trading suspensions or temporary halts. For traders, establishing a fair price after such closures is critical to trading strategy. The importance of the pre-open to price discovery is demonstrated by Biais et al. (1999) and Cao et al. (2000) who show evidence of 'learning' through the posting of non-binding quotes on the Paris Bourse and NASDAQ respectively.

One may argue that the significance of the opening price has been reduced by the rise of Electronic Communication Network (ECNs), which makes after hours trading possible, albeit with higher levels of informed trading and lower trading volumes (see for example Barclay and Hendershott, 2003). The price discovery process during the after hours trading period is also fraught with inefficiencies relative to the normal trading hours (NTH) session. The prices are more volatile, the adverse selection costs are higher, along with attendant information asymmetry, and thus spreads are generally wider. Barclay and Hendershott (2003) thus find that price efficiency after hours is less than during the NTH because very little new information is released while trading is also thin. Therefore, even if post-NTH trading does provide some foundation for opening prices, most market participants are unlikely to trade on that basis because of the noise levels during the price discovery process once the market has officially closed. This underscores the significance of the opening price and the process that generates it. Thus markets around the world have evolved their opening practices in order to facilitate the efficiency of the price discovery process. The most widely adopted pre-open mechanism by platforms has been the call auction. In this paper we will examine how the call auction contributes to the pricing efficiency on a hybrid market, the London Stock Exchange (LSE). On the LSE's Stock Exchange Electronic Trading System (SETS), there is direct competition between the broker-dealer market, market makers and investors who submit limit orders. This is an interesting mix that naturally should enhance market quality. The introduction of the call auction mechanism to open, as the LSE has done, should also contribute to the efficiency of the opening price.

A stream of literature has examined the impact of the introduction of opening and closing call auctions on market quality. However, to our knowledge there is no linkage between *informational* efficiency and other market quality characteristics evolving in the opening auction to the NTH market efficiency within an intraday modelling framework. The general approach has been to test whether the introduction or evolution of a trading system/mechanism positively or negatively influences market characteristics. A number of these studies mainly adopt an event study framework employing daily data (opening and closing prices) rather than conducting detailed intraday analyses. Thus none of the contributions have actually examined these issues on an intraday basis using high frequency trading data. Further, most of the focus has been on the introduction of closing auctions rather than opening auctions. For example, Chelley-Steeley (2008) and Chelley-Steeley (2009) investigate the market quality impact of the introduction of the closing auction on the LSE. Both studies document market quality improvements based on daily level data. The studies however do not isolate the direct market quality impacts of auction trades during the opening or closing call auction periods on continuous trading during the NTH. Pagano and Schwartz (2003) and Comerton-Forde et al. (2007) examine the introduction of the closing auction on the Paris Bourse and the Singapore Stock Exchange respectively; both papers suggest that the introduction of the call closing auction improves market quality. Comerton-Forde et al. (2007) also consider the impact of the closing auction in tandem with the opening auction without decomposing the impacts since both were introduced during the same month, and their study also employ daily data in an event study context. Another study, which focuses on the Singapore Stock Exchange, is Chang et al. (2008); they confirm the "*spillover* effect", which was first documented by Pagano and Schwartz (2003) based on their analysis of trading on the Paris Bourse.

Since previous literature streams support the notion that the introduction of call auction enhances market quality, the past decade has seen the introduction of call auctions for closing, and in many cases as well, the opening of trading venues across the world. There is a strong theoretical argument for congregating all available market liquidity at a single point in order to determine the fair price of an instrument. Schwartz (2001) asserts that this enhances the accuracy of the price discovery process. The view that the efficiency of the price discovery process is inextricably linked with liquidity is widely supported in the literature and has been further established by Chordia et al. (2008) amongst others. According to

Madhavan (1992), since all traders are given access to the same prices at the same time, call auctions reduce information asymmetry. However, this comes at higher information (and thus transaction) costs over time as auctions can only be periodic at best. Barclay et al. (2008) also show that the consolidation of orders, which occurs during a call auction, rather than the nearness of traders, or the involvement of market makers, is the vital factor for price efficiency in a market opening. Further, their results imply that call auctions are more likely to absorb extreme liquidity shock without yielding inefficient prices and volatility. Amihud et al. (1990) find on the Milan Stock Exchange that when a continuous trading period is preceded by a call auction, volatility associated with that continuous trading session is lower than if it had not been preceded by a call auction. The improvement in market quality, usually associated with reduced volatility, perhaps explains why Schnitzlein's (1996) experimental study finds that under a call auction, despite no significant reduction in average price efficiency, there is a reduction in adverse selection costs incurred by uninformed traders. Interestingly however, empirical evidence presented by Ellul et al. (2005) suggests that call markets are less suited than the dealership system to deal with adverse selection. They also find that on days when uncertainty is higher, there is increased migration from the call market to the dealership during the LSE pre-open, suggesting that traders prefer the dealership when information asymmetry is on the rise. They argue that small stocks/orders traders are more likely to trade using the dealership rather than the call because they are more likely to find counterparties by using that option (coordination theory). Somewhat contradictorily, their results also indicate that small orders obtain lower transaction costs on the call market when compared to the dealership. Thus one would expect small stocks/orders traders to prefer the call market at the open and close, and that this should drive the availability of counterparties in the auction system for small stocks. Despite a number of contributions addressing issues around the use of the call auction to open or close, only a few published papers have examined inter-temporal links between the opening auction and continuous trading sessions. Brooks and Moulton (2004) provide evidence on interactions between the opening auction on an exchange, the NYSE, and the continuous regular trading day. Yet even then they only focus on trading activities such as volume. Volume in itself does not imply liquidity or market efficiency; Johnson (2008) shows that volume and liquidity are unrelated over time and Chordia et al. (2008) show that liquidity is inextricably linked to market efficiency.

Our study is related to both Ellul et al. (2005) and Barclay et al. (2008). However, this paper is different as they focus on the comparison of two different trading mechanisms/options, whilst we focus on how the price discovery and other relevant trading parameters from one mechanism evolve as the market shifts to a different trading mechanism. Specifically, Ellul et al. (2005) and Barclay et al. (2008) focus on traders' selection of trading mechanism(s) and the market's capacity to absorb order imbalances respectively.[2] We are motivated differently; our aim is to first examine the efficiency levels of the opening price and how that evolves as the continuous trading period commences. This examination should shed some light on whether the opening auction period contributes to the NTH in terms of efficient price discovery. This main focus is also partially influenced by the findings of Barclay and Hendershott (2008). In their paper, which compares trading and non-trading mechanisms of price discovery, they suggest that the pre-open trading on NASDAQ contributes to the efficiency of the opening price. We aim to find out whether this holds true on the LSE where the pre-open is structured such that the opening price is determined by a call auction, and the NTH is a continuous order-driven market. If informed traders do not employ the opening call

[2] Our research questions may also be linked to Amihud et al. (1990). However, the Milan Stock Exchange call method on which their study is based is significantly different from the one we study. Further, there are significant differences in the methodological approach they employ and ours; this is further amplified by the thin trading observed on the Milan stock exchange at the time of their study.

auction, given high failure rates to open, as implied by Ellul et al. (2005)[3], then the pre-open price on the LSE may not provide a more informative or efficient opening price than say the first 10-20 minutes of the NTH. If indeed, the opening auction/pre-open contributes to market quality during the NTH, then we expect the price efficiency for this period to be higher than, or equal to, other 10-minute periods across the NTH. Specifically, our contributions to this literature area are encapsulated by the four questions we pose in this paper: (1) what proportion of price information relative to the trading day is revealed during the opening call auction/pre-open and the closing call auction? (2) How *informationally* efficient relative to the NTH is the opening call auction/pre-open and closing auction price on the LSE? (3) More specifically, how noisy is the pricing process during the pre-open price relative to the NTH? (4) And finally, do informed traders drive the price discovery process during the pre-open?

We find that the SETS pre-open price is only informative for the highest volume stocks, while for the low volume stocks, price discovery only really starts after the market open as there is a high rate of failure to open at the call for small volume stocks. Further the dealer-broker trades entered during the pre-open reveal very little information, which is not significantly different from zero. Given the noise levels in the dealer-broker trades, only the highest volume stocks that succeed at the call are able to post significantly high levels of informational price efficiency. For all stocks however, there is a high level of price efficiency during the NTH, which only declines slightly after the NTH. We also find that small volume stock traders likely shun the opening call auction because of the high level of information asymmetry/informed trading occurring during the period. Thus, the decision to avoid the opening call may be due to the need to avoid trading in an environment dominated by informed traders.

[3] Friederich and Payne (2007:1176) even went as far as stating that: "The opening batch auctions in particular were never successful in London…".

2. Institutional Background

2.1. Trading on the London Stock Exchange

Until 1997 the LSE functioned as a pure dealership market. The market was heavily criticised for its lack of transparency and the high transaction costs imposed on low level investors. In response to the criticisms, on the 20th October 1997, the LSE introduced an electronic order-matching system called the Stock Exchange Electronic Trading System (SETS) for all FTSE 100 stocks. The FTSE 100 includes the largest firms by market value as listed on the LSE, and they account for about 81% of the total market capitalisation on the exchange. Subsequently, in September 1999, the most liquid FTSE 250 stocks were also migrated to SETS. The introduction of SETS on the LSE encapsulates a shift from a strictly quote driven market to an order driven one. The SETS has since grown to become one of the most liquid electronic order books in the world. In addition to FTSE 100 stocks, it now incorporates trades in all FTSE 250 stocks along with the FTSE Small Cap constituents, ETFs as well as other less liquid instruments.

Floor trading is preceded by a 10-minute call auction period at 07:50:00hrs London local time. However, generally during the pre-open (including prior to the opening auction), dealer trades can also be reported. During the pre-open, limit and market orders may be entered and deleted at will, and all order book data are communicated to the market. In advance of the batch auction at 08:00:00hrs, the order book is suspended, and no further orders can be entered. An uncrossing algorithm subsequently runs to facilitate execution of orders at prices that maximise the volume of instruments traded. Once the buy and sell orders are crossed, indicative uncrossing prices for each instrument are displayed as the corresponding opening prices for the NTH. Extensions to the opening auction can be activated under two scenarios.

First, a Market Order Extension (MOE) could be activated for two minutes plus random 30-second end periods where there are unexecuted market orders on the order book after the uncrossing. Secondly, a Price Monitoring Extension (PME) can be activated where the indicative uncrossing price is at least 20% at variance with the final continuous session trade of the previous day. The MOE and PME can each only occur once for a trading session, thus all unexecuted orders after this point are retained on the order book for possible execution during the continuous trading phase. If the order book is not crossed for any instrument, the first automatic trade during the continuous trading session will be its opening price for trading on that day.

The continuous trading period (NTH) is normally the longest period of the day and it concludes at 16:30:00 hrs. The period may be interrupted when an order executable at 5% or more below or above the last automatic trade is submitted. At that point, a five-minute call period AESP (Automatic Execution Suspension) plus a random 30-second end period is activated with the option of an MOE afterwards. Should the order book not be crossed, continuous trading will resume after the MOE, and the first automatic trade after the AESP will be the new reference price for the affected instrument. Traded volumes and prices in the last 10 minutes of the continuous trading period from 16:20:00hrs to 16:30:00hrs are used to compute the Volume Weighted Average Price (VWAP) for the day. In order to ensure that continuous trading runs during the last 10 minutes, AESPs cannot be activated after 16:12:00hrs. Following the continuous trading session, an auction call period ensues for five minutes at 16:30:00hrs. During the closing auction, limit and market orders can be submitted. If buy and sell orders are crossed during this period, the uncrossing price is released to the market as the closing price, and the indicative price at which crossed orders are executed. If there are remaining unexecuted orders following the uncrossing, an MOE is activated. And if the uncrossing price is at least 5% away from the VWAP (if there is no VWAP, then the last automatic trade), a PME is activated. Should the uncrossing price remain at least 5% away from the VWAP (or the last automatic trade) an Additional PME (APME) will be activated. The APME runs for 10 minutes plus a random 30-second end period. All these extensions can occur only once per closing of a trading day. If the closing procedure does not yield an indicative uncrossing price, then the last automatic trade during the trading day will be the closing price.[4]

3. Data

3.1. Sample Selection

Our data is made up of 70 FTSE 100 stocks, which account for 91.23% of the index's market capitalisation on 30th September 2013. Please see Appendix A for the stocks and their corresponding FTSE composition. Combined, all FTSE 100 firms account for more than 81% of the total market capitalisation of the LSE listed firms, thus we assume that our results will be representative of the general market conditions on the LSE. We obtain two ultra-high frequency datasets from Thomson Reuters Tick History (TRTH) database; these datasets are for stocks traded on the SETS segments SETS0 and SETS1. SETS0 and SETS1 segments contain the most liquid FTSE 100 and FTSE 250 firms. The datasets we obtained cover the 253 LSE trading days between 1st October 2012 and 30th September 2013, which is also our sample period. The number of observations in the two datasets equal approximately 1.65 billion observations including both quotes and transactions data, and all observations are time stamped to the nearest millisecond. Specifically, the following variables are included in the datasets: Reuters Identification Code (RIC), date, timestamp, price, volume, bid price, ask price, bid volume and ask volume. All trades reported after 16:50:00hrs are excluded from

[4] See London Stock Exchange (2000a, 2000b, 2001 and 2013) for more details of the institutional framework.

the final sample because they are reported after the time a possible APME could have run each day as the APME can only run once as previously detailed.

In the dataset, quotes account for a little over 1.498 billion (90.79%) of the observations. This means that quotes are updated regularly relative to trading or order submission frequency, and thus we can easily obtain the best prevailing bid and ask quotes for each trade. We first employ the quotes in determining the prevailing best bid and ask quotes, as well as quote midpoints for each transaction; thereafter the quote rows are eliminated from the dataset, thus leaving us with only the trades, totalling 150,660,824. Each of the trades have now been allocated corresponding prevailing best bid and ask quotes, and quote midpoints computed from the discarded quote rows. We observe a number of anomalous observations in the 150,660,824 trade observations that could only have been as a result of data input errors. Thus we proceed to clean up the dataset by removing all observations with any evidence of data input errors as well as all non-FTSE 100 stocks; specifically we delete all observations satisfying any of the following criteria:

1. Transaction price during the NTH is greater than the prevailing best ask price;
2. The quoted bid price exceeds the quoted ask price;
3. The quoted bid-ask spread, defined as the difference between the ask and the bid price, exceeds £4;
4. The value of the quoted bid-ask spread divided by the transaction price is greater than 0.35;[5]
5. Any of the following variables is missing for that observation: price, volume, quoted bid and ask prices;

[5] Conditions 3 and 4 are inspired by Chordia et al. (2001); given the improved levels of trading frequency, the conditions stipulated in the earlier paper are adjusted for higher trading frequency.

6. Non-FTSE 100 stock transaction;
7. Transaction is for FTSE 100 stock added to or removed from the index between the period 30th September 2012 and 30th September 2013.

These conditions yield in a final combined dataset with 73,616,187 transactions for 70 FTSE 100 stocks trading over the sample period. The 70 stocks account for 91.23% of the total FTSE 100 market capitalisation on 30th September, 2013, the last date in our sample. To the best of our knowledge, this sample size surpasses any volume of observations employed in any prior study of the microstructure of the LSE. The sample period is also more recent, by more than a decade, than any used in an existing study.

3.2. Sample Description

The combined FTSE 100 stocks in the sample averages a total trading value of over £21.54 billion per day from a daily average of 290,973 transactions. The total traded value over the 253 trading day-period is about £5.45 ($8.96) trillion. Table 1 shows the summary statistics for the sample used in this paper. Panel A presents a trade-based summary, while Panel B shows daily averages of transaction volumes. In both panels, we rank the sample stocks into quintiles on the basis of transaction volumes for the sample period. Quintile 5 contains the 14 highest trading stocks by daily pound value, and Quintile 1 contains the 14 least trading stocks by daily pound value. The panels are divided into three main time periods for each quintile: Pre-open (07:10:00hrs - call end), NTH (08:00:30hrs - 16:30:00hrs) and Post-NTH (16:30:01hrs - 16:50:00hrs). Pre-open is also further divided into Pre-opening call auction (07:10:00hrs - 07:50:00hrs) and the Opening auction (07:50:01hrs - call end). Post-NTH includes the Closing auction (16:30:01hrs - 16:38:00hrs) and the Post-close (16:38:01hrs - 16:50:00hrs).

In this section, most of the focus will be on the daily averages presented in Panel B. The highest grossing stocks have the highest number of transactions and pound value per day. The combined daily number of transactions (pound value) for the highest trading stocks is about six (207.33) times greater than the total for the lowest trading stocks. Also, most of the daily transactions occur during the NTH; almost 98% (284,548) of all transactions are recorded for the NTH. However, the trend is very different when one considers the value of those transactions; on an average day, the NTH accounts for only about 13.89% (£2.99 billion) of total traded value, while the post-NTH accounts for 84.86% (£18.28 billion). This is quite an interesting yet consistent occurrence for nearly every day in the sample. A closer analysis shows that the unusual phenomenon occurs only for the highest trading stocks grouped into Quintile 5; for the other four quintiles, the NTH easily accounts for 73.81% (£1.27 billion) of daily average traded value, while post-NTH only accounts for 23.04% (£395.48 million) of the daily average of traded value. Further, we find that the trades responsible for the massive values traded during the post-NTH period usually occur post-close and are off-floor dealer trades reported on the LSE. Since the large Quintile 5 post-NTH trades are off-floor broker-dealer trades, they are likely to be upstairs trades registered on SETS after the close (during and after closing auction). They are also likely to be institutional trades pre-agreed with dealers to execute at the closing price (see Friederich and Payne, 2007). We observe that they usually result in large price movements relative to other trades. Of course this could be because of microstructure impacts due to their sizes. It is on the basis of this interesting impact that we extend the trading time of interest to 16:50:00hrs so we could capture their after hours effects. Their impact can however be isolated since our analytical approach is mainly based on estimating values within time-specific intervals.

INSERT TABLE 1 ABOUT HERE

While the post-NTH period is a relatively active interval of the day for all the quintiles with even the first quintile averaging nearly 600 transactions per day, the pre-open is only significantly active for the highest volume quintile. However, pre-open trades are on average larger than trades during any other phase of the trading day, and this is confirmed in Panel A of Table 1. The mean for trades occurring in the first period is higher than other periods for four of the five quintiles, the only exception being the largest volume quintile where the post-NTH has a larger size per trade. Given the propensity of large trades to elicit microstructure impacts and because the period, with the exception of the largest volume stocks, is characterised by thin trading, we expect the pre-open to be noisier for lower volume stocks than the other periods of the day. Literature suggests that trading activity enhances price discovery, thus when trading is thin, the price discovery process is less efficient. Although we also note that quotes are frequently posted and updated by market makers during the 10-minute auction period and prior to the auction period proper. Thus the level of market support available during the period prior to the NTH is not significantly less than during the NTH, and this may help to improve the price discovery process prior to the NTH. The question of whether posting of quotes can help improve price discovery is also dependent on the quote spreads. If the market makers are cautious, the posting and updating of quotes may not do much to help since the spreads will be wide in order to reflect adverse selection costs. We consider this issue in subsequent sections.

3.3. Trading Activity on the LSE

Figure 1 shows the daily volume per minute for the five quintiles; the logs of the values are plotted given the high variability in volume differences among the three trading periods. During the pre-open and prior to the call auction period, some trading is registered. However, as shown earlier in Table 1, these trades are few, leading to a slow start to the pre-open. This is consistent for all five quintiles, with all categories showing evidence of high variation in average trading values per minute prior to the opening call auction. For example, in the first minute of the pre-open included in the sample (07:16:00hrs), the average trading volume for all quintiles is about £33.65 million, this falls some 99.86% to approximately £48,714 at 07:50:00hrs, just microseconds before the call auction period. The average daily trading volume then rises sharply to more than £173.33 million for the entire call auction from 07:50:00 - 08:00:00hrs. The final 50-odd seconds of the opening call auction itself accounts for approximately 58.41% of the call auction period trading value as most of the orders are entered just before the auction algorithm runs.[6] The vast majority of trades during the opening call auction are for the highest volume stocks. Although, with the exception of the minute ending 16:35:00hrs when the closing auction algorithm usually runs, 08:00:00hrs has the highest trading value, the number of trades for the minute is very small in comparison to the rest of the trading day minutes. Microstructure literature suggests that large trades are naturally more informative than medium and small trades, thus we expect that trades at 08:00hrs, and during other minutes of the entire pre-open, will be more informative than trades at any point during the NTH or post-NTH. We test this hypothesis in Section 4.2.2.

INSERT FIGURE 1 ABOUT HERE

The trading value is sustained at over £170 million only on account of a steep increase in the value of lower volume stocks traded within the first 10 minutes of the NTH following their failure at the opening call auction. The lower volume stocks seem to have settled for a de-facto price referencing period between 08:00:00 - 08:10:00hrs because the trading value for Quintiles 4 to 1 then rise relative to the Quintile 5 levels during this period. To underscore this evolution, the trading value of the four lower quintiles combined approaches 45.14% of Quintile 5 trading value for the period. This is the highest level relative to Quintile 5 stocks,

[6] We find that some dealer trades are also registered on SETS during this period.

which the combined lower quintile stocks attain at any point during a typical trading day.[7] Afterwards, and for the rest of the day, the trading value settles down to a relatively stationary value, starting at approximately £2.87 million for the minute ending 08:11hrs, throughout the trading day, and prior to the closing call auction. Figure 1 shows a slight evidence of the characteristic U-shape reported by several studies such as Barclay and Hendershott (2003) and Chan et al. (1995).

Although there are far fewer trades per minute in both the pre-open and post-NTH than there are in the NTH, their sizes are larger. In Figures 2 and 3, we show the mean and median trade sizes per minute for each quintile. Due to the large differences between the trade sizes in the three periods, we plot the logarithmic values of the mean and median rather than the raw values. With the exception of Quintile 5, the mean trade sizes are stationary once the market opens. The median values however are better behaved, with all the quintiles in sync. This is because the median is less affected by extreme trade sizes executed off the floor through the broker-dealer channels. However, both measures tell the same story. 08:01:00hrs has the highest mean trade size for the entire NTH at £157,872.44 however this is only 0.85% (0.87%) of the average trade size at 07:16:00hrs (16:34:00hrs). These comparisons evidence the extent of variability in trade sizes during the different trading periods. With such large variations, we also expect dramatic variations in the identity of dominant market participants during the different trading periods. Microstructure literature shows that with the large average trade sizes in the pre-open and post-NTH, one should expect to find more informed trades being executed, thus those periods will have more active informed and sophisticated traders. We test this hypothesis in Section 4.3.

[7] Ellul et al. (2005) already report on the case of failure to open at the call. Their analysis shows that the call is not optimal for medium and small cap stocks. In this paper, we provide microstructure evidence that suggests this is a function of trading activity rather than market capitalisation. Further evidence provided in successive sections will explore this phenomenon further and provide more insight.

INSERT FIGURES 2 AND 3 ABOUT HERE

4. Results and Discussion

4.1. Price Discovery on the London Stock Exchange

The variation of trading activity across the trading day also has implications for the evolution of price discovery. According to the literature (see for example Chordia et al., 2011; Barclay et al., 1990), trading activity is inextricably linked to the price formation process. Since our main interest in this paper is to examine the efficiency of incorporating information in the prices of stocks around the open and close, i.e. the informational efficiency of price discovery, we commence our analysis by examining the intraday price discovery process around those periods and throughout the entire trading day.

4.1.1. Weighted Price Contribution

We estimate the proportion of close-to-close price evolution discovered for different periods across the day starting with the first period when off floor trades are sent to SETS between 07:10:00 and 07:20:00hrs. The periods for which we estimate the proportion of close-to-close price discovery includes the first 10 and the final five 10-minute periods across the trading periods as well as the block of trading hours between 09:00:00 - 16:00:00hrs. Since we measure period by period price discovery, we use the well-established weighted price contribution (WPC) (see Barclay and Warner, 1993; Barclay et al., 1990; Cao et al., 2000; Barclay and Hendershott, 2004; van Bommel, 2011).[8]

For each trading session/day and period *k*, we define the WPC as:

[8] van Bommel (2011) show that the WPC is consistent; it is also the only unbiased and asymptotically normal measure for price discovery if the price process follows is a *driftless* martingale.

$$WPC_k = \sum_{s=1}^{S}\left(\frac{|ret_s|}{\sum_{s=1}^{S}|ret_s|}\right)\times\left(\frac{ret_{k,s}}{ret_s}\right), \tag{1}$$

ret_s corresponds to the close-to-close return for stock *s* and $ret_{k,s}$ is the logarithmic return for period *k* and for stock *s*. In Equation (1), $\frac{ret_{k,s}}{ret_s}$ is a measure of relative proportion of the day's return given by stock *s*; $|ret_s| / \sum_{s=1}^{S}|ret_s|$, which is the standardised absolute value of ret_s, is the weighing factor for each stock. With the introduction of a weighing factor, smaller $|ret_s|$ are thus given small weights. The WPC is normally computed on a stock-by-stock basis and then averaged out across the stocks (see Cao et al., 2000). For this procedure however, stock correlations, due to the common constituents, complicates statistical inferences about the mean. In our sample, we compute the WPC for each stock and obtain average cross-sectionally across stocks and also compute WPCs for each day and average across days; however similarly to Barclay and Hendershott (2003), we only notice slight qualitative differences. Following Fama and MacBeth (1973), we obtain the mean WPC for each day, and employ the time series standard error of the daily WPCs for statistical inference.

INSERT TABLE 2 ABOUT HERE

Table 2 presents the WPCs for five quintiles and all the stocks combined; the results for each category of stocks are for 10-minute periods from 07:10:00 - 09:00:00hrs and 16:00:01-16:50:00hrs, as well as for the NTH period between 09:00:01 and 16:00:00hrs. There are four striking results emerging from this analysis. The first is the huge disparity in the proportion of price discovery recorded during the opening call auction period for Quintile 5[9] stocks on one

[9] There are a few Quintile 5 stocks (e.g. BAES, BLT and RIO) that suffer failure at the open call auction or post no trades/auction orders during the call auction; they are excluded from aggregate WPC of Quintile 5 stocks as

hand, and the lower quintile stocks on the other. So striking is the difference that none of the lower quintile stock WPCs during the opening call auction are significantly different from zero. This clearly illustrates the general lack of informativeness of dealer transactions favoured by the lower quintile stocks during the call auction period. It further suggests that platform/floor orders/trades are still primarily the drivers of opening price change on the LSE; this much is underscored by the general lack of statistical significance for the pre-call period WPCs as well.[10] Second, approximately 30% or more of the close-to-close price discovery occurs during the call auction (08:00:00 - 08:10:00hrs) period for Quintile 5 (other quintiles) stocks. This shows that information accumulated overnight is incorporated into stock prices during the call auction for high volume stocks and within the first few minutes of the NTH for other stocks. It is tenable to expect that firm-relevant information is accumulated overnight since firms routinely time the releasing of their earnings and other reports for the post-NTH; further these releases have been shown to impact trading during afterhours trading sessions (see for example Jiang et al., 2012). Further, price innovation in the early trading could have been influenced by activities from dealer activity. Thus for stocks that are not extensively traded/reported post-NTH, the first opportunity to incorporate new information will be during the first minutes of NTH or the pre-open. The puzzling aspect however is that the early broker-dealer trades do not reflect all of the overnight information. Indeed price discovery does not really start until the call auction period at 07:50:00hrs; even then it only starts for the highest volume stocks and not the lower volume ones, their price discovery only start when the market opens at 08:00:01 hrs. This leads to the third striking aspect of the results. More than 50% of price discovery occurs before 09:00:01hrs in the morning for the

well as further analyses of the 10-minute opening call auction period in order to ensure comparability of samples.

[10] The statistical significance and value of these estimates are at variance with those obtained by Ellul et al. (2005). While we do not postulate as to the reasons why, we expect that this difference is related to the fact that our sample is more recent by more than 13 years than Ellul et al.'s (2005) and the market has evolved over time. However, we note that our results are more in line with the observation of Friederich and Payne (2007) that the opening auction on the LSE hardly succeeds; their data is slightly more recent than Ellul et al.'s (2005).

lower quintile stocks. And if one considers the call auction period as well, then the same phenomenon is true for the highest volume quintile. Thus information is only normally incorporated into stock prices in small drips after the heavy absorption of information into stock prices in the morning. Finally, the fourth main observation from Table 2 involves the dramatic correction of prices recorded once the market closes. It does appear that the closing auction and the broker-dealer trades after the continuous trading session/NTH provide the opportunity for traders to revise downwards their valuation of stocks, especially for the higher volume quintile stocks.

The results obtained here are consistent with the conclusions from after hours trading analysis of NASDAQ stocks by Barclay and Hendershott (2003). Since the high volume stocks have a greater percentage, than other stocks, of their total daily trading in the pre-open (see Table 1), a large proportion of price discovery thus shifts to the pre-open, specifically to the opening call auction period. Thus, the question of why there is a high level of failure to open at the opening call for lower volume stocks is not only related to traders making a decision based on transaction costs; it may also be a question of the non-execution of trades. With lower trading volumes (including dealership trades), such as an average of 7.60 trades in the pre-open per day for Quintile 1 stocks, finding counterparty to trade with must be difficult; Ellul et al. (2005) make this argument by proposing the coordination theory as an explanation of low volume stocks traders' behaviour, by avoiding the call auction. However, it is perhaps possible to encourage low volume stock traders to use the opening call auction if a slight adjustment could be made to the call auction algorithm. At present, the algorithm is tailored to maximise volumes rather than executing at the best ask/bid prices; assuming the algorithm prioritises prices, with necessary circuit breakers, rather than volume. For example, a volume weighted price during the call auction will ensure that low volume stock trades stand a better probability of execution. Low volume stock traders could then place market orders with a higher expectation of execution. The changes made to SETS regarding the introduction of the opening and closing call auction, at present only works for a fraction of the stocks traded on the LSE.

4.2. Price Discovery and Informational Efficiency

4.2.1. Unbiasedness Regressions

The WPCs indicate that approximately 30% or more of the close-to-close price discovery occurs during the call auction (08:00:00 - 08:10:00hrs) period for Quintile 5 (other quintiles) stocks. It is assumed that these respective periods set the pace for price discovery throughout the NTH and beyond, since they are the most informative intervals during the entire trading periods. Considering how important it is that the prices revealed during these periods be *informationally* efficient, we proceed to measure their informational efficiency by employing what Biais et al. (1999) call 'unbiasedness regressions' despite their slopes having a natural interpretation that encapsulates the degree of noise during an estimated period. We examine efficiency of the price discovery process due to the significance of the opening price for investors. This is vital when one considers that a market's informational efficiency is a critical requirement for investor participation in markets.

In order to compute the level of price efficiency for specified periods, for each stock and each day, Equation (2) is estimated separately for each time period; where ret_{cc} is the close to close return and ret_{ck} is the return from the close to the end time of period *k*:

$$ret_{cc} = \alpha + \beta ret_{ck} + \varepsilon_{ck} \qquad (2)$$

According to Barclay and Hendershott (2003), the slope coefficient β measures the ratio of signal to the noise. Consider the standard errors-in-variables problem a la regression analysis; if we assume no errors in the stock returns computation as well as no correlations, the slope coefficient in (2) will be equal to one. Further, if we assume that the actual return is not observable since the observable return is a combination of the real return plus some noise element. Noise may include microstructure effects such as spread components or reversible price impacts. Thus we will observe $ret_{cc} = RET_{cc} + v$ and $ret_{ck} = RET_{ck} + u$ and we assume that RET_{cc} and RET_{ck} are the actual returns, and v and u have zero mean and respective variances equivalent to σ_v^2 and σ_u^2. An ordinary least squares estimation of Equation (2) will yield an estimated slope coefficient β*, where

$$\beta^* \xrightarrow{p} \beta\left(\frac{\sigma^2 RET_{ck}}{\sigma^2 RET_{ck} + \sigma_u^2}\right) \tag{3}$$

$\sigma^2 RET_{ck}$ encapsulates the total observable information from the previous close to the time period k and σ_u^2 is the noise effect in prices at period k. The slope therefore is a measure of the ratio of information content (signal) to signal plus noise in prices at period k. Therefore, the extent to which the slope is less than unity is the extent of noisiness in period k, since if there is no noise element the slope will yield one. Equation (2) is estimated for each stock and each period k. From these regressions, we obtain the slope coefficient estimates for each stock and in turn compute the mean stock slope for each time period. We also follow Biais et al. (1999) to compute the confidence bands by using the time series' standard errors of the mean of the slope coefficient estimates. The mean coefficient and estimates along with the confidence bands are charted in Figure 4a - 4e. As pointed out by Biais et al. (1999), the time series estimation of stock returns in the presence of learning is problematic as a result of non-stationarity, which can be induced by non-stationarity. In order to avoid the spurious regression problem, we examine each time series for unit roots using the Augmented Dickey-Fuller test; and the obtained results suggest that the variables are stationary. We also ensure that we obtain robust standard errors by applying the Newey and West (1987) heteroscedasticity and autocorrelation consistent covariance (HAC) matrix estimator, which is consistent in the presence of both heteroscedasticity and autocorrelation of unknown form. The results obtained from the HAC estimation are not materially different from those obtained for the regressions using only OLS.

INSERT FIGURE 4 ABOUT HERE

Given the variation in the onset of price discovery for the highest volume and lower volume stocks, it is important that we present the charts for the mean coefficients individually for the quintiles. The charts for the lower volume quintiles are quite consistent; however, as expected Quintile 5's chart looks slightly different. For the highest volume stocks (Quintile 5), the informational efficiency of stock prices is low prior to the call auction period when only broker-dealer trades are submitted. During the call auction interval, a dramatic rise in the mean coefficients is registered; the mean estimate increases nearly five times to 0.83 from 0.17 during the 10-minute interval ending 08:00:00hrs. And within 10 minutes later at 08:10:00hrs, the mean coefficient has risen to 0.97; this level of price efficiency is thereafter largely maintained until about 09:00:00hrs. The informational efficiency of the stock prices remains high, above 0.84, for the rest of the trading day even after the market has closed. The evolution of the price discovery efficiency as shown in Figure 4 does suggest that the call auction price discovery is *informationally* efficient for the highest volume stocks. However, for lower volume stocks, which experience failure to open at the call auction, the mean coefficients at 08:00:00 hrs are very low. The highest at 08:00:00hrs is for Quintile 2 at 0.23. Thereafter however, once the continuous order-driven trading period gets under way, the mean coefficient estimates for all the lower volume stocks rise dramatically, as well in a fashion similar to Quintile 5's rising, during the call auction. These results are at variance with Barclay and Hendershott (2003) who report high informational efficiency in the pre-open for all stocks in their sample, although they fail to make distinctions on the basis of trading activity. Our results are however similar to Biais et al.'s (1999) findings. We put this disparity in results down to trading activity. Biais et al.'s (1999) results are based on an analysis of a market, the Paris Bourse, where no actual trading occurs during the pre-open, while Barclay and Hendershott's (2003) results are based on a sample of NASDAQ stocks traded in the pre-open with a relatively higher number of transactions than in our sample. Also in our analysis, we further divide the pre-open into five intervals before conducting our analysis, thereby yielding a reduced average number of transactions for each interval. Thus, the results in this section further cement the prior literature findings that trading activity is a critical part of the price discovery process and its efficiency. The opening and closing call auctions are both *informationally* efficient for the highest volume stocks because of their adequately high level of trading activity. As shown in Table 1, the lower volume stocks also have appreciable levels of trading activities in the post-NTH, therefore their informational efficiency is largely sustained even after the market has closed, and the transaction numbers have dropped sharply. We therefore propose that if measures are introduced to increase the trading activity in the opening call for lower volume stocks, the pricing efficiency of stocks during the call auction will increase and more price discovery will shift to the opening call.

4.2.2. Weighted Price Contribution per Trade (WPCT)

The high level of price efficiency recorded for the opening call auction (10-minute period ending 08:10:00hrs) for Quintile 5 stocks (other quintiles) and the high WPCs for those periods when considered, along with the relatively low number of transactions, suggest that individual trades reveal more information for all stocks in the pre-open than during the NTH. Lower volume stocks trades during the first 10 minutes of the NTH are also expected to reveal more information than the rest of the NTH. We examine this by constructing the weighted price contribution per trade (WPCT), which measures the amount of price return observed for each of those intervals. The WPCT is computed by dividing the WPC per trading interval by the weighted ratio of trades executed during that period (interval). If for each day, $t_{k,s}$ is the number of executed trades in time period *k* for contract *s*, and t_s is the total sum of $t_{k,s}$ for all the periods, then $WPCT_k$ is defined as:

$$WPCT_k = \frac{\sum_{s=1}^{S}\left(\frac{|ret_s|}{\sum_{s=1}^{S}|ret_s|}\right)\times\left(\frac{ret_{k,s}}{ret_s}\right)}{\sum_{s=1}^{S}\left(\frac{|ret_s|}{\sum_{s=1}^{S}|ret_s|}\right)\times\left(\frac{t_{k,s}}{t_s}\right)} \qquad (4)$$

Since the WPCT refers to the ratio of the aggregate price shift occurring in a period scaled by the ratio of trades in that same period, the measure should equal approximately one if all the trades contain similar information levels.

INSERT TABLE 3 ABOUT HERE

Table 3 reports the results for the WPCT analysis. As hypothesised, trades in the pre-open are very informative and are all highly statistically significant. Given that most of the price discovery per minute occurs between 08:00:00 and 08:10:00hrs for the lower quintile stocks, WPCTs are also high and statistically significant for that period and for those stocks. Generally the WPCTs are very high, and somewhat noisy given the low trading levels, prior to the open. Thereafter they decline as the NTH commences. This shows that the informativeness of individual transactions has dwindled, and that during the NTH one trade hardly moves prices in a significant manner; i.e. price movements are likely to occur on account of order flow rather than just a trade (see for example Chordia et al., 2008). The results in this section are further confirmation that the market is more efficient during the NTH than other trading periods, since it is unlikely that one trade's information content will be large enough to cause a significant shift in price. Also, the trades have become less disproportionately informative as they seem to be during the pre-open. Further, the results here considered in tandem with the increasing liquidity evidenced in the spread analysis shown in Figures 5a and 5b, suggest that as the market progresses from the opening call auction period towards the NTH the stock prices, especially for large volume stocks, become more efficient.

We contend that the improvement in stock price efficiency in the case of Quintile 5 stocks during the opening call is a function of the informativeness of the transactions. As the day progresses, trades become less informative after the information accumulated the previous day's close has been incorporated in the early trading, starting with the opening call auction for the Quintile 5 stocks. Had the lower quintile stocks been able to muster trading depth during the call, their price discovery would have commenced earlier, at the open call auction, as well. However, given a fear of lack of counterparty to fill orders, many lower volume stock traders opt to either hold off trading until the floor opens at 08:00:00hrs or trade through the broker-dealer route. Trading activity evidence suggests that the majority of this class of traders do the former. Thus, based on the data in our sample, lower volume stock traders are not really choosing between the broker-dealer route and the call auction as suggested by Ellul et al. (2005), rather they are largely withholding trades until the market opens, where they are more likely to have their orders filled, or perhaps to avoid trading in an environment dominated by informed traders. Since lower volume stock traders are likely to be largely uninformed or noise traders, they will normally avoid trading with informed traders or seek a premium for doing so. This view is underscored by resent theoretical evidence presented by Malinova and Park (2014). They show that in a dynamic market where several heterogeneously informed traders choose to place orders, better informed traders trade immediately, while worse informed traders delay even when they know that the market could move against them. We therefore suggest that small volume stock traders avoid trading during the call auction because of the dominant presence of informed traders, thereby leading to the failure of lower volume stocks at the opening call auction. In Section 4.3, we examine the evolution of informed trading/information asymmetry across the different trading periods. If the opening call period has higher adverse selection costs than other trading periods, this will support our hypothesis. Based on the evolution of the spread estimates in Figure 5, we expect higher level of informed trading during the opening call auction period. The pre-open and post-NTH spreads are generally wider than the NTH. Even surprising is the sustained widening of spreads during the opening call auction period for mainly the highest volume stocks. For example, the bid-ask (effective) spread increases more than 43 (17) times at the opening call auction start (07:51:00hrs) from the previous minute. This unexpected evolution however resonates with the relative and uneven informativeness of the high volume stock trades during the entire pre-open period. Curiously, the relative informativeness of the opening call auction trades help in raising the level of price efficiency despite their widening of the spreads because they are information-driven trades. Thus the new prices they reveal are unlikely to be reversed in the short term. The spreads are therefore wider during the opening call auction period because market makers recognise the impact of the auction transactions and respond accordingly. The informativeness of the transactions is evidenced further by the rapid improvement in price efficiency starting at 07:51:00hrs.

INSERT TABLE 3 ABOUT HERE

4.3. Modelling Adverse Selection Costs

4.3.1. Adverse Selection Costs by Trading Pressure

We now return to the question of the type of traders dominating trades at specific intervals during the trading day. As stated in the preceding section, low volume stock traders are likely to avoid trading in an environment dominated by informed traders. Trading periods dominated by informed traders are characterised by higher adverse selection costs. The type of traders who dominate different periods during the trading day will also directly influence the price discovery process and its efficiency. Given the variation in the various spread measures obtained across the day (see Figure 5), there is ample reason to expect that the composition of traders evolves quite dramatically from period to period. Since the spreads are higher in the pre-open and post-NTH, we expect the trades during those periods to be of the informed variety. Thus the spreads widen to accommodate increasing market makers' adverse selection costs in addition to relatively stationary inventory and transaction costs.

We estimate the adverse selection costs using the Huang and Stoll (1997) spread decomposition model; we expect this to give us an indication of the type of traders dominating different points across the trading day. This approach employs the fact that quote shifts due to inventory costs do not arise from inventory alterations in just one stock, i.e. the instrument of interest, but from other stocks held in a given portfolio of stocks.[11] This is thus a portfolio approach to decomposing the spread, it is based on the assumption that adverse

[11] Consider a liquidity supplier purchasing stock *x* at the bid quote. The trade will lower the bid and offer prices of the stock as well as for other correlated stocks. The opposite of this trade is a sale in the correlated stocks; this hedges his position in stock *x*. In reverse, if we assume that the other stocks are constrained by trading pressure, the liquidity supplier may choose not to induce lowering of the quoted prices for *x* if his aim is to hedge his buying of other stocks thus spurring sales in *x*. This approach recognises that there is a probability that *x*'s quotes are driven by more than just inventory impacts and the information components of only *x*. Specifically, trading pressure on account of other stocks should result in alterations in quotes of *x* due to the efforts of liquidity suppliers to retain the balance of their portfolios.

information relates to instruments on individual basis, yet inventory impacts are portfolio wide. In employing this approach, we assume, similarly to Heflin and Shaw (2000), that 'liquidity suppliers'/market makers take the opposite of all executed trades or submitted call auction orders, which are then executed when the call algorithm runs. Liquidity providers may not be interpreted strictly as market makers submitting all orders or executing all the trades, but also as sophisticated traders watching more than just one stock at a time. This is tenable since liquidity may be defined as the availability of counterparties to trade with. Indeed Huang and Stoll (1997) propose a refinement of their approach through the nomination of specific portfolios other than purely a market maker's. An example of such a portfolio is an index portfolio such as the FTSE 100, which we employ in this paper.

4.3.2. A Trade Indicator Model

Assuming that there are no transaction costs; V_t the hidden core value of a stock is established just before the bid, and offer quotes are published at time *t*. Quote mid-price is denoted as M_t will only be computed as the quotes are released. Let trade price at time *t* be P_t and Q_t be the purchase/sale indicator variable for the trade price, P_t. Q_t equals +1 if the trade is initiated by the buyer and also executes at a price higher than the mid-price, -1 if the trade is seller initiated and also executes below the mid-price and finally Q_t takes the value of *0* if the trade executes at the mid-price. The hidden V_t is modelled as below:

$$V_t = V_{t-1} + \alpha \tfrac{S}{2} Q_{t-1} + \varepsilon_t, \qquad (5)$$

S corresponds to the constant spread, α is the percentage of half-spread due to adverse selection costs, while ε_t represents the serially uncorrelated public information shock. The Equation (5) decomposes transaction costs, V_t into two elements. The first is the private information element uncovered from the previous trade, $\alpha \frac{S}{2} Q_{t-1}$ (see Copeland and Galai, 1983; Glosten and Milgrom, 1985). And second, public information element encapsulated by ε_t. Although, transaction cost V_t is purely theoretical, the midpoint, M_t of the spread is observable. Liquidity suppliers aim to achieve inventory equilibrium therefore effect equilibrium-inducing transactions by modifying quotes (hence mid-price). The adjustments are carried out in relation to the core value stocks as is informed by inventory levels (see for example Ho and Stoll, 1981; Stoll, 1978). Suppose that previous transactions are of a normal size of one, the midpoint (mid-price) in relation to the core stock value then correspond to:

$$M_t = V_t + \beta \tfrac{S}{2} \sum_{t=1}^{t-1} Q_i, \tag{6}$$

β corresponds to the magnitude of the half-spread measure due to inventory costs, where $\sum_{t=1}^{t-1} Q_i$ is the aggregate inventory from when the market opens to time t_{-1}, and Q_1 is the inceptive inventory for that trading day. If there are no inventory holding costs, the ratio of V_t to M_t will be one. Equation (6) holds for bid, offer and mid-prices since it is already assumed that the spread is constant.

First differencing of Equations (6) and (5) suggests that quotes are generally modified to show inventory costs and information exposed by the last transaction. Specifically, we have:

$$\Delta M_t = (\alpha + \beta) \tfrac{S}{2} Q_{t-1} + \varepsilon_t \tag{7}$$

with Δ as the first difference operator.

Equation (8) cites the assumption of a constant spread:

$$P_t = M_t + \tfrac{S}{2} Q_t + \eta_t \tag{8}$$

Where η_t is the error term, and it encapsulates the deviation of the observable half-spread, $P_t - M_t$ from the constant half-spread, $\frac{S}{2}$, with the inclusion of price discreteness-induced rounding errors. The estimable traded spread, *S* is distinguishable from the observable spread, S_t, because it is representative of trades outside the midpoint but within the spread. Transactions within the quoted spread and executed above the midpoint are regarded as ask transactions, and trades within the spread and executed below the midpoint are the bid trades. When *S* is estimated, it will be larger than the effective spread, which is the absolute value of transaction price minus the prevailing midpoint, $|P_t - M_t|$. This is due to the exclusion of midpoint trades $(Q_t = 0)$ from the estimation. In contradiction to this, the unobserved estimated spread *S*, obtained from serial covariance of transaction prices (see Roll, 1984) are swayed by volume of midpoint transactions. Harris (1990) however suggests that the Roll (1984) spread estimator may be significantly biased.

When Equations (7) and (8) are integrated, the basic regression Model (9) is produced:

$$\Delta P_t = \tfrac{S}{2}(Q_t - Q_{t-1}) + \lambda \tfrac{S}{2} Q_{t-1} + e_{t,}, \tag{9}$$

whereby $\lambda = \alpha + \beta$ and $e_{t,} = \varepsilon_t + \Delta\eta_t$. The regression Model (9) is a nonlinear indicator variable model with within-equation restrictions. The requirement for estimation is the indication of whether the transactions at *t* and t_{-1} execute at any of ask, bid or mid prices. The model estimation yields the traded spread, *S*, and the aggregate modification of quotes to transactions, $\lambda(S/2)$. The estimation Equation (9) does not yield independent estimates of adverse selection component, α and the inventory holding component, β. Nevertheless, the proportion of the half-spread, which is not attributable to adverse information or inventory holding, can be estimated as $1-\lambda$. This is the order processing costs estimate.

Equation (9) does not consider the effects of normal trading pressure because the inventory modification earlier modelled in Equation (6) is based on the individual stock inventory held. The next step therefore is to differentiate buys and sells for each stock in a pool. If *k* corresponds to stock *k*, Equation (6) then becomes:

$$M_{k,t} = V_{k,t} + \beta_k \tfrac{S_k}{2} \sum_{t=1}^{t-1} Q_{Ai}, \tag{10}$$

where $Q_{A,t}$ corresponds to the aggregate buy-sell indicator variable defined as follows:

$$\begin{aligned} Q_{A,t-1} &= 1 for \sum_{k=1}^{n} Q_{k,t-1} > 0 \\ Q_{A,t-1} &= -1 for \sum_{k=1}^{n} Q_{k,t-1} < 0 , \\ Q_{A,t-1} &= 0 for \sum_{k=1}^{n} Q_{k,t-1} = 0 \end{aligned} \tag{11}$$

and *n* equals the number of FTSE 100 stocks that liquidity providers review to determine the mood of the market. Equation (10) can be written as

$$\Delta P_{k,t} = \tfrac{S_k}{2} \Delta Q_{k,t} + \alpha_k \tfrac{S_k}{2} Q_{k,t-1} + \beta_k \tfrac{S_k}{2} Q_{A,t-1} + e_{k,t} \tag{12}$$

Equation (12) remains an indicator variable model; in the absence of portfolio trading effects and frictions, it reverts to Equation (5). A key distinction however is that with Equation (12) all spread components of the bid-ask spreads can be estimated individually.[12]

Equation (12) can also be expressed as:

$$\Delta P_{k,t} = \beta_{1,k} Q_{k,t} + \beta_{2,k} Q_{k,t-1} + \beta_{3,k} Q_{A,t-1} + e_t, \tag{13}$$

[12] This approach is also related to the Ho and Stoll (1983) model that shows the connection between quote adjustments in a stock and inventory changes in others. They show that the quote shifts in stock *a* in reaction to a trade in another stock *b* is dependent on $cov(R_a, R_b)/\sigma^2(R_b)$.

where $\Delta P_{k,t}$ is the change in price from the previous retained trade, $Q_{k,t}$ is equal to 1 (-1) when the transaction at period t for stock k is a market maker sell (buy) and $Q_{A,t-1}$ is the aggregate buy-sell indicator variable used in encapsulating portfolio trading pressure on market makers' inventory levels, it is measured as in (11). The original datasets do not include information on trade direction, we therefore employ Lee and Ready's (1991) algorithm to determine the direction of trade. Specifically, we classify trades at a price above the prevailing quote midpoint, as market maker sells and those at a price lower than the prevailing quote midpoint as market maker buys. If the current and the previous trades are the same price, we classify using the next previous trade. This algorithm is established in microstructure literature. Further, independent analysis by Aitken and Frino (1996) supports Lee and Ready's (1991) suggestion that the algorithm's accuracy exceeds 90%. The adverse selection spread component, and the half spread, are thus computed by estimating Equation (13) using LS as adopted by Heflin and Shaw (2000); the $\beta_{1,k}$ estimate is one-half the estimated effective spread, and the adverse selection component is equivalent to $2(\beta_{2,k} + \beta_{1,k})$.[13] This approach is established in the literature, (see Van Ness et al., 2001; Heflin and Shaw, 2000). Van Ness et al. (2001) even suggest that the Huang and Stoll (1997) approach is superior to other commonly used models in measuring adverse selection information costs. However, this seeming superiority comes at a cost. The possibility of obtaining implausible estimates from the model estimation when using the probability of trade reversal approach, rather than the trading pressure approach, has been reported. For example Clarke and Shastri (2000) report this problem in their analysis of 320 NYSE firms, Van Ness et al. (2001) also report similar issues. There seems to be a correlation between reduced probability of trade reversal and the implausible estimates. This paper reports only the trade aggregator

[13] Equation (13) can also be estimated using the GMM procedure with appropriate adjustments to the orthogonality conditions. The GMM levies relatively weak distributional requirements unlike maximum likelihood (see Madhavan et al., 1997; Huang and Stoll, 1997). In addition to following Heflin and Shaw's (2000) estimation approach, we also estimate using the Newey and West (1987) HAC.

estimation, and there is no suggestion that we are faced with this problem. Also it is necessary to align the trading times across all stocks involved in the estimation. This paper follows an approach described by Huang and Stoll (1997); specifically, we employ only the last trade at every five-minute interval in formulating our variables.[14] Huang and Stoll (1997) stated that a cross-sectional estimation of Equation (13) is likely to lead to an overestimation of the adverse selection costs. We avoid this potential anomaly by adopting a time series estimation.[15] Finally, we also use the Wilcoxon-Mann-Whitney test for obtaining statistical inference on the level of differences between NTH intervals and the corresponding pre-open or post-NTH periods.

INSERT TABLE 4 ABOUT HERE

Table 4 presents the cross-sectional mean of the adverse selection costs by time period and pound volume quintile. The opening call auction adverse selection costs for lower volume stocks could not be obtained because of the very low number of trades over the sample period. Given that we could not robustly estimate their values with our chosen model, we report adverse selection costs for only the highest volume stocks. The available results however support our hypothesis that the opening call auction period for the highest volume stocks has a significantly higher level of informed trading than other trading periods across the day. The results also confirm that informed trading is lowest during the NTH, while the pre-open and post-NTH periods generally have higher levels of informed trading across all

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[14] Huang and Stoll (1997) observe that big orders are sometimes broken into smaller trades (see also Barclay and Warner, 1993; Chakravarty, 2001). To account for the associated problems arising from this practice, they devise a 'bunching' technique, such that trades executed at the same price, with same quotes and within five-minute intervals of one another are bunched into one trade and treated as such. They however conclude that using one trade every five minutes greatly reduces any problem that may arise from breaking up large orders. Heflin and Shaw (2000) also adopt this approach. Moreover the results obtained by Huang and Stoll (1997) utilising the bunching technique suggest that the method unnecessarily increases the adverse selection component estimates.

[15] We also employ panel GMM estimation, although this method led to the loss of many observations in order to ensure *synchronity*, the overall trend of the evolution of adverse selection costs is consistent with the time series averages.

quintiles. Adverse selection costs are lowest across the trading periods for Quintile 2 stocks; the pre-opening auction (closing auction) adverse selection costs is 14 (6) times the value for the NTH. Overall, there is higher level of informed trading recorded for the higher volume stocks during the pre-open and post-NTH, however during the NTH, the lowest volume stocks (Quintile 1) post the highest adverse selection costs. With these results, our expectation that the opening auction, and generally the pre-open, contain higher levels of informed trading is therefore confirmed. Thus our results contradict previous submissions in literature, which suggest that call auctions lead to lower information asymmetry (see for example Schnitzlein, 1996; Madhavan, 1992). Given, the significance of the results obtained, we propose that the lack of trading for lower volume stocks during the opening call auction is related to the significantly higher presence of informed traders during the period. This is further strengthened by the fact that for lower volume stocks, more dealer trades are recorded per minute for the 40-minute period prior to the opening call auction, than for the call auction period. This suggests that unless a more transparent opening call auction market is ensured, even when there is a higher level of potential counter parties for lower volume stock traders, they are unlikely to engage with the opening call auction.

5. Conclusion

The opening and closing prices are important reference points for investors and the general public. Opening prices may affect trader sentiment throughout the day, and opening/closing prices may be used to settle derivative contracts. They are therefore of great importance. Our results, however, suggest that the opening call auction often fails, and, on average, the pre-open incorporates little of the overnight information for low volume stocks. This may have repercussions for the value of investor portfolios - whether these portfolios are composed of the stock itself or a derivative of the stock- outside of this trading window. Thus this paper conducts an ultrahigh frequency analysis of the opening and closing auction prices in a hybrid market - the LSE. We examine whether the opening and closing prices yielded by the call auction mechanism are *informationally* efficient. We find very large variability in our results with respect to trading volumes, such that higher volume stocks are more likely to be traded during the opening call auction than lower volume stocks. In fact lower volume stocks routinely fail at the opening call auction. Results suggest that this is due to both the unavailability of trading counterparties, as well as a conscious decision by lower volume stock traders to avoid the opening call auction given the domination of the period by informed traders. Although, Ellul et al. (2005) suggest that lower volume stock traders opt for the dealership during the opening call auction because of lack of trading partners, we find very little evidence to support this. Rather lower volume stock traders generally abstain from any form of trading during the 10-minute opening auction period. Thus, the price discovery process mainly commences for those stocks after the market opens, with more than 30% of the daily close-to-close price discovery occurring within the first 10 minutes of the market opening. For the higher volume stocks however, the highest rate of price discovery (31.8% over 10 minutes) occurs during the opening call auction period. Given the distribution of price discovery across the day, the opening call auction period (07:50:00-8:00:00hrs) London time yields a highly *informationally* efficient opening price for higher volume stocks, while an efficient price is not obtained for lower volume stocks until within the opening 10 minutes of the NTH. So inefficient is the price yielded during the call auction period for lower volume stocks, that price discovery efficiency is generally higher in the 30 minutes prior to the opening call auction period than during it.

The closing price yielded by the closing call auction for all stocks is however better behaved and highly *informationally* efficient. This is because the NTH is a very efficient trading period, thus providing a strong price discovery platform for the closing auction and the immediate market period afterwards (post-NTH). The results relating to the closing call auction are therefore consistent with previous literature on the issue (see for example Chelley-Steeley, 2008). However, having examined the LSE's microstructure, we find no evidence that the closing call auction market quality characteristics impacts on the next day's early trading as suggested by Chelley-Steeley (2009). If this were the case, price discovery and its efficiency would be high in the pre-open, especially for low volume stocks. Further, we document an interesting phenomenon, which runs contrary to Amihud et al.'s (1990) observation on the Milan exchange. We show that the call auction preceded by continuous trading leads to enhanced price discovery and efficiency for low volume stock rather than otherwise.

Considered together, the results in this study suggest that the influence of the call auction for opening the market might have been exaggerated by previous literature (see Section 1) and oversold to investors by platforms eager to please the markets. According to Madhavan (1992), the advantage of a call auction comes from two offerings: transparency, because all orders are released to the market as at when placed, and higher liquidity, because all orders are in before auction. However, in an era where high frequency trading is increasingly pre-eminent, this 'advantage' can no longer be considered as such, because higher volumes of trading are achieved during the NTH and the order book, on the LSE for example, is regularly updated in a fashion that allows for comparable transparency as during the call auction. Our results suggest that the LSE pre-open does not yield *informationally* efficient prices for low volume stocks, and that only high volume stocks benefit from price discovery efficiency during the opening call auction. We however believe that the opening call auction could be made more transparent and lower volume stock-friendly if the exchange de-emphasises volume during the opening call. The call auction algorithm executes with the aim of maximising volume, and this means that trades may not be executed at the best possible prices from an uninformed trader's point of view. We propose that the exchange prioritise prices instead, and aim for executing at a volume weighted price during the opening call auction, while moving all unexecuted orders on to the order book for trading during the NTH. The call auction algorithm should include appropriate circuit breakers. Should this not improve the situation, we have demonstrated ample evidence to suggest that doing away with the opening call auction altogether will not diminish the efficiency of the opening reference price. Therefore, markets should consider doing this after conducting appropriate simulation experiments.

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Figure 1: Daily Trading Volume per Minute for FTSE 100 Stocks

The average pound daily volume is computed for each minute and for each quintile. The logs of the quintile values are graphed due to the large variability of trading volumes across different trading periods. The time covered is from the first recorded trade at 07:16:00hrs until 16:50:00hrs London trading time over the sample period between 1st October 2012 and 30th September 2013.

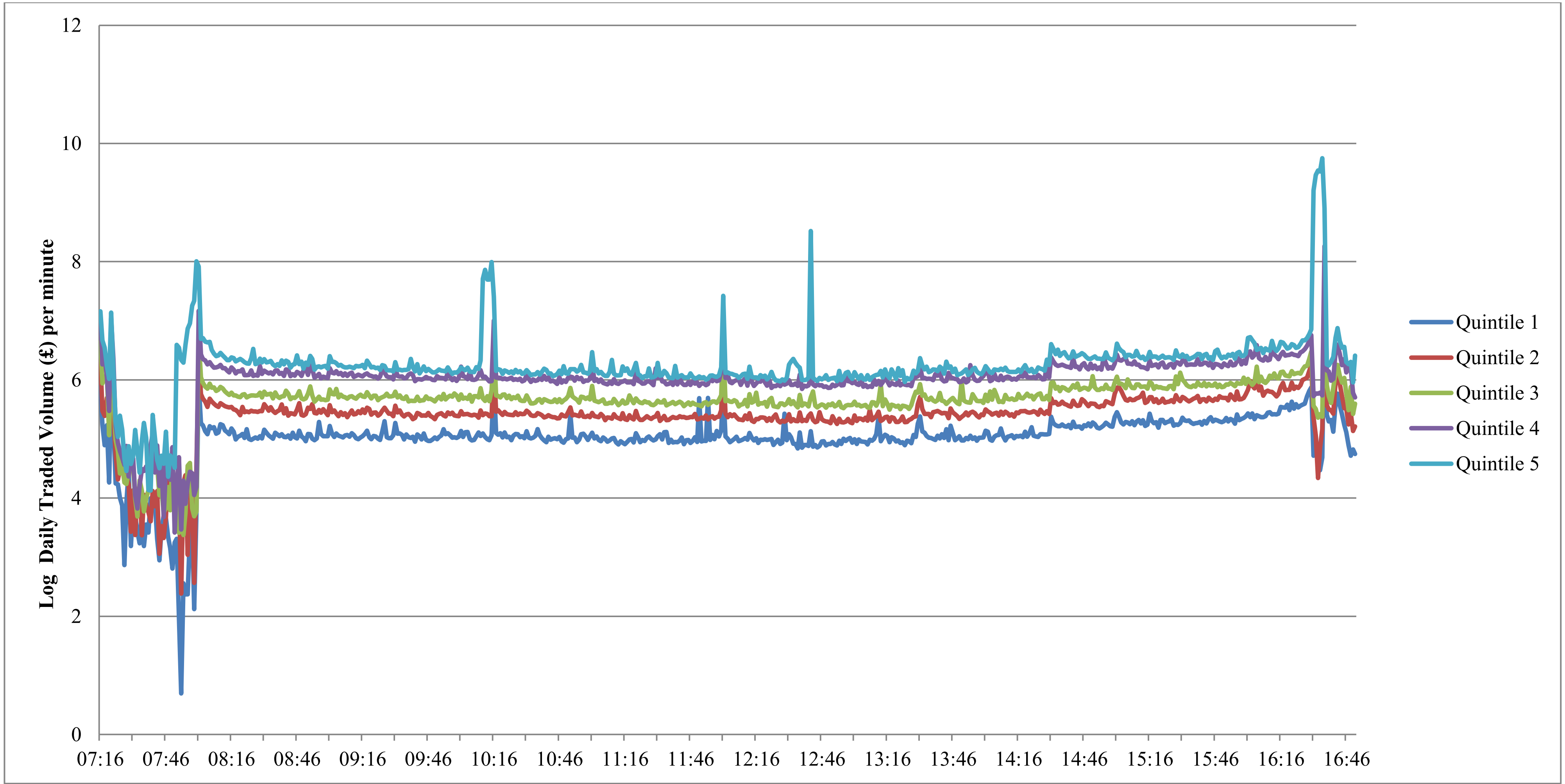


Figure 2: Mean Trade Size per Minute across Quintiles

The mean trade sizes per minute are computed for each quintile. The logs of the mean estimates are graphed due to the large variability of trading volumes across the three periods. The time covered is from the first recorded trade at 07:16:00hrs until 16:50:00hrs London trading time over the sample period between 1st October 2012 and 30th September 2013.

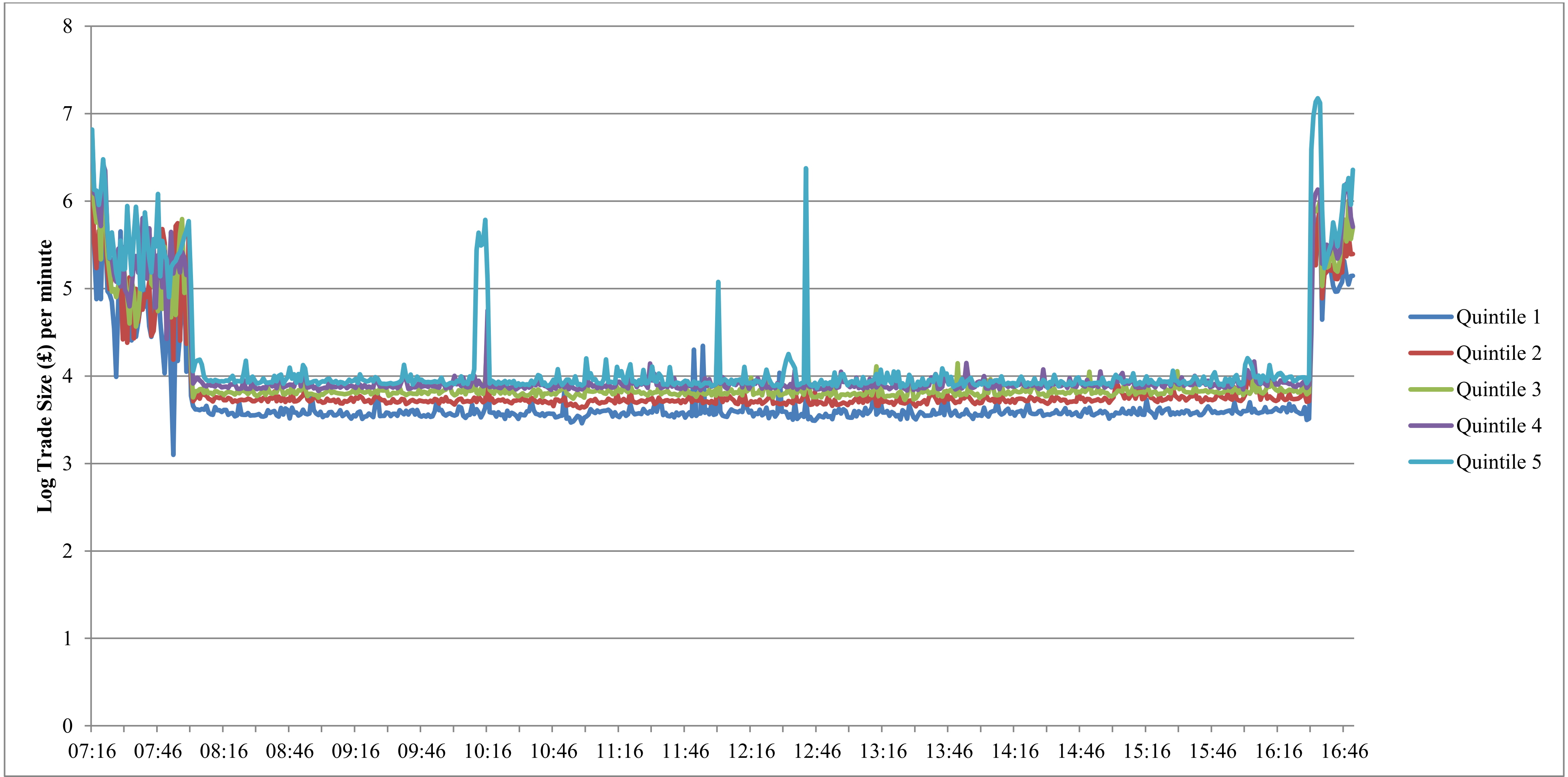


Figure 3: Median Trade Size per Minute across Quintiles

The median trade sizes per minute are computed for each quintile. The logs of the median estimates are graphed due to the large variability of trading volumes across the three periods. The time covered is from the first recorded trade at 07:16:00hrs until 16:50:00hrs London trading time over the sample period between 1st October 2012 and 30th September 2013.

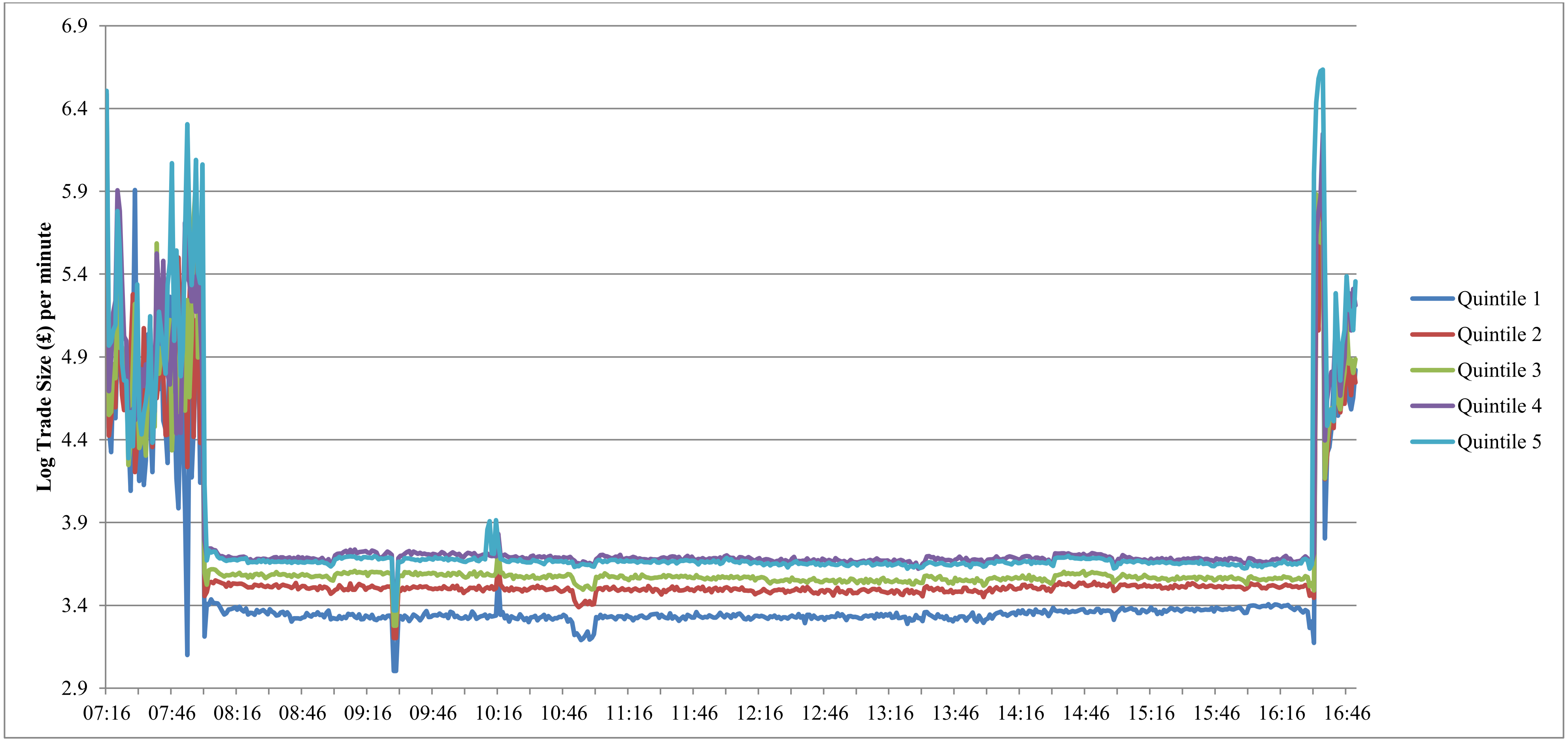


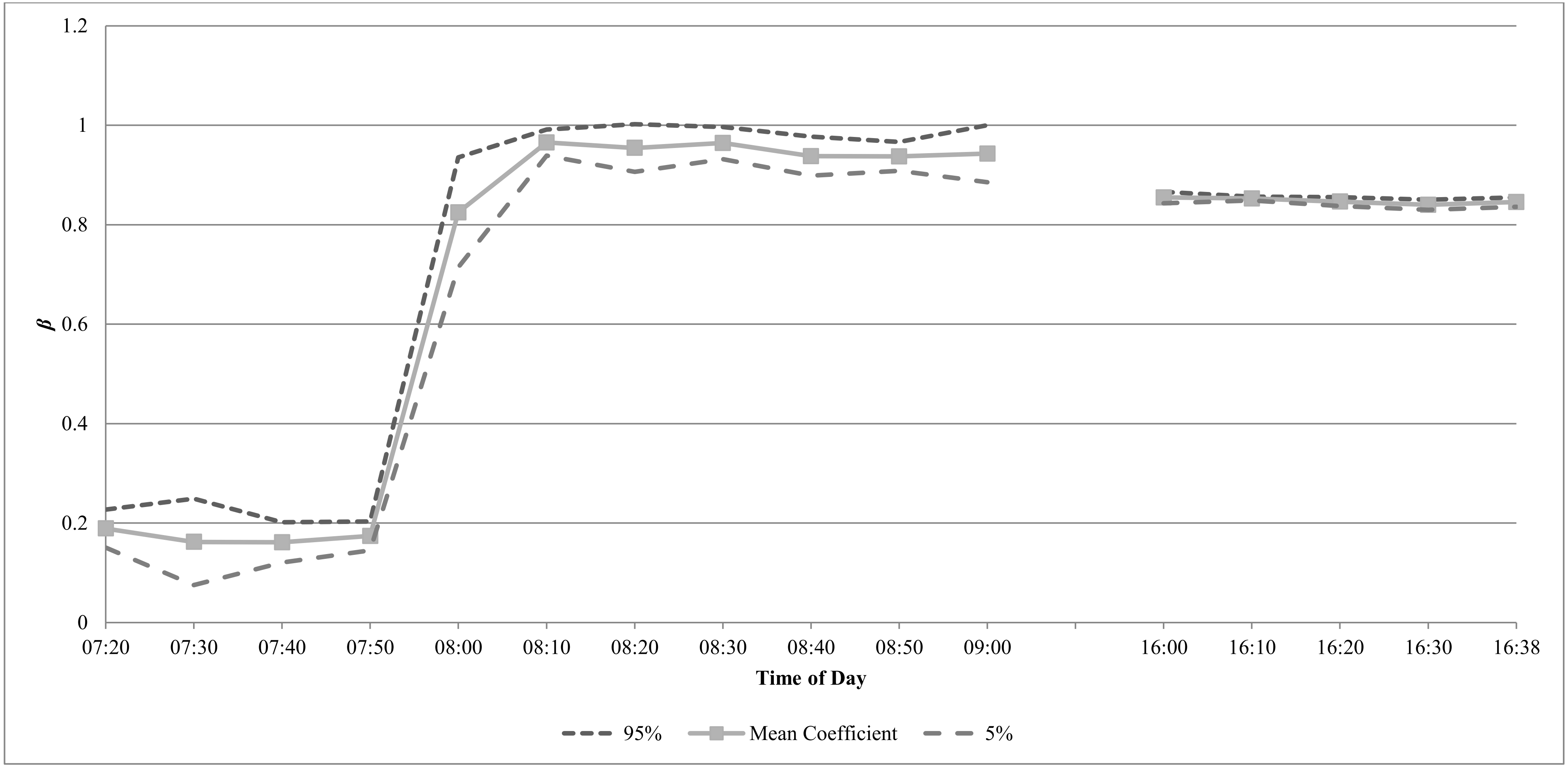
Figure 4 Informational Efficiency by Time periods

The signal:noise ratio is computed for 10 minute intervals by regressing close-to-close return on the return from close to time period, *k* for FTSE 100 stocks trading between 1st October 2012 and 30th September 2013. For each stock, the following equation is estimated separately for each time interval where ret_{cc} is the close-to-close return and ret_{ck} is the return from the close to the end time of period *k*:

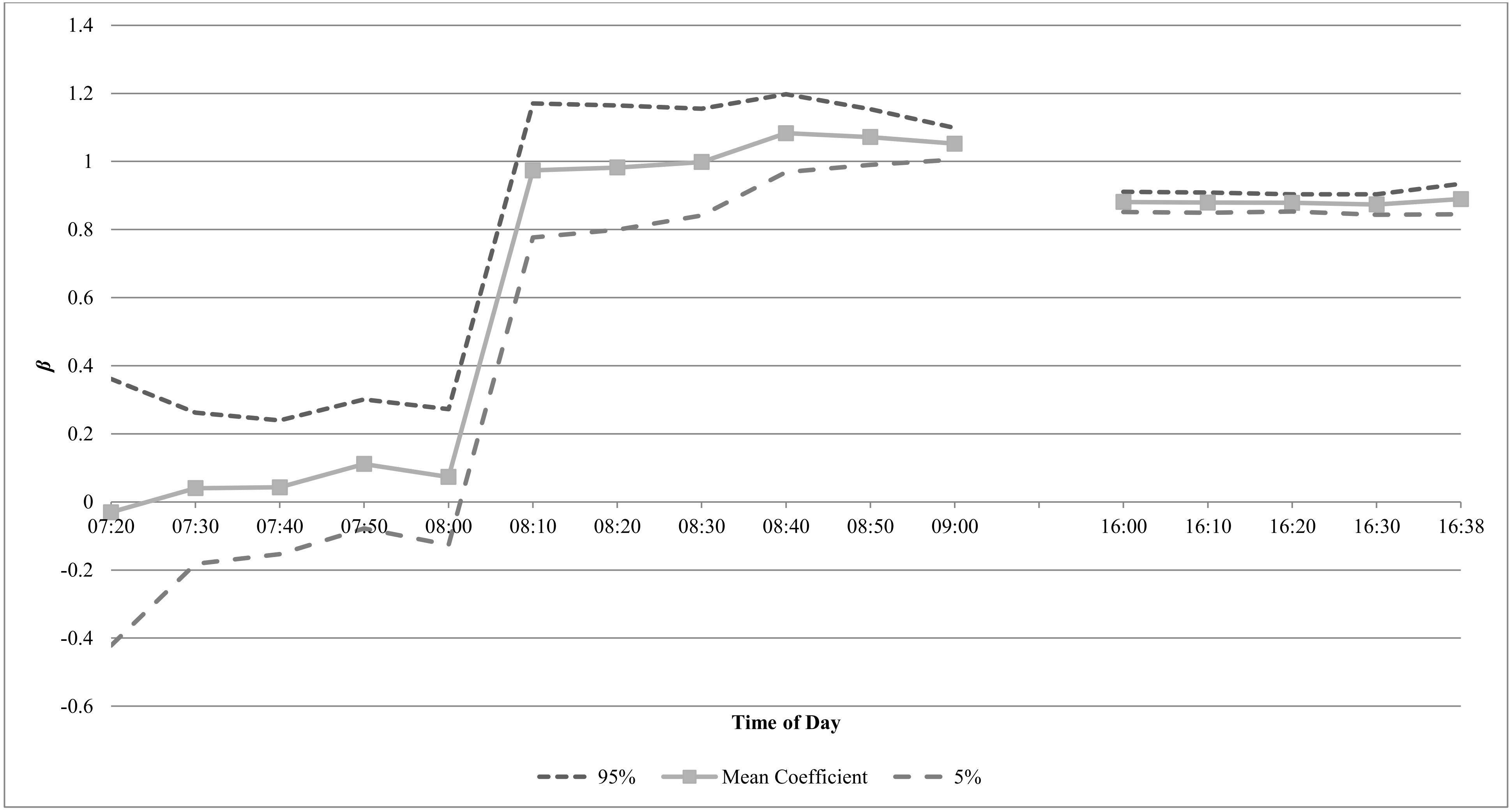
$$ret_{cc} = \alpha + \beta ret_{ck} + \varepsilon_k$$

Mean value of the coefficient estimates are obtained for each quintile in the sample and sub-figures A to E graph the informational efficiency as measured by the signa:noise ratio per interval for each of those five quintiles. Confidence intervals are computed by employing the time series standard errors of the mean of the coefficient estimates.

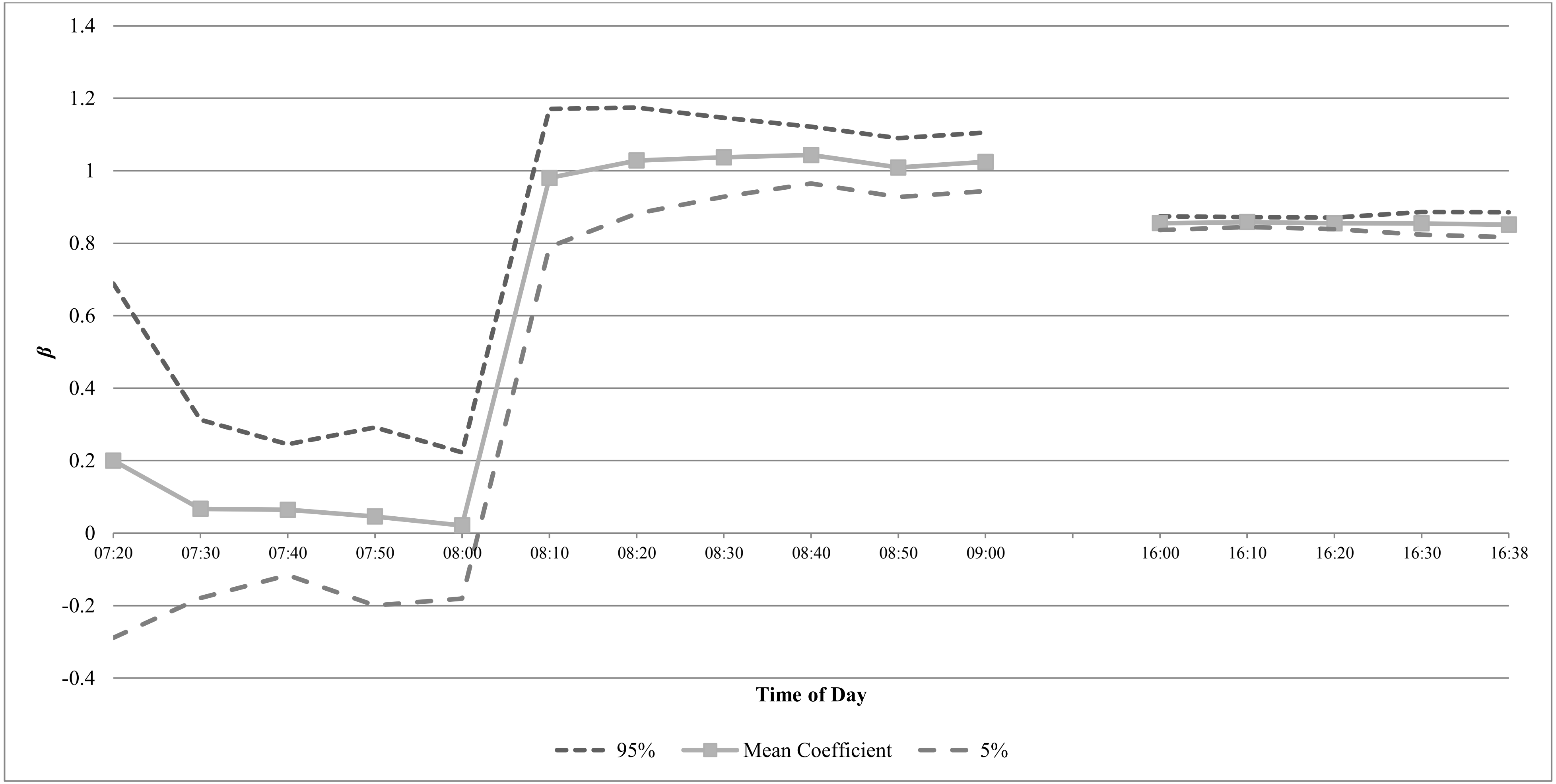
A: Quintile 5 Stocks (Highest)



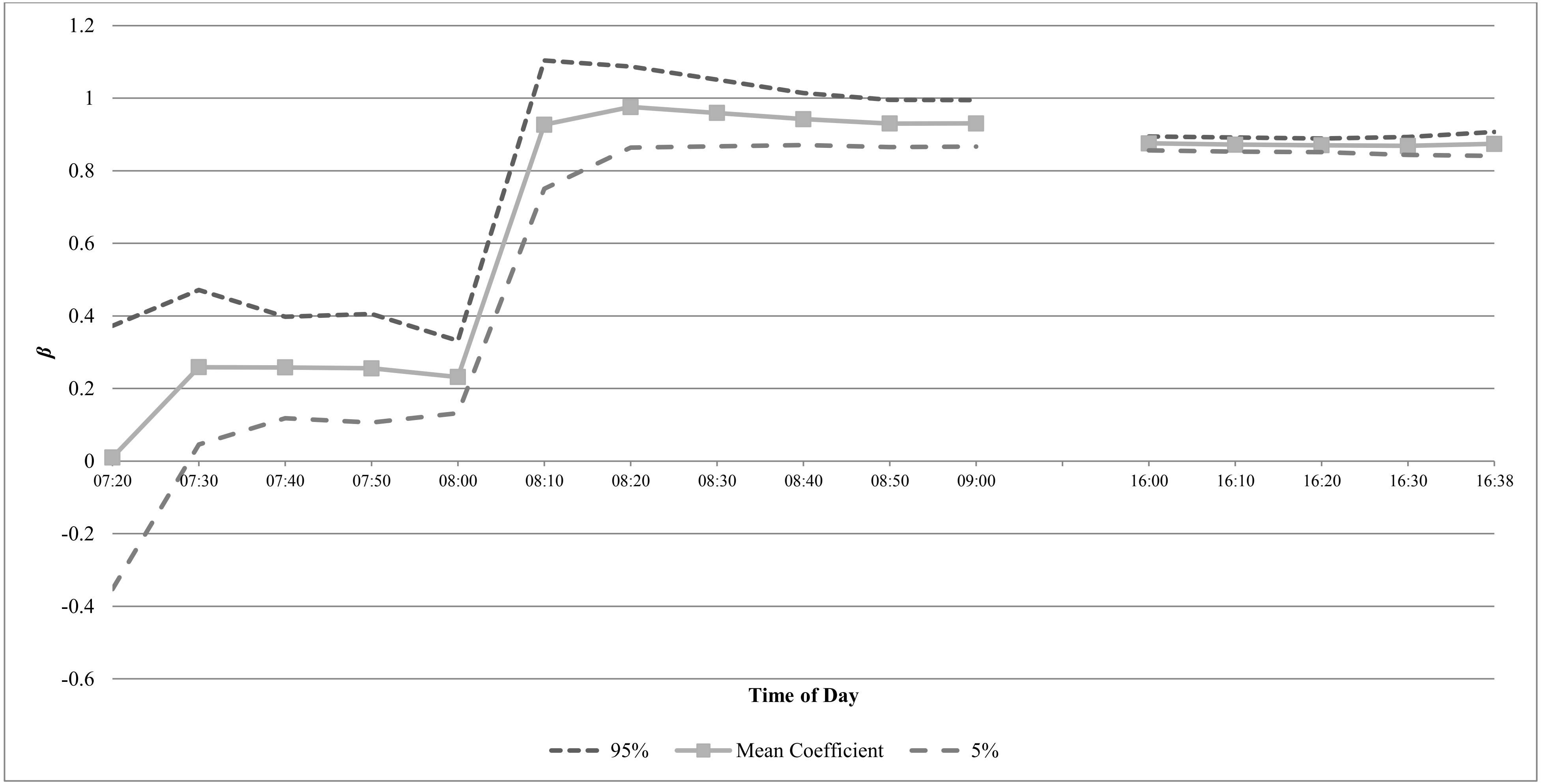
B: Quintile 4 Stocks



C: Quintile 3 Stocks



D: Quintile 2 Stocks



E: Quintile 1 Stocks (Lowest)

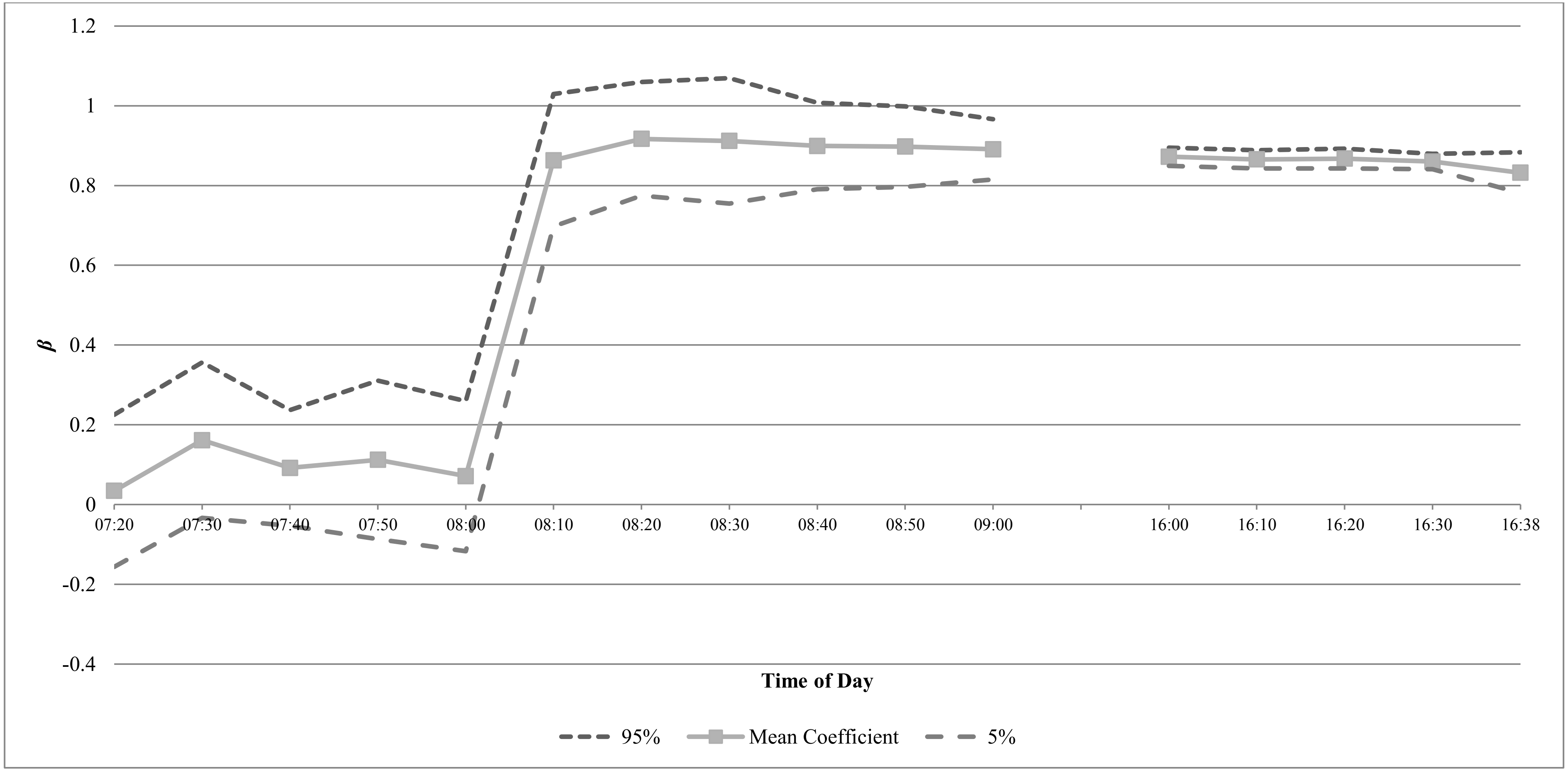
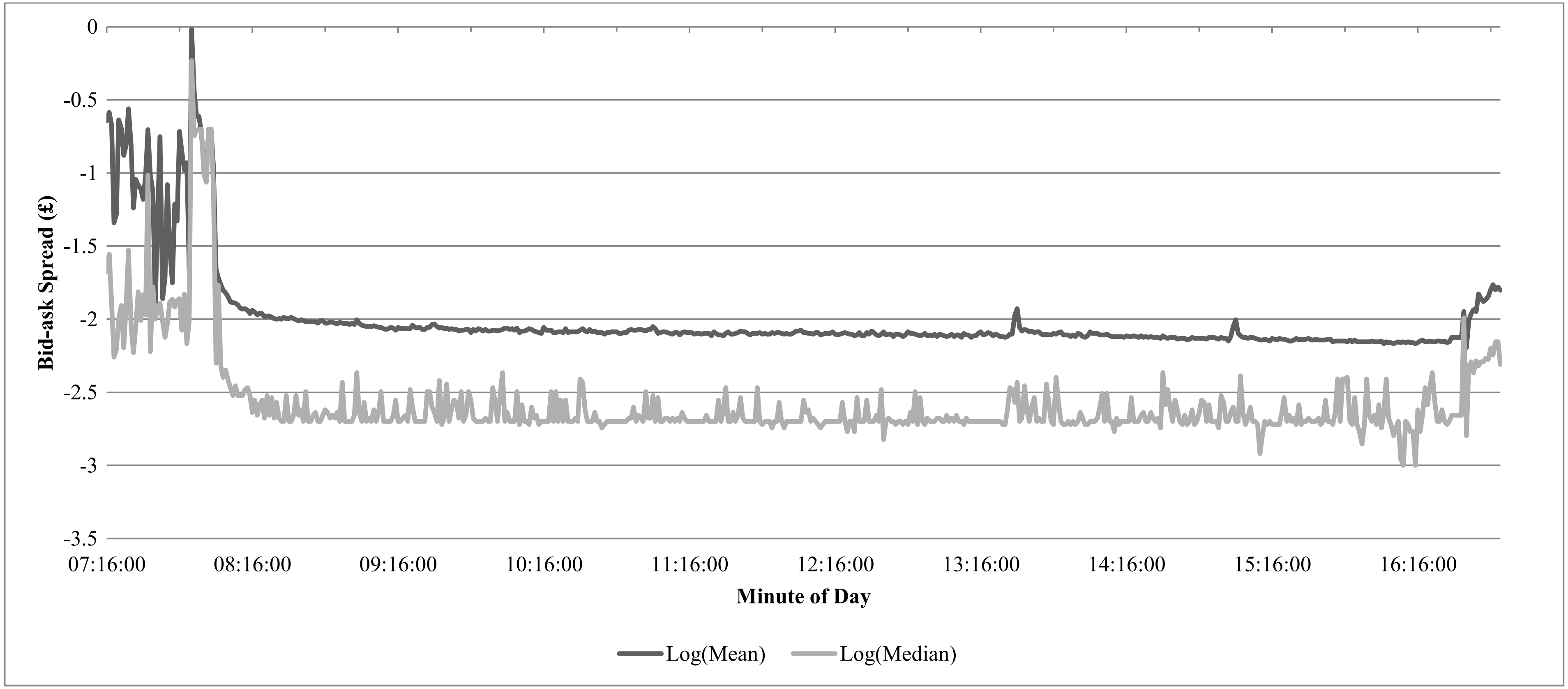


Figure 5: Liquidity by Time Periods for FTSE 100 Stocks

Liquidity proxies per minute are computed for FTSE 100 Stocks trading between 1st October 2012 and 30th September 2013. Figure A shows the Quoted Bid-Ask spread, measured as the difference between the best ask and the best bid price, while Figure B shows the Effective Spread, measured as twice the absolute value of the difference between the best trade price and prevailing midpoint per minute. The logs of the spread estimates are graphed because of the large variability of spreads across the trading periods. The time covered is from the first recorded trade at 07:16:00hrs until 16:50:00hrs London trading time over the sample period between 1st October 2012 and 30th September 2013.

A: Quoted Bid-Ask Spread



B: Effective Spread

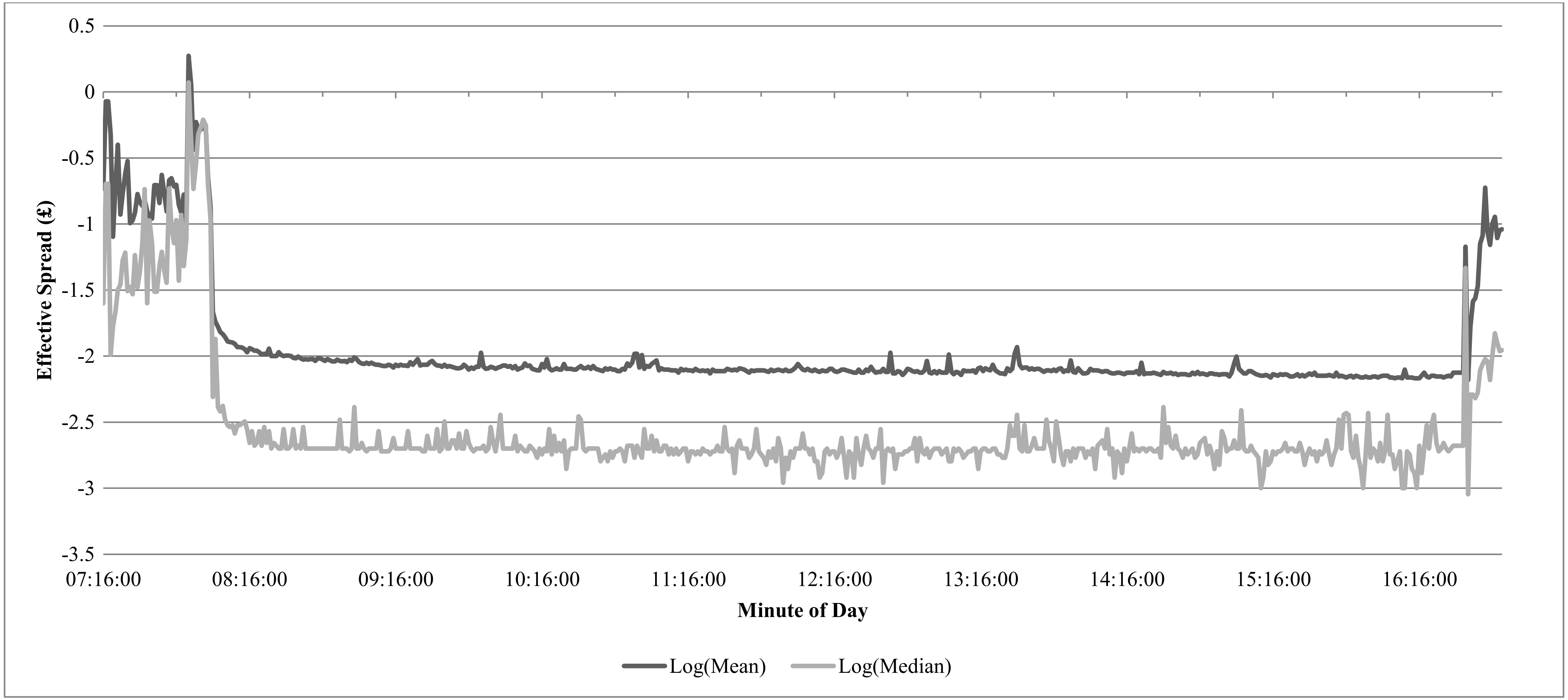


Table 1: Trading Summary Statistics for FTSE 100 Stocks

Full and daily summary statistics for FTSE 100 stocks between 1st October 2012 and 30th September 2013. Panel A shows the full statistics, whilst Panel B has the daily summary statistics.

Panel A: Trade-Based Summary Statistics

Pound Volume Quintile	Number of Transactions ('000)				Volume (£'000,000)				Mean (£'000)			
	Pre-Open	Normal Trading Hours (NTH)	Post-NTH	All	Pre-Open	NTH	Post-NTH	All	Pre-Open	NTH	Post-NTH	All
Lowest	1.92	4654.98	150.54	4807.44	625.89	18517.33	7143.64	26286.86	325.47	3.98	47.45	5.47
2	2.88	7837.15	180.81	8020.83	1393.58	43959.05	14870.00	60222.63	484.39	5.61	82.24	7.51
3	3.89	11413.85	213.31	11631.04	3510.60	78704.95	24486.01	106701.57	903.17	6.90	114.79	9.17
4	4.99	21338.70	262.76	21606.45	8149.78	179357.73	53557.96	241065.46	1632.57	8.41	203.83	11.16
Highest	114.26	26745.97	690.20	27550.43	54564.28	436277.91	4524868.09	5015710.29	477.55	16.31	6555.93	182.06
Overall	127.94	71990.64	1497.61	73616.19	68244.13	756816.97	4624925.70	5449986.81	533.42	10.51	3088.21	74.03

Panel B: Daily-Based Summary Statistics

Pound Volume Quintile	Number of Transactions				Volume (£'000,000)			
	Pre-Open	NTH	Post-NTH	All	Pre-Open	NTH	Post-NTH	All
Lowest	7.60	18399.14	595.01	19001.75	2.47	73.19	28.24	103.90
2	11.37	30976.87	714.65	31702.89	5.51	173.75	58.77	238.03
3	15.36	45114.02	843.11	45972.49	13.88	311.09	96.78	421.75
4	19.73	84342.67	1038.57	85400.97	32.21	708.92	211.69	952.83
Highest	451.62	105715.30	2728.04	108894.96	215.67	1724.42	17884.85	19824.94
Overall	505.68	284548	5919.39	290973.07	269.74	2991.37	18280.34	21541.45

Table 2: Price Discovery by Time Period for FTSE 100 Stocks

The Weighted Price Contribution (WPC) is computed by the pound volume quintile for FTSE 100 stocks. For each trading session/day and period *k*, we define the WPC as:

$$WPC_k = \sum_{s=1}^{S}\left(\frac{|ret_s|}{\sum_{s=1}^{S}|ret_s|}\right)\times\left(\frac{ret_{k,s}}{ret_s}\right),$$

ret_s corresponds to the close-to-close return for stock *s* and $ret_{k,s}$ is the log-return for period *k* and for stock *s*. The final row shows the fraction of days with their close-to-close return equalling 0. * indicates the WPCs, which are significantly different from 0 at 1% level. The data covers the trading period between 1st October 2012 and 30th September 2013.

		Pound Volume Quintile	Highest	4th	3rd	2nd	Lowest	Overall
Time Periods	Pre-Open/Opening Auction	07:10 - 07:20	0.009	0.086	0.041	-0.026	-0.024	0.017
		07:20 - 07:30	0.029	-0.005	0.014	0.096	0.046	0.031
		07:30 - 07:40	0.002	-0.013	0.016	-0.072	-0.005	-0.014
		07:40 - 07:50	0.016	0.017	-0.012	0.006	0.011	0.007
		07:50 - 08:00	0.318*	0.004	0.004	-0.001	-0.001	0.065
	Open-Close/NTH	08:00 - 08:10	0.068*	0.286*	0.424*	0.369*	0.369*	0.303*
		08:10 - 08:20	0.056*	0.076*	0.048*	0.069*	0.071*	0.064*
		08:20 - 08:30	0.034*	0.021	0.037*	0.042*	0.033*	0.033*
		08:30 - 08:40	0.054*	0.019	0.033*	0.047*	0.027*	0.036*
		08:40 - 08: 50	0.030*	0.028*	0.031*	0.042*	0.032*	0.033*
		08:50 - 09:00	0.024	0.005	0.029*	0.031*	0.005	0.019*
		09:00 - 16:00	0.350*	0.465*	0.406*	0.417*	0.460*	0.420*
	Closing Auction/Post Close	16:00 - 16:10	0.005	-0.001	0.005	0.019	0.003	0.006
		16:10 - 16:20	0.012	-0.005	-0.004	-0.001	0.006	0.001
		16:20 - 16:30	0.015	0.000	-0.004	-0.01	0.003	0.001
		16:30 - 16:38	-0.032*	-0.03	-0.002	0.001	-0.005	-0.014
		16:38 - 16:50	0.016	0.052	-0.034	-0.031	-0.025	-0.004
	Days with zero price change		0.02	0.01	0.01	0.00	0.01	0.01

Table 3: Price Discovery per Trade and by Time Period for FTSE 100 Stocks

The Weighted Price Contribution per Trade (WPCT) is computed by the pound volume quintile for FTSE 100 stocks. The WPCT is computed by dividing the WPC per trading interval by the weighted ratio of trades executed during that period (interval). If for each day, $t_{k,s}$ is the number of executed trades in time period k for contract s, and t_s is the total sum of $t_{k,s}$ for all the periods, then $WPCT_k$ is defined as:

$$WPCT_k = \frac{\sum_{s=1}^{S}\left(\frac{|ret_s|}{\sum_{s=1}^{S}|ret_s|}\right)\times\left(\frac{ret_{k,s}}{ret_s}\right)}{\sum_{s=1}^{S}\left(\frac{|ret_s|}{\sum_{s=1}^{S}|ret_s|}\right)\times\left(\frac{t_{k,s}}{t_s}\right)}$$

The final row shows the fraction of days with their close-to-close return equalling 0. * indicates the WPCTs, which are significantly different from 0 at 1% level. The data covers the trading period between 1st October 2012 and 30th September 2013.

		Pound Volume Quintile	Highest	4th	3rd	2nd	Lowest	Overall
Time Periods	Pre-Open/Opening Auction	07:10 - 07:20	99.24*	967.37*	374.12*	-196.72*	-144.38*	219.92*
		07:20 - 07:30	331.57*	-66.32*	-104.47*	805.06*	320.11*	257.19*
		07:30 - 07:40	94.24*	-634.92*	573.85*	-2205.55*	-107.76*	-456.03*
		07:40 - 07:50	1109.12*	770.30*	-532.08*	253.73*	357.23*	391.66*
		07:50 - 08:00	26.74*	318.75*	338.74*	-72.33*	-36.51*	115.08*
	Open-Close/NTH	08:00 - 08:10	1.93	8.56*	12.20*	11.37*	14.17*	9.64*
		08:10 - 08:20	2.36	3.30	2.09	3.23	3.59	2.91
		08:20 - 08:30	1.64	1.09	1.80	2.10	2.06	1.74
		08:30 - 08:40	2.66	0.94	1.58	2.38	1.57	1.83
		08:40 - 08: 50	1.73	1.49	1.64	2.40	2.06	1.86
		08:50 - 09:00	1.40	0.28	1.56	1.75	0.31	1.06
		09:00 - 16:00	0.50	0.62	0.54	0.58	0.63	0.58
		16:00 - 16:10	0.17	-0.03	0.19	0.60	0.10	0.21
		16:10 - 16:20	0.37	-0.15	-0.13	-0.02	0.14	0.04
		16:20 - 16:30	0.31	0.00	-0.09	-0.17	0.05	0.02
	Closing Auction/Post Close	16:30 - 16:38	-0.58	-2.95	-0.17	0.07	-0.16	-0.76
		16:38 - 16:50	28.05*	84.35*	-54.55*	-38.36*	-21.72*	-0.45
	Days with '0' price change		0.02	0.012	0.008	0.00	0.012	0.0104

Table 4: Adverse Selection Costs by Period for FTSE 100 Stocks

The table shows adverse selection costs components for FTSE 100 stocks trading between 1st October 2012 and 30th September 2013. The estimates are computed by estimating the following time series model for each stock and time period using ordinary least squares:

$$\Delta P_{k,t} = \beta_{1,k} Q_{k,t} + \beta_{2,k} Q_{k,t-1} + \beta_{3,k} Q_{A,t-1} + e_t$$

where $\Delta P_{k,t}$ is the change in price from the previous retained trade, $Q_{k,t}$ is equal to 1 (-1) when the transaction at period t for stock k was a market maker sell (buy) and $Q_{A,t-1}$ is the aggregate buy-sell indicator used in encapsulating portfolio trading pressure, it equals 1(-1, 0) when the sum of $Q_{k,t-1}$ across all FTSE stocks in the sample is positive (negative, zero). The adverse selection cost component is given as: $2(\beta_{2,k} + \beta_{1,k})$. The lower level quintile observations are very low in number, and thus could not provide robust estimates, hence their exclusion from the estimated contents in the table below. The standard deviations of the adverse selection costs estimates are given in parenthesis. Wilcoxon-Mann-Whitney (tie-adjusted) tests are used to determine whether pre-open or post-NTH values are significantly different from the NTH period. The pre-open or post-NTH periods that differ from the NTH at 1% level are denoted with *.

Pound Volume Quintile	**Pre-Open**		**Normal Trading Hours (NTH)**	**Post-NTH**	
	Pre-Opening Auction (07:10-07:50)	Opening Auction (07:50:01-08:00)	(08:00:30-16:30)	Closing Auction (16:30:01-16:38)	Post-Close (16:38:01-16:50)
Highest	0.102*	0.935*	0.004	0.041*	0.093*
	(0.090)	(0.456)	(0.003)	(0.033)	(0.060)
4	0.069*		0.002	0.027*	0.072*
	(0.049)	-	(0.001)	(0.014)	(0.031)
3	0.016*	-	0.001	0.021*	0.039*
	(0.010)		(0.0006)	(0.013)	(0.018)
2	0.014*	-	0.001	0.006*	0.016*
	(0.011)		(0.0007)	(0.003)	(0.010)
Lowest	0.046*	-	0.005	0.023*	0.061*
	(0.013)		(0.002)	(0.008)	(0.029)
Overall	0.049*	0.935*	0.003	0.024*	0.056*
	(0.033)	(0.456)	(0.002)	(0.011)	(0.027)

Appendix

List of stocks used in this study

ISIN	RIC	Constituent name	Index Weight (%)	Country	ICB Supersector Code
GB00B02J6398	ADM.L	Admiral Group	0.14	UK	8500
GB0000282623	AMEC.L	Amec	0.19	UK	0500
GB00B1XZS820	AAL.L	Anglo American	1.19	UK	1700
GB0000456144	ANTO.L	Antofagasta	0.17	UK	1700
GB0000595859	ARM.L	ARM Holdings	0.83	UK	9500
GB0006731235	ABF.L	Associated British Foods	0.39	UK	3500
GB0009895292	AZN.L	AstraZeneca	2.41	UK	4500
GB0002162385	AV.L	Aviva	0.70	UK	8500
GB0009697037	BAB.L	Babcock International Group	0.26	UK	2700
GB0002634946	BAES.L	BAE Systems	0.88	UK	2700
GB0031348658	BARC.L	Barclays	2.56	UK	8300
GB0008762899	BG.L	BG Group	2.41	UK	0500
GB0000566504	BLT.L	BHP Billiton	2.31	UK	1700
GB0007980591	BP.L	BP	4.89	UK	0500
GB0002875804	BATS.L	British American Tobacco	3.77	UK	3700
GB0001367019	BLND.L	British Land Co	0.35	UK	8600
GB0001411924	BSY.L	British Sky Broadcasting Group	0.51	UK	5500
GB0030913577	BT.L	BT Group	1.62	UK	6500
GB00B23K0M20	CPI.L	Capita	0.39	UK	2700
GB00B033F229	CNA.L	Centrica	1.14	UK	7500
GB0005331532	CPG.L	Compass Group	0.93	UK	5700
IE0001827041	CRH.I	CRH	0.64	UK	2300
GB0002335270	CRDA.L	Croda International	0.21	UK	1300
GB0002374006	DGE.L	Diageo	2.97	UK	3500
GB00B19NLV48	EXPN.L	Experian	0.71	UK	2700
GB0009252882	GSK.L	GlaxoSmithKline	4.60	UK	4500
JE00B4T3BW64	GLEN.L	Glencore Xstrata	1.94	UK	1700
GB00B1VZ0M25	HRGV.L	Hargreaves Lansdown	0.13	UK	8700
GB0005405286	HSBA.L	HSBC Hldgs	7.48	UK	8300
GB0004579636	IMI.L	IMI	0.28	UK	2700
GB0004544929	IMT.L	Imperial Tobacco Group	1.34	UK	3700

GB00B85KYF37	IHG.L	InterContinental Hotels Group	0.28	UK	5700
GB0033195214	KGF.L	Kingfisher	0.55	UK	5300
GB0031809436	LAND.L	Land Securities Group	0.43	UK	8600
GB0005603997	LGEN.L	Legal & General Group	0.69	UK	8500
GB0008706128	LLOY.L	Lloyds Banking Group	2.13	UK	8300
GB0031274896	MKS.L	Marks & Spencer Group	0.48	UK	5300
GB0005758098	MGGT.L	Meggitt	0.26	UK	2700
GB00B8L59D51	MRON.L	Melrose Industries	0.23	UK	2700
GB0006043169	MRW.L	Morrison (Wm) Supermarkets	0.36	UK	5300
GB00B08SNH34	NG.L	National Grid	1.63	UK	7500
GB0032089863	NXT.L	Next	0.47	UK	5300
GB00B77J0862	OML.L	Old Mutual	0.55	UK	8500
GB0006776081	PSON.L	Pearson	0.61	UK	5500
GB0007099541	PRU.L	Prudential	1.76	UK	8500
GB00B24CGK77	RB.L	Reckitt Benckiser Group	1.75	UK	3700
GB00B2B0DG97	REL.L	Reed Elsevier	0.59	UK	5500
GG00B62W2327	RSL.L	Resolution	0.26	UK	8500
GB0007188757	RIO.L	Rio Tinto	2.26	UK	1700
GB00B63H8491	RR.L	Rolls-Royce Holdings	1.25	UK	2700
GB00B7T77214	RBS.L	Royal Bank Of Scotland Group	0.45	UK	8300
GB00B03MLX29	RDSa.L	Royal Dutch Shell A	4.65	UK	0500
GB00B03MM408	RDSb.L	Royal Dutch Shell B	3.22	UK	0500
GB0006616899	RSA.L	RSA Insurance Group	0.27	UK	8500
GB0004835483	SAB.L	SABMiller	1.78	UK	3500
GB00B8C3BL03	SGE.L	Sage Group	0.22	UK	9500
GB00B019KW72	SBRY.L	Sainsbury (J)	0.33	UK	5300
GB0002405495	SDR.L	Schroders	0.17	UK	8700
GB00B1FH8J72	SVT.L	Severn Trent	0.25	UK	7500
GB0009223206	SN.L	Smith & Nephew	0.41	UK	4500
GB00B1WY2338	SMIN.L	Smiths Group	0.33	UK	2700
GB0007908733	SSE.L	SSE	0.85	UK	7500
GB0004082847	STAN.L	Standard Chartered	1.76	UK	8300
GB00B16KPT44	SL.L	Standard Life	0.49	UK	8500
GB0008847096	TSCO.L	Tesco	1.73	UK	5300

GB0001500809	TLW.L	Tullow Oil	0.56	UK	0500
GB00B10RZP78	ULVR.L	Unilever	1.77	UK	3500
GB00B39J2M42	UU.L	United Utilities Group	0.28	UK	7500
GB00B16GWD56	VOD.L	Vodafone Group	6.31	UK	6500
JE00B8N69M54	WOS.L	Wolseley	0.52	UK	2700
		Total weight	91.23		