Light versus Dark: Commonality in Lit and Dark liquidity

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This Version: August 2017

Abstract

Modern financial markets have experienced fragmentation in lit (displayed) order books as well as an increase in the use of dark (non-displayed) liquidity. Recent dark pool proliferation has raised regulatory and academic concerns about market quality implication. We empirically study the liquidity commonalities in lit and dark venues. We find that compared with lit venues, dark venues proportionally contribute more liquidity to the aggregate market. This is because dark pools facilitate trades that otherwise might not easily have occurred in lit venues when the spread widens and the limit order queue builds up. We also find that informed and algorithmic trading hinder liquidity creation in lit and dark venues. Evidence also suggests that stocks exhibiting low levels of informed trading across the aggregate market drive dark venues' liquidity contribution to the market.

JEL classification: G10, G14, G15

Keywords: Dark pools, MiFID, Multilateral Trading Facilities (MTFs), Liquidity commonality, trading liquidity, Probability of informed trading (PIN), Algorithm trading

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1. Introduction:

The last decade has seen an unprecedented proliferation of new trading places. For example, in Europe, riding on the back of the implementation of the Markets in Financial Instruments Directive (MiFID) in 2007, more than 100 new trading venues have been established over the last decade. The entrant venues are mostly high tech Multilateral Trading Facilities, enabled by MiFID rules. Many trading venues, including the more established national exchanges, rely in existing MiFID waivers to operate dark order books in addition to the standard and more transparent lit (visible) limit order book. The main advantage of dark order books (or dark pools) over traditional lit markets is the ability to execute large orders anonymously and with minimum price impact, since pre-trade transparency is waived for orders submitted to such platforms. However, recent studies suggest average trade sizes in some European dark pools are comparable to those in the lit market (see as an example, Ibikunle et al., 2016). The lure of trading with no pre-trade transparency has led to a significant growth in the proportion of dark trading across the developed markets. According to Degryse et al. (2015), approximately 30% and 40% of all executed orders in the United States and European Blue chip stocks are executed in the dark Despite the growing popularity of dark pools among a section market participants, mainly institutional traders, the operation of dark pools has generally been subjected to debate and controversy due to the lack of pre-trade transparency. Apart from industry and academic contributors raising concerns that dark pool trading might tarnish the credibility of primary equity markets, politicians are increasingly wading into the debate. In a letter from US Senator Kaufman to SEC Chair Schapiro mentions, the Senator notes the need to *"examine whether too much order flow is being shielded from the lit markets by dark venues"*.

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

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

Specifically, we pose four distinct questions. Firstly, when compared with lit venues, do dark pools have larger or smaller co-movement with market-wide liquidity? Secondly, if such relationship exists, is the observed co-movement related to the market gaining liquidity or does it drain liquidity from the overall market; i.e. do dark pools play a complementary role to lit venues, especially in periods of liquidity constraints or do they exacerbate the constraints? Thirdly, what factors drive co-movement in dark and lit liquidity? Finally, since both Ye (2011) and Zhu (2014) suggest the possibility that informed traders may use dark venues in order to reduce their transactions costs and maximise their information-based profits, we investigate whether variations in dark pool liquidity could be linked with informed trading activities. Our findings are fourfold. First, we find that the degree of dark venues' liquidity commonality with the wider market is larger than that of lit venues, indicating that liquidity effects in dark pools is more pronounced. Further analysis suggests that dark liquidity commonality with the wider market is linked to increasing levels of liquidity in the wider market rather than a decreasing trend. This implies that, when market-wide liquidity starts to increase, dark venues proportionally contribute more liquidity than lit venues. Secondly, results suggest that when limit order spread increases and limit order queue builds up traders are incentivised to route their trades to dark venues. This is an indication of the complementary role dark venues play in the aggregate market, by facilitating trades that otherwise could not be easily executed at lit venues. We also show that informed trading and algorithm trading (AT) reduce liquidity-creation effects in both lit and dark venues. This finding is consistent with the related literature (for example see Zhu, 2014; Comerton-Forde and Putniņš, 2015) in that when an informed event occurs informed traders are likely to gravitate to the same side of the market and trade in the same direction, thereby facing a lower execution probability in the dark than in the lit.

Hence, lit venues attract traders that are more informed and informed order flows. Finally, we show that the stocks with lower levels of informed trading activity and higher volatility generate stronger liquidity commonality effects in both lit and dark venues.

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

2. Related Literature

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

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

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

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

3. Data and Methodology

3.1. Data

Our data consists of the constituents of the FTSE100 index from 1st June 2010 to 30 September 2014; the FTSE100 includes the 100 largest firms listed on the LSE and they account for more than 80% of the exchange's total market capitalisation. Our data consists of one primary exchange LSE and the three largest MTFs operating in Europe: BATS Europe, Chi-X Europe and Turquoise. The three latter venues operate both lit and dark order books. We obtain intraday tick data from the Thomson Reuters Tick History (TRTH) database. TRTH provides time and sales tick data, which includes variables such as the Reuters Identification Code (RIC), date, timestamp, price, volume, bid price, ask price, bid volume and ask volume, as well as qualifiers indicating whether a trade is executed in the dark or not. We allocate each trade a pair of corresponding prevailing best bid and ask quotes. Since dark orders are only entertained during normal trading hours, we delete the opening auction (7:50hrs – 8:00hrs) and closing auction (16:30hrs – 16:35hrs) periods from the dataset. In addition to the TRTH, we also obtain daily lit and dark trading data from the Market Quality Dashboard (MQD) database managed by the Capital Markets Cooperative Research Centre, Sydney.[1] Finally, we merge the order book level data for the four trading venues in order to create a single 'global' order book for the London market. Dataset cleaning and merging of the order book data from the four

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

venues yield a consolidated dataset containing 638 million transactions valued at 3.08 trillion British Pounds Sterling executed in 95 stocks over the sample period.

3.2. Methodology

3.2.1. Main liquidity measures

Liquidity is an important component of the cost of trading and its measures could be multi-dimensional. Microstructure literature usually employs the bid-ask spread as a proxy for liquidity. However, given that dark pools in our dataset do not document the spread since they execute orders using the LSE midpoint for reference, we employ other measures of liquidity. Specifically, five measures aimed at capturing liquidity for lit and dark venues, as well as for the aggregate market are identified. The first two measures are theAmihud (2002) and Florackis et al. (2011) illiquidity ratios; these are inverse proxies of liquidity. In less liquid markets, a given level of volume of shares traded will give rise to a greater price response than in more liquid markets. The Amihud (2002) illiquidity ratio is therefore defined as the ratio of the absolute return to volume of shares traded. The Amihud (2002) illiquidity ratio is well-established in the microstructure literature and has been extensively used to capture systematic liquidity risk and commonality in liquidity among stocks (see as examples Kamara et al., 2008; Korajczyk and Sadka, 2008). Marshall et al. (2012) also examine a range of liquidity proxies and show that the Amihud ratio performs well in liquidity commonality tests. Thus, for each stock in each day, we compute the Amihud ratio for lit and dark venues and for the aggregate market as shown in Equations (1), (2) and (3) respectively.

$$lit\_Amihud_{i,t} = \left| \frac{r_{close-to-open,i,t}}{lit\_volume_{i,t}} \right| \tag{1}$$

$$dark\_Amihud_{i,t} = \left| \frac{r_{close-to-close,i,t}}{dark\_volume_{i,t}} \right| \tag{2}$$

$$market\_Amihud_{i,t} = \left| \frac{r_{close-to-open,i,t}}{total\_volume_{i,t}} \right| \tag{3}$$

However, we also note that trading volume is likely to be greater for economically larger instruments, thus potentially creating a large firm bias. Therefore, for robustness, we also use the Florackis et al. (2011) illiquidity ratio, in which volume in the Amihud (2002) ratio is replaced by the turnover ratio. The principle is similar, in that a greater price movement is anticipated for illiquid markets for any given proportion of the asset traded. The advantage of this measure over the Amihud (2002) ratio is that there is no significant correlation between instrument trading size and the turnover ratio. For each stock in each day, we compute the Florackis ratio for lit and dark venues and the aggregate market as given in Equations (3), (4) and (5) respectively.

$$lit\_Florackis_{i,t} = \left| \frac{r_{close-to-open,i,t}}{(mkt\_cap/lit\_volume)_{i,t}} \right| \tag{4}$$

$$dark\_Florackis_{i,t} = \left| \frac{r_{close-to-close,i,t}}{(mkt\_cap/dark\_volume)_{i,t}} \right| \tag{5}$$

$$market\_Florackisi_{i,t} = \left| \frac{r_{close-to-open,i,t}}{(mkt\_cap/total\_volume)_{i,t}} \right| \tag{6}$$

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

3.2.2. Descriptive statistics

Panel A of Figure 1 plots the trading value series for both the lit and dark venues in the London market for the four-year period ending September 2014; all values are in pounds. The cumulative growth in dark trades appears consistent with the trading value for the lit throughout the time series, and for most of the period under consideration the dark trades' growth rate appears larger than that of the aggregate lit venues. Hence, the evidence here is that an increasing proportion of trades are now executed in the dark. Panel B, which plots the dark trading values as percentages of the total market trading value, shows that dark trade values continue to grow as a proportion of total market values. However, the average percentage of dark trading does not exceed 12% during our sample period. Panel C suggests that the average trading size in overall lit and dark values appear to be in lockstep throughout the four-year period. Table 1 shows descriptive statistics for key variables. This table shows that lit venues have larger Amihud and Florackis ratio than dark venues. This implies that trading generates a larger impact in lit markets than dark venues. One way of interpreting this estimate is that lit venues are less liquid when compared to dark venues. However, a more apt interpretation is that lit venues attract more informed trades than dark venues, hence the larger price impact generated. Furthermore, given that the dark pools we examine use prices from lit venues as reference prices, it is unlikely that trading in dark venues contribute significantly enough to price discovery for those trades to generate larger impacts than lit venues' trades.

INSERT FIGURE 1 ABOUT HERE

INSERT TABLE 1 ABOUT HERE

3.2.3. The baseline model

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

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \varepsilon_{i,t} \tag{7}$$

Specifically, we regresses daily percentage changes in liquidity for an individual stock against market measures of liquidity. In Equation (7), $DL_{i,t}$ is, for stock i, the percentage change from trading day $_{t-1}$ to day$_t$ in liquidity as proxied by several variables (including Amihud ratio, Florackis ratio, volume of shares traded, number of trades and pound volume). volume of shares traded , transaction numbers and pound volume are naturally considered as measures of trading activity rather than traditional measures of liquidity. However, given their high levels of correlation with liquidity variables, we adopt them in this paper variously as both liquidity proxies and trading activity measures. $DL_{i,t}$ will be tested as lit liquidity and dark liquidity respectively. $DL_{M,t}$, $DL_{M,t-1}$ and $DL_{M,t+1}$ are the concurrent, one-day lag and lead of percentage change in a cross-sectional equally weighted market liquidity proxies of our sample stocks.[2] We examine percentage changes rather than levels for two reasons: firstly, our interest is fundamentally in discovering whether liquidity co-moves, and secondly, time series of liquidity levels are more likely to be plagued by econometric problems. We define the coefficient β_1 as the *elasticity of liquidity commonality* (ELC) as each estimated coefficient in regression Equation (7) represents the averaged percentage change in liquidity of each stock given 1% in market liquidity. ELC also measures the co-movent of trading venues' liquidity with market-wide liquidity. We run the regression for both lit and dark venues and obtain the sizes of ELC in lit and dark venues as indicators of which venue exhibit more pronounced co-movement with market-wide liquidity.

3.2.4. What drives dark pool trading activities?

As a next step, we examine what drives dark pool liquidity. Previous studies postulate that trades in dark pools and upstairs markets are trades that otherwise might not have easily occurred in traditional lit venues (see for examples Smith et al., 2001; Jain et al., 2003; He and Lepone, 2014; Kwan et al., 2015). Following the existing literature, we argue that, dark pools liquidity is aided by the liquidity constraints in lit venues and thus work as complementary venues to lit venues. Thus, when spreads are wider in lit markets and the queue for order

[2] In order to reduce the outliers, we follow Korajczyk and Sadka (2008) to 'winsorize' the daily liquidity measures in lit and dark venues using the 1st and 99th percentile.

execution is lengthy, traders, especially the uninformed kind, are incentivized to migrate to dark pools where they can trade at the midpoint, ensuring minimum or no price impact. In order to examine this intuition, we design the following model (8) and (9), which captures the relationship between dark venues' share of trading, spread market depth and order queue index in lit markets.

$$DL_{i,t} = \alpha_1 + \beta_1 DBAS_{M,t} + \beta_2 DBAS_{M,t-1} + \beta_3 DBAS_{M,t+1} + \varepsilon_{i,t} \quad (8)$$

$$DL_{i,t} = \alpha_1 + \beta_1 DQueue_{M,t} + \beta_2 DQueue_{M,t-1} + \beta_3 DQueue_{M,t+1} + \varepsilon_{i,t} \quad (9)$$

In Equation (8), $DL_{i,t}$ is, for stock i, the percentage change from trading day_{t-1} to day_t market share variables including volume of shares traded, number of trades and pound volume. $DBAS_{M,t}$, $DBAS_{M,t-1}$ and $DBAS_{M,t+1}$ are the concurrent, one-day lag and lead of percentage change in a cross-sectional equally weighted effective bid ask spread of our sample stocks as observed in lit venues. Effective spread equals twice the absolute value of the difference between transaction price and the corresponding best bid and ask quotes midpoint at the transaction time. In Equation (9), We continue to examine the relationship between order queue and dark trading activities. Following Kwan et al. (2015) and He and Lepone (2014), we use the market market depth at the best bid and ask price as an index of order queue. However, this index is adjusted by message-to-trade-ratio. The reason for including a message-to-trade-ratio adjusted market depth is because we aim to minimise the impact of high frequency traders (HFTs) and algorithm traders (ATs), who typically place and cancel bids andoffers at high speed. This order queue proxy is calculated as total pound volume of orders submitted at the best bid and ask prices divided by the message to trade ratio (*ALGO*) in the market. $DQueue_{M,t}$, $DQueue_{M,t-1}$ and $DQueue_{M,t+1}$ are the concurrent, one-day lag and lead of percentage change in a cross-sectional equally weighted market queue index of our sample stocks. Estimates from Equations (8) and (9) offer insights into the impact of liquidity constraints in lit venues on dark pool trading share of trading.

3.2.5. Extended Model with Informed Trading Factors

Several theoretical papers (see as examples Ye, 2011; Zhu, 2014; Nimalendran and Ray, 2014) examine trading strategies of informed and liquidity traders in the presence of dark pools and the impact of dark trading on price discovery primary exchanges, under differing conditions. Specifically, assumptions used in their models' development mainly differ in terms of uninformed traders' ability to access dark pools. However, all of these studies assume that informed traders may use dark pools in order to reduce their transactions costs and maximise profits from their use of private information (Nimalendran and Ray, 2014). Despite the consensus on the theoretical validity of informed traders accessing dark pools, the impact of informed trading on dark venues' liquidity is still an open empirical question. We therefore extend our analysis to examine this question. In order to study the impact of informed trading on lit and dark liquidity, we extend Equation (7) to include two informed trading proxies as shown in Equations (12) and (13). The first proxy is the probability of informed trading (*PIN*) as computed for the aggregate market. *PIN* can be used to proxy the proportion of the unobservable informed trades across normal trading hours (see for example Easley et al., 1996a; 1996b; 1997). The *PIN* model allows us to compute an approximation of the unobservable distribution of trades between informed and uninformed traders by modelling purchases and sales.[3] Hence, the 'normal level' of sales and purchases executed within a stock on a given day over several trading cycles is interpreted as relatively uninformed trading activity by the model, and this information is employed when estimating ε. An unusual volume of purchase or sale transactions is interpreted as information-based trading and used to compute μ. Furthermore, the frequency of intervals during which 'abnormal' levels of purchases and sales are transacted is employed when computing the values of α and δ. These calculations are conducted in a

[3] We infer purchase and sales by running the Lee and Ready (1991) trade classification algorithm.

simultaneous fashion using maximum likelihood estimation. Suppose the arrival of uninformed and informed traders in the market follow a Poisson distribution, the likelihood function for the PIN model for each interval estimated can be expressed as:

$$
\begin{aligned}
L((B,S)\,|\,\theta) = {} & (1-\alpha)\, e^{-\varepsilon_b} \frac{\varepsilon_b^B}{B!}\, e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!} + \alpha\delta\, e^{-e_b} \frac{\varepsilon_b^B}{B!}\, e^{-(\mu+\varepsilon_s)} \frac{(\mu+\varepsilon_s)^S}{S!} \\
& + \alpha(1-\delta)\, e^{-\varepsilon_s} \frac{\varepsilon_s^S}{S!}\, e^{-(\mu+\varepsilon_b)} \frac{(\mu+\varepsilon_b)^B}{B!}
\end{aligned}
\tag{10}
$$

where *B* and *S* respectively represent the total number of purchase and sale transactions for each one hour trading period within each trading day. $\theta = (\alpha, \delta, \mu, \varepsilon)$ is the parameter vector for the structural model. Equation (10) represents a system of distributions in which the possible trades are weighted by the probability of a one hour trading period with no news ($1 - \alpha$), a one hour trading period with good news ($\alpha\ (1 - \delta)$) or a one hour trading period with bad news ($\alpha\delta$). Based on the assumption that this process occurs independently across the different trading periods, Easley et al. (1997) and Easley et al. (1996b) calculate the parameter vector estimates using maximum likelihood estimation procedure. Thus, we obtain the parameters for each trading day and for each stock in the sample by maximum likelihood estimation. Following Easley et al. (1996b) and Easley et al. (1997), PIN is then computed as:

$$
PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \tag{11}
$$

PIN, as computed, technically only proxies informed trading in the lit venues. However, we argue that the measure is a direct proxy for informed trading in the overall market rather than just the lit venues alone. This is because, as earlier stated, the dark pools included in our sample are midpoint order books; hence, they source execution prices from the lit venue by executing orders against the midpoint or within the spread as posted on lit platforms. This implies that the posted orders at the lit venues effectively relate directly to the dark venues as well. However, for completeness, we employ a second proxy for informed trading. The second informed trading proxy is the ratio of messages to trades (*ALGO*) across all trading venues.

This is a typical measure for AT/HFT activity, since ATs/HFTs apply advanced computer power to extract superior information and profit from market movements; thus they arrive at new conclusions regarding shifts in underlying value of instruments faster than most of the rest of the market. Their ability of being able to decipher new information earlier than most other market participants therefore implies that they could be considered as informed traders. This view is consistent with the finding that HFTs can anticipate buying and selling pressure over short horizons (see Hirschey, 2013). Two regression models are run regression in order to avoid a potential multicollinearity problem; thus, PIN and ALGO are used as substitutes in an extension of Equation (7).

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \beta_4 PIN_{M,t} + \beta_5 PIN_{M,t-1} + \beta_6 PIN_{M,t+1} + \varepsilon_{i,t} \tag{12}$$

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \beta_4 ALGO_{M,t} + \beta_5 ALGO_{M,t-1} + \beta_6 ALGO_{M,t+1} + \varepsilon_{i,t} \tag{13}$$

3.2.6. Drivers of elasticity of liquidity commonality

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

$$ECL_{i,t} = \alpha_1 + \beta_1 PRICE_{i,t} + \beta_2 MKT_{i,t} + \beta_3 COUNT_{i,t} + \beta_4 PV_{i,t} + \beta_5 VOLA_{i,t} + \beta_6 Info_{i,t} + \varepsilon_{j,t} \tag{14}$$

where ELC is the stock-quarter estimated coefficient, β_1, for stock *i* from Equation (7). $PRICE_i$ is the log of quarterly average share price of stock *i*, $COUNT_i$ is the log of quarterly averaged number of transaction of stock *i*, PV_i is the log of quarterly averaged pound volume traded of of stock *i*, $VOLA_i$ is quarterly return volatility for stock *i*, $Info_i$ is the quarterly average of either of two informed trading proxies, *PIN* or *ALGO*.

4. Empirical results and Discussion

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

4.1.Liquidity commonality in lit and dark venues

Table 2 reports the regression results for lit and dark venues. Panels A and B indicate that market-wide liquidity is contemporaneously linked with bothlit and dark liquidity; however there is a difference in the order of magnitude. In Panel A, the elasticity of liquidity commonality suggests that a 0.01 change in market liquidity $DL_{M,t}$ induces a contemporaneous average percentage change in individual stock liquidity at lit venues ranging from 0.608% to 1.85%, depending on the liquidity proxy, all coefficient estimates for lit venues are significantly different from zero at 0.01 level. The average concurrent coefficients are close to those in Chordia et al.'s (2000) study, which ranges from 0.28% to 1.37%. The coefficients for $DL_{M,t-1}$ and $DL_{M,t+1}$ are smaller (in absolute values), indicating a rapid adjustment in lit liquidity commonality, as $DL_{M,t-1}$ and $DL_{M,t+1}$ are designed to capture any lagged adjustment in commonality. Panel B reports the results for dark liquidity commonality. Results show that individual stock liquidity in dark venues are positively related with market-wide liquidity since all concurrent coefficients are positive and statistically significant at the 0.01 level of statistical significance. The concurrent coefficients of dark liquidity commonality range from 1.225% to 2.407%. depending on the liquidity proxy. Since ELC coefficients of dark venues are larger than the corresponding lit venues ones, individual stocks traded in dark venues appear to exhibit a higher level of liquidity commonality than when they are traded in lit venues. Thus, dark venues have a greater elasticity of liquidity commonality than lit venues. In other words, when market-wide liquidity evolves, dark venues have a larger reaction to market-wide liquidity than lit venues. It should be noted that Amihud and Florackis ratios are inverse proxies of liquidity;

hence, when the market starts to gain (lose) liquidity, these two ratios decrease (increase). The other three varibles are positively related with trading liquidity.

INSERT TABLE 2 ABOUT HERE

Thus far, we have shown that dark venues have larger liquidity comovement with market liquidity than lit venues. This indicates that dark pools can have two effects on the market; they can help inject liquidity into the market as well as drain liquidity from the market. In order to investigate which case holds, we decompose our liquidity proxies into two parts; i.e. when market-wide liquidity increases and when market-wide liquidity decreases Panel A and B in Table 3 show the regression results when market-wide liquidity increases and decreases respectively.

INSERT TABLE 3 ABOUT HERE

When market-wide liquidity is increasing the ELC coefficients in lit and dark venues are greater than the corresponding coefficients for when market-wide liquidity is decreasing. This indicates that, during the sample period, both lit and dark venues are more likely to contribute liquidity to the aggregate market rather than drain it. This is unsurprising given the general tightening of the spread over the past decade in the UK equity market. We further compute a simple ratio of ELC of dark venues to the ELC of lit venues. Since the ratios are all greater than one in both Panels A and B, the result implies that, compared with lit venues, dark venues inject (drain) more liquidity to (from) market when market-wide liquidity is increasing (decreasing). Panel A's ratios range from 1.08 to 2.12 with a mean value of 1.63 and Panel B's multipliers range from 1.22 to 2.10 with a mean of 1.45.

4.2. What drives dark pool trading activities

We next test the argument that dark pools can work as complementary venues to traditional (lit) exchanges, especially in the event of worsening liquidityd and long limit order queues at lit markets. This is because, such conditions may incentivise traders to migrate to dark pools where they can trade at or within the midpoint with relatively minimal price impact. The estimates from our tests are presented in Table 4.

INSERT TABLE 4 ABOUT HERE

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

When the spread widens, the high savings arising from trading at the midpoint attracts traders to move their orders from lit markets to dark pools. This point is also consistent with Madhavan and Cheng (1997) and Smith et al. (2001) who study the role of upstairs market. Similar to dark pools, upstairs markets allow traders to execute large institutional client orders without pre-trade transparency. However, some upstairs markets do have market makers to intermediate trades and upstairs transactions will incur price impact subsequently. Madhavan and Cheng (1997) show that upstairs markets enable transactions that would not otherwise occur in the downstairs market. The key differences between the upstairs markets of old and the modern midpoint dark pool, which we study is that execution prices in the latter are constrained within the downstairs market spread and dark pools are not usually subject to trading intermediation as it conceptually affords complete opacity of trading intentions. Nevertheless, the similarities in the functions of the upstairs markets and dark pools are striking. For example, Smith et al. (2001) show that upstairs markets play a complementary role to the downstairs, because trades are more likely to be executed upstairs when the spread on the downstairs limit order book widens. The estimates as obtained in Table 4 suggest that the modern midpoint dark pool performs a similar function, but perhaps even more important is that participation in dark pools is not limited to large institutional traders as is the case for upstairs market. Thus dark pools absorbs those trades that would not be easily executed otherwise, in a similar manner to the upstairs market (see as examples Madhavan and Cheng, 1997; Gresse, 2006).

Panel B in Table 4 reports the impact of limit order queue on lit and dark trading activities. With a 1% increase in limit order queue, individual stock trading activities in lit and dark markets will contemporaneously increase from 0.21% to 0.24% and 0.67% to 1.02% respectively, depending on the trading activity proxy. It can be observed that dark venues are likely to be more attractive than lit venues when the order queue in lit venues starts to lengthen. This is consistent with queue jumping hypothesis suggested by Kwan et al. (2015). When order queue builds up, new traders will have to join the queue and wait for their orders to be executed. As a result, the risk of non-execution of newer orders increases. In this case, dark venues become more attractive than lit ones as dark pools may offer liquidity traders the ability to bypass the limit order queues and also allow for faster execution with minimum price impact.

Thus, we find that when the spread widens or the order queue lengthens traders may take advantage of the dark venues due to its potentially faster execution and propensity for lower price impact. This implies that dark pools act as complementary trading mechanisms to the traditional lit stock exchanges.

4.3.Liquidity and informed trading activities

We next consider the association between liquidity commonality and informed trading activity. Theoretical studies (see for examples Hendershott and Mendelson, 2000; Ye, 2011; Zhu, 2014; Buti et al., 2016) (see as examples Hendershott and Mendelson, 2000; Ye, 2011; Zhu, 2014; Buti et al., 2016)base their modelling on differing assumptions regarding the accessibility of dark pools to uninformed traders. However, all studies agree that informed traders may aim to execute their orders in dark pools in order to reduce their transactions costs and maximise profits from their information (Nimalendran and Ray, 2014). We now examine this issue empirically by extending our baseline model to include informed trading proxies related to the dark pools in our sample.[4] We use the probability of informed trading (*PIN*) to proxy informed trading activity in the aggregate market. For completeness, we also include the ratio of messages in the market to trade (*ALGO*) in order to capture AT activity from the aggregate market. In order to avoid potential multi-collinearity issues, we execute the base-line regression with these two variables separately.

Table 5 shows the regression results based on *PIN*. We observe that in lit venues, the daily change in market-wide *PIN* has a positive and significant impact on daily change in the illiquidity proxies, Amihud and Florackis ratios and negative impact on the more traditional trading activity variables of volume of shares traded, trading frequency and pound volume factors. The coefficients imply an inverse relationship between liquidity commonality and

[4] This method is similar to Chung and Chuwonganant (2014, JFE) who add Chicago Board Option Exchange (CBOE) Market Volatility Index (VIX) into liquidity commonality test.

informed trading. This result is inconsistent with Chordia et al. (2000) who hypothesise that informed trading could result in liquidity commonality because simultaneous holding of superior information could result in correlated demand for liquidity by informed traders. However our result is consistent with Chung et al. (2005) in that market makers post wider spreads and smaller depths for stocks with higher probability of information-based trading in order to account for higher levels of adverse selection risks when informed trading activity rises. Furthermore, the coefficients of dark liquidity show that informed trading activities in lit venues also have a negative impact on dark liquidity commonality and coomonality in relation to the trading activity variables of volume of shares traded , transaction numbers and pound volume. Most importantly, the coefficients of dark liquidity and trading activity commonality are all larger than corresponding ones in lit venues, indicating that informed trading activity in the aggregate market has a larger impact on dark liquidity than lit liquidity. The values for the dark venues are 1.14, 2.78, – 0.37, –0.18 and –0.33 for Amihud, Florackis, volume of shares traded , transaction numbers and pound volume respectively. This is unsurprsing and consistent with the self-selection hypothesis (see Zhu, 2014; Comerton-Forde and Putnins, 2015), which implies that informed traders gravitate towards lit venues while uninformed traders are attracted to the dark trading structure. Our results imply that while informed trading reduces trading activity in lit markets, it does so to a much larger extent in dark venues.

INSERT TABLE 5 ABOUT HERE

The results in Panel B, based on an alternate informed trading proxy, ALGO, is consistent with the trend in Panel A. AT activity exerts a negative influence on liquidity in both lit and dark venues. And just as it is the case for *PIN*, *ALGO* has a larger negative impact on dark liquidity than on lit liquidity. Together, both *PIN* and *ALGO* have an overall stronger negative impact on dark venues than lit venues, indicating that when informed trading activities increases, lit venues' liquidity is less affected than dark venues. This finding is consistent with

Comerton-Forde and Putniņš (2015) and Zhu (2014) that lit venues are more attractive to informed traders whereas dark pools are more attractive to uninformed traders because informed traders are likely to gravitate on the same side of the dark venues and when information event occurs these informed trades face low execution probabilities. As a result, informed trading activities reduce the two-sideness of the dark pools as well as dark liquidity.

4.4.Determinants of elasticity of liquidity commonality

In conclusion, we examine the elasticity of liquidity commonality (ELC). Our approach is consistent with the earlier analysis presented in the preceding sections. First, we run stock quarter analysis for our baseline regression Equation (7), collect the ELC, measured as the coefficients of β_1 , and run ELC against quarterly averaged stock attributes. Panel A in Table 6 shows the results with *PIN* as informed trading proxy in lit venues. When liquidity is measured by Amihud and Florackis ratios, *PIN* has negative impact on ELC, suggesting that stocks with low levels of informed trading have stronger liquidity correlations with the wider market. Thus, informed trading in an individual stock reduces its liquidity commonality with the wider market. Based on the volume of shares traded , trading frequency and pound volume coefficient estimates, we do not observe that informed trading exerts statistically significant impact on trading activity. In the last column, we show the estimates for the overall lit ELC, which equals to the sum of the β_1 from the baseline models under five different liquidity proxies. The last column shows that informed trading activity reduces the level of liquidity commonality in lit markets when all measures of liquidity are considered in unison, and that volatility tends to increase the level of liquidity commonality. Overall, this section of the results suggests that stocks with low level of informed trading and high level of volatility generate the strongest liquidity commonality with the wider market.

INSERT TABLE 6 ABOUT HERE

Panel B in Table 6 shows the results of dark venues. First, when liquidity is proxied by the Florackis ratio and trading frequency, *PIN* exerts a negative and statistically significant impact on liquidity commonality. Further, when liquidity is proxied by Amihud ratio, volume of shares traded, trading frequency and pound volume, volatility tends to have positive and statistically significant impact on liquidity commonality. The last column suggests that the liquidity commonality in dark venues tends to shrink with increases in informed trading activity. The reduction in liquidity commonality when a stock is traded in the dark is on a magnitude almost three times higher than when the stock is traded in the lit market.

5. Conclusion:

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

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

Reference

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets,* 5 (1)**,** 31-56.

Boulatov, A., and George, T. J. (2013). Hidden and Displayed Liquidity in Securities Markets with Informed Liquidity Providers. *Review of Financial Studies,* 26 (8)**,** 2096-2137.

Brockman, P., and Chung, D. Y. (2008). Commonality under market stress: Evidence from an order-driven market. *International Review of Economics & Finance,* 17 (2)**,** 179-196.

Brugler, J. (2015). Into the light: dark pool trading and intraday market quality on the primary exchange. *Bank of England Staff Working Paper*.

Buti, S., Rindi, B., and Werner, I. (2011). Diving into Dark Pool. *Working Paper*.

Buti, S., Rindi, B., and Werner, I. M. (2016). Dark Pool Trading Strategies, Market Quality and Welfare. *Journal of Financial Economics*.

Chordia, T., Roll, R., and Subrahmanyam, A. (2000). Commonality in liquidity. *Journal of Financial Economics,* 56 (1)**,** 3-28.

Chung, K. H., and Chuwonganant, C. (2014). Uncertainty, market structure, and liquidity. *Journal of Financial Economics,* 113 (3)**,** 476-499.

Chung, K. H., Li, M., and Mcinish, T. H. (2005). Information-based trading, price impact of trades, and trade autocorrelation. *Journal of Banking & Finance,* 29 (7)**,** 1645-1669.

Comerton-Forde, C., and Putniņš, T. J. (2015). Dark trading and price discovery. *Journal of Financial Economics,* 118 (1)**,** 70-92.

Degryse, H., De Jong, F., and Kervel, V. V. (2015). The Impact of Dark Trading and Visible Fragmentation on Market Quality. *Review of Finance,* 19**,** 1587-1622.

Easley, D., Kiefer, N. M., and O'hara, M. (1996a). Cream-skimming or profit-sharing? The curious role of purchased order flow. *The Journal of Finance,* 51 (3)**,** 811-833.

Easley, D., Kiefer, N. M., and O'hara, M. (1997). The information content of the trading process. *Journal of Empirical Finance,* 4 (2–3)**,** 159-186.

Easley, D., Kiefer, N. M., O'hara, M., and Paperman, J. B. (1996b). Liquidity, information, and infrequently traded stocks. *The Journal of Finance,* 51 (4)**,** 1405-1436.

Florackis, C., Gregoriou, A., and Kostakis, A. (2011). Trading frequency and asset pricing on the London Stock Exchange: Evidence from a new price impact ratio. *Journal of Banking & Finance,* 35 (12)**,** 3335-3350.

Foley, S., and Putniņš, T. J. (2016). Should we be afraid of the dark. *Journal of Financial Economics*.

Gresse, C. (2006). The Effect of Crossing-Network Trading on Dealer Market's Bid-Ask Spreads. *European Financial Management,* 12 (2)**,** 143-160.

Hasbrouck, J., and Seppi, D. J. (2001). Common factors in prices, order flows, and liquidity. *Journal of Financial Economics,* 59 (3)**,** 383-411.

He, W. P., and Lepone, A. (2014). Determinants of liquidity and execution probability in exchange operated dark pool: Evidence from the Australian Securities Exchange. *Pacific-Basin Finance Journal,* 30**,** 1-16.

Hendershott, T., and Mendelson, H. (2000). Crossing Networks and Dealer Markets: Competition and Performance. *The Journal of Finance,* 55 (5)**,** 2071-2115.

Hirschey, N. (2013). Do High-Frequency Traders Anticipate Buying and Selling Pressure? *Working paper*.

Huberman, G., and Halka, D. (2001). SYSTEMATIC LIQUIDITY. *Journal of Financial Research,* 24 (2)**,** 161-178.

Ibikunle, G., Aquilina, M., Sun, Y., and Ivan, D.-R. (2016). Aggregated Market Quality Implications of Dark Trading.

Jain, P. K., Jiang, C., Mcinish, T. H., and Taechapiroontong, N. (2003). Informed trading in parallel auction and dealer markets: an analysis on the London Stock Exchange. *Manuscript, Indiana University*.

Kamara, A., Lou, X., and Sadka, R. (2008). The divergence of liquidity commonality in the cross-section of stocks. *Journal of Financial Economics,* 89 (3)**,** 444-466.

Korajczyk, R. A., and Sadka, R. (2008). Pricing the commonality across alternative measures of liquidity. *Journal of Financial Economics,* 87 (1)**,** 45-72.

Kwan, A., Masulis, R., and Mcinish, T. H. (2015). Trading rules, competition for order flow and market fragmentation. *Journal of Financial Economics,* 115 (2)**,** 330-348.

Lee, C. M. C., and Ready, M. J. (1991). Inferring Trade Direction from Intraday Data. *The Journal of Finance,* 46 (2)**,** 733-746.

Madhavan, A., and Cheng, M. (1997). In Search of Liquidity: Block Trades in the Upstairs and and Downstairs Markets. *The Review of Financial Studies,* 10 (1)**,** 175-203.

Marshall, B. R., Nguyen, N. H., and Visaltanachoti, N. (2012). Commodity Liquidity Measurement and Transaction Costs. *Review of Financial Studies,* 25 (2)**,** 599-638.

Nimalendran, M., and Ray, S. (2014). Informational linkages between dark and lit trading venues. *Journal of Financial Markets,* 17**,** 230-261.

Smith, B. F., Turnbull, D. a. S., and White, R. W. (2001). Upstairs Market for Principal and Agency Trades: Analysis of Adverse Information and Price Effects. *The Journal of Finance,* 56 (5)**,** 1723-1746.

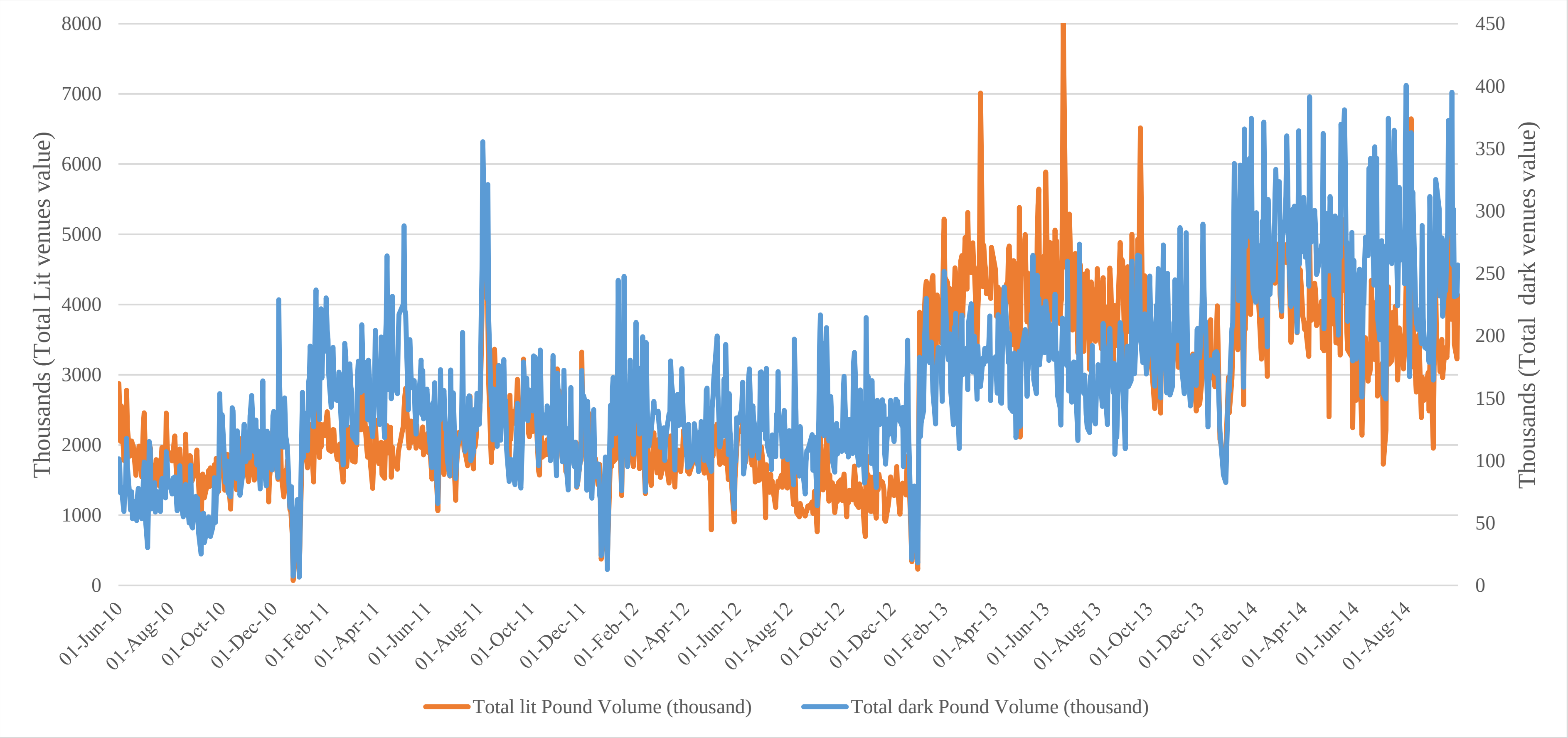
Ye, M. (2011). A Glimpse into the Dark: Price Formation, Transaction Cost and Market Share of the Crossing Network. *Working Paper*.

Zhu, H. (2014). Do Dark Pools Harm Price Discovery? *Review of Financial Studies,* 27**,** 747-789.

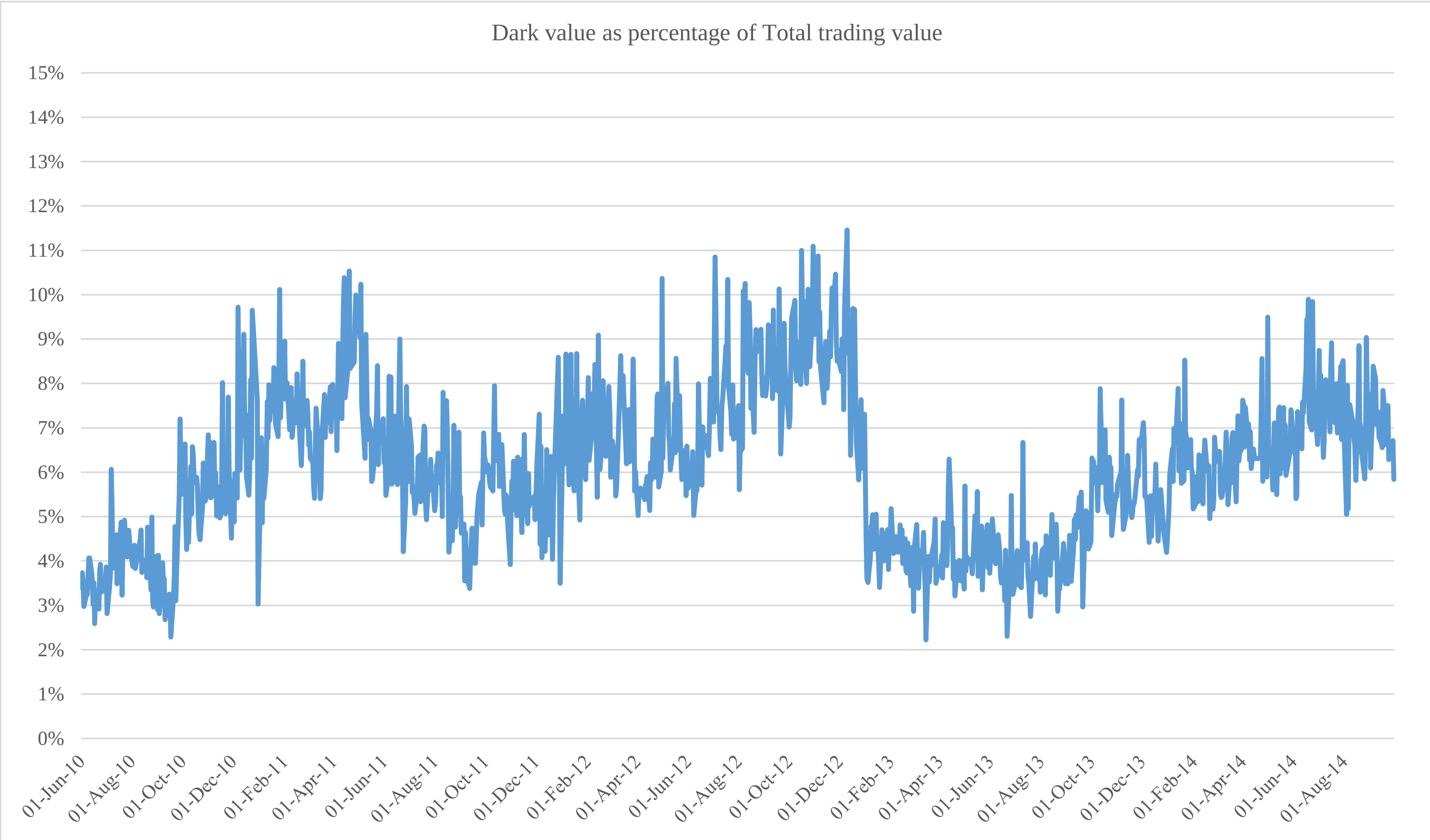
Figure 1: Trading values

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

PANEL A



PANEL B


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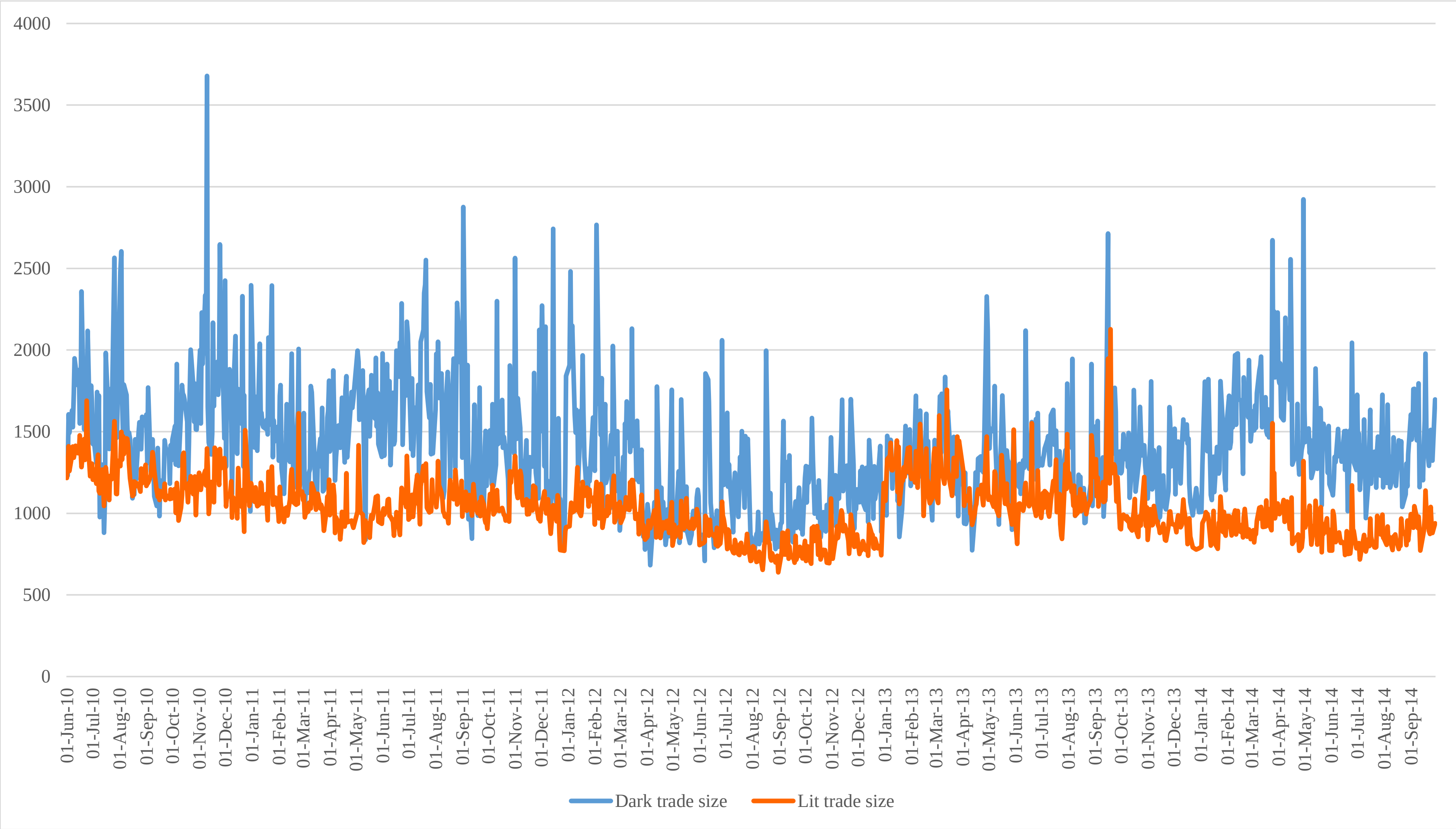
01-Feb-14
01-Apr-14
01-Jun-14
01-Aug-14

PANEL C



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

Table 1: Descriptive statistics

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

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

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

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

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

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

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

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

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

	Percentile					
	25%	50%	75%	95%	mean	std
Dark Amihud	1.65E-08	5.85E-08	1.90E-07	1.18E-06	6.43E-07	3.5477E-05
Lit Amihud	9.15E-10	2.96E-09	8.35E-09	3.43E-08	8.78E-09	7.87E-08
Dark Florackis	2.51E-05	7.97E-05	2.29E-04	1.11E-03	8.12E-04	1.64E-02
Lit Flora Florackis	0.0005	0.0014	0.0033	0.0129	0.0097	0.1170
Dark Volume	47.37	127.90	343.84	1827.19	492.34	1602.55
Lit Volume	990.11	2296.05	5387.60	29880.06	7542.54	20538.06
Number of dark trade	111	223	439	1125	354.98	416.17
Number of lit trades	2985	4931	8826	22330	7356.47	7108.83
Dark £volume ('000)	442.22	1088.66	2552.05	7740.52	2162.46	3296.88
Lit £volume ('000)	9176.38	18629.70	41946.64	124107.97	34906.91	44986.42
PIN	0.16	0.22	0.32	0.52	0.25	0.13
ALGO	26.17	38.79	69.35	334.88	99.71	311.93

Table 2. Baseline results: liquidity commonality in lit and dark venues

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

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

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

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

Panel B. Dark venues

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

Table 3. Asymmetry in liquidity commonality in lit and dark venues under different market conditions

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

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

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

Panel A. When market liquidity improves

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

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

Panel B. When market liquidity deteriorates

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

Table 4. What drive dark pool trading activity

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

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

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

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

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

Panel B. Order Queue

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

Table 5. Liquidity commonality and informed trading

Panel A and B in Table 4 shows estimated coefficients results for the following stock day panel regression model:

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

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

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

Panel A. PIN

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

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

Panel B. ALGO

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

Table 6. Stock attributes and elasticity of liquidity commonality

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

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

$PRICE_i$ is the log of quarterly average share price of stock *i*, $COUNT_i$ is the log of quarterly averaged number of transaction of stock *i*, PV_i is the log of quarterly averaged pound volume traded of of stock *i*, $VOLA_i$ is quarterly volatility of return of stock *i*. PIN_i is quarterly averaged probability of informed trading of stock *i*. PIN measure computed as outlined in Table 1.

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

Panel B. Dark Venues

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