The Bright sides of Dark Liquidity

YUXIN SUN[1], GBENGA IBIKUNLE[*2], DAVIDE MARE[3]

This Version: June 2018

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 limit order queue builds up. We also find that the spread of the trades subsquent to dark trades tends to be narrow. This is consistent with the order flow competition between venues in that dark trade might give market makers a signal of uninformed liquidity demand to narrow the spread. Based on the recent dark volume cap regulation under MiFID II, we provide causal evidence that dark trading cap brings a negative impact on transaction cost.

JEL classification: G10, G14, G15

Keywords: Dark pools, dark trading, MiFID, Multilateral Trading Facilities (MTFs), Liquidity commonality, trading liquidity, Double Volume Cap (DVC), regulation

---

We thank Carol Alexander, Carlo Gresse, Thomas Martha, Sean Foley, Petko Kalev, Tom Steffen, Khaladdin Rzayev, Satchit Sagade, Monika Trepp, Elvira Sojli, Micheal Brolley and Lars Norden for helpful comments and discussions. We are also grateful to the participants at the 2nd Dauphine Microstructure Workshop, the 1st SAFE Market Microstructure Conference, the 1st European Capital Markets Workshop and the 2018 EFMA conference. All errors and omissions are the authors' own.

[1] Queen's University Belfast; e-mail:Y.sun@qub.ac.uk

[2] [*] *Corresponding Author Contact information:* University of Edinburgh Business School, 29 Buccleuch Place, Edinburgh EH8 9JS, United Kingdom; e-mail: Gbenga.Ibikunle@ed.ac.uk; phone: +44 (0) 1316515186.

[1]University of Edinburgh; [2]*Fondazione* European Capital Markets Cooperative Research Centre (ECMCRC), Pescara, Italy. The usual disclaimer applies.

[3] The World Bank Group

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., 2018). 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. In lit venues, both pre-trade and post-trade information is instantly available to all marekt participants. This facilitate transparent orderbook and price discovery process on lit venues. However, dark venues do not report pre-trade information. Even after the order order gets executed, less information is disclosed than the lit order. Market participants do not know the size of dark order submitted, how long it has been rested in the market and whether the dark trade is initiated by a buyer or a seller (Comerton-Forde, 2017). Regulatory and academic contributors are raising concerns that dark pool trading might tarnish the credibility of primary equity markets. Even 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 dark trading suspension of 6 months on a single venue if dark volume exceeds 4%; and or aggregate dark volume breaches the 8% cap across all venues based on a 12-month trading history. This double volume cap (DVC) is scheduled for implementation at the start of 2018, having been delayed by a year. The dark volume cap will be calculated and assessed by the European Securities and Markets Authority (ESMA).

However, on 3rd January 2018 ESMA unexpectly delayed the dark volume cap until 12th of March due to the insufficient data issue. Industry and academia show concerns about the potential detrimental consequences caused by DVC. According to *Financial Times* (March 15, 2018), more than three-quarters of FTSE100 stocks will be affected by DVC. Comerton-Forde (2017) indicates that DVC might adversely affect the market quality as the cap is likely to distrupt trading strategies and execution costs for institutional investors.

Despite the growing debate over of regulating dark pool, limited finance research offers insight into the impact of dark trading 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, across the four-year period from 1st January 2015 to 11th March 2018. We contribute to the literature by posing entirely new questions concerning how dark trading is shaping trading in financial markets. This is the first paper to characterise the interactions between dark and lit liquidity in relation to the wider market. Indeed,

In the next part of this paper, we conduct a laboratory-like experiment to investigate the impact of the recent DVC under MiFID II. We apply a difference-in-differences estimation with capped stocks to be the treatment group. The implementation of dark volume cap allows us to control for potential confounding effects that are not related to dark trading. Our second major contribution is to to document the stark impact of DVC on stock liquidity. As far as we know, this is the first paper to investigate the effect of DVC. Our results have important implications for the future dark pool regulation.

Specifically, we pose five distinct questions regarding the dark liquidity. 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 drives dark trading activity? Fourthly, how do market makers on lit venues interpret dark trades ? Finally, what is the impact of the recent dark trading cap under the MiFID II ? Our findings are fivefold. 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, empirical results suggest that when limit order queue builds up traders are incentivised to route their trades to dark venues. This is an indication of the complementary role of dark venues play in the aggregate market, by facilitating trades that otherwise could not be easily executed at lit venues. We also find that dark liquidity begets lit liquidity. Our results indicate that the bid-ask spread subsequent to dark trades tend to be narrower. This is in line with the competition between lit and dark venues (Foucault and Menkveld, 2008, Zhu, 2014, Kwan et al., 2015). Market makers on lit venues might interpret dark trades as uninformed liquidity demand and therefore they tend to narrow the spread after dark trades to attract more order to lit venues. Finally, our results suggest that DVC can exhibit negative impact on transaction cost. When dark liqudity is capped by DVC , intervenue competition for orderflow is reduced and market makers on lit venues are likely to be relaxed in posting a wider spread.

Overall, this paper extends the most recent empirical literature on the dynamic of dark liquidity in the wider microstructure literature on the other. Our 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 and discusses the first part of our empirical results. Section 5 discuss the results based on the natrual experiment study of DVC and 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. (2018), 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. (2018) , who show that in the London market, overall market quality is enhanced by low levels of midpoint dark trading.

3. Data sources and variable description

3.1. Data

Our initial study sample consists of the constituents of the FTSE100 index from 1st January 2015 to 11th March 2018; 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 includes 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. These three dark order books match the anonymous trades at the mid point of the best bid and ask prices derived from lit venues. 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 the daily market data from the Thomson Reuters Datastream. 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 venues yield a consolidated dataset containing 938 million transactions valued at 786 billion British Pounds Sterling executed in 101 stocks over the sample period.

3.2. Main liquidity measures

Liquidity is an important component of the cost of trading and its measures could be multi-dimensional. To measure the liquidity in lit and dark venues, we first employ trading activity proxies including trading volume, trading pound volume and the number of trades. These factors 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. Next, to measure cost of trading, we employ the quoted bid-ask spread and effective bid-ask spread. Quoted spread is calculated as the difference between best bid and ask price divided by prevailing mid-point; effective spread is defined as twice the absolute value of the difference between transaction price and prevailing mid-point. These two spreads are common liquidity measures in microstructure literature. However, given that dark pools in our dataset do not document the spread since they execute orders using the LSE midpoint for reference, we match dark trades with the spread of the latest trade on lit venuens. This reference spread for dark trade picks up the market status that leads to the subsequent dark trades. We also include the Amihud illiquidity ratio, which is defined as the ratio of the absolute return to volume of shares traded. 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 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. Since dark trading volume is generally less than lit trading volume, we would expect that dark amihud ratio is larger than lit amihud ratio. This, however, will not affect our estimation results since we are using the proportional daily change of liquidity variables.

$$LitAmihud_{i,t} = \left| \frac{r_{close-to-open,i,t}}{lit\_volume_{i,t}} \right| \quad (1)$$

$$DarkAmihud_{i,t} = \left| \frac{r_{close-to-close,i,t}}{dark\_volume_{i,t}} \right| \quad (2)$$

$$MarketAmihud_{i,t} = \left| \frac{r_{close-to-open,i,t}}{total\_volume_{i,t}} \right| \quad (3)$$

Specifically, six measures are aimed to capture liquidity for lit and dark venues, as well as for the aggregate market.

3.2.1. Descriptive statistics

Panel A of Figure 1 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 13% during our sample period. Panel B presents the average size of lit and dark trades.The size of dark trades is consistently larger than that of lit trades. Obviously dark venues have been playing a role in facilitating large trades. Table 1 shows descriptive statistics for key variables. This table shows that the ratio dark to lit volume (pound volume) is about 5.76% (5.52%). As would be anticipated, dark amihud ratio is larger than lit amihud ratio in absolute value. In the regression, all key liquidity variables will be calculated as proportional daily change.

INSERT FIGURE 1 ABOUT HERE

INSERT TABLE 1 ABOUT HERE

4. Lit vs dark: liquidity commonality in lit and dark venues

In this section, we compare the liquidity commonality in lit and dark venues and analyze this commonality in different market states.

4.1.The baseline model

We estimate the following regression models for each stock using daily timeseries data from January 1 2015 through March 11 2018 to exam the commonality in liquidity in lit and dark venues. Our basline models are based on Chordia et al.'s (2000, 2001), we model the systematic liquidity factors in lit and dark venues by estimating the following time-series regression model.

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \beta_4 MKTRET_{M,t} + \beta_5 MKTRET_{M,t-1} + \beta_6 MKTRET_{M,t+1} + \beta_7 vola_{i,t} + \varepsilon_{i,t} \quad (4)$$

Specifically, we regresses daily percentage changes in liquidity for an individual stock against market measures of liquidity. In Equation (4), $DL_{i,t}$ is, for stock *i*, the percentage change from trading day $_{t-1}$ to day$_t$ in liquidity as proxied by several variables (including volume of shares traded, number of trades, pound volume, quoted spread, effective spread and amihud ratio). 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, excluding stock *i*.[1] $MKTRET_{M,t}$, $MKTRET_{M,t-1}$ and $MKTRET_{M,t+1}$ are the FTSE100 index return on day *t, t-1* and *t+1*. $Vola_{i,t}$ measures the volatility. It equals to the square term of return for stock *i* on day *t*.

We examine the 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

[1] In order to reduce the outliers, we winsorize the stock daily variables at the 1% level for each stock and each date. Similar approch can be found in Foley and Putnis (2016).

coefficient β_1 as the *elasticity of liquidity commonality* (ELC) as each estimated coefficient in regression Equation (4) 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.

We follow Chung and Chuwonganant (2014) to report two sets of results from model (4). Panel A in Table 2 shows the coefficients and *t*-statistics from the average regression. Panel B reports the mean coefficients and mean *t*-values across all individual stock regressions. The results in Panel A are calculated under the assumption that the estimation errors in β s are indepent across stocks. We also provide a specification test in Panel C to make sure that the estimation errors are independent. For brevity, we only report coefficients for the stock's own liquidity measure $\beta_1, \beta_2, \beta_3$ and adjusted R^2.

INSERT TABLE 2 ABOUT HERE

Table 2 reports the regression results for lit and dark venues. Panels A and B indicate that market-wide liquidity is contemporaneously linked with both lit and dark liquidity; however there is a difference in the order of magnitude. In Panel A, the concurrent ELC of lit and dark venues are all positive and statistically significant at 1% level except for the effective spread factor in dark venues. The ELC of lit venues suggests that a 1% change in market liquidity $DL_{M,t}$ induces a contemporaneous average percentage change in individual stock liquidity at lit venues ranging from 0.007% to 1.011%, depending on the liquidity proxy, all coefficient estimates for lit venues are significantly different from zero at 0.01 level. 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. By contrast, the ELC of dark venues are all greater than the corresponding coefficients, indicating that individual stocks traded in dark venues have a greater reaction to the change of market-wide liquidity.

Panel B reports qualitatively identical results. Individual stock liquidity in lit venues are positively related with market-wide liquidity since all ELCs are positive and statistically significant. The concurrent coefficients of lit liquidity commonality range from 0.459 to 1.201. depending on the liquidity proxy. Turning to dark venues, we can observe that statisticall significant dark ELCs range from 0.642 5.426, depending on liquidity measures. More importantly, ELC of dark venues are all larger than corresponding ones lit venues, suggesting that 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[2].

4.2.A specification check

As explained, Panel A in Table 2 illustrates the coefficients and *t*-values of the average regression and Panel B shows the mean coefficients and *t*-values across all individual stock regressions. The realibility of the *t*-values in Table 2 depends on the independence of the residuals across stock regression. We conduct the independence test from regression model (4) using the method in Chordia et al. (2000), Coughenour and Saad (2004) and Chung and Chuwonganant (2014). We first sort 108 stock alphabetically using ticker symbols and assign each stock a serial number *i* (*i*=1, … , 108). We then estimate the following models:

$$\varepsilon_{1i+1,t} = \theta_0 + \theta_1 \varepsilon_{1i,t} + \mu_{1i,t} \tag{5}$$

[2] It should be noted that quote spread, effective spread and Amihud ratios are inverse proxies of liquidity; hence, when the market starts to gain (lose) liquidity, these three variables decrease (increase).

$$\varepsilon_{2i+1,t} = \delta_0 + \delta_1 \varepsilon_{2i,t} + \mu_{2i,t} \tag{6}$$

where $\varepsilon_{1i,t}$ and $\varepsilon_{2i,t}$ are the residuals for stock *i* from model (4) in lit and dark venues. We aim to test the level of independence between the residuals for stock *i* and *i+1*. Table 3 shows the average cofficient and t-statistics of θ_1 and δ_1 under different liquidity measures. The mean *t*-statistics ranges from -0.145 to -0.093 for lit venues and -0.164 to -0.143 for dark venues. The percentage of significant t-statistics at the 5% level ranges from 2.64% to 6.42% in lit venues and 2.27% to 5.29% in dark venues, which are slightly lower than that reported by Chordia et al. (2000). The results indicate that the mean values of coefficients θ_1 and δ_1 are not statistically different from zero, suggesting the independence of the residuals across our sample stocks from regressions based on lit and dark venues. Therefore our coefficients and t-statistics from Table 2 are valid in explaining the liquidity commonality.

INSERT TABLE 1 ABOUT HERE

4.3. Liquidity commonality under different market conditions

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 market liquidity proxies into two parts; i.e. when market-wide liquidity increases and when market-wide liquidity decreases. Similar to Panel A and B in Table 4 show the average regression results when market-wide liquidity increases and decreases respectively; Panel C and D presents the mean coefficients and *t*-values across all stock regressions when market-wide liquidity increases and decreases respectively.

INSERT TABLE 1 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 design a simple ELC ratio under two estimation methods:

$$ELC\_Ratio = \frac{ELC_{market\_liquidity\_increases}}{ELC_{market\_liquidity\_decreases}} \tag{7}$$

If this ratio is greater than 1, then it tells that trading venues tend to inject more liquidity rather than drain liquidity from the market. The ELC ratios under the first estimation, the average regression, are plotted in Panel B. Lit ELC ratios range from 0.617 to 2.4 and dark ELC ranges Dark ELC ratios range from 1.009 to 2.861. The only statistically insignificant ELC is based on effective spread variables. It is imporatant to note that statistically significant dark ELC are all larger than the corresponding ones in lit venues. This suggests that, compared to lit venues, dark venues are very likely to contribute more liquidity to the market. Panel C and D tell a qualititatily identical story. The ELC ratios under the second estimation method, mean coefficient and *t*-value, are illustrated in Panel D. It can be observed that four statistically significant dark ELC ratios are all greater than the corresponding lit ELC ratios.

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

$$DL_{i,t} = \alpha_1 + \beta_1 DQueue_{M,t} + \beta_2 DQueue_{M,t-1} + \beta_3 DQueue_{M,t+1} + \beta_4 MKTRET_{M,t} + \beta_5 MKTRET_{M,t-1} + \beta_6 MKTRET_{M,t+1} + \beta_7 vola_{i,t} + \varepsilon_{i,t} \quad (8)$$

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. We use the market depth at the best bid and ask price as an index of order queue. This order queue proxy is calculated as total pound volume of orders submitted at the best bid and ask prices in the lit markets. $DQueue_{M,t}$, $DQueue_{M,t-1}$ 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. The market depth os stock i is excluded from the Estimates from Equations (8) . $MKTRET_{M,t}$, $MKTRET_{M,t-1}$ and $MKTRET_{M,t+1}$ are the FTSE100 index return on day t, $t-1$ and $t+1$. $Vola_{i,t}$ measures the volatility. It equals to the square term of return for stock i on day t.

INSERT TABLE 1 ABOUT HERE

Table 5 reports the impact of limit order queue on lit and dark trading activities. Panel A and B shows the results based on two estimation methods. Panel A shows the results from the average regression. With a 1% increase in limit order queue, individual stock trading activities in lit and dark markets will contemporaneously increase from 0.42% to 0.451% and 1.209% to 3.06% respectively, depending on the trading activity proxy. In Panel B all coefficients and t-statistics are calculated as the mean values across all stock regressions. Panel B suggests that with 1% increase in limit order queue individual stock trading activities in lit and dark markets will contemporaneously increase from 0.452% to 0.474% and 1.209% to 2.941% respectively.

Panel A and B show similar results. 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 Buti et al. (2015) and Kwan et al. (2015) that 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 the empirical evidence that when the limit 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.

4.5. Dark liquidity begets lit liquidity

We have shown that dark venues can potentially help market to gain liquidity and assist traders to reduce execution risk by jumping the limit order queue. Another related question to ask is how dark trading impact sequential trades on intrady level. To investigate this issue, we estimate the following regression:

$$Spread\_ratio_{i,t} = \alpha_1 + \beta_1 \frac{dark\_trading_{i,t}}{lit\_trading_{i,t}} + \beta_2 vola_{i,t} + \beta_3 MKTRET_{i,t} + \beta_4 depth_{i,t} + \beta_5 Time_t + \varepsilon_{i,t} \quad (9)$$

where Sets 1 $Spread\_ratio_{i,t} = \frac{spread_{dark\_trade+5}}{spread_{i,t}}$ and

Sets 2 $Spread\_ratio_{i,t} = \frac{spread_{dark\_trade+5}}{spread_{dark\_trade-5}}$

The first sets of spread ratio is the ratio between the averaged spread of 5 trades after dark trades and the daily average spread on lit venues for stock *i* on day *t*; the second set of spread ratio equal to the averaged spread of 5 trades after dark trades divided by the averaged spread of 5 trades before dark trades. All the average spread is calculated on time-weighed basis. The spread ratio aims to captrue the changes of spread after dark trades relative to the spread on lit venues. To make sure we well capture the spread change after dark trades, we calculate both quote spread and effective spread before and after dark trades in our regression results. Variable $\frac{dark\_trading_{i,t}}{lit\_trading_{i,t}}$ measures the propotion of dark trading to lit trading activity for stock *i* on day *t* and it includes three factors, trading volume, pound volume and the number of trades. Coefficient β_1 is out parameter of interests; it will tell how liquidity providers and market participants behave after dark trades. If β_1 is statistically significant and negative(positive), then liquidity providers tend to tighten (widen) the spread after dark trades. Therefore dark liquidity begets (drains) lit liquidity.

INSERT TABLE 6 ABOUT HERE

The rest of variables in model (9) are common control variables that have been applied in the literature. $vola_{i,t}$ is the stock-day volatility calculated as the standard deviation of intrday trade-by-trade midquote return. $MKTRET_{i,t}$ is the daily return of FTSE100. $Depth_{i,t}$ is the market depth at the best bid and ask price for stock *i* on day *t*. $Time_t$ is a trend variable that starts at zero at the beginning of the sample period and increases by one unit every trading day.

Panel A and B in Table 6 presents the results based on quote spread from model (5). In Panel A the spread ratio equals to the averaged quoted spread of 5 trades after dark trading divided by the daily averaged quoted spread. Coefficients of β_1 s are all negative and statistically significant. Column (1) confirms that as dark to lit volume increase by one percent, on average, the spread ratio will decline by 1.41%. Similarly, in column (2) and (3), if dark pound volume (number of trades) to lit pound volume (number of trades) goes up by 1%, the spread ratio reduces by 1.49% (3.12%).

Literature has documents that dark pool can encourage competition for liquidity provision in limit orders (Foucault and Menkveld, 2008). Consistent with exisitng literature, our results indicate that when dark trading activity increases relative to lit trading activity, the post-dark trade quoted spread tends to be tightened. This means that market participants are likely to interpret dark trades as uninfomred liquidity demand and therefore post narrower spread after each dark trade. This finding is also consistent with the studies which finds dark trades are less informative than lit trades (see for example Zhu, 2014, Ibikunle et al., 2018).In Panel B, the set 2 spread ratio tells an identical story. With more dark trading relative to lit trading activity, the post dark trade effective spread tends to be narrower compared to the spread before the dark trade. Hence, dark liquidity begets lit liquidity.

In control varibles, $vola_{i,t}$ exhibits positive and statistically significant coefficient. This is in line with fact that market makers will widen spread to get compensated for uncertainty when market is volatile. $MKTRET_{i,t}$ also shows positive and statistically significant coefficients, which is consistent with Alzahrani et al. (2013) that market return has a positive effect on price impact of large trades. depth is negatively correlated with spread ratio. As we suggested, $Depth_{i,t}$ measures the stock-day limit order queue. If market depth increases, more orders are waiting in the queued to be executed and traders are incentivised to route their order to dark venues and therefore spread ratio shall reduced with increased dark trading activities.

In Panel C and D, we repeat our test with for spread ratios measured by effective spread and we find very similar results. We have shown that the bid-ask spread after each dark trade tends to be narrower. Hence more liquidity is likely to occur on lit venues. Our evidence suggest that dark liquidity begets lit liquidity[3].

5. Dark volume cap – a natural experiment study

In this section, we analyze how dark volume cap in MiFID II affects the market quality using data surrounding policy changes in London Equity markets.

5.1. Impacot of Dark volume cap

In europe, policy makers' concerns are focused on the rapid growth of dark pool trading and its opcity that might distort price discovery process. With increasing concern over dark pool trading, regulators seek to bring more transparency to equity markets by forcing trading onto RMs and MTFs and implement the most restrictive rules to regulate dark trading. Dark pools now have twin volume cap, meaning that only 4% of a stock can be traded in any single dark venue and only 8% of total volume can be traded across all dark pools. ESMA is responsible for calculating the dark volume over the 12-month backwardation. If the cap is hitted, then suspension will come into effect on the specific venue or all dark venues for 6 month. It worth to note that the dark volume cap was originally expected to launch on 3rd January 2018. However, ESMA decided to delay the implementation of dark volume cap to 12th March 2018 due to insufficient data issue.

It still remain to see what is the real impact of DVC on equity market. In this section, we employ the implementation of DVC of a natrual experiment. We consider the implementation of dark trading cap on March 12 2018 to be the event that might shock the London equity market. This exogenous shocks ~~field experiment~~ provides a unique opportunity to apply difference-in-differences estimate to investigate the effect of DVC to market quality.

[3] So far we use the five-trade benchmark to calculate spread ratio in model (9). We also repeat the test with ten-trade benchmark and we find highly consistent results. We put this part in Appendix.

Our experiment has advantage of eliminating the selection issue that can impact causal inference of market quality measures.

5.2.Data and model design

The data sample in this section consists of FTSE100 stocks and FTSE250 stocks data from the four main markets where these stocks trade – the LSE, BATS Europe, Chi-X Europe and Turquoise. These 350 includes the 350 largest firms listed on the LSE. These firms account for more than 90% of the total market capitalisation of the FTSE. Our sample covers from 11th January to 11th May 2018, two months before and two month after the implementation of DVC. The four-month window is carefully constructed considering the following tradeoff. If the window is too wide, the analysis around the regulation can be influenced by confounding factors that are unrelated with dark trading; if the window is too narrow, the analysis will lack power and will not sufficiently capture the changes in market quality and trading behaviours[4].

We obtain the intraday quote and price data from the TRTH and combine tick-level data. The core of our study is to employ the implementation of DVC as a natural experiment and source of exgenous shock to identify the causal effects of dark trading. To apply difference-in-differences estimation. We carefully construct treatment and control groups. In FTSE100 constituents, we find that 90 stocks that are affected by DVC and 10 stocks does not affected by DVC at all. In our treatment group, we include the 90 stocks whose dark trading has been consistently capped from FTSE100 index after the first two months of regulation. The control group consists of 10 FTSE100 stocks and the 112 stocks from FTSE 250 index. All these 122 stocks are not affected by DVC during our sample period.

To fully explore this laboratory-like experiment in financial markets, we estimate the following OLS estimation:

[4] Similar window size has been applied by Foley and Putnins (2016) and Comerton-Forde et al. (2018)

$$y_{i,t} = \alpha_1 + \beta_1 Post_t * Tret_i + \beta_2 Post + \beta_3 Tret_{i,t} + \delta^{'} X_{i,t} + \varepsilon_{i,t}$$

where $y_{i,t}$ is liquidity measures including qouted spread, effective spread, amihud ratio and market depth for each stock on each day. We also include the absolute autocorrelation of trade-by-trade midpoint return as informational efficiency for each stock on each day. This variable manages to capture the transitory deviation, which could be caused by order imbalances and imperfect liquidity (Foley and Putniņš, 2016).

We denote $Post_t$ a dummy variable that equals to 1 for trading days in the first two months of dark trading cap, March 12 to May 11 2018. $Tret_i$ is a dummy variable that equals to 1 if the stock belong to our treatment group, otherwise 0. $Post_t \times Tret_i$ captures the impact of dark trading cap on treatment group. $X_{i,t}$ is a set of control variables: the inverse of price, daily volatility of trade-by-trade midpoint return and daily return of the stock. We also include the time trends factor and firm fixed effects that control for invariant difference in stocks.

5.3.Empirical analysis

Table 7 reports the statistical analysis of our sample stocks in before and after the implementation of DVC. Panel A shows that, during 11th January to 11th May 2018, the percentage of dark trading of 90 FTSE100 stocks in our treatment group reduce from, the percentage of dark trading falls from 4.84% to zero. Meanwhile, the average proportional quoted spread and effective spread increased from 0.0% to 0.062% and 0.15% to 0.447% respectively. Furthermore the log value of daily market depth also declined from 25.468 to 25.394. We do witness a reduction in illqidity ratio amihud and an improvement in informational inefficiency and autocorrelation of intraday return. However, we will draw more detailed and realible results from our difference-in-difference estimatie later.

INSERT TABLE 7 ABOUT HERE

Panel C and D presents the descriptive results of control group before and after the regulation. With uncapped dark trading, the illiquidity ratios quoted spread and amihud ratio reduce from 0.777% to 0.665% and from 863.518 to 416.593 respectively. We also witness that the natrual log of market depth increases from 22.464 to 22.537. It seems , compared with the capped stocks, exisitng dark pools play a positive role in faciliating liquidity after the regulation. However, we do observe that effective spread increases from 0.562% to 0.996% after the regulation. To make sure we choose the apporiate control group, we calculate the differences of key variables between treatment and control group and present the results in Panel E. We find that none of the difference is statistically distinguishable from zero. These results ensure that stocks in the treatment group and control groups share similarity in many diamensions.

INSERT TABLE 8 ABOUT HERE

Table 8 presents the results from model (7). The coefficients of $QuotedSpread_{i,t}$ and $Amihud_{i,t}$ increase by about 0.07 and 0.22 respectively for our treatment group compared to the control group. This changes is statistically significant at 1%. We also find a statistically significant decrease of 0.202 in $Depth_{i,t}$ in treatment group. So far the results suggest that after the regulation the transaction cost increases for stocks affected by DVC, leading a wealth transfer regime from liquidity takers to liquidity providers. Due to the emergence of dark trading cap, the intervenue competition pressure for orderflow declines and therefore market makers are less incentised in posting the best quote. As a results, bid-ask spread on lit venues tend to be widened and transaction cost consequently increases. Furthermore, we also witness the $EffectiveSpread_{i,t}$ has a positive coefficient, but its *t*-value is not statistically significant. Column (5) suggests that $Autocorrelation_{i,t}$ generates a negative coefficient at 1% statistical significance level. This indicates that the price efficiency in our treatment group increased after the regulation. This result is consistent with Xin and H. (2006) that large transaction cost might improve pricing efficiency by making it more expensive for front-runners to jump the exisiting order queue[5]. In another word, large spread reduces front-running risk and increases the profit for informed traders, prompting price efficiency.

6. Conclusion:

This paper uncovers the first set of evidence aimed at informing our understanding of the dynamics of dark liquidity. We compare and contrast the liquidity comovement of FTSE100 stocks in lit and dark venues from January 2015 to May 2018. 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 queue bulks up. This finding is consistent with He and Lepone (2014) and Kwan et al. (2015). We further test what drives dark liquidity and our evidence suggests that more dark liquidity is likely to occur when limit order queue bulks up, which is consistent with queue jumping hypothesis suggested by Buti et al. (2015) and Kwan et al. (2015).

We also provide empirical evidence of a causal impact of a the implementation of dark trading cap under MiFID II. We show that stocks with zero dark liquidity under trading cap experienced an increase in transcation cost and deterioration in market depth. Without the competitative pressure for orderflow, market makers in lit venues have more monoploy power in determining the spread. This leads to a larger transaction cost and wealth transfer from liquidity takers to liquidity providers.

[5] However our results are inconsistent with Parlour and Rajan (2005) that large transaction cost makes liquidity traders to trade less aggressive and reduces price efficiency.

Our evidence reveals the bright side of dark liquidity. Our finding is consistent with Buti et al. (2011), He and Lepone (2014) Comerton-Forde and Putniņš (2015) and Brugler (2015) that dark pool trading seems do not have detrimental impact on market liquidity. Obviously, more theoretical and empirical research is needed 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

Alzahrani, A. A., Gregoriou, A. & Hudson, R. 2013. Price impact of block trades in the Saudi stock market. *Journal of International Financial Markets, Institutions and Money,* 23**,** 322-341.

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

Brockman, P. & Chung, D. Y. 2008. Commonality under market stress: Evidence from an order-driven market. *International Review of Economics & Finance,* 17**,** 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., Consonni, F., Rindi, B., Wen, Y. & Werner, I. M. 2015. Sub-penny and queue-jumping.

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

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

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

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

Comerton-Forde, C. 2017. Shedding light on dark trading in Europe *CEPR-Imperial-Plato Inaugural Market Innovator (MI3) Conference*

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

Coughenour, J. F. & Saad, M. M. 2004. Common market makers and commonality in liquidity. *Journal of Financial Economics,* 73**,** 37-69.

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

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

Foucault, T. & Menkveld, A. J. 2008. Competition for Order Flow and Smart Order Routing Systems. *The Journal of Finance,* 63**,** 119-158.

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

He, W. P. & 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. & Mendelson, H. 2000. Crossing Networks and Dealer Markets: Competition and Performance. *The Journal of Finance,* 55**,** 2071-2115.

Huberman, G. & Halka, D. 2001. SYSTEMATIC LIQUIDITY. *Journal of Financial Research,* 24**,** 161-178.

Ibikunle, G., Aquilina, M., Sun, Y. & Ivan, D.-R. 2018. City goes dark: dark trading and adverse selection in aggregate markets. *Working Paper*.

Jain, P. K., Jiang, C., Mcinish, T. H. & 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. & Sadka, R. 2008. The divergence of liquidity commonality in the cross-section of stocks. *Journal of Financial Economics,* 89**,** 444-466.

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

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

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

Nimalendran, M. & 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. & White, R. W. 2001. Upstairs Market for Principal and Agency Trades: Analysis of Adverse Information and Price Effects. *The Journal of Finance,* 56, 1723-1746.

Xin, Z. & H., C. K. 2006. Decimal Pricing and Information‐Based Trading: Tick Size and Informational Efficiency of Asset Price. *Journal of Business Finance & Accounting,* 33, 753-766.

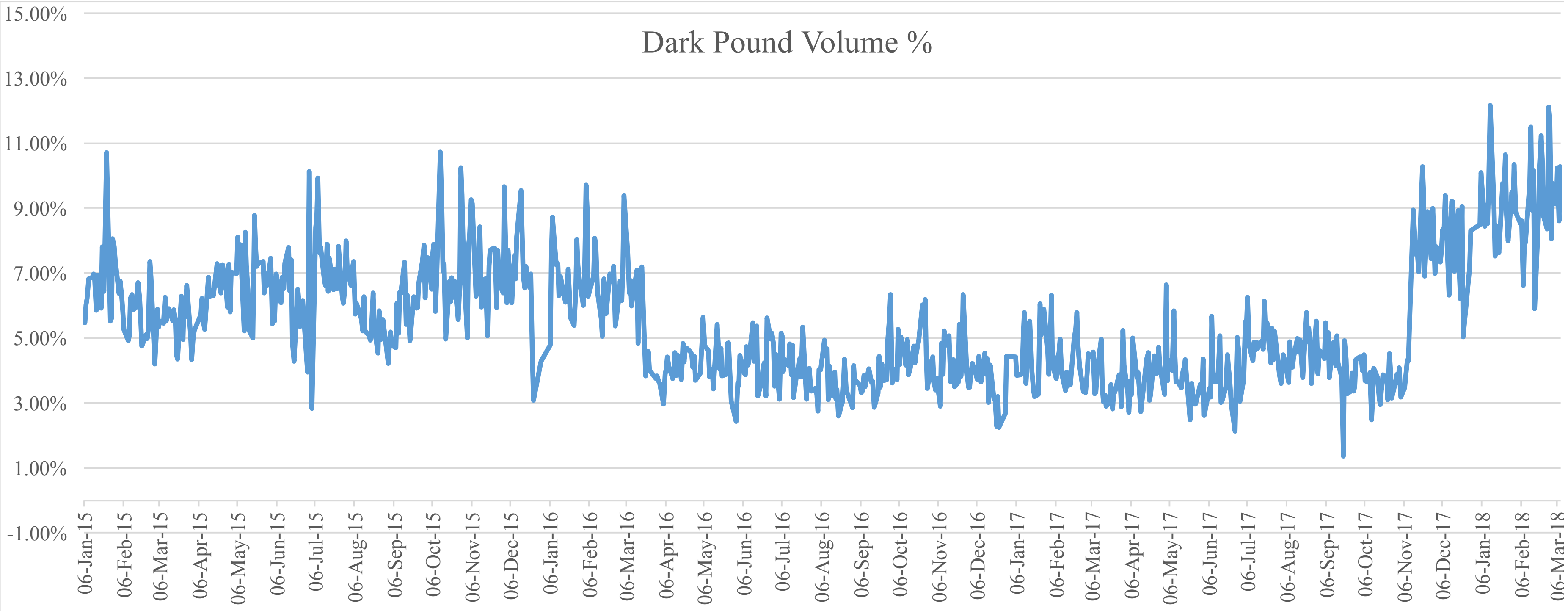
Ye, M. 2011. A Glimpse into the Dark: Price Formation, Transaction Cost and Market Share of the Crossing Network. *Working Paper*.

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

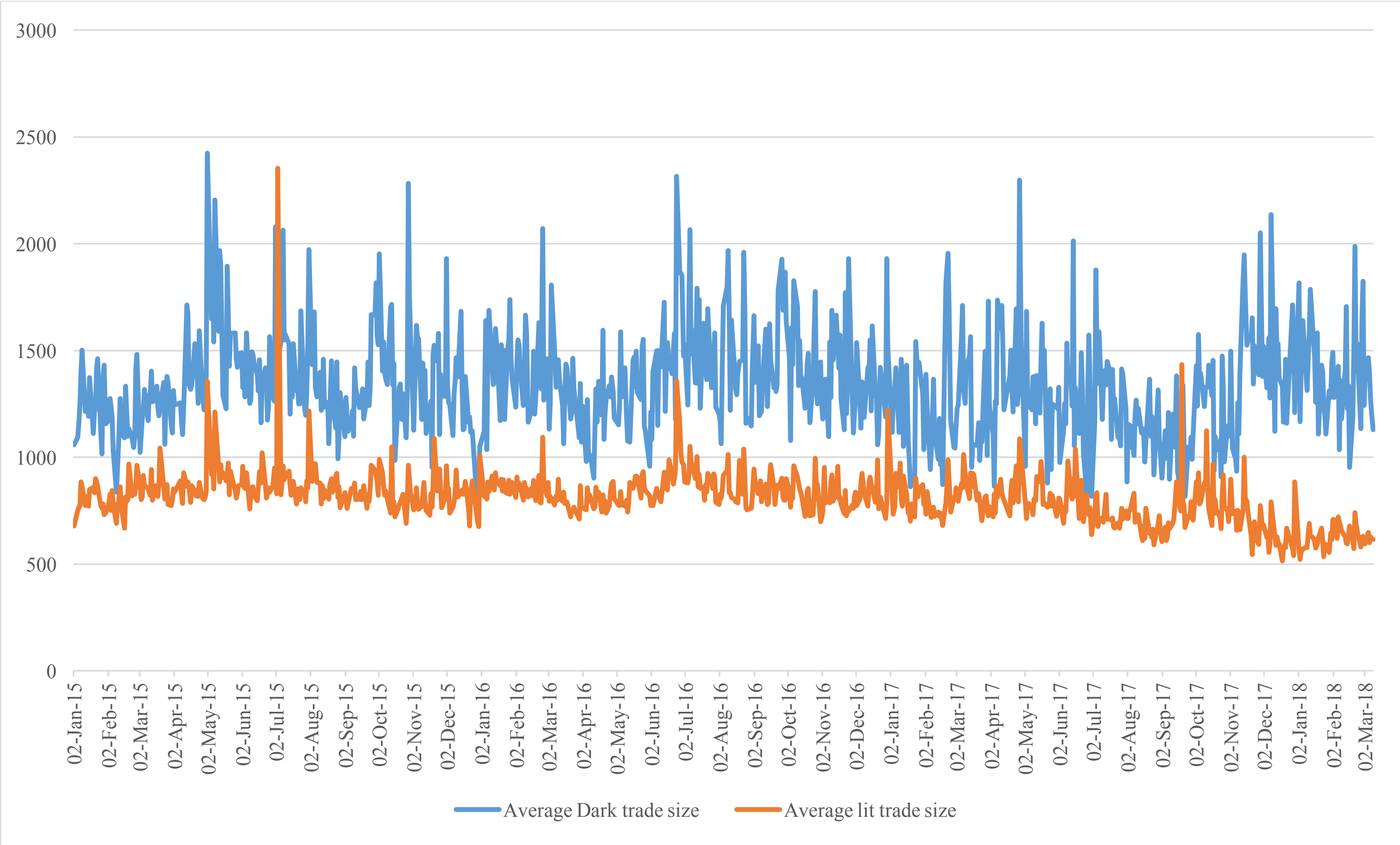
Figure 1: Trading values

Panel A plots the lit and dark pound trading values for 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 January 2015 to 11th March 2018. Panel B plots the average pound sizes per day of lit and dark trades.

PANEL A



PANEL B



3000
2500
2000
1500
1000
500
0
02-Jan-15
02-Feb-15
02-Mar-15
02-Apr-15
02-May-15
02-Jun-15
02-Jul-15
02-Aug-15
02-Sep-15
02-Oct-15
02-Nov-15
02-Dec-15
02-Jan-16
02-Feb-16
02-Mar-16
02-Apr-16
02-May-16
02-Jun-16
02-Jul-16
02-Aug-16
02-Sep-16
02-Oct-16
02-Nov-16
02-Dec-16
02-Jan-17
02-Feb-17
02-Mar-17
02-Apr-17
02-May-17
02-Jun-17
02-Jul-17
02-Aug-17
02-Sep-17
02-Oct-17
02-Nov-17
02-Dec-17
02-Jan-18
02-Feb-18
02-Mar-18
Average Dark trade size
Average lit trade size

Figure 2: Spread ratio

This figure shows the construction of spread ratio. Two sets of spreat ratios are calculated in the following

Set 1 $Spread\_ratio_{i,t} = \frac{spread_{dark\_trade+5}}{spread_{i,t}}$ and Set 2 $Spread\_ratio_{i,t} = \frac{spread_{dark\_trade+5}}{spread_{dark\_trade-5}}$

where $spread_{dark\ trade\text{-}5}$ ($spread_{dark\ trade+5}$) is the averaged spread of five trades before (after) the execution of dark trade. $Spread_{\ i,t}$ is the daily average spread. We calculate both quoted spread and effective spread and all calculation is based on time-weighted average.

date	time	trades type	spread
...	...	...	...
10/03/2016	16:30:00	lit	0.002
...	...	...	...
11/03/2016	11:03:00	lit	0.002
11/03/2016	11:03:01	lit	0.002
11/03/2016	11:03:02	lit	0.001
11/03/2016	11:03:02	lit	0.001
11/03/2016	11:03:02	lit	0.001
11/03/2016	11:03:02	lit	0.0005
11/03/2016	11:03:03	lit	0.0005
11/03/2016	11:03:03	dark	0.0005
11/03/2016	11:03:03	lit	0.001
11/03/2016	11:03:04	lit	0.001
11/03/2016	11:03:04	lit	0.0008
11/03/2016	11:03:04	lit	0.0007
11/03/2016	11:03:04	lit	0.0006
11/03/2016	11:03:04	lit	0.0003
11/03/2016	11:03:04	lit	0.0003
...	...	...	...
14/03/2016	08:01:04	lit	0.0003
...	...	...	...

$spread_{i,t}$

$spread_{dark\_trade-5}$

$spread_{dark\_trade+5}$

Table 1: Descriptive statistics

This table reports means, standard deviations, and quartile points (25%, Median, 75%) for 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. *Dark QuotedSpread* is the time-weighted proportional quoted spread that matched for dark trades. *Lit QuotedSpread* is the time-weighted proportional quoted spread on lit venues. *Dark EffectiveSpread* is the time-weighted proportional effective spread that matched for dark trades. *Lit EffectiveSpread* is the time-weighted proportional effective spread on lit venues. Dark and Lit Amihud are the Amihud ratio for lit and dark venus. Both of them are adjusted by 1 billion shares. These measures write as follows:

$$LitAmihud_{i,t} = \left| \frac{r_{close-to-open,i,t}}{lit\_volume_{i,t}(billion)} \right| \qquad DarkAmihud_{i,t} = \left| \frac{r_{close-to-close,i,t}}{dark\_volume_{i,t}(billion)} \right|$$

The sample period covers 1st January 2015 and 11th March 2018. All variables are averaged for each stock-day.

Variable	Mean	25th Pctl	Median	75th Pctl	Std Dev
Lit volume	10547264.910	1349383.000	3235936.000	8539163.000	28889766.590
Dark volume	616384.590	49147.000	145500.000	441301.000	2083274.250
Dark/Lit volume	5.760%	2.588%	4.468%	7.358%	0.050
Lit Pound volume	52215442.440	17525301.420	31121458.210	66312397.310	58466478.400
Dark pound volume	2809780.240	616755.270	1440522.460	3336414.990	4317225.440
Dark/Lit pound volume	5.522%	2.525%	4.323%	7.075%	0.0472512
Number of lit trades	11129.240	4782.000	7602.000	13437.000	10409.720
Number of dark trade	405.935	117.000	243.500	495.000	517.151
Number of dark trades/number of lit trades	3.70%	1.82%	2.97%	4.69%	0.0297499
Dark QS	0.095%	0.058%	0.084%	0.114%	0.1104
Lit QS	0.061%	0.040%	0.056%	0.078%	0.0337
Dark ES	0.036%	0.021%	0.030%	0.041%	0.0005
Lit ES	0.069%	0.040%	0.056%	0.077%	0.0062
Dark Amihud	311.661	13.852	51.677	170.934	5911.980
Lit Amihud	5.985	0.608	2.020	5.814	13.787

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:

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \beta_4 MKTRET_{M,t} + \beta_5 MKTRET_{M,t-1} + \beta_6 MKTRET_{M,t+1} + \beta_7 vola_{i,t} + \varepsilon_{i,t}$$

$DL_{i,t}$ 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, quoted spread, effective spread and Amihud ratio for both lit and dark venues. $DL_{i,t}$ will be tested as lit liquidity and dark liquidity respectively. Lit and dark Amihud 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 volume of shares, number of trades, pound volume, quoted spread, effective spread and Amihud ratio. $MKTRET_{M,t}$, $MKTRET_{M,t-1}$, $MKTRET_{M,t+1}$, are the concurrent, one-day lag and lead of percentage change in FTSE100 return. $Vola_{i,t}$ is the volatility which measured by the square term of daily return for stock i in t. Panel A reports the results from the average regression while Panel B shows the mean coefficients and t-values across all stock regressions. 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 January 2015 and 11th March 2018.

Panel A	Lit venues						Dark venues					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Quote Spread*	*Effective Spread*	*Amihud*	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Quote Spread*	*Effective Spread*	*Amihud*
$DL_{m,t}$	0.550***	0.544***	0.700***	0.465***	0.007***	1.011***	0.989***	1.246***	3.513***	0.643***	0.000	1.161***
	(54.89)	(53.95)	(60.20)	(54.76)	(9.70)	(14.45)	(34.98)	(25.10)	(6.61)	(27.91)	(0.21)	(9.62)
				-	-							
$DL_{m,t-1}$	-0.042***	-0.043***	-0.044***	0.049***	0.004***	-0.093*	-0.090***	-0.110***	0.042	-0.046***	0.002	-0.028
	(-6.40)	(-6.44)	(-7.90)	(-12.63)	(-9.49)	(-1.69)	(-4.40)	(-3.63)	(0.76)	(-4.65)	(1.56)	(-0.30)
				-	-							
$DL_{m,t+1}$	0.012**	0.011*	-0.012**	0.033***	0.001***	-0.033	0.093***	0.210***	0.490***	-0.030***	-0.001*	-0.011
	(2.03)	(1.83)	(-2.41)	(-8.92)	(-4.83)	(-0.59)	(4.73)	(7.18)	(4.64)	(-3.33)	(-1.68)	(-0.12)
Observations	64269	64269	64269	64269	64269	64269	64269	64269	64269	64269	64269	64269
Adj R-squared mean	20.53%	20.10%	29.13%	9.13%	2.24%	2.82%	4.59%	0.87%	7.66%	2.59%	0.04%	2.03%

Table 2 - *continued*

Panel B	Lit venues						Dark venues					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Quote Spread*	*Effective Spread*	*Amihud*	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Quote Spread*	*Effective Spread*	*Amihud*
$DL_{m,t}$	0.536***	0.714***	0.681***	0.459***	1.201*	1.173*	1.262***	1.637***	1.441***	0.642***	0.011	5.426**
	(5.68)	(8.46)	(6.67)	(5.48)	(1.66)	(1.66)	(2.67)	(3.21)	(4.26)	(3.00)	(-0.80)	(2.51)
$DL_{m,t-1}$	0.536	-0.026	-0.041	-0.071	0.045	-0.087	-0.101	-0.071	-0.058	-0.050	-0.004	25.693
	(-0.67)	(-0.46)	(-0.80)	(-1.54)	(0.46)	(-0.19)	(-0.43)	(-0.31)	(-0.41)	(-0.68)	(-0.63)	(0.04)
$DL_{m,t+1}$	0.013	0.012	-0.010	-0.057	0.008	-0.001	0.251	0.291	0.127	-0.075	-0.008	0.826
	(0.19)	(0.19)	(-0.17)	(-1.08)	(-0.37)	(-0.79)	(0.73)	(0.76)	(0.39)	(-0.47)	(-1.02)	(-0.01)
Observations	64269	64269	64269	64269	64269	64269	64269		64269	64269	64269	64269
Adj R-squared mean	22.70%	26.17%	31.37%	10.93%	29.46%	3.15%	6.07%	6.93%	8.27%	3.48%	0.00%	4.52%

Table 3. A specification test

This table reports the cross-equation correlation of estimation errors. We first sort 108 stock alphabetically using ticker symbols and assign each stock a serial number i (i=1, … , 108). We then estimate the following models: $\varepsilon_{1i+1,t} = \theta_0 + \theta_1 \varepsilon_{1i,t} + \mu_{1i,t}$ and $\varepsilon_{2i+1,t} = \delta_0 + \delta_1 \varepsilon_{2i,t} + \mu_{2i,t}$ where $\varepsilon_{1i,t}$, $\varepsilon_{2i,t}$ are residuals for stock i in lit and dark venues respectively from regression model (3). $\mu_{1i,t}$ and $\mu_{2i,t}$ are disturbance terms. Panel A shows our test results of cross-equation dependence in lit venues and Panel B presnets the results from dark venues.

Panel A

Lit Venues	Average correlation	average t-statistic	$\|t\|$ > 1.96 (percent)
Volume of shares	-0.011	-0.096	5.79%
Pound Volume	-0.010	-0.093	5.42%
Number of trades	-0.010	-0.086	5.29%
Quote Spread	-0.015	-0.129	4.03%
Effective Spread	-0.015	-0.145	6.42%
Amihud	-0.015	-0.127	2.64%

Table 3 - *continued*

Panel B

Dark Venues	Average correlation	average t-statistic	|t| > 1.96 (percent)
Volume of shares	-0.017	-0.154	5.16%
Pound Volume	-0.018	-0.159	3.40%
Number of trades	-0.016	-0.143	3.65%
Quote Spread	-0.017	-0.151	5.29%
Effective Spread	-0.016	-0.145	4.66%
Amihud	-0.020	-0.164	2.27%

Table 4. Asymmetry in liquidity commonality in lit and dark venues under different market conditions

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

$$DL_{i,t} = \alpha_1 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t+1} + \beta_4 MKTRET_{M,t} + \beta_5 MKTRET_{M,t-1} + \beta_6 MKTRET_{M,t+1} + \beta_7 vola_{i,t} + \varepsilon_{i,t}$$

$DL_{i,t}$ 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, quoted spread, effective spread and Amihud ratio for both lit and dark venues. $DL_{i,t}$ will be tested as lit liquidity and dark liquidity respectively. Lit and dark Amihud 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 volume of shares, number of trades, pound volume, quoted spread, effective spread and Amihud ratio. $MKTRET_{M,t}$, $MKTRET_{M,t-1}$, $MKTRET_{M,t+1}$, are the concurrent, one-day lag and lead of percentage change in FTSE100 return. $Vola_{i,t}$ is the volatility which measured by the square term of daily return for stock *i* in *t*. Panel A (Panel B) presents the result of the average regression when market-wide liquidity increases (decreases). Panel C (Panel D) presents the averaged result across all stock regression when market-wide liquidity increases (decreases). ELC ratio equals to the ELC when market-wide liquidity increases divided by the ELC when market-wide liquidity increases. 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 January 2015 and 11th March 2018.

Panel A. When Market experiences increases

	Lit venues						Dark venues					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Quote Spread*	*Effective Spread*	*Amihud*	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Quote Spread*	*Effective Spread*	*Amihud*
$DL_{m,t}$	0.432***	0.638***	0.585***	0.507***	0.012***	1.128***	1.537***	1.860***	4.784***	0.740***	0.073***	1.027***
	(29.84)	(46.70)	(43.77)	(28.01)	(2.93)	(6.30)	(16.58)	(18.58)	-5.48	(16.05)	(3.04)	(2.77)
$DL_{m,t-1}$	-0.099***	-0.050***	-0.050***	-0.051***	-0.003***	-0.159**	-0.571***	-0.260***	-0.072	-0.047***	0.006***	-0.172
	(-8.28)	(-3.98)	(-4.37)	(-11.63)	(-6.49)	(-2.42)	(-8.56)	(-3.82)	(-0.80)	(-4.03)	(3.77)	(-1.20)
$DL_{m,t+1}$	0.097***	0.081***	0.030***	-0.055***	-0.001*	-0.081	0.324***	0.434***	0.462***	-0.043**	0.000	-0.060
	(9.37)	(6.62)	-2.82	(-7.43)	(-1.71)	(-1.14)	(6.02)	(6.77)	(5.41)	(-2.23)	(0.35)	(-0.40)
Constant	0.043***	0.030***	0.028***	0.010***	-0.009***	1.190***	0.401***	0.406***	-0.066	0.043***	0.034***	2.065***
	(12.28)	(9.28)	-11.01	(11.01)	(-10.37)	(28.08)	(20.39)	(20.49)	(-0.54)	(17.72)	(5.19)	(23.27)
Observations	31081	31563	31728	32705	32548	32233	31081	31563	31728	32705	32548	32233
R-squared	16.98%	18.86%	23.33%	4.68%	0.71%	1.57%	4.71%	1.18%	9.74%	1.24%	0.04%	1.58%

Table 4 - *continued*

Panel B. When Market experiences decreases

	Lit venues						Dark venues					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Quote Spread*	*Effective Spread*	*Amihud*	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Quote Spread*	*Effective Spread*	*Amihud*
$DL_{m,t}$	0.700***	0.913***	0.971***	0.513***	0.005***	1.168***	1.242***	1.497***	1.672***	0.690***	-0.002	1.018***
	(34.63)	(45.89)	(55.32)	(35.67)	(8.05)	(5.95)	(12.74)	(14.85)	(15.56)	(16.38)	(-1.40)	(9.04)
$DL_{m,t-1}$	0.007	-0.004	-0.022***	-0.039***	0.000	0.230	0.042	0.001	-0.064*	-0.020	0.013	0.102
	(0.92)	(-0.49)	(-3.75)	(-5.02)	(0.06)	(1.32)	(1.20)	(0.04)	(-1.73)	(-1.03)	(0.44)	(0.96)
$DL_{m,t+1}$	-0.022***	0.008	0.026***	-0.024***	-0.002***	0.004	0.049	0.115***	0.070**	-0.024**	-0.003***	0.073
	(-3.10)	(1.09)	(4.47)	(-5.84)	(-3.72)	(0.03)	(1.45)	(3.03)	-2.14	(-2.33)	(-2.79)	(0.83)
Constant	0.012***	0.021***	0.010***	-0.006***	0.017***	1.879***	0.507***	0.506***	0.389***	0.021***	0.071***	1.037***
	(3.40)	(6.14)	(3.84)	(-6.82)	(16.64)	(25.55)	(29.10)	(30.18)	-21.96	(8.79)	(8.60)	(24.48)
ELC ratio	0.617***	0.699***	0.602***	0.988***	2.40***	0.966***	1.238***	1.242***	2.861***	1.072***	-36.000	1.009***
Observations	33188	32706	32541	31564	31721	32036	33188	32706	32541	31564	31721	32036
R-squared	10.60%	12.75%	16.71%	9.82%	3.58%	2.02%	1.80%	0.30%	1.66%	2.79%	0.06%	2.97%

Table 4 - *continued*

Panel C. When Market experiences increases

	Lit venues						Dark venues					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Quote Spread*	*Effective Spread*	*Amihud*	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Quote Spread*	*Effective Spread*	*Amihud*
$DL_{m,t}$	0.495***	0.670***	0.657***	0.510***	-0.025	1.201	0.834***	1.977***	1.554***	0.704*	-0.003	0.808***
	(3.26)	(5.03)	(5.53)	(2.936)	(-0.75)	(0.648)	(2.06)	(2.30)	(3.20)	(1.68)	(-0.09)	(2.91)
$DL_{m,t-1}$	0.473	-0.043	-0.044	-0.080	-0.009	-0.172	0.834	-0.256	-0.144	-0.049	-0.002	0.056
	(-0.77)	(-0.38)	(-0.41)	(-1.547)	(-1.27)	(-0.364)	(-0.68)	(-0.44)	(-0.35)	(-0.62)	(-0.34)	(-0.11)
$DL_{m,t+1}$	0.099	0.076	0.024	-0.079	-0.001	0.023	0.353	0.498	0.248	-0.074	-0.016	0.182
	(0.82)	(0.60)	(0.21)	(-0.830)	(-0.76)	(-0.423)	(0.83)	(0.62)	(0.34)	(-0.32)	(-1.12)	(-0.10)
Observations	31081	31563	31728	32705	32548	32233	31081	31563	31728	32705	32548	32233
R-squared	17.50%	19.60%	25.40%	7.17%	5.64%	1.36%	5.00%	7.02%	8.25%	1.71%	0.00%	7.90%

Table 4 – *continued*

Panel D. When Market experiences decreases

	Lit venues						Dark venues					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Quote Spread*	*Effective Spread*	*Amihud*	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Quote Spread*	*Effective Spread*	*Amihuc*
$DL_{m,t}$	0.669***	0.874***	0.960***	0.553***	1.228	1.225	0.954*	1.296***	1.589**	0.682**	-0.008	2.705
	(3.49)	(4.41)	(5.535)	(3.98)	(1.491)	(1.01)	(1.65)	(4.324)	(2.13)	(2.03)	(-0.85)	(0.54)
$DL_{m,t-1}$	0.669	0.012	-0.017	-0.057	0.663	0.117	0.994	0.068	-0.006	-0.028	-0.192	0.209
	(0.16)	(0.00)	(-0.332)	(-0.56)	(0.068)	(0.02)	(0.11)	(-0.023)	(-0.22)	(-0.23)	(-0.03)	(0.07
$DL_{m,t+1}$	-0.031	0.001	0.013	-0.052	-0.071	0.005	0.026	0.075	0.090	-0.074	0.002	0.589
	(-0.45)	(0.02)	(0.302)	(-0.80)	(0.330)	(-0.48)	(0.09)	(0.280)	(0.22)	(-0.41)	(-0.41)	(-0.09
ELC ratio	0.740***	0.767***	0.684***	0.922***	-0.020	0.980	0.874*	1.545***	0.978**	1.03*	0.375	0.298
Observations	33188	32706	32541	31564	31721	32036	33188	32706	32541	31564	31721	32036
R-squared	10.10%	12.43%	16.40%	13.09%	32.62%	4.30%	1.76%	1.90%	2.64%	3.89%	0.00%	3.11%

Table 5. What drive dark pool trading activity

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

$$DL_{i,t} = \alpha_1 + \beta_1 DQueue_{M,t} + \beta_2 DQueue_{M,t-1} + \beta_3 DQueue_{M,t+1} + \beta_4 MKTRET_{M,t} + \beta_5 MKTRET_{M,t-1} + \beta_6 MKTRET_{M,t+1} + \beta_7 vola_{i,t} + \varepsilon_{i,t}$$

$DL_{i,t}$ is, for stock *i*, the percentage change (D) from trading day_{t-1} to day_t in trading activity variables,including volume of shares, number of trades and pound volume. $DL_{i,t}$ will be tested as lit liquidity and dark liquidity respectively. $DQueue_{M,t}$, $DQueue_{M,t-1}$ 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) offer insights into the impact of liquidity constraints in lit venues on dark pool trading share of trading. $MKTRET_{M,t}$, $MKTRET_{M,t-1}$, $MKTRET_{M,t+1}$, are the concurrent, one-day lag and lead of percentage change in FTSE100 return. $Vola_{i,t}$ is the volatility which measured by the square term of daily return for stock *i* in *t*. Panel A reports the results from the average regression while Panel B shows the mean coefficients and *t*-values across all stock regressions. 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 January 2015 and 11th March 2018.

Panel A	Lit venues			Dark venues		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Volume Of shares*	*Pound Volume*	*Number of trades*
$Ddepth_{m,t}$	0.451***	0.450***	0.420***	1.209***	1.217***	3.060***
	(34.50)	(34.25)	(32.93)	(19.86)	(19.80)	(5.53)
$Ddepth_{m,t-1}$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000
	(-18.97)	(-19.21)	(-21.10)	(-9.51)	(-9.56)	(-1.02)
$Ddepth_{m,t+1}$	-0.049***	-0.050***	-0.047***	0.053***	0.052**	0.421***
	(-11.27)	(-11.64)	(-12.40)	(2.63)	(2.52)	(3.74)
Constant	0.126***	0.127***	0.102***	0.770***	0.774***	0.406***
	(18.78)	(18.94)	(18.73)	(23.68)	(23.69)	(4.88)
Observations	64269	64269	64269	64269	64269	64269
R-squared	19.32%	19.14%	23.26%	5.17%	5.11%	9.55%

Table 5 - *continued*

Panel B	Lit venues			Dark venues		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Volume Of shares*	*Pound Volume*	*Number of trades*	*Volume Of shares*	*Pound Volume*	*Number of trades*
$DL_{m,t}$	0.473***	0.474***	0.452***	1.207***	1.223***	2.941***
	(4.28)	(4.28)	(4.143)	(3.55)	(3.573)	(2.99)
$DL_{m,t-1}$	0.000	0.000	0.000	0.000	0.000	0.000
	(-1.80)	(-1.82)	(-1.949)	(-0.95)	(-0.945)	(-0.62)
$DL_{m,t+1}$	-0.038	-0.039	-0.035	0.117	0.120	0.430
	(-0.97)	(-1.01)	(-1.051)	(0.30)	(0.320)	(0.59)
Constant	0.110	0.11	0.087	0.749	0.753	0.323
	(1.61)	(1.62)	(1.57)	(2.16)	(2.17)	(1.51)
Observations	64269	64269	64269	64269	64269	64269
R-squared	22.10%	21.96%	26.14%	6.78%	6.76%	14.32%

Table 6. Dose dark liquidity begets lit liquidity ?

Panel A, B, C and D reports the coefficient results for the following stock day panel regression

$$Spread\_ratio_{i,t} = \alpha_1 + \beta_1 \frac{dark\_trading_{i,t}}{lit\_trading_{i,t}} + \beta_2 volatility_{i,t} + \beta_3 MKTRET_{i,t} + \beta_4 depth_{i,t} + \beta_5 Time_t + \varepsilon_{i,t}$$

where Sets 1 $Spread\_ratio_{i,t} = \frac{spread_{dark\_trade+5}}{spread_{i,t}}$ and Sets 2 $Spread\_ratio_{i,t} = \frac{spread_{dark\_trade+5}}{spread_{dark\_trade-5}}$

$spread_{dark\ trade+5}$ is the time-weighted spread of ten trade subsequent to each dark trade; $spread_{dark\ trade-5}$ is the time-weighted spread of ten trade before each dark trades. $spread_{i,t}$ is the time-weighted average spread calculated stock-day. QS and ES represent quoted spread and effective spread respectively. $Volatility_{i,t}$ is the daily standard deviation of midquote return. $MKTRET_{i,t}$ is the daily return of FTSE100 index. $Depth_{i,t}$ is measures the pound volume of total order submitted at the best bid and ask price. $Time_t$ is a trend variable that starts at zero at the beginning of the sample period and increments by one every trading day. Panel A reports results based on quoted spread and Panel B presents results on effective spread. Standard errors are clustered both by stock and date, t -statistics are reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate statistical significance at 1%, 5%, and 10% levels, respectively. The sample period covers 1st January 2015 and 11th March 2018.

Panel A

	Spread ratio= *(Dark $QS_{i,\ trade+5}$)/$QS_{i,T}$*		
VARIABLES	(1)	(2)	(3)
(Dark Volume/ Lit Volume)	-1.409***		
	(-57.69)		
(Dark PV/Lit PV)		-1.492***	
		(-55.85)	
(Dark Number of trades)/(Lit number of trades)			-3.132***
			(-57.44)
Volatility	58.428***	58.365***	58.527***
	(22.20)	(22.19)	(22.10)
MKTRET	0.503***	0.552***	0.515***
	(5.79)	(6.35)	(5.97)
Depth	-0.032***	-0.032***	-0.030***
	(-16.21)	(-16.07)	(-15.53)
Time	0.000***	0.000	-0.000***
	(6.85)	(0.03)	(-3.00)
Constant	2.153***	2.157***	2.145***
	(40.27)	(40.30)	(40.78)
Firm Fixed Effect	YES	YES	YES
Observations	64269	64269	64269
Adj R-squared	19.17%	19.09%	21.78%

	Spread ratio= *(Dark $QS_{i,\ trade+5}$)/$QS_{i,trade-5}$*		
VARIABLES	(4)	(5)	(6)
(Dark Volume/ Lit Volume)	-2.002***		
	(-78.97)		
(Dark PV/Lit PV)		-2.122***	
		(-76.91)	
(Dark Number of trades)/(Lit number of trades)			-4.375***
			(-76.32)
Volatility	44.411***	44.323***	44.531***
	(16.36)	(16.34)	(16.38)
MKTRET	0.279***	0.348***	0.298***
	(3.28)	(4.09)	(3.56)
Depth	-0.081***	-0.081***	-0.079***
	(-39.57)	(-39.41)	(-39.53)
Time	-0.000***	-0.000***	-0.000***
	(-12.20)	(-21.60)	(-26.29)
Constant	3.466***	3.472***	3.451***
	(61.94)	(62.04)	(63.57)
Firm Fixed Effect	Yes	Yes	Yes
Observations	64269	64269	64269
Adj R-squared	24.44%	24.28%	28.89%

Table 6 - *continued*

Panel B

VARIABLES	Spread ratio= $(Dark\ ES_{i,\ trade+5})/ES_{i,T}$ (1)	(2)	(3)
(Dark Volume/ Lit Volume)	-2.037***		
	(-78.61)		
(Dark PV/Lit PV)		-2.239***	
		(-79.79)	
(Dark Number of trades)/(Lit number of trades)			-4.656***
			(-81.31)
Volatility	49.267***	49.216***	49.446***
	(21.64)	(21.62)	(21.60)
MKTRET	-0.038	0.031	-0.023
	(-0.43)	(0.35)	(-0.27)
Depth	-0.042***	-0.042***	-0.039***
	(-21.38)	(-21.39)	(-20.95)
Time	0.000***	-0.000***	-0.000***
	(4.61)	(-5.54)	(-10.01)
Constant	2.230***	2.247***	2.227***
	(41.76)	(42.20)	(43.43)
Firm Fixed Effect	YES	YES	YES
Observations	64269	64269	64269
Adj R-squared	21.47%	22.11%	27.46%

VARIABLES	Spread ratio= $(Dark\ ES_{i,\ trade+5})/ES_{i,trade-5}$ (4)	(5)	(6)
(Dark Volume/ Lit Volume)	-2.082***		
	(-73.83)		
(Dark PV/Lit PV)		-2.212***	
		(-72.27)	
(Dark Number of trades)/(Lit number of trades)			-4.543***
			(-73.43)
Volatility	44.332***	44.244***	44.455***
	(15.86)	(15.85)	(15.92)
MKTRET	0.294***	0.365***	0.313***
	(2.97)	(3.68)	(3.21)
Depth	-0.088***	-0.088***	-0.085***
	(-37.87)	(-37.76)	(-37.63)
Time	-0.000***	-0.000***	-0.000***
	(-4.67)	(-13.27)	(-17.12)
Constant	3.671***	3.678***	3.655***
	(58.24)	(58.38)	(59.42)
Firm Fixed Effect	Yes	Yes	Yes
Observations	64269	64269	64269
Adj R-squared	21.31%	21.29%	24.98%

Table 7. Descriptive statistics of control and treatment groups

This table reports the descriptive statistics on key variables including liquidity and informational efficiency in London equity market two months before the implementation of dark trading cap and two months after. Trading pound volumes are calculated in both lit and dark venues. $OTR_{i,t}$ is the stock-day's total number of volume submitted divided by the volume actually traded. Logdepthi,t is the natural log of stock-day's pound depth at the best bid and ask prices. Amihudi,t is the illiquidity measure, which equals to stock-day's return divided by daily volume in billion shares. Autocorrelationi,t is an inverse measure of informational efficiency which equals to the absolute value of stock-day's trade-by-trade return of midquote. Panel A shows the key statistics of the treament group which consists of 90 stocks whose dark trading is capped in FTSE100 index. Panel B shows the key statistics of the control group which consists the 10 uncapped FTSE100 stocks and 112 uncapped FTSE250 stocks. Panel C presnets the difference of key variables between control and treatment groups.

Panel A: Pre regulation treatment group (capped 90 stocks in FTSE100)

Variable	Mean	Median	Std Dev
Lit £volume	42995505.120	24237747.000	48307996.660
log(Lit £volume)	17.100	17.003	0.975
dark £volume	2207918.440	1022441.410	3288069.480
log(dark £volumei,t)	13.826	13.838	1.315
percentage of dark trading %	4.86%	4.02%	0.037
EffectiveSpread	0.150%	0.047%	1.252%
QuotedSpread	0.058%	0.049%	0.055%
Logtotaldepth	25.468	25.394	1.116
Depth	205303617289	106743113026	246444886356
Amihud	7.759	2.525	16.707
Autocorrelation	0.081	0.066	0.197

Panel A: post regulation treatment group (capped 90 stocks in FTSE100)

Variable	Mean	Median	Std Dev
Lit £volume	41169750.990	23867292.520	47009206.710
log(Lit £volume)	17.065	16.988	1.013
dark £volume	.	.	.
log(dark £volume)	.	.	.
percentage of dark trading %	.	.	.
EffectiveSpread	0.447%	0.043%	4.293%
QuotedSpread	0.062%	0.049%	0.100%
Logtotaldepth	25.333	25.348	1.063
Depth	167247603383	101839497922	178296609355
Amihud	7.062	2.505	15.040
Autocorrelation	0.072	0.061	0.059

Table 7 - *continued*

Panel C: Pre regulation: others (Uncapped 10 stocks in FTSE100 + uncapped 112 stocks from FTSE250)

Variable	Mean	Median	Std Dev
Lit £volume	9288775.940	951703.380	22775913.050
log(Lit £volume)	14.122	13.766	2.153
dark £volume	676092.230	128893.880	1678317.280
log(dark £volume)	11.511	11.767	2.338
percentage of dark trading %	6.410%	3.930%	0.09
EffectiveSpread	0.562%	0.220%	1.956%
QuotedSpread	0.777%	0.226%	3.706%
logtotaldepth	22.464	21.949	2.106
depth	49093001122	3406110418	141717302170
amihud	863.518	21.672	12308.000
Autocorrelation	0.057	0.034	0.069

Panel D: Post regulation: others (Uncapped 10 stocks in FTSE100 + uncapped 112 stocks from FTSE250)

Variable	Mean	Median	Std Dev
Lit £volume	9792501.990	1397725.110	23987204.610
log(Lit £volume)	14.324	14.150	2.065
dark £volume	581728.570	43102.050	1935531.720
log(dark £volume)	10.663	10.671	2.571
percentage of dark trading %	6.260%	2.780%	0.10
EffectiveSpread	0.996%	0.188%	13.906%
QuotedSpread	0.665%	0.206%	3.734%
logtotaldepth	22.537	22.007	1.944
depth	39450719749	3611542024	104162988299
amihud	416.593	16.592	2772.816
Autocorrelation	0.055	0.033	0.067

Table 7 - *continued*

Panel D

Difference between control and treatment group	Mean	Std Dev	*t*-stats
Lit £ volume	-33710000.000	35984228.000	-0.937
Log(lit £ volume)	-2.978	1.749	-1.702
Dark £ volume	-1531826.000	2613290.000	-0.586
log(dark £volume)	0.040	0.199	0.200
percentage of dark trading %	3.98%	19.92%	0.200
EffectiveSpread	0.41%	0.017	0.243
QuotedSpread	0.72%	0.028	0.257
depth	-3.003	1.752	-1.714
Amihud	0.000	0.000	0.092
Autocorrelation	-0.025	0.139	-0.176

Table 8. Impact of dark trading cap

This table shows estimated coefficients results for the following stock-day difference-in-difference regression model:

$$y_{i,t} = \alpha_1 + \beta_1 Post_t * Tret_i + \beta_2 Post + \beta_3 Tret_{i,t} + \delta^{'} X_{i,t} + \varepsilon_{i,t}$$

Post is a dummy variable if the trading day is after the 11th March 2018, otherwise zero. Tret is a dummy variables that equals to one if the stock belongs to the treatment group, otherwise zero. Our treament group consists of 43 stocks whose dark trading is capped in FTSE100 index. Our control group consists the largest 43 stocks in terms of market capitalisation with no dark trading cap. $y_{i,t}$ consists of a series of liquidity and informational efficiency variables, such as $QuotedSpread_{i,t}$, $EffectiveSpread_{i,t}$, $Amihud_{i,t}$, log(depth $_{i,t}$), $OTR_{i,t}$ and $Autocorrelation_{i,t}$. $QuotedSpread_{i,t}$ is the stock-day time-weighted proportional quoted spread on lit venues. $EffectiveSpread_{i,t}$ is the stock-day time-weighted proportional effective spread on lit venues. $Amihud_{i,t}$ is the illiquidity measure, which equals to stock-day's return divided by daily volume in billion shares. $Log(depth_{i,t})$ is the natural log of stock-day's pound depth at the best bid and ask prices on lit venues. $Autocorrelation_{i,t}$ is an inverse measure of informational efficiency which equals to the absolute value of stock-day's trade-by-trade return of midquote. $X_{i,t}$ contains a series of control variables such as $Time_t$, $InversePrice_{i,t}$, $Volatility_{i,t}$ and $Return_{i,t}$. $Time_t$ is a trend variable that starts at zero at the beginning of the sample period and increments by one every trading day. $InversePrice_{i,t}$ captures the inverse value of stock-day closing price. $Volatility_{i,t}$ and $Return_{i,t}$ are the stock-day standard deviation of midquote and daily return respectively. Standard errors are clustered both by stock and date, *t* -statistics are reported in parentheses. ∗∗∗, ∗∗, and ∗ indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Variable	*QuotedSpread*	*EffectiveSpread*	*Amihud*	*Depth*	*Autocorrelation*
*POST*TRET*	0.070***	0.001	0.222***	-0.202***	-0.006**
	(3.05)	(1.49)	(6.96)	(-16.39)	(-2.08)
POST	-0.115***	-0.005***	-0.051	0.198***	-0.002
	(-3.53)	(-7.67)	(-1.51)	(13.45)	(-0.53)
TRET	-0.223	-0.008***	0.130	3.313***	0.121
	(-0.63)	(-2.65)	(0.66)	(31.84)	(1.41)
time	0.001***	0.000***	-0.005***	-0.003***	-0.000
	(2.63)	(7.60)	(-8.04)	(-9.59)	(-0.13)
InversePrice	-54.054	-1.910***	18.664	4.789	18.849
	(-0.71)	(-3.52)	(0.74)	(0.49)	(1.03)
Volatility	32.857***	0.210***	0.786	-1.402***	-0.006
	(14.79)	(12.73)	(1.41)	(-5.54)	(-0.10)
return	-0.180	-0.012	-1.727***	0.626*	0.009
	(-0.43)	(-1.33)	(-3.19)	(1.80)	(0.19)
Constant	0.244	0.004*	-0.184	21.669***	-0.050
	(0.66)	(1.86)	(-1.14)	(25.27)	(-0.58)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	17866	17866	17866	17866	17866
Adj R-squared	49.92%	6.06%	81.16%	86.39%	2.42%

Appendix A

Table A1. Does Dark liquidity begets lit liquidity ?

Panel A, B, C and D reports the coefficient results for the following stock day panel regression

$$Spread\_ratio_{i,t} = \alpha_1 + \beta_1 \frac{dark\_trading_{i,t}}{lit\_trading_{i,t}} + \beta_2 volatility_{i,t} + \beta_3 MKTRET_{i,t} + \beta_4 depth_{i,t} + \beta_5 Time_t + \varepsilon_{i,t}$$

where Sets 1 $Spread\_ratio_{i,t} = \frac{spread_{dark\_trade+5}}{spread_{i,t}}$ and Sets 2 $Spread\_ratio_{i,t} = \frac{spread_{dark\_trade+5}}{spread_{dark\_trade-5}}$

$spread_{dark\ trade+5}$ is the time-weighted spread of ten trade subsequent to each dark trade; $spread_{dark\ trade-5}$ is the time-weighted spread of ten trade before each dark trades. $spread_{i,t}$ is the time-weighted average spread calculated stock-day. QS and ES represent quoted spread and effective spread respectively. $Volatility_{i,t}$ is the daily standard deviation of midquote return. $MKTRET_{i,t}$ is the daily return of FTSE100 index. $Depth_{i,t}$ is measures the pound volume of total order submitted at the best bid and ask price. $Time_t$ is a trend variable that starts at zero at the beginning of the sample period and increments by one every trading day. Panel A reports results based on quoted spread and Panel B presents results on effective spread.

Panel A

Spread ratio=	*(Dark $QS_{i,\ trade+10}$)/$QS_{i,T}$*			*(Dark $QS_{i,\ trade+10}$)/$QS_{i,trade-10}$*		
VARIABLES						
(Dark Volume/ Lit Volume)$_{i,t}$	-1.066***			-1.484***		
	(-55.71)			(-77.09)		
(Dark PV/Lit PV)$_{i,t}$		-1.121***			-1.575***	
		(-53.51)			(-75.12)	
(Dark Number of trades)/(Lit number of trades)$_{i,t}$			-2.356***			-3.226***
			(-54.15)			(-74.61)
Volatility$_{it}$	42.663***	42.612***	42.734***	32.663***	32.599***	32.747***
	(21.74)	(21.73)	(21.67)	(15.93)	(15.92)	(15.97)
Market Return*it*	0.413***	0.450***	0.422***	0.199***	0.249***	0.213***
	(6.16)	(6.71)	(6.34)	(3.09)	(3.88)	(3.36)
Depth$_{it}$	-0.016***	-0.016***	-0.015***	-0.061***	-0.061***	-0.059***
	(-10.75)	(-10.60)	(-9.99)	(-39.00)	(-38.86)	(-38.91)
Time$_t$	0.000***	0.000***	0.000***	-0.000***	-0.000***	-0.000***
	(14.36)	(7.60)	(4.77)	(-11.47)	(-20.69)	(-25.06)
Constant	1.626***	1.627***	1.619***	2.837***	2.842***	2.825***
	(39.21)	(39.20)	(39.67)	(66.57)	(66.69)	(68.21)
Firm Fixed Effect	YES	YES	YES	Yes	Yes	Yes
Observations	64269	64269	64269	64269	64269	64269
Adj R-squared	17.87%	17.70%	20.35%	24.11%	23.99%	28.24%

Panel B

Spread ratio=	$(Dark\ ES_{i,\ trade+10})/ES_{i,T}$			$(Dark\ ES_{i,\ trade+10})/ES_{i,trade-10}$		
VARIABLES						
(Dark Volume/ Lit Volume)$_{i,t}$	-1.528***			-1.514***		
	(-76.01)			(-73.11)		
(Dark PV/Lit PV)$_{i,t}$		-1.669***			-1.612***	
		(-76.62)			(-71.44)	
(Dark Number of trades)/(Lit number of trades)$_{i,t}$			-3.514***			-3.291***
			(-80.47)			(-72.24)
Volatility$_{it}$	35.680***	35.637***	35.821***	30.754***	30.691***	30.839***
	(20.76)	(20.75)	(20.76)	(15.44)	(15.43)	(15.53)
Market Return*it*	-0.069	-0.017	-0.058	0.180**	0.232***	0.194***
	(-1.01)	(-0.25)	(-0.87)	(2.53)	(3.26)	(2.77)
Depth$_{it}$	-0.022***	-0.022***	-0.020***	-0.065***	-0.064***	-0.063***
	(-14.10)	(-14.05)	(-13.41)	(-38.23)	(-38.12)	(-38.00)
Time$_t$	0.000***	0.000	-0.000***	-0.000***	-0.000***	-0.000***
	(9.93)	(0.20)	(-4.19)	(-5.60)	(-14.28)	(-18.07)
Constant	1.644***	1.655***	1.643***	2.945***	2.951***	2.933***
	(39.16)	(39.50)	(40.71)	(64.08)	(64.24)	(65.40)
Firm Fixed Effect	YES	YES	YES	Yes	Yes	Yes
Observations	64269	64269	64269	64269	64269	64269
R-squared	20.14%	20.61%	26.04%	21.68%	21.62%	25.30%