Dark matters? The effects of dark trading restrictions on liquidity and informational efficiency

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Abstract We exploit the implementation of the double volume cap regulation introduced under the Markets in Financial Instruments Directive II in the European equity markets to investigate the impact of dark trading on liquidity and informational efficiency. We show that stocks subject to trading suspension in dark pools suffer a deterioration in liquidity compared to those that are not. The limiting of trading in dark pools also tends to reduce informational efficiency. Our results support recent theory arguing that dark pools encourage inter-venue order flow competition, underscoring the significance of dark trading for market quality.

JEL classification: G10, G14, G15
Keywords: dark trading, MiFID, liquidity commonality, Double Volume Cap (DVC)

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1. Introduction

The last decade has seen an unprecedented rate of proliferation of trading places in financial markets. For example, in Europe, riding on the back of the implementation of the Markets in Financial Instruments Directive (MiFID) introduced in 2007, more than 100 new trading venues were established over a five-year period. The entrant venues are mostly high-tech Multilateral Trading Facilities (MTFs), enabled by MiFID rules. Many trading venues, including the more established national exchanges, rely on 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 minimal price impact, since pre-trade transparency is waived for orders submitted to such platforms. However, recent studies suggest that average trade sizes in some European dark pools are comparable to those in the lit market (see as an example Aquilina *et al.*, 2017). The lure of trading with no pre-trade transparency has led to significant growth in the proportion of dark trading across 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, respectively, are executed in the dark.

Despite the growing popularity of dark pools among a section of market participants - mainly institutional traders - the operation of dark pools remains the subject of ongoing debate. Stakeholders are concerned about the effects of the lack of pre-trade transparency in dark pools. In 2010 the U.S. Senator Kaufman notes, in a letter to SEC Chair Schapiro, the need to *"examine whether too much order flow is being shielded from the lit markets by dark venues"*. In March 2018, the European Commission introduced the so-called double volume cap (DVC) under MiFID II/MiFIR to limit the execution of transactions in dark venues. The DVC is calculated for each affected instrument on a daily rolling basis using the average daily trading volume over the preceding 12-month period. The venue and aggregate market trading limits for each instrument are 4% and 8%, respectively. If the DVC is triggered on an instrument, then dark trading in that instrument will subsequently be suspended for six months. In that case, large traders can only trade the affected stock in a dark pool if the order size is large enough to pass the large-in-scale (LIS) waiver. Nevertheless, concerns were raised that the thresholds required to qualify for the LIS waiver are too high and would disadvantage many small- and medium-cap stocks. Another popular alternative to dark pools is periodic auctions in which orders are not made public until they reach a certain volume. However, the market share of periodic auctions is relatively small when compared to dark pools' volumes. According to a 2019 ESMA report, periodic auctions accounted for about 2% of total trading volume in September 2018.

We exploit the implementation of the DVC to investigate the impact of dark trading on two market quality characteristics, i.e. liquidity and informational efficiency, and associated factors such as resilience of the limit order book and trading activity.[1] Unlike in Foley and Putniņš (2016), where the minimum price improvement instrument (for dark trades) used does not imply a clean halt in dark trading, the DVC effectively halts dark trading, thus allowing for a clean test of the impact of the elimination of trading in dark pools.

We find that restricting dark trading is associated with higher transaction costs on lit venues. This finding is consistent with market makers becoming less incentivised to post competitive quotes in lit venues after dark trading restrictions come into effect. The results are also in line with

[1] We note that a recent working paper (Johann *et al.*, 2020), developed and circulated subsequent to the earlier versions of this current paper, also exploit the implementation of the DVC in a quasi-natural experiment. While there are similarities in the frameworks of both papers, especially in relation to the use of the DVC, there are distinctions in terms of focus. While we address the question of the wide-ranging market quality effects of halting dark trading, Johann *et al.* (2020) focus on DVC-induced volume spill-overs and their investigation of the liquidity and short-term efficiency effects of the DVC is limited to this context.

the expectation that the presence of dark pools encourages the submission of liquidity/uninformed orders that otherwise would not have been submitted because trading in dark pools is safer for uninformed traders (it lowers adverse selection risk for uninformed traders) and cheaper (no spread or price impact due to large order sizes, as in Nimalendran and Ray, 2014). Thus, when dark trading facilities are restricted, it can result in a loss of liquidity. This effect is comparable to the observed contributions of the traditional upstairs market as reported by Madhavan and Cheng (1997). Furthermore, as informed traders need uninformed order flow to be able to execute their orders (informed orders cluster on one end of the order book) when liquidity order flow is reduced on account of dark trading restrictions, informational efficiency is impaired. Indeed, when liquidity order flow is scarce, traders are not incentivised to acquire information that could be incorporated into prices through their trading activities (see Kyle, 1985; Glosten and Milgrom, 1985; Glosten, 1998).

The theoretical contributions on the impact of dark trading on market quality are very limited and mixed. Zhu (2014) shows that under normal conditions, uninformed traders gravitate towards dark pools, while informed traders mainly choose to trade on lit markets. This self-selection ultimately improves price discovery on the lit exchange. However, Ye (2012), who employs a different framework of informed and uninformed traders, disagrees with Zhu's (2014) predictions. The difference between the two models' predictions is due to the distinctions in modelling approaches. While the Zhu (2014) model allows both informed and uninformed traders to freely select their trading venues, in the Ye (2012)'s model only informed traders can self-select trading venues. Brolley's (2020) approach to addressing the question of the impact of dark trading on market quality yields a conditional set of predictions. Modelling informed trading in a market with a displayed limit order book and a price-improving dark pool, Brolley (2020) predicts that higher valuation investors sort into order types with lower execution risk, thereby generating an immediacy hierarchy, which is predicted by the order of dark pool price improvement. Specifically, a price improvement closer to (farther from) the mid-quote positions dark orders below (above) limit orders and improves (worsens) market quality and welfare. A further theoretical attempt to explain venue selection in the presence of dark pools is that Menkveld *et al.* (2017). Using a simple stylized model, Menkveld *et al.* (2017) also propose the pecking order hypothesis, which predicts that as investors' trading needs become more urgent, they relocate their trading activity from low cost and low-immediacy venues, i.e. dark pools, to high-cost and high-immediacy venues, i.e. lit venues.

Empirical evidence on the impact of dark trading market quality is also similarly mixed. In the US, for example, Hendershott and Mendelson (2000) show that the introduction of a competing crossing network can attract new uninformed order flow, which in turn reduces inventory holding costs and adverse selection risk. Buti *et al*. (2011) find no supporting evidence that dark pool trading can harm market liquidity. Boulatov and George (2013) compare a lit only exchange with a dark only exchange and find that the dark pool offers better price discovery as it encourages more informed traders to provide liquidity. Kwan *et al.* (2015) investigate the mechanism through which dark pools affect market liquidity and show that when stock prices are constrained by tick size, market participants use U.S. dark pools to obtain a finer pricing grid. However, Nimalendran and Ray (2014), using data from one of the 32 U.S. dark venues, find that dark trading is associated with increased price impact on primary exchanges. Consistent with Nimalendran and Ray (2014), Chung et al. (2020) find that a significant reduction in dark trading is linked to a significant reduction in the effective bid-ask spread.

The results from other markets are also mixed. Degryse *et al*. (2015), analysing trading data for 51 Dutch stocks, find that dark venues attract uninformed order flow and that dark trades are associated with wider bid-ask spreads, while Brugler (2015) documents that dark trading leads to improved liquidity on the primary exchange for FTSE100 stocks. Foley and Putniņš (2016) show that while dark limit order markets are beneficial to liquidity, dark midpoint crossing systems are not beneficial for market quality in the Australian equity market. Aquilina *et al*. (2017) reconcile these competing impacts of dark trading on market quality by proposing two effects. They argue that at moderate levels of dark trading, a positive liquidity effect dominates an information acquisition disincentive effect. Dark trading induces reductions in both adverse selection risk and pricing noise while enhancing liquidity. However, at higher levels of dark trading, there is an unsustainable rise in adverse selection, which also leads to a loss of liquidity (see also Comerton-Forde and Putniņš, 2015).

Finally, similarly to our case, Neumeier *et al.* (2021), investigating a different set of questions, employ the imposition of the DVC in the European equity market as an event study. They find that a higher proportion of dark or large-in-scale dark executions in a parent order is associated with a lower implementation shortfall. Their results also suggest that periodic batch auctions may reduce implementation shortfall when stocks are serving dark trading suspensions.

2. Institutional background

In November 2007, the enactment of MiFID introduced alternative high-tech trading venues called multilateral trading platforms (MTFs). MTFs operate as intermediaries that facilitate the exchange of financial instruments between several market participants. At the same time, MiFID imposed pre-trade and post-trade transparency regulations for all trading venues to reduce potential adverse selection costs accompanied by trading fragmentation. However, MiFID also offers pre-trade transparency waivers to certain types of orders. These pre-trade transparency waivers include (1) reference price waivers (RPW); (2) negotiated trade waivers (NTW); (3) large in scale (LIS) and (4) order management facilities (OMF). RPW applies to trading systems that match trading at the midpoint of the current bid and ask price range. NTW allows two parties to formalise negotiated transactions. LIS gives block traders the right to hide trading intention when transaction size is larger than normal market size. OMF allows orders to be held by exchanges in an order management facility pending disclosure.

Since the start of MiFID, trades in dark pools operated by MTFs have benefited from RPW and LIS. Pre-trade opacity and midpoint execution help fund managers to protect their trading intention and reduce transaction costs. However, European regulators were concerned that dark pools that match trades at the midpoint did not contribute to the price discovery process, and that dark trading activity was less transparent and hence difficult to monitor. To tackle these issues, MiFID II and Market in Financial Instruments Regulation (MiFIR) were published in June 2014. An important goal of MiFID II and MiFIR is to secure a high level of market transparency and fairness. As a result, DVC was introduced to curb dark trading and force more trades to be executed on lit venues. DVC dictates that the venue and aggregate market trading limits for each instrument are 4% and 8%, respectively. If the DVC is triggered in an instrument, then dark trading in that instrument will subsequently be suspended for 6 months. The DVC is calculated for each affected instrument on a daily rolling basis using the average daily trading volume over the preceding 12-month period. According to the data published in March 2018 by the European Securities and Markets Authority (ESMA), a total of 744 and 643 instruments breached at least one of the caps in January and February 2018 respectively, and were therefore subject to a 6-month trading suspension from 12th March 2018. As of September 2018, 6 months after the implementation of DVC, more than 1200 instruments, mainly equities, were suspended for dark trading. The affected instruments include about 35% of the most liquid European stocks.

It is worth mentioning that even after the DVC is enforced, large block trades are still allowed to trade in dark pools if the trade size is large enough to qualify for LIS waiver. The LIS waiver threshold is calculated based on the average daily volume (ADV) for each instrument. For small-cap stocks with an average daily volume of less than €50,000, the LIS waiver threshold is €15,000 and for large-cap stocks with ADV greater than €100 million, the LIS waiver threshold can be up to €650,000. Concerns arise because LIS waiver thresholds are too high and would preclude many less-traded stocks. Another trading system alternative to dark pools is periodic auctions, in which orders are not displayed to the public until they reach a certain volume. Periodic auctions operate on randomized batch auctions and execute trades several times a day. Although periodic auctions increasingly attract order flow, their market share is still relatively low. From April 2018 to September 2018, the market share of periodic auctions volume increased from about 0.6% to 2%.[2]

3. Data sources and method of analysis

3.1. Data

We employ the constituents of the FTSE 350 index sampled from 11th January 2018 to 11th May 2018. The sample period corresponds to a four-month study window for studying the effects of the DVC implementation, which is in line with Foley and Putniņš (2016) and Comerton-Forde

[2] See Financial Times, 26th March 2018 (https://app.ft.com/content/dad1e852-30da-11e8-ac48-10c6fdc22f03) and ESMA (2019).

et al. (2017). On the one hand, if the window is too wide, the analysis around the policy change - i.e. the implementation of DVC in this case - can be influenced by confounding factors that are unrelated to dark trading. On the other hand, narrowing the window may result in the analysis lacking the power to sufficiently capture the changes in market quality. A four-month window is a reasonable compromise.

The FTSE 350 constituents are the 350 largest firms listed on the LSE. The index is made up of firms included in the FTSE 100 and FTSE 250 stock indices. The FTSE 350 stocks account for over 90% of the total market capitalisation of the FTSE All-Share index. Our data includes trading data from the primary exchange, the LSE, and the three largest alternative trading venues for FTSE 350 stocks: BATS Europe, Chi-X Europe, and Turquoise. The three latter venues operate both lit and mid-point dark order books. We obtain intraday tick data from the Thomson Reuters Tick History (TRTH) database. TRTH provides time and sales 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 the corresponding prevailing best bid and ask quotes. Since dark orders are only settled during normal trading hours, we drop the opening auction (7:50hrs – 8:00hrs) and closing auction (16:30hrs – 16:35hrs) periods from the dataset. We also obtain the daily number of outstanding shares of individual stocks and index data for FTSE 100 stocks from the Thomson Reuters Datastream database. Finally, we merge the order book level data for the four trading venues to create a single 'global' order book for the London market using the real times provided by the exchanges, in order to avoid inaccurate concatenation that could arise when using TRTH time. The final dataset contains 2,014,738,496 observations, including 155,617,274 transactions and 1,859,121,222 quotes.

We identify the stocks with dark trading suspensions based on the DVC implementation by reviewing the data provided by ESMA on their website.[3] Based on ESMA reports, which are updated monthly, during our sample period, 82 stocks included in the FTSE 100 index are affected by the DVC, while 11 stocks are not affected. The remaining stocks either have their dark trading rights partially suspended or experience a revoking of a previous order. 150 stocks included in the FTSE 250 index are affected by the DVC implementation, while 77 are not affected during the sample period. 23 FTSE 250 index stocks affected by a single volume cap (either on venue level or aggregate level) or with their DVC suspension revoked during the sample period are excluded from our sample. Finally, we obtain SBF 120 index stocks data for a placebo test, i.e. stocks that are not affected by any regulatory imposition of dark trading restrictions between 11th January and 11th May 2018. The SBF 120 stock index includes the most actively traded stocks listed in Paris.

3.2. Empirical design

The introduction of the DVC allows us to analyse the impact of dark trading suspensions on the market quality characteristics of the affected group of stocks using a difference-in-differences (DiD) approach. This implies that we examine the relative effect of the suspension on the affected stocks relative to another group of identical stocks (the control group) that are not affected by the regulatory action.

Our analysis focuses on linking observed improvements or deterioration in market quality to the date of the implementation of the DVC in specific European stocks, i.e. 12th March 2018. Specifically, we compare the changes in the liquidity and informational efficiency for stocks affected by the DVC implementation to the changes for a control group of stocks not affected by

[3] See ESMA reports: https://www.esma.europa.eu/double-volume-cap-mechanism

the trading ban. In our sample, 159 FTSE 350 stocks are identified as affected by the implementation of the DVC, while the remaining constituents of the stock index are not affected. The affected stocks form the treatment group, while the unaffected stocks are included in the control group of stocks. However, given the critical nature of the selection of the control group, and especially since the market quality metrics we employ are sensitive to size, we select two sets of treatment and control groups respectively based on the level of trading activity and stock size. Specifically, 82 of the affected FTSE 350 stocks are also listed as FTSE 100 stocks, implying a higher level of trading activity and stock size than the remaining 77 affected stocks that are also classed as FTSE 250 stocks. Therefore, we identify the 82 affected FTSE 100 stocks as the first treatment group; the remaining 77 affected FTSE 250 stocks are the second treatment group.

The control groups for both treatment groups each consist of an equal number of size-matched FTSE 350 stocks unaffected by the DVC during the sample period. For both sets of treatment and control groups, each capped stock is matched with an uncapped stock using the Huang and Stoll (1996) algorithm to minimise the sum of squared relative differences in daily averaged market capitalisation and trading volume, X_i, during the two months prior to the DVC implementation announcement:

$$Matching_i = \sum_{i=1}^{2}\left(\frac{X_i^C - X_i^U}{(X_i^C + X_i^U)/2}\right)^2 \quad (1)$$

where C and U correspond to capped and uncapped stocks respectively. This approach ensures that we compare like-for-like as much as possible. Specifically, the approach minimizes the sum of squared relative differences in daily averaged market capitalization, X_1, and trading volume, X_2. The matching involves first ranking the stocks affected by DVC (capped stocks) by market capitalization in a descending order, and thereafter pairing them with an uncapped stock. By computing the matching algorithm, we are able to match each capped stock with the uncapped stock that has the lowest variation in difference in market capitalization and trading volume with it.

After constructing the two sets of treatment and control groups, we estimate the following stock-day panel data regression model individually for the two sets:

$$MKTQuality_{i,t} = a_1 + \beta_1 DVC_t + \beta_2 TRET_i + \beta_3 DVC_t \times TRET_i + \beta_4 Time_t + \delta' \boldsymbol{X}_{i,t} + FE_i + \varepsilon_{i,t} \quad (2)$$

where $MKTQuality_{i,t}$ corresponds to a liquidity proxy, LOB resilience, or informational efficiency, as defined in Sections 4.3, 4.4, and 4.5 respectively. DVC_t is a dummy variable equalling 1 for all of the days when the DVC-induced trading halt in dark pools is in effect for the treated stocks, and 0 otherwise. $TRET_i$ is a dummy variable, which equals 1 if the stock belongs to the treatment group of capped stocks, and 0 otherwise. We include a time trend, $Time_t$, and firm fixed effects, FE_i, to control for stock invariant and time invariant differences in stocks. $\boldsymbol{X}_{i,t}$ is a vector of stock-day control variables: the log of closing market capitalisation, the standard deviation of trade-by-trade midpoint return, and daily stock return *i* on day *t*. The coefficient of interest is β_3, which is the difference-in-differences estimator and captures the effect of the trading halt on the market quality of the affected stocks.

A visual inspection of the outcome variables for the treatment and control groups during pre-treatment is a useful guide as to whether the parallel assumption holds.[4] Visually, the outcome variables employed in Equation (2) generally have similar trends during the pre-treatment period;

[4] The parallel trend assumption requires that the dependent variables (in our case, these are the variables corresponding to $MKTQuality_{i,t}$ in Equation (2)) for the treatment and control groups have parallel trends in the period pre-event.

this is also supported by the statistical evidence.[5] Thus, our empirical approach satisfies the parallel trend assumption.

3.3. Liquidity measures

For robustness, we compute five liquidity proxies at the daily frequency, based on several dimensions of liquidity. The proxies are relative spread, effective spread, realized spread, the Amihud (2002) price impact ratio, and market depth. Relative spread captures a round trip cost of a trade, the effective spread is the actual transaction cost of submitting a marketable order, while realized spreads reflect the proportion of the transaction cost earned by the liquidity provider after removing the adverse selection cost (Foley and Putniņš, 2016). All three spread measures are inverse proxies of liquidity. The Amihud price impact ratio is yet another inverse proxy of liquidity, capturing illiquidity responses during trading. 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. Finally, market depth reflects the extent of immediacy in order execution.

The relative spread, effective spread, and realized spread measures are computed as follows:

$$relative\ spread = \frac{Ask_\tau - Bid_\tau}{Ask_\tau + Bid_\tau} \tag{3}$$

$$effective\ spread = \begin{cases} 2 * \frac{p_\tau - M_\tau}{M_\tau} & for\ buyer\ initiated\ trades \\ 2 * \frac{M_\tau - p_\tau}{M_\tau} & for\ seller\ initiated\ trades \end{cases} \tag{4}$$

$$realized\ spread = \begin{cases} 2 * \frac{p_\tau - M_{\tau+5}}{M_\tau} & for\ buyer\ initiated\ trades \\ 2 * \frac{M_{\tau+5} - p_\tau}{M_\tau} & for\ seller\ initiated\ trades \end{cases} \tag{5}$$

[5] The statistical evidence relates to testing that the difference between the control and treatment groups before and after the introduction of the DVC is statistically different from 0. For parsimony, the visual plots and test results, which include the control groups paired with each of the two treatment groups (22 pairs in all) are not presented in the paper but are available from the authors on request.

where Ask_τ and Bid_τ correspond to the best ask and bid quotes respectively at time τ , and p_τ and M_τ are the respective transaction price and the midpoint of the best ask and bid prices at time τ. The direction of trades is assigned according to the Lee and Ready (1991) algorithm. The effective and realized spreads are volume-weighted. All three bid-ask spreads are high-frequency measures and calculated during continuous trading hours.

The Amihud price impact ratio is computed as follows:

$$Amihud_{i,t} = \frac{1}{H}\sum_{h=1}^{H}\left(\frac{|r_{i,t,h}|}{vol_{i,t,h}}\right) \quad (6)$$

where $r_{i,t,h}$ is the mid-quote return for stock *i* during hour *h* on day *t*, and $vol_{i,t,h}$ is the aggregate volume in pounds for stock *i*, during hour *h* on day *t*.

Market depth is the natural log of the daily pound volume of the total order submitted at the best bid and ask price for each stock on each day.

3.4. Limit order book (LOB) resilience

LOB resilience is related to liquidity because it captures the speed with which liquidity suppliers can replenish the order book. This also makes it a significant factor for market quality. Modelling the effects of regulatory shocks on the resilience of the LOB takes on an added significance for regulators, academics, and other market stakeholders in the current trading era dominated by algorithmic/high-frequency trading (AT/HFT) and increased occurrence of flash crashes. Large orders can consume the depth of the limit order book and cause extreme price movements. In a resilient market, market makers will readily fill orders at the minimum spread, after extreme price movements or during periods of market stress, thereby ensuring restoration of normalcy. We follow two recent studies by Kempf *et al*. (2015) and Griffith and Roseman (2019) to estimate the average speed of liquidity adjustment by estimating the following mean-reversion model:

$$\Delta L_{i,t+1} = a_{i,t} + k_{i,T}^{1}(\theta - L_{i,t})^{+} + k_{i,T}^{2}(\theta - L_{i,t})^{-} + \sum_{i=1}^{10} \gamma_{i,t-1} \Delta L_{i,t-1} + \varepsilon_{i,t} \tag{7}$$

where $\Delta L_{i,t+1}$ is the change in liquidity and is calculated as the difference in liquidity between time t and $t+1$; t corresponds to one minute. θ is the normal level of liquidity calculated as the average level of daily liquidity. The term following $k_{i,T}^{1}$ has a maximum value of either zero or $\theta - L_{i,t}$. The term following $k_{i,T}^{2}$ has a minimum value of either zero or $\theta - L_{i,t}$. Following Griffith and Roseman (2019), we also include up to 10 lags of $\Delta L_{i,t}$. We proxy liquidity by using effective spread, realized spread and market depth.[6] Since effective and realized spread are inverse proxies of liquidity, $k_{i,T}^{2}$ is our parameter of interest and it measures the speed of adjusting from low-liquidity to the long-run mean, or, in other words, the LOB resilience. Equivalently, $k_{i,T}^{1}$ is our parameter of interest for market depth measure. For market effective and realized spread measures, θ is calculated as the volume-weighted one-minute spread on day_T. For market depth, θ is the average one-minute depth interval on day_T. The size of $k_{i,T}^{1}$ (or $k_{i,T}^{2}$) tells us how long it will take the LOB to revert back to the normal level of liquidity. For example, if $k_{i,T}^{1}$ ($k_{i,T}^{2}$) is estimated to be 0.5 for market depth (effective spread) measure, it means that one minute after a liquidity shock, market depth (effective spread) reverts back to 50% of its normal level and hence, on average, it takes market depth (effective spread) about two minutes to return to the average daily level of liquidity. This implies that a high $k_{i,T}^{1}$ ($k_{i,T}^{2}$) with respect to market depth (effective spread and realized spread) estimate is associated with a more resilient LOB.

[6] We do not use time-weighted relative spread here. This is because the time-weight could capture the liquidity deviation from the next 1-minute window and bias the results.

3.5. Informational efficiency

We next define the informational efficiency proxies employed in our analysis of the impact of the DVC implementation on market quality. The proxies include variance-ratio and short-term return predictability computed using both lagged order imbalance and autocorrelation of intraday mid-quote return. Consistent with O'Hara and Ye (2011), we construct our intraday variance ratio as follows:

$$Variance\ ratio = |1 - \frac{\sigma^2_{10second;i,t}}{10\sigma^2_{1second;i,t}}| \quad (8)$$

where $\sigma^2_{10second;i,t}$ and $\sigma^2_{1second;i,t}$ are the variances of 10 -second and one-second mid-quote returns for a given stock-day. In an efficient market, stock price follows a random walk, such that the variance of returns measured over longer horizons is equal to the sum of variances of shorter horizon returns, as long as the summation of the shorter horizons is equal to that of the longer horizon. Therefore, values closer to one would imply higher levels of informational efficiency, while higher values will imply worsening efficiency levels.

The second informational efficiency proxy is an intraday adaptation of the return predictability-based inverse measure of market efficiency described by Chordia *et al*. (2008). Specifically, we extract adjusted R^2 estimates from a series of intraday return predictability models shown in Equation (9).

$$Ret_{i,t} = a_1 + \beta_1 OIB_{i,t-1} + \varepsilon_{i,t} \quad (9)$$

where Ret_t is the one-minute return for stock *i* at time *t*, and $OIB_{i,t-1}$ is the one-minute order imbalance for stock *i* at time *t-1*. The predictability of short-horizon stock returns from lagged order imbalance is an inverse measure of market efficiency; hence, the adjusted R^2 from Equation (9) is an inverse proxy for market efficiency (Chordia *et al*., 2008). This predictability is denoted as $Predict_{i,t}$. Lower values of $Predict_{i,t}$ imply higher levels of informational efficiency.

Finally, we also proxy informational efficiency by computing the absolute value of the stock-day 10-second mid-quote return autocorrelation coefficient. This metric captures the transitory deviation in the pricing process, which could be caused by order imbalances and imperfect liquidity (Foley and Putniņš, 2016). In line with the two previous proxies, a smaller value corresponds to a higher level of informational efficiency.

4. Empirical results

4.1. Descriptive statistics

Panel A of Figure 1 presents the dark trading pound volume as percentages of the total market trading pound volume for the first set of treatment and control groups. We observe that the proportion of dark trading in the treatment group is consistently higher than that of the control group of stocks before the implementation of DVC on 12th March 2018. The proportion of trading that qualifies as dark in the treatment group of stocks plummets following the implementation of the trading halt on 12th March. As expected, Panel B shows a strikingly similar trend for the second set of treatment and control groups of stocks. It is worth noticing in both panels that dark trading still occurs in stocks that have faced DVC action. This is because stocks subjected to DVC dark trading suspensions can still be traded in the dark as long as the size of orders submitted exceeds the LIS waiver threshold. This implies that for dark trades to occur in stocks subjected to dark trading halts in the EU, average dark trade sizes in those stocks would have to rise significantly. Figure 1 is consistent with this expectation.

Panel A of Figure 2 shows the natural log of average trade size in lit and dark venues for the first set of treatment and control groups. While the average size of dark trades is consistently larger than that of lit trades across the sample period, the difference in average sizes surged following the DVC implementation on 12^{th} March. The trend is also observed for Panel B. With traders now forced to trade on lit exchanges, one strategy available to them to cloak their trades is by exploiting the LIS waiver, hence the increase in the surge in the average dark trade size following the imposition of the DVC. Furthermore, the fact that dark trades are, on average, larger than lit trades underscores the role dark venues play in facilitating large trades or trades that otherwise would not have been negotiated in the absence of dark trading facilities (Aquilina *et al*., 2017).

INSERT FIGURES 1 AND 2 ABOUT HERE

Table 1 reports the pre- and post-DVC implementation mean estimates of trading activity and other key variables for the two sets of treatment and control groups of stocks. The differences in the pre- and post-mean estimates are also presented, with stock-day standard errors of the differences used for statistical inference. Panel A shows the descriptive data for the first set of stock groups. In the treatment group, the percentage of dark trading fell more than 83.24% from 9.25% to 1.55% following the implementation of the DVC; the difference is statistically significant at the 0.001 level. A fall in dark trading is also observed for the control group of stocks; however, the fall is of a much lower magnitude, with only a 13.32% reduction in dark trading as a proportion of total trading value recorded. The log of daily market depth also declines from 25.47 to 25.33, while increasing for the group of control stocks. Furthermore, the relative, effective and realized spreads for the stocks experiencing the dark trading halt increase from 0.051% to 0.054% (p-value <0.05), 0.161% to 0.425% (p-value <0.01), and 0.043% to 0.045% (p-value <0.1) respectively. The spread estimates for the control group of stocks are more varied and inconsistent, except in the case of the effective spread where a widening of the spread is also observed. The implication here is that liquidity, and by extension, trading quality, deteriorates in the stocks affected by dark trading halts and that this effect may generally affect the provision of liquidity in other stocks not directly affected. The trade-to-order ratio increased for all four groups, indicating an increase in HFT activity following the implementation of the dark trading halt. This is not surprising since lit venues play an increased role in facilitating liquidity in the absence of dark venues. The picture presented by the informational efficiency proxies is less clear due to large cross-sectional variations. Panel B estimates, showing results for the second set of treatment and control groups of stocks, are largely consistent with the estimates in Panel A.

INSERT TABLE 1 ABOUT HERE

4.2. The impact of DVC on stock liquidity

Table 2 presents the estimation results for Equation (2) with the liquidity variables as the dependent variables. Panel A of Table 2 reports the baseline results from the first groups of treatment and control stocks, while Panel B presents the estimates for the second set of stock groups made up entirely of FTSE 250 stocks. The models for $RelativeSpread_{i,t}$, $EffectiveSpread_{i,t}$, and $RealizedSpread_{i,t}$ explain the evolution of their respective market quality variables, with $\overline{R^2}$ values of 52.14%, 18.19% and 16.31% respectively. The β_3 estimates suggest that, depending on the liquidity proxy, transaction costs increase on average from between 0.097% to 0.389% after 12th March when compared to the control group; the estimates are statistically significant at the 0.01 level. The positive and statistically significant (<0.05) β_3 estimate for the $Amihud_{i,t}$ regression suggests that stocks affected by the DVC implementation yield a higher illiquidity ratio. Similarly, the corresponding estimate for the $Depth_{i,t}$ regression indicates that stock depth declines by 0.172% for stocks affected by the DVC implementation when compared to the control stocks. Additionally, we estimate Equation (2) with the $X_{i,t}$ control variables, and present results in Panel A columns (6) to (10). The results are consistent in that the β_3 estimates obtained from the illiquidity proxies' regressions are positive and statistically significant at the 0.01 and 0.05 levels, while the $Depth_{i,t}$ β_3 regression estimates are negative and statistically significant at the 0.01 level.

As previously explained, the second set of treatment and control groups of stocks is employed to account for the trading activity disparity between the first set of treatment and control groups. Panel B presents the results for this group based on a re-run of Equation (2) in line with the regressions reported in Panel A. As expected, all the β_3 estimates are in line with those in Panel A, the only exception being that the $EffectiveSpread_{i,t}$ regressions β_3 estimates (Columns 2 and 7) are not statistically significant.

INSERT TABLE 2 ABOUT HERE

The β_3 estimates obtained imply that the imposition of a dark trading halt induces a deterioration in market liquidity, as expected, and is reflected in the widening spreads for the impacted stocks and an increase in transaction costs for those stocks relative to those not experiencing dark trading halts. With the draining of liquidity afforded through dark trading, the transaction costs increase, leading to an inevitable transfer of wealth from liquidity takers to liquidity providers in the treatment group. Due to the emergence of the DVC trading halt, inter-venue competition for order flow declines for stocks without dark trading, and therefore market makers are less incentivised to post competitive quotes. Consequently, the spread on lit venues widens along with increases in transaction costs. The other estimates are largely in line with our expectations and the literature. For example, the β_4 estimates, capturing the effect of the time trend, suggest that $EffectiveSpread_{i,t}$ increases, while $Depth_{i,t}$ decreases over the course of our sample period. These trends are in line with our expectations. However, the β_4 estimates based on the $Amihud_{i,t}$ regressions suggest a reduction in price impact over time. Furthermore, the δ_2 estimates, capturing the effect of volatility on the liquidity proxies, are all statistically significant and in line with expectations, except for the $Amihud_{i,t}$ regressions. The estimates indicate that market makers will widen the spread in an attempt to protect themselves against uncertainties reflected in volatile markets (see Barclay *et al*., 2003; Ibikunle, 2015).

Our results are robust to a range of alternative approaches to measuring market liquidity. We repeat our analysis estimating Equation (2) with daily averaged bid-ask spreads, which are used in previous studies to measure liquidity (see for example Brockman *et al*., 2009; Marshall *et al*., 2013). Daily average relative, effective, and realized spreads are calculated by assigning each trade the same weight throughout each trading day. We also include the daily Amihud ratio averaged on an hourly basis in the test for the dark trading halt effect on liquidity. Panel A in Table 3 reports the robustness test for the FTSE 350 stocks (set 1 group). Consistent with our baseline results, the β_3 coefficients for the $EffectiveSpread_{i,t}$ and $RealizedSpread_{i,t}$ regressions are positive and statistically significant at the 0.01 level. The β_3 estimates for hourly-averaged stock-day $Amihud_{i,t}$ regression yield positive and statistically significant results at the 0.1 level of statistical significance. Qualitatively similar results can be found in Panel B of Table 3, the coefficients of all daily average spreads are positive and statistically significant, with the $RelativeSpread_{i,t}$ coefficient significant at the 0.01 level. Our results, based on different measures and samples, suggest that the DVC implementation is associated with lower market liquidity.

INSERT TABLE 3 ABOUT HERE

The results in Tables 2 and 3 show the effect of the dark trading halt. Spreads are wider and market depth declines for stocks with dark trading halts. Inter-venue competition forces market makers to post the competitive quotes in lit venues in order to attract order flow from other venues, including dark pools. This state of competition is weakened as a result of the DVC and hence market makers on lit venues are not fully incentivised to attract order flow from dark venues as they would be in a market with competing (dark) venues. Furthermore, these results could be explained by the loss of the liquidity-inducing effect of dark trading (see Aquilina *et al*., 2017). Consistent with Zhu (2014), uninformed/liquidity traders gravitate towards dark pools, while informed traders are more likely to trade in lit markets. Thus, the removal of a dark trading option may lead to a reduction in the volume of liquidity providing market participants. This hypothesised effect of dark pools is akin to that of the traditional upstairs market. Madhavan and Cheng (1997) show that upstairs markets[7] enable transactions that would otherwise not occur in the downstairs (the typical lit exchange) market. Thus, if dark pools improve liquidity, their removal could also impair it.

Our finding is consistent with the previous literature investigating order flow competition between lit and dark venues (see for example Foucault and Menkveld, 2008; Zhu, 2014; Kwan *et al*., 2015; Gresse, 2017).

4.3. The impact of DVC on LOB resilience

In this section, we investigate how LOB resilience evolves around the DVC implementation. We define LOB resilience as the speed at which the LOB reverts to its long-run

[7] The main differences between the upstairs markets and the modern mid-point dark pools, which we study, are that execution prices in the latter are constrained within the downstairs market spread and that dark pools are not usually subject to trading intermediation as it conceptually affords complete opacity of trading intentions.

state after a liquidity shock. Table 4 presents the estimation results for Equation (2) with LOB resilience variables as the dependent variables. In Panel A, the β_3 estimates are negative and statistically significant from Columns (1) to (3), suggesting that the DVC implementation has a negative effect on the resilience of the order book. For stocks in the treatment group, the reduction in LOB resilience ranges from 0.020 to 0.041, depending on the LOB resilience variables. The results suggest that it takes a longer time for stocks affected DVC to recover from negative liquidity shocks. We can estimate the size of the change in LOB resilience for stocks in the treatment group. For example, we know that the average of $Resilience\_depth_{i,t}$ is about 0.4 for the treatment group (see Panel A in Table 1) and that β_3 is -0.037 for $Resilience\_depth_{i,t}$ in Column (3) of Panel A. This implies that, compared to the control group of stocks, the liquidity recovery time for the treatment group increases from about 2.5 minutes (1minute ÷ 0.4) to about 2.75 minutes (1minute ÷ (0.4-0.037)) during our sample period. 0.25 minutes is a significant lag in a market dominated by HFT activity. The magnitudes of the effects are economically meaningful and the results hold when we include the additional controls (see Columns 4 – 6).

INSERT TABLE 4 ABOUT HERE

Panel B reports the results based on the second set of treatment and control groups. We find qualitatively similar results, with negative and statistically significant β_3 estimates in Columns (1), (4), and (6). Hence, we show that, relative to the control group of stocks, stocks in the treatment groups are less resilient after the DVC kicks in. The limit order books for these stocks are less capable of absorbing liquidity shocks. As a result, DVC increases the likelihood that a large trade will exhaust shares available at the inside quotes, consequently leading to price swings. Our results are robust to alternating the measurement frequency of the LOB. We repeat our analysis for Equation (2) with the LOB resilience estimated at the 5-minute interval as done by Kempf *et* *al*. (2015); the results of the regression analysis presented in Table 5 show that our findings are unchanged.

INSERT TABLE 5 ABOUT HERE

4.4. Trade-to-order ratio

Order book resilience, or lack of it, is linked to the level of engagement in trading. Therefore, we extend our analysis to investigate the impact of the DVC implementation on trading activity. This analysis is also aimed at informing our understanding of the impact of the DVC implementation on liquidity since trading activity informs liquidity (see Chordia et al., 2001) Specifically, the analysis tests whether trading activity as a channel offers a plausible explanation for the impact of dark trading dynamics on liquidity. We proxy trading activity using total trade volume divided by total order volume submitted at the best bid and ask quotes, i.e. $TOR_{i,t}$. Previous studies apply a similar measure as a proxy for algorithmic or computerized low-latency trading activity (for example Hendershott *et a*l., 2011, use the order to trade ratio). However, we follow Comerton-Forde *et al*. (2019) and employ it as a proxy of the profit accruing to liquidity providers since it captures the probability of execution at the top of the limit order book.

INSERT TABLE 6 ABOUT HERE

We estimate Equation (2) with $TOR_{i,t}$ as the dependent variable to capture the impact of the DVC implementation on it. Table 6 reports the estimation results for both sets of control and treatment groups of stocks. In Panel A, the β_3 estimates are negative and statistically significant at the 0.05 and 0.01 levels for the regressions reported in Columns (1) and (2) respectively. This indicates that the implementation of the DVC has the effect of impairing $TOR_{i,t}$ in the first treatment group relative to its control group by about 1.1 to 1.3 basis points. The β_3 estimate for the second set of control and treatment stocks regression are also negative, but the level of statistical significance is lower. Thus, consistently, the results appear to support the view that trading activity is a channel through which the DVC implementation impairs liquidity. Specifically, the DVC implementation has an ameliorating effect on the volume of marketable orders, which in turn negatively impacts the exchange of stock units through trading. The difference in $TOR_{i,t}$ observed between the treatment and control groups of stocks is even starker when considering that the positive and statistically significant (at the 0.01 level) estimate on the time trend suggests that the execution probability increases over the course of our sample period.

There are further estimates in Table 6 that deserve attention. Firstly, it can be observed that the estimate on market capitalization is negative and statistically significant at the 0.05 level; hence, large-cap stocks tend to have lower $TOR_{i,t}$. This is because large-cap stocks are typically liquid and have longer limit order queues, which deflate their trade-to-order ratio. Volatility is also negatively related to $TOR_{i,t}$ (δ_2 is negative and statistically significant at the 0.01 level) because liquidity providers expect a reduction in profits during periods of high market uncertainty.

Generally, we document a significant fall in the volume of marketable orders executed at the top of the limit order book for the treatment group of stocks following the DVC implementation; this implies a reduction in market-making expected profit. Having also shown in earlier results that the imposition of a dark trading halt leads to higher transaction costs and shallower market depth, we would expect that the DVC implementation impairs market efficiency for the affected stocks. This is explained by previous studies indicating that a liquid trading environment and competitive market making are key factors in fostering informational efficiency (see as an example, Chordia *et al*., 2008; Chung and Hrazdil, 2010). In the next section, we investigate how informational efficiency changes following the DVC implementation.

4.5. The impact of DVC on informational efficiency

Panel A in Table 7 reports the regression estimates of the impact of DVC on informational efficiency for the first group of control and treatment stocks. Four of the β_3 estimates are positive and statistically significant at 0.01 and 0.05 levels. Columns (3) and (6) estimates are not statistically significant. The results are robust to the inclusion of control variables from the regressions. While the units of the informational efficiency measures do not have a natural interpretation other than relative efficiency, Panel A estimates indicate that the implementation of the DVC is associated with a deterioration in informational efficiency. For example, the implementation is linked with an increase of about 80 basis points in $Predict_{i,t}$. This effect gives credence to the argument that there is an increase in uninformed trading volume in the aggregate market in the presence of dark trading, because dark pools allow uninformed/liquidity traders to trade safer (it lowers adverse selection risk for uninformed traders) and cheaper (no spread or price impact due to large order sizes, as in Nimalendran and Ray, 2014). Thus, orders that otherwise would not have been submitted get submitted. This is similar to the effect of the traditional upstairs market as reported by Madhavan and Cheng (1997) and several others,[8] and implies that when the dark trading mechanism is withdrawn, a shortfall in liquidity is not easily satisfied by existing trading avenues arises. As informed traders typically execute against uninformed order flow, informational efficiency is impaired when uninformed trading volume falls. Specifically, in the

[8] The main differences between the upstairs markets of old and the modern mid-point dark pools which we study are 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.

absence of sufficient uninformed trading volumes, informed traders become disincentivised to acquire information that could be incorporated into prices through their trading activity (see Kyle, 1985; Glosten, 1998). The Panel B coefficient estimates are qualitatively similar to those in Panel A.

INSERT TABLE 7 ABOUT HERE

The consistency of our findings in this section with those on the impact of the DVC implementation on liquidity is due to the inextricable link between these market quality characteristics. For example, Chordia *et al*. (2008) document that liquid markets are typically more informationally efficient. When a market becomes relatively illiquid, trading on fundamental information becomes costly and market participants may not submit the arbitrage trades critical to making asset price converge to its fundamental value. Furthermore, informed traders typically congregate on lit venues. Thus, when they face uninformed traders precluded from trading in dark venues on account of the implementation of the DVC, they are less incentivised to collect more information due to the informational advantage they already have. Hence, the overall information efficiency of the price discovery in the market may be impaired.

4.6. Placebo test

As a further robustness check, we execute a series of placebo tests aimed at determining whether the introduction of the DVC affects market liquidity and informational efficiency. In the placebo tests, we employ a group of stocks that are not affected by DVC during the sample period as the fake treatment group. We match the fake treatment group with the control group and repeat our analysis. We do not expect to see that DVC yields statistically significant results in the placebo group. In order to find the appropriate matching group, we look at another major European equity index, namely the SBF 120, which consists of the 120 most actively traded stocks in Paris. We first identify 50 active stocks that are unaffected by the DVC within the SBF index and then use these as a fake treatment group. The 77 unaffected FTSE 250 stocks are included as the control group. Panel A in Table 8 shows the placebo test for market liquidity. The interaction term's coefficients for the $RelativeSpread_{i,t}$, $RealizedSpread_{i,t}$ and $Amihud_{i,t}$ suggest that, compared to the 77 FTSE stocks in the control group, the illiquidity proxies for the placebo group increase after the introduction of the DVC. However, the differences are not statistically significant at any conventional level. The interaction coefficients for $EffectiveSpread_{i,t}$ and $Depth_{i,t}$ are also not statistically significant. Furthermore, we fail to obtain significant coefficient estimates even when the control variables are excluded.

INSERT TABLE 8 ABOUT HERE

Panels B and C present the placebo test results with LOB resilience and informational efficiency proxies as the dependent variables. As expected, the coefficients for the key interaction variables are not statistically significant at any conventional level. This implies that equities that are unaffected by the DVC in London and Paris have statistically significant differences in terms of liquidity, LOB resilience, and informational efficiency. In summary, the placebo tests provide additional evidence that the implementation of the DVC leads to higher transaction costs and impairs informational efficiency.

5. Conclusion

This paper presents evidence of the direct impact of recent regulatory restrictions on dark trading on several market quality proxies. Specifically, we exploit the introduction of the double volume cap (DVC) regulation introduced under MiFID II to test for the impact of the loss of dark trading volumes on market quality. We find that, following the implementation of the associated trading halt, the market share of the affected stocks on dark venues fell to virtually zero. We provide evidence that stocks affected by the examined dark trading caps experience an increase in transaction costs and suffer a deterioration in liquidity. When dark trading is restrained, the order flow competition between lit and dark venues is reduced and therefore market makers in lit venues tend to exploit monopoly power in setting spreads for the exchange of stocks. This increased leverage/power inevitably leads to larger transaction costs and wealth transfer from liquidity takers to liquidity providers.

Our analysis also includes other dimensions of market quality. We find that the DVC leads to lower LOB resilience and informational efficiency. In a less liquid market, the cost of replenishing market liquidity after a liquidity shock becomes higher and leads to a longer wait for liquidity on LOBs to revert back to pre-shock levels. Hence, we find that LOB resilience declines for stocks with DVC. Furthermore, a less liquid market might discourage agents to trade on information about fundamentals as transaction costs are high. This leads to asset price deviating from its true value, i.e. relatively lower informational efficiency. Our results are also consistent with the literature streams that find that inter-venue order flow competition enhances market quality (e.g., Biais *et al*., 2010; Buti *et al*., 2014), and that dark trading benefits informational efficiency (e.g.,Comerton-Forde and Putniņš, 2015; Aquilina *et al*., 2017; Brogaard and Pan, 2019).

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, and already implemented in Europe. We show that limiting dark pool trading using regulatory thresholds might not be an optimal approach for regulation. Banning dark trading without providing effective alternative venues will likely increase the transaction costs, especially for liquidity traders, and reduce informational efficiency. As discussed in Foley and Putniņš (2016), another way to regulate dark trading could be by introducing a minimum price improvement for dark pools. Alternatively, regulators can also expand the existing off-exchange trading venues, such as periodic auctions, to accommodate volumes that otherwise would have been executed in dark pools.

References

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. J. Financ. Markets. 5, 31-56.

Aquilina, M., Diaz-Rainey, I., Ibikunle, G., Sun, Y. (2017) Aggregate Market Quality Implications of Dark Trading. Financial Conduct Authority's Occasional Papers. August 2017. London: Financial Conduct Authority.

Barclay, M. J., Hendershott, T. and Mccormick, D. T., 2003. Competition among trading venues: Information and trading on electronic communications networks. J. Finance. 58. 2637-2665.

Biais, B., Bisiere, C., Spatt, C., 2010. Imperfect competition in financial markets: An empirical study of island and nasdaq. Manage. Sc. 56, 2237-2250.

Boulatov, A., George, T. J., 2013. Hidden and displayed liquidity in securities markets with informed liquidity providers. Rev. Financ. Stud. 26, 2096-2137.

Brockman, P., Chung, D. Y., Pérignon, C., 2009. Commonality in liquidity: A global perspective. J. Financ. Quant. Anal. 44, 851-882.

Brogaard, J., Pan, J., 2019. Dark trading and the fundamental information in stock prices. Unpublished Working Paper.

Brolley, M., 2020. Price improvement and execution risk in lit and dark markets. Manage. Sc. 66, 863-886.

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., 2014. Sub-penny and queue-jumping. Unpublished Working Paper.

Buti, S., Rindi, B., Werner, I., 2011. Diving into dark pool. Unpublished Working Paper.

Chordia, T., Roll, R., Subrahmanyam, A., 2001. Market Liquidity and Trading Activity. The J. Finance. 56, 501-530.

Chordia, T., Roll, R., Subrahmanyam, A., 2008. Liquidity and market efficiency. J. Financ. Econ. 87, 249-268.

Chung, D., Hrazdil, K., 2010. Liquidity and market efficiency: A large sample study. J. Bank. Financ. 34, 2346-2357.

Chung, K.H., Lee, A.J., Rösch, D., 2020. Tick size, liquidity for small and large orders, and price informativeness: Evidence from the Tick Size Pilot Program. J. Financ Econ, 136, 879-899.

Comerton-Forde, C., Gregoire, V., Zhong, Z., 2019. Inverted fee structures, tick size, and market quality. J. Financ. Econ. 134, 141-164.

Comerton-Forde, C., Malinova, K., Park, A., 2017. Regulating dark trading: Order flow segmentation and market quality. J. Financ. Econ. 130, 347-366.

Comerton-Forde, C., Putniņš, T. J., 2015. Dark trading and price discovery. J. Financ. Econ. 118, 70-92.

Degryse, H., De Jong, F., Kervel, V. V., 2015. The impact of dark trading and visible fragmentation on market quality. Rev. Fin. 19, 1587-1622.

ESMA, 2019. Esma report on trends, risks and vulnerabilities.

Foley, S., Putniņš, T. J., 2016. Should we be afraid of the dark. J. Financ. Econ. 122, 456-481

Foucault, T., Menkveld, A. J., 2008. Competition for order flow and smart order routing systems. J. Finance. 63, 119-158.

Glosten, L. R., 1998. Competition, design of exchanges and welfare. Unpublished Working Paper.

Glosten, L. R., Milgrom, P. R., 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. J. Financ. Econ. 14, 71-100.

Gresse, C., 2017. Effects of lit and dark market fragmentation on liquidity. J. Financ. Markets. 35, 1-20.

Griffith, T. G., Roseman, B. S., 2019. Making cents of tick sizes: The effect of the 2016 U.S. SEC tick size pilot on limit order book liquidity. J. Bank. Finance. 101, 104-121.

Hendershott, T., Jones, C. M., Menkveld, A. J., 2011. Does algorithmic trading improve liquidity? J. Finance. 66, 1-33.

Hendershott, T., Mendelson, H., 2000. Crossing networks and dealer markets: Competition and performance. J. Finance. 55, 2071-2115.

Huang, R. D., Stoll, H. R., 1996. Dealer versus auction markets: A paired comparison of execution costs on Nasdaq and the nyse. J. Financ. Econ. 41, 313-357.

Ibikunle, G., 2015. Opening and closing price efficiency: Do financial markets need the call auction? J. Int. Financ. Markets Inst. Money. 34, 208-227.

Ibikunle, G., Rzayev, K., 2020. Volatility, dark trading and market quality: evidence from the 2020 COVID-19 pandemic-driven market volatility. Centre for Economic and Policy Research's Covid Economics: Vetted and Real-time Papers.

Johann, T., Putniņš, T. J., Sagade, S., Westheide, C., 2020. Quasi-dark Trading: The effects of banning dark pools in a world of many alternatives. Unpublished Working Paper.

Kempf, A., Mayston, D. L., Gehde-Trapp, M., Yadav, P. K., 2015. Resiliency: A dynamic view of liquidity. Unpublished Working Paper.

Kwan, A., Masulis, R., Mcinish, T. H., 2015. Trading rules, competition for order flow and market fragmentation. J. Financ. Econ. 115, 330-348.

Kyle, A. S., 1985. Continuous auctions and insider trading. Econometrica, 53, 1315-1335.

Lee, C. M. C., Ready, M. J., 1991. Inferring trade direction from intraday data. Journal. Finance. 46, 733-746.

Madhavan, A., Cheng, M., 1997. In search of liquidity: Block trades in the upstairs and and downstairs markets. Rev. Financ. Stud. 10, 175-203.

Marshall, B. R., Nguyen, N. H., Visaltanachoti, N., 2013. Liquidity commonality in commodities. J. Bank. Finance. 37, 11-20.

Menkveld, A. J., Yueshen, B. Z. and Zhu, H., 2017. Shades of darkness: A pecking order of trading venues. J. Financ. Econ. 124, 503-534.

Neumeier, C., Gozluklu, A., Hoffmann, P., O'Neill, P., Suntheim, F., 2021. Banning Dark Pools: Venue Selection and Investor Trading Costs. Financial Conduct Authority's Occasional Papers. February 2021. London: Financial Conduct Authority.

Nimalendran, M., Ray, S., 2014. Informational linkages between dark and lit trading venues. J. Financ. Markets. 17, 230-261.

O'Hara, M., Ye, M., 2011. Is market fragmentation harming market quality? J. Financ. Econ. 100, 459-474.

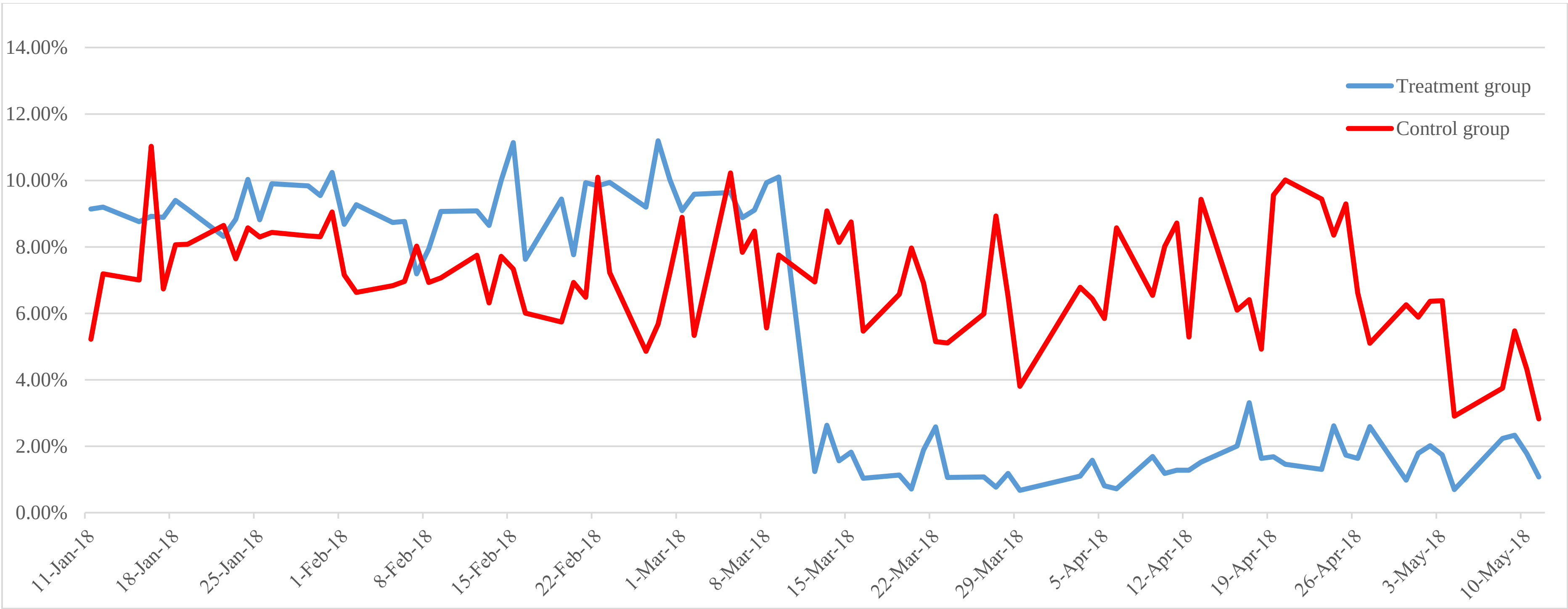
Ye, M., 2012. Price manipulation, price discovery and transaction costs in the crossing network. Unpublished Working Paper.

Zhu, H., 2014. Do dark pools harm price discovery? Rev. Financ. Stud. 27, 747-789.

Figure 1:

Panel A plots the pound volume of dark pools as a percentage of total pound volume for set 1 treatment and control groups on the four main London exchanges/trading venues. Panel B shows the pound volume of dark pools as a percentage of total pound volume for set 2 treatment and control groups. The sample period is between 11th January 2018 and 11th May 2018. Set 1 treatment and control groups include 82 capped FTSE100 and 84 uncapped FTSE350 stocks respectively. Set 2 treatment and control groups have 77 capped and uncapped FTSE250 stocks respectively. The venues are the London Stock Exchange, BATS, Chi-X, and Turquoise.

PANEL A: Percentage of dark pound volume for set 1 treatment and control groups



PANEL B: Percentage of dark pound volume for set 2 treatment and control groups

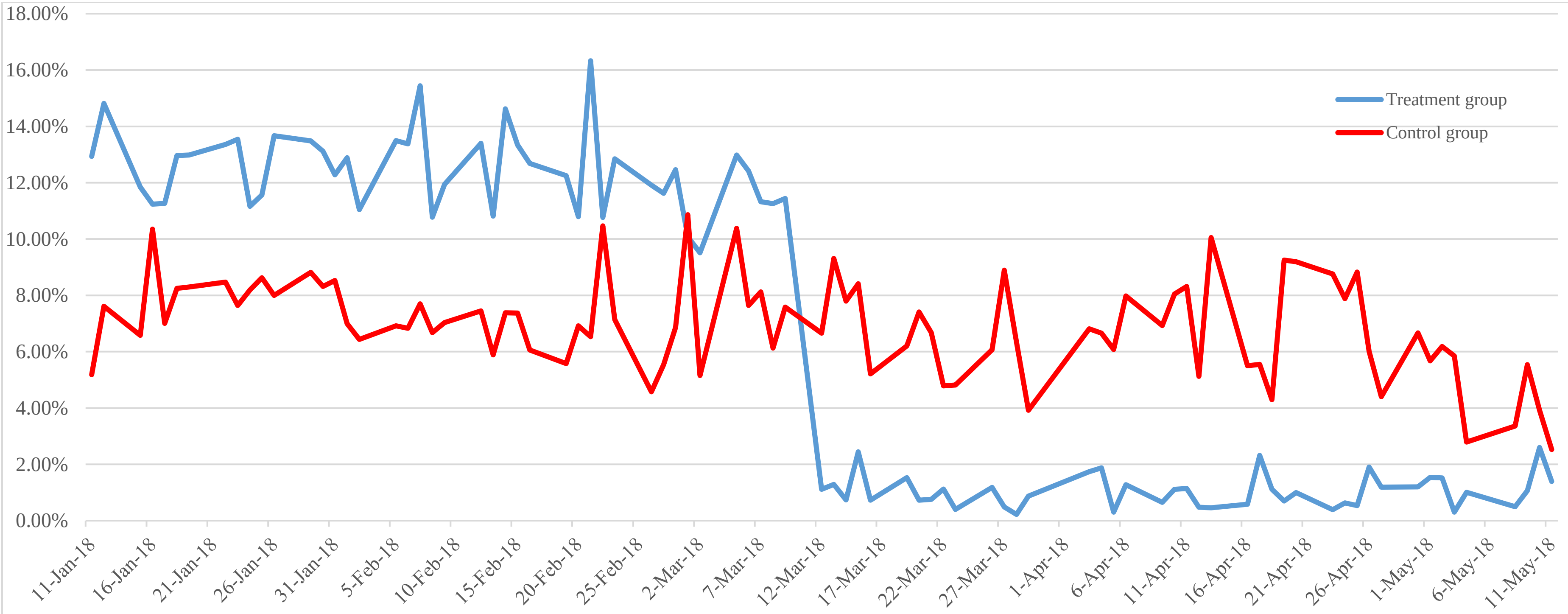
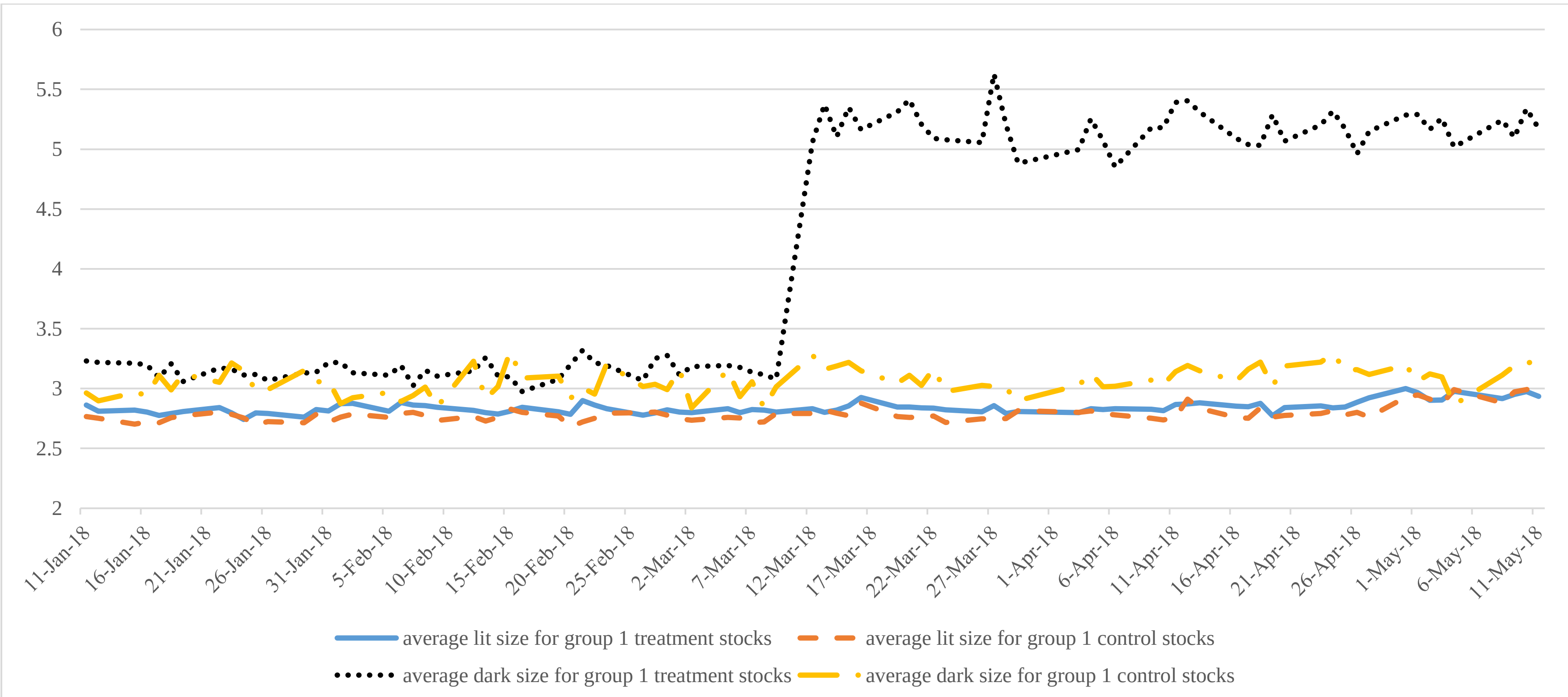

18.00%
16.00%
14.00%
12.00%
10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
11-Jan-18
16-Jan-18
21-Jan-18
26-Jan-18
31-Jan-18
5-Feb-18
10-Feb-18
15-Feb-18
20-Feb-18
25-Feb-18
2-Mar-18
7-Mar-18
12-Mar-18
17-Mar-18
22-Mar-18
27-Mar-18
1-Apr-18
6-Apr-18
11-Apr-18
16-Apr-18
21-Apr-18
26-Apr-18
1-May-18
6-May-18
11-May-18
Treatment group
Control group

Figure 2: Average trade size

Panel A plots the log value of the average size of lit trades and dark trades for set 1 treatment and control groups on the four main London exchanges/trading venues. Panel B plots the log value of the average size of lit trades and dark trades for set 2 treatment and control groups. Set 1 treatment and control groups include 82 capped FTSE100 and 84 uncapped FTSE350 stocks respectively, while Set 2 treatment and control groups have 77 capped and uncapped FTSE250 stocks respectively. The sample period is between 11th January 2018 and 11th May 2018.

PANEL A: The log value of trade size on lit and dark venues for set 1 groups



PANEL B: The log value of trade size on lit and dark venues for set 2 groups

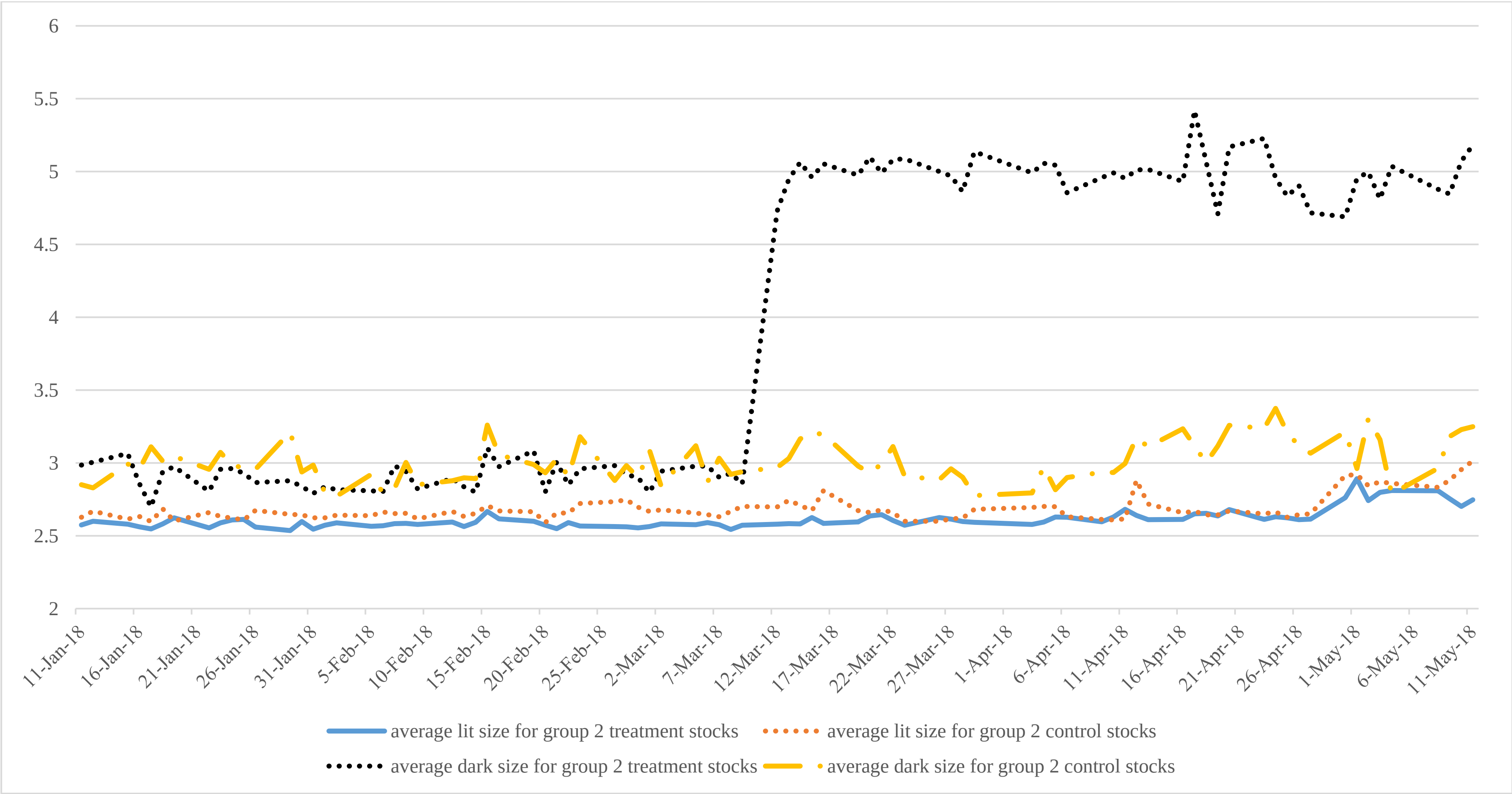


Table 1. Descriptive statistics of control and treatment groups

This table reports the descriptive statistics for key liquidity, trading activity, and efficiency variables for the treatment and control group of FTSE350 stocks. Statistical analysis of the differences between the variables of both groups is also presented. The treatment group of stocks are affected by the 12th March 2018 dark trading halt imposed by European authorities, while the control group stocks are not affected by the halt. $EffectiveSpread_{i,t}$ and $RealizedSpread_{i,t}$ are as defined in Equations (3) and (4) and are volume-weighted. $AmihudRatio_{i,t}$ is the stock-day's return divided by daily volume in billion shares. $Depth_{i,t}$ is the natural log of daily pound volume of the total order submitted at the best bid and ask price for stock *i* on day *t*. $Resilience\_ES_{i,t}$ and $Resilience\_RS_{i,t}$ are computed in relation to $EffectiveSpread_{i,t}$ and $RealizedSpread_{i,t}$ respectively using Equation (7) with a time interval of one minute. $Resilience\_depth_{i,t}$ is computed in relation to $Depth_{i,t}$ using Equation (7) with a time interval of one minute. $TOR_{i,t}$ is the stock-day trade-to-order ratio calculated by the volume of trade divided by the volume of shares submitted at the best bid and ask price. $VarianceRatio_{i,t}$ is computed as defined in Equation (8) using ten and one second time intervals. $Predict_{i,t}$ is the stock-day predictability of one-minute mid-quote returns using lagged order imbalance, and is computed by estimating Equation (9) and obtaining the $\overline{R^2}$ value stock *i* on day *t*. $Autocorrelation_{i,t}$ is defined as the absolute value of the stock-day's 10-second mid-quote return autocorrelations. Panel A includes descriptive statistics for the set 1 treatment and control groups, which are 82 capped FTSE100 and 82 uncapped FTSE350 stocks respectively, while Panel B presents statistics for the set 2 treatment and control groups, which are 77 capped and uncapped FTSE250 stocks respectively. *t* -statistics are reported in parentheses. *, ** and *** correspond to statistical significance at the 0.1, 0.05 and 0.01 levels respectively.

Panel A

	Treatment group (capped 82 stocks in FTSE100)			Control group (Uncapped 82 stocks from FTSE350)		
	Before regulation	After regulation	difference	Before regulation	After regulation	difference
$lit\ £volume_{i,t}$	45214520.438 (25850134.986)	46190525.628 (26092486.429)	976005.000 (0.800)	8526371.014 (514904.500)	8512717.457 (659817.849)	-13653.600 (-0.020)
$dark\ £volume_{i,t}$	2271208.056 (1053718.110)	1147758.269 (759734.100)	-1123450.000*** (-4.140)	574781.965 (51013.655)	554395.706 (33646.060)	-20386.300 (-0.330)
$percent\ of\ dark\ t$	9.250% (9.254%)	1.550% (1.549%)	-7.700%*** (-48.490)	7.470% (7.645%)	6.690% -221.000%	-0.779%*** (6.686%)
$RelativeSpread_{i,t}$ (%)	0.051 (0.048)	0.054 (0.047)	0.003** (2.160)	0.806 (0.287)	0.747 (0.267)	-0.059 (-0.690)
$EffectiveSpread_i$ (%)	0.161 (0.045)	0.425 (0.042)	0.264*** (3.710)	0.609 (0.278)	1.144 (0.245)	0.535* (1.730)

$RealizedSpread_{i,t}$ (%)	0.043 (0.037)	0.045 (0.037)	0.002* (1.910)	0.792 (0.274)	0.678 (0.238)	-0.114 (-1.300)
$AmihudRatio_{i,t}$	0.070 (0.023)	0.064 (0.022)	-0.006* (-1.800)	5.134 (0.381)	3.383 (0.295)	-1.751** (-2.040)
$Depth_{i,t}$	25.655 (25.528)	25.524 (25.460)	-0.131*** (-5.850)	21.993 (21.302)	22.011 (21.372)	0.018 (0.340)
$Resilience\_ES_{i,t}$	0.508 (0.476)	0.455 (0.460)	-0.052 （-1.072）	0.826 (0.824)	0.748 (0.825)	-0.068 (-1.101)
$Resilience\_RS_{i,t}$	0.870 (0.865)	0.851 (0.849)	-0.019*** （-4.061）	0.854 (0.897)	0.822 (0.845)	-0.033 (-0.582)
$Resilience\_depth_{i,}$	0.394 (0.382)	0.404 (0.387)	0.024 (1.17)	0.549 (0.603)	0.606 (0.663)	0.057*** (3.890)
$TOR_{i,t}$ (%)	2.656 (2.260)	3.015 (2.530)	0.359*** (8.070)	4.071 (2.542)	5.772 (2.596)	1.701*** (3.630)
$VarianceRatio_{i,t}$ (%)	0.387 (0.235)	0.415 (0.212)	0.028 (0.740)	11.347 (1.497)	10.177 (1.353)	-1.170 (-1.340)
$Predict_{i,t}$ (%)	0.551 (0.191)	0.496 (0.189)	-0.055* (-1.870)	3.682 (0.618)	2.957 (0.474)	-0.726*** (-2.970)
$Autocorrelation_{i,t}$	2.391	2.403	-0.093	2.655	2.629	-0.026

(%)	(2.663)	(2.543)	(-0.18)	(2.028)	(2.179)	(-0.120)

Panel B

	Treatment group (capped 77 stocks in FTSE250)			Control group (uncapped 77 stocks in FTSE250)		
	Before regulation	After regulation	difference	Before regulation	After regulation	difference
$lit\ £volume_{i,t}$	5370581.435 (2341229.863)	5544754.096 (2657879.844)	174173.000 (0.650)	5848380.741 (460567.098)	5477163.866 (593649.530)	-371217.000 (-0.920)
$dark\ £volume_{i,t}$	272230.176 (107989.325)	363.217 (0.000)	-271867*** (-27.540)	245882.449 (2648.459)	126857.406 (545.680)	-119025.000*** (-6.160)
$percent\ of\ dark\ trading_i$	12.430% (12.441%)	1.050% (1.039%)	-11.380%*** （-48.053）	7.430% (7.377%)	6.440% (6.271%)	-0.986%*** （-2.710）
$RelativeSpread_{i,t}$(%)	0.228 (0.150)	0.203 (0.148)	-0.025*** (-2.770)	1.131 (0.306)	0.966 (0.280)	-0.165 (-1.410)
$EffectiveSpread_{i,t}$ (%)	0.2047 (0.143)	0.4509 (0.134)	0.2462** (2.240)	0.780 (0.298)	1.218 (0.259)	0.437 (1.460)
$RealizedSpread_{i,t}$ (%)	0.2040 (0.129)	0.1881 (0.124)	-0.0159 (-1.360)	1.084 (0.291)	0.883 (0.254)	-0.202* (-1.750)
$AmihudRatio_{i,t}$	1.132 (0.187)	0.797 (0.145)	-0.335*** (-3.060)	4.930 (41.916)	3.400 (31.622)	-1.530* (-1.840)
$Depth_{i,t}$	22.853 (22.824)	22.892 (22.880)	0.040 (1.190)	21.797 (21.210)	21.839 (21.297)	-1.850 (0.042)
$Resilience\_ES_{i,t}$	0.705	0.648	-0.051	0.830	0.749	-0.081

	(0.694)	(0.720)	(-1.401)	(0.842)	(0.835)	(-1.183)
$Resilience\_RS_{i,t}$	0.823 (0.817)	0.788 (0.826)	-0.039 (-0.73)	0.863 (0.901)	0.829 (0.898)	-0.04 (-0.653)
$Resilience\_depth_{i,t}$	0.518 (0.519)	0.552 (0.564)	0.034*** (3.403)	0.552 (0.612)	0.615 (0.678)	0.064*** (4.193)
$TOR_{i,t}$ (%)	3.6190 (3.096)	4.4895 (3.323)	0.8705*** (7.180)	4.390 (2.604)	6.153 (2.633)	1.763*** (3.500)
$VarianceRatio_{i,t}$ (%)	3.1187 (0.802)	2.5023 (0.755)	-0.6165*** (-2.730)	14.499 (1.592)	12.254 (1.430)	-2.245** (-2.230)
$Predict_{i,t}$ (%)	1.0518 (0.321)	0.9761 (0.312)	-0.0757 (-1.300)	4.058 (0.662)	3.190 (0.508)	-0.868*** (-3.360)
$Autocorrelation_{i,t}$(%)	16.565 (13.360)	15.988 (13.370)	-0.576 (-0.630)	23.893 (19.895)	24.680 (21.505)	-0.787 (0.280)

Table 2. Impact of dark trading cap on stock liquidity

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

$$MKTQuality_{i,t} = a_1 + \beta_1 DVC_t + \beta_2 TRET_i + \beta_3 DVC_t \times TRET_i + \beta_4 Time_t + \delta' X_{i,t} + FE_i + \varepsilon_{i,t}$$

DVC_t is a dummy variable equalling one if the trading day is 12th March 2018 or afterwards, and otherwise zero. $TRET_i$ is a dummy variable that equals to one if the stock belongs to the treatment group, and otherwise zero. $MKTQuality_{i,t}$ corresponds to one of $RelativeSpread_{i,t}$, $EffectiveSpread_{i,t}$, $RealizedSpread_{i,t}$, $Amihud_{i,t}$ or $Depth_{i,t}$. $RelativeSpread_{i,t}$ is the stock-day time-weighted relative spread for lit venues. $EffectiveSpread_{i,t}$ and $RealizedSpread_{i,t}$ are as defined in Equations (3) and (4) and are volume-weighted. $Amihud_{i,t}$ is the stock-day's return divided by daily volume in billion shares. $Depth_{i,t}$ is the natural log of daily pound volume of the total order submitted 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 every trading day. $MktCap_{i,t}$ is the log of closing market capitalisation for stock *i* on day *t*. $Volatility_{i,t}$ is the daily standard deviation of mid-quote return. $return_{i,t}$ measures the daily return for stock *i* on day *t*. FE_i denotes firm fixed effects. Panels A and B report the estimation results for the two sets of treatment and control stocks described in Table 1. Standard errors are clustered both by stock and date, t -statistics are reported in parentheses. *, ** and *** correspond to statistical significance at the 0.1, 0.05 and 0.01 levels respectively. The sample period is from 11th January 2018 to 11th May 2018.

Panel A: results based on set 1 groups

	$RelativeSpread$	$EffectiveSpreac$	$RealizedSpreac$	$Amihud_{i,t}$	$Depth_{i,t}$	$RelativeSpread_i$	$EffectiveSprea$	$RealizedSpread$	$Amihud_{i,t}$	$Depth_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DVC_t	-0.392*** (-2.74)	-0.037 (-1.53)	-0.166*** (-3.45)	-1.885** (-2.34)	0.050*** (3.81)	-0.155 (-0.95)	-0.201*** (-6.51)	-0.111** (-2.55)	-0.983 (-0.99)	0.194*** (11.19)
$TRET_i$	1.058*** (8.74)	-0.133 (-1.02)	-0.438*** (-4.97)	-0.913** (-2.20)	3.293*** (35.18)	1.726*** (6.69)	0.087 (0.64)	0.007 (0.06)	0.529 (1.11)	3.214*** (36.40)
DVC_t*$TRET_i$	0.389*** (2.72)	0.097*** (3.12)	0.169*** (3.51)	1.879** (2.34)	-0.172*** (-11.49)	0.287** (2.11)	0.078*** (2.76)	0.140*** (3.32)	2.057** (2.40)	-0.179*** (-11.97)
$Time_t$						-0.003 (-1.41)	0.004*** (7.16)	-0.001 (-0.74)	-0.026** (-2.21)	-0.003*** (-10.44)
$MktCap_{i,t}$						0.088 (1.64)	0.009 (1.08)	-0.000 (-0.02)	-0.399** (-2.26)	0.018*** (4.03)
$Volatility_{i,t}$						77.488*** (11.66)	19.883*** (18.74)	35.053*** (8.45)	1.779 (0.71)	-1.147*** (-4.30)
$return_{i,t}$						-2.183 (-1.00)	-2.000*** (-3.89)	-0.089 (-0.14)	-12.181** (-1.96)	0.345 (1.09)
Constant	0.833*** (7.19)	0.320*** (7.24)	0.478*** (5.43)	1.040** (2.50)	21.615*** (243.99)	-2.189 (-1.63)	-0.288 (-1.32)	0.050 (0.15)	11.261** (2.44)	21.290*** (150.92)
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13647	13647	13647	13647	13647	13647	13647	13647	13647	13647

$\overline{R^2}$	52.14%	18.19%	16.31%	18.03%	86.95%	58.73%	31.06%	36.20%	18.65%	86.98%

Panel B: results based on set 2 groups

	$RelativeSpread_{i,}$	$EffectiveSpread_{i,}$	$RealizedSpread_{i}$	$Amihud_{i,t}$	$Depth_{i,t}$	$RelativeSpread_{i}$	$EffectiveSpread$	$RealizedSpread_{i}$	$Amihud_{i,t}$	$Depth_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DVC_t	-0.442*** (-3.08)	0.074 (0.82)	-0.240*** (-3.55)	-1.758** (-2.26)	0.082*** (6.04)	-0.191 (-1.14)	-0.412*** (-3.20)	-0.125 (-1.64)	-0.608 (-0.61)	0.207*** (10.32)
$TRET_i$	1.146*** (9.11)	-0.169** (-2.25)	-0.338*** (-3.67)	0.285 (0.68)	0.483*** (4.75)	2.016*** (10.61)	0.223** (2.01)	0.246** (2.06)	0.237 (0.46)	0.459*** (4.58)
DVC_t*$TRET_i$	0.401*** (2.77)	0.108 (0.89)	0.217*** (3.18)	1.424* (1.82)	-0.052*** (-2.96)	0.301** (2.26)	0.069 (0.57)	0.149*** (2.61)	1.406* (1.81)	-0.051*** (-2.91)
$Time_t$						-0.003 (-1.21)	0.013*** (3.29)	-0.001 (-0.55)	-0.027** (-2.15)	-0.003*** (-8.04)
$MktCap_{i,t}$						-0.002 (-0.04)	-0.043* (-1.73)	-0.003 (-0.32)	0.162 (1.39)	0.008** (2.34)
$Volatility_{i,t}$						70.541*** (14.23)	28.567*** (8.64)	47.341*** (11.15)	7.993 (1.34)	-1.270*** (-5.12)
$return_{i,t}$						-1.902 (-0.86)	0.435 (0.24)	0.253 (0.30)	-8.377 (-1.29)	0.331 (1.03)
Constant	0.857*** (7.37)	0.264*** (4.24)	0.515*** (5.61)	0.977** (2.44)	21.599*** (241.32)	0.028 (0.03)	0.604 (0.98)	-0.013 (-0.04)	-2.440 (-0.91)	21.502*** (175.79)
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	12795	12795	12795	12795	12795	12795	12795	12795	12795	12795
$\overline{R^2}$	49.73%	3.16%	16.72%	17.91%	81.97%	57.17%	6.74%	41.82%	17.92%	82.04%

Table 3. Robustness test for stock liquidity

The table shows results of robustness test for our baseline model below:

$$MKTQuality_{i,t} = a_1 + \beta_1 DVC_t + \beta_2 TRET_i + \beta_3 DVC_t \times TRET_i + \beta_4 Time_t + \delta' X_{i,t} + FE_i + \varepsilon_{i,t}$$

DVC_t is a dummy variable equalling one if the trading day is 12th March 2018 or afterwards, and otherwise zero. $TRET_i$ is a dummy variable that equals to one if the stock belongs to the treatment group, and otherwise zero. $MKTQuality_{i,t}$ corresponds to one of $RelativeSpread_{i,t}$, $EffectiveSpread_{i,t}$, $RealizedSpread_{i,t}$ or $Amihud_{i,t}$. $EffectiveSpread_{i,t}$ and $RealizedSpread_{i,t}$ are as defined in Equations (3) and (4) and are equally-weighted. $Amihud_{i,t}$ is calculated each stock-day using hourly return and volume observations. $Time_t$ is a trend variable that starts at zero at the beginning of the sample period and increases by one every trading day. $MktCap_{i,t}$ is the log of closing market capitalisation for stock *i* on day *t*. $Volatility_{i,t}$ is the daily standard deviation of mid-quote return. $return_{i,t}$ measures the daily return for stock *i* on day *t*. FE_i denotes firm fixed effects. Panels A and B report the estimation results for the two sets of treatment and control stocks described in Table 1. Standard errors are clustered both by stock and date, *t* -statistics are reported in parentheses. *, ** and *** correspond to statistical significance at the 0.1, 0.05 and 0.01 levels respectively. The sample period is from 11th January 2018 to 11th May 2018.

	Panel A: results based on set 1 groups				Panel B: results based on set 2 groups			
	$RelativeSprea$	$EffectiveSpreaa$	$RealizedSpread$	$Amihud_{i,t}$	$RelativeSpread_{i,t}$	$EffectiveSpread$	$RealizedSpread_{i,t}$	$Amihud_{i,t}$
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
DVC_t	-0.255*	-0.305**	-0.384*	-0.048	-0.206	-0.000***	-0.244*	-1.892
	(-1.94)	(-2.24)	(-1.78)	(-0.01)	(-1.46)	(-3.55)	(-1.76)	(-0.31)
$TRET_i$	1.757***	1.607***	1.732***	5.159	1.594***	0.001**	1.318***	0.646
	(9.12)	(7.59)	(5.12)	(1.15)	(11.52)	(2.33)	(10.98)	(0.22)
DVC_t*	0.017	0.329***	0.602***	9.314*	0.200*	0.000*	0.295***	6.779
$TRET_i$	(0.16)	(2.74)	(3.17)	(1.84)	(1.90)	(1.78)	(2.75)	(1.39)
$Time_t$	0.006***	0.000	-0.004	-0.222***	0.000	0.000***	-0.000	-0.152*
	(2.85)	(0.01)	(-1.18)	(-2.79)	(0.07)	(4.20)	(-0.17)	(-1.80)
$MktCap_{i,t}$	0.088**	-0.019	-0.034	-2.936**	0.064***	-0.000**	0.062***	1.630***
	(2.41)	(-0.35)	(-0.39)	(-2.23)	(2.98)	(-2.51)	(2.72)	(2.62)
$Volatility_{i,t}$	77.567***	63.962***	72.240***	-71.674	65.690***	0.172***	54.862***	-32.400
	(17.75)	(13.53)	(9.70)	(-1.26)	(19.77)	(52.22)	(16.16)	(-0.82)
$return_{i,t}$	-0.384	0.940	-3.014	-23.675	0.063	-0.001	1.062	35.416
	(-0.38)	(0.84)	(-1.23)	(-0.45)	(0.06)	(-0.60)	(0.92)	(0.61)
Constant	-2.559***	0.390	0.900	81.869**	-1.739***	0.002***	-1.497***	-31.137**
	(-2.75)	(0.29)	(0.42)	(2.44)	(-3.37)	(2.95)	(-2.80)	(-2.03)
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13647	13647	13647	13647	12795	12795	12795	12795
$\overline{R^2}$	92.94%	90.46%	81.52%	25.08%	80.51%	76.51%	89.97%	24.05%

Table 4. Impact of dark trading cap on LOB resilience

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

$$MKTQuality_{i,t} = a_1 + \beta_1 DVC_t + \beta_2 TRET_i + \beta_3 DVC_t \times TRET_i + \beta_4 Time_t + \delta' X_{i,t} + FE_i + \varepsilon_{i,t}$$

DVC_t is a dummy variable equalling one if the trading day is 12th March 2018 or afterwards, and otherwise zero. $TRET_i$ is a dummy variable that equals to one if the stock belongs to the treatment group, and otherwise zero. $MKTQuality_{i,t}$ corresponds to one of $Resilience\_ES_{i,t}$, $Resilience\_RS_{i,t}$ or $Resilience\_depth_{i,t}$. $Resilience\_ES_{i,t}$ and $Resilience\_RS_{i,t}$ are computed in relation to $EffectiveSpread_{i,t}$ and $RealizedSpread_{i,t}$ respectively using Equation (5) with a time interval of one minute. $Resilience\_depth_{i,t}$ is computed in relation to $Depth_{i,t}$ using Equation (5) with a time interval of one minute. $Time_t$ is a trend variable that starts at zero at the beginning of the sample period and increases by one every trading day. $MktCap_{i,t}$ is the log of closing market capitalisation for stock *i* on day *t*. $Volatility_{i,t}$ is the daily standard deviation of mid-quote return. $return_{i,t}$ measures the daily return for stock *i* on day *t*. FE_i denotes firm fixed effects. Panels A and B report the estimation results for the two sets of treatment and control stocks described in Table 1. Standard errors are clustered both by stock and date, *t* -statistics are reported in parentheses. *, ** and *** correspond to statistical significance at the 0.1, 0.05 and 0.01 levels respectively. The sample period is from 11th January 2018 to 11th May 2018.

Panel A: results based on set 1 groups

	$Resilience\_ES_{i,t}$	$Resilience\_RS_{i,t}$	$Resilience\_depth_{i,t}$	$Resilience\_ES_{i,t}$	$Resilience\_RS_{i,t}$	$Resilience\_depth_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
DVC_t	0.005 (1.24)	0.002 (0.25)	0.048*** (4.50)	0.015** (2.07)	0.041*** (4.26)	0.104*** (6.74)
$TRET_i$	0.392*** (12.13)	-0.083** (-2.28)	-0.216*** (-3.51)	0.393*** (12.20)	-0.062* (-1.69)	-0.212*** (-3.36)
DVC_t*$TRET_i$	-0.041*** (-6.02)	-0.020** (-2.53)	-0.037*** (-3.03)	-0.040*** (-5.89)	-0.019** (-2.31)	-0.037*** (-2.97)
$Time_t$				-0.000 (-1.40)	-0.001*** (-6.02)	-0.001*** (-5.44)
$MktCap_{i,t}$				-0.000 (-0.09)	-0.005** (-2.10)	-0.002 (-0.52)
$Volatility_{i,t}$				0.067 (0.88)	0.363** (1.98)	-0.148 (-0.70)
$return_{i,t}$				-1.219*** (-8.22)	0.093 (0.67)	0.597*** (3.11)
Constant	-0.977*** (-55.95)	0.888*** (30.76)	0.579*** (10.85)	-0.971*** (-25.16)	1.019*** (16.56)	0.667*** (6.40)
Firm fixed effects	YES	YES	YES	YES	YES	YES
Observations	13647	13647	13647	13647	13647	13647
$\overline{R^2}$	39.21%	4.81%	20.89%	39.62%	5.13%	21.08%

Panel B: results based on set 2 groups

	$Resilience\_ES_{i,t}$	$Resilience\_RS_{i,t}$	$Resilience\_depth_{i,t}$	$Resilience\_ES_{i,t}$	$Resilience\_RS_{i,t}$	$Resilience\_depth_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
DVC_t	0.006 (1.56)	-0.004 (-0.45)	0.057*** (5.17)	0.033*** (5.05)	-0.021 (-0.27)	0.085*** (5.12)
$TRET_i$	0.048** (2.17)	-0.101** (-2.56)	-0.104* (-1.68)	0.049** (2.26)	-0.004 (-0.04)	-0.108* (-1.75)
DVC_t*$TRET_i$	-0.042*** (-6.62)	0.017 (1.62)	-0.022 (-1.59)	-0.042*** (-6.63)	-0.002 (-0.02)	-0.022* (-1.64)
$Time_t$				-0.001*** (-4.71)	-0.000 (-0.55)	-0.001** (-2.34)
$MktCap_{i,t}$				0.000 (0.32)	0.008 (0.97)	0.002 (0.71)
$Volatility_{i,t}$				0.129* (1.92)	-0.977 (-0.79)	-0.095 (-0.46)
$return_{i,t}$				-0.244** (-2.09)	0.166 (0.23)	0.560** (2.42)
Constant	-0.980*** (-60.35)	0.906*** (32.82)	0.575*** (10.87)	-0.975*** (-27.45)	0.649*** (3.01)	0.542*** (5.79)
Firm fixed effects	YES	YES	YES	YES	YES	YES
Observations	12795	12795	12795	12795	12795	12795
$\overline{R^2}$	30.78%	2.55%	10.67%	30.94%	0.12%	10.71%

Table 5. Robustness test for LOB resilience

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

$$MKTQuality_{i,t} = a_1 + \beta_1 DVC_t + \beta_2 TRET_i + \beta_3 DVC_t \times TRET_i + \beta_4 Time_t + \delta' X_{i,t} + FE_i + \varepsilon_{i,t}$$

DVC_t is a dummy variable equalling one if the trading day is 12th March 2018 or afterwards, and otherwise zero. $TRET_i$ is a dummy variable that equals to one if the stock belongs to the treatment group, and otherwise zero. $MKTQuality_{i,t}$ corresponds to one of $Resilience\_ES_{i,t}$, $Resilience\_RS_{i,t}$ and $Resilience\_depth_{i,t}$. $Resilience\_ES_{i,t}$ and $Resilience\_RS_{i,t}$ are computed in relation to $EffectiveSpread_{i,t}$ and $RealizedSpread_{i,t}$ respectively using Equation (5) with a time interval of five minutes. $Resilience\_depth_{i,t}$ is computed in relation to $Depth_{i,t}$ using Equation (5) with a time interval of five minutes. $Time_t$ is a trend variable that starts at zero at the beginning of the sample period and increases by one every trading day. $MktCap_{i,t}$ is the log of closing market capitalisation for stock *i* on day *t*. $Volatility_{i,t}$ is the daily standard deviation of mid-quote return. $return_{i,t}$ measures the daily return for stock *i* on day *t*. FE_i denotes firm fixed effects. Panels A and B report the estimation results for the two sets of treatment and control stocks described in Table 1. Standard errors are clustered both by stock and date, *t* -statistics are reported in parentheses. *, ** and *** correspond to statistical significance at the 0.1, 0.05 and 0.01 levels respectively. The sample period is from 11th January 2018 to 11th May 2018.

	Panel A: results based on set 1 groups			Panel B: results based on set 2 groups		
	$Resilience\_ES_{i,t}$	$Resilience\_RS_{i,t}$	$Resilience\_depth_{i,t}$	$Resilience\_ES_{i,t}$	$Resilience\_RS_{i,t}$	$Resilience\_depth_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
DVC_t	-0.125	0.265**	0.103***	-0.492	0.598**	0.064***
	(-0.75)	(2.15)	(4.77)	(-1.58)	(2.03)	(2.74)
$TRET_i$	0.591	-0.372	0.043	0.667	-0.706	0.077
	(1.21)	(-0.72)	(0.49)	(1.23)	(-0.60)	(0.90)
DVC_t*$TRET_i$	-0.027	-0.218**	-0.027*	0.043	-0.389*	-0.031*
	(-0.21)	(-2.27)	(-1.65)	(0.18)	(-1.79)	(-1.68)
$Time_t$	0.000	-0.001	-0.002***	0.005	-0.007	-0.001*
	(0.12)	(-0.67)	(-5.30)	(1.24)	(-1.45)	(-1.69)
$MktCap_{i,t}$	0.038	-0.015	-0.016***	-0.005	0.017	-0.001
	(1.19)	(-0.51)	(-3.39)	(-0.20)	(0.45)	(-0.33)
$Volatility_{i,t}$	3.474	-3.284	-0.077	4.444	0.571	-0.219
	(1.07)	(-1.43)	(-0.23)	(1.50)	(0.14)	(-0.79)
$return_{i,t}$	-5.371***	1.616	0.506**	-1.708	-4.711	0.829***
	(-2.84)	(1.42)	(2.03)	(-0.52)	(-1.61)	(3.10)
Constant	-2.125**	1.677**	0.978***	-1.163	1.168	0.604***
	(-1.96)	(1.97)	(7.58)	(-1.47)	(0.78)	(5.29)
Firm fixed effects	YES	YES	YES	YES	YES	YES
Observations	13647	13647	13647	12795	12795	12795
$\overline{R^2}$	0.53%	0.77%	12.22%	0.00%	0.00%	6.31%

Table 6. Impact of dark trading cap on trading activity

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

$$TOR_{i,t} = a_1 + \beta_1 DVC_t + \beta_2 TRET_i + \beta_3 DVC_t \times TRET_i + \beta_4 Time_t + \delta' X_{i,t} + FE_i + \varepsilon_{i,t}$$

DVC_t is a dummy variable equalling one if the trading day is 12th March 2018 or afterwards, and otherwise zero. $TRET_i$ is a dummy variable that equals to one if the stock belongs to the treatment group, and otherwise zero. $TOR_{i,t}$ is the stock-day trade-to-order ratio calculated by the volume of trade divided by the volume of shares 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 increases by one every trading day. $MktCap_{i,t}$ is the log of closing market capitalisation for stock *i* on day *t*. $Volatility_{i,t}$ is the daily standard deviation of mid-quote return. $return_{i,t}$ measures the daily return for stock *i* on day *t*. FE_i denotes firm fixed effects. Panels A and B report the estimation results for the two sets of treatment and control stocks described in Table 1. Standard errors are clustered both by stock and date, t -statistics are reported in parentheses. *, ** and *** correspond to statistical significance at the 0.1, 0.05 and 0.01 levels respectively. The sample period is from 11th January 2018 to 11th May 2018.

Panel A: results based on set 1 groups			Panel B: results based on set 2 groups		
	$TOR_{i,t}$			$TOR_{i,t}$	
	(1)	(2)		(1)	(2)
DVC_t	0.017*** (3.63)	-0.014*** (-3.11)	DVC_t	0.009*** (7.25)	-0.013*** (-7.58)
$TRET_i$	-0.014*** (-6.13)	-0.008** (-2.30)	$TRET_i$	-0.001 (-1.34)	-0.002* (-1.83)
DVC_t* $TRET_i$	-0.013*** (-2.85)	-0.011** (-2.42)	DVC_t* $TRET_i$	-0.003* (-1.73)	-0.002* (-1.65)
$Time_t$		0.001*** (5.69)	$Time_t$		0.001*** (15.06)
$MktCap_{i,t}$		-0.005*** (-3.66)	$MktCap_{i,t}$		-0.000** (-2.55)
$Volatility_{i,t}$		-0.199*** (-6.96)	$Volatility_{i}$		-0.061*** (-5.46)
$return_{i,t}$		0.171 (1.43)	$return_{i,t}$		-0.039 (-1.54)
Constant	0.041*** (17.76)	0.160*** (4.28)		0.037*** (48.11)	0.035*** (4.07)
Firm fixed effects	YES	YES		YES	YES
Observations	13647	13647		12,777	12,777
$\overline{R^2}$	34.47%	34.03%		28.55%	27.96%

Table 7. Impact of dark trading cap on informational efficiency

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

$$MKTQuality_{i,t} = a_1 + \beta_1 DVC_t + \beta_2 TRET_i + \beta_3 DVC_t \times TRET_i + \beta_4 Time_t + \delta' X_{i,t} + FE_i + \varepsilon_{i,t}$$

DVC_t is a dummy variable equalling one if the trading day is 12th March 2018 or afterwards, and otherwise zero. $TRET_i$ is a dummy variable that equals to one if the stock belongs to the treatment group, and otherwise zero. $MKTQuality_{i,t}$ corresponds to one of $VarianceRatio_{i,t}$, $Predict_{i,t}$ or $Autocorrelation_{i,t}$. $VarianceRatio_{i,t}$ is computed as defined Equation (8) using ten and one second time intervals. $Predict_{i,t}$ is the stock-day predictability of one-minute mid-quote returns using lagged order imbalance, and is computed by estimating Equation (9) and obtaining the $\overline{R^2}$ value stock *i* on day *t*. $Autocorrelation_{i,t}$ is defined as the absolute value of the stock-day's 10-second mid-quote return autocorrelations. $Time_t$ is a trend variable that starts at zero at the beginning of the sample period and increases by one every trading day. $MktCap_{i,t}$ is the log of closing market capitalisation for stock *i* on day *t*. $Volatility_{i,t}$ is the daily standard deviation of mid-quote return. $return_{i,t}$ measures the daily return for stock *i* on day *t*. FE_i denotes firm fixed effects. Panels A and B report the estimation results for the two sets of treatment and control stocks described in Table 1. Standard errors are clustered both by stock and date, *t* -statistics are reported in parentheses. *, ** and *** correspond to statistical significance at the 0.1, 0.05 and 0.01 levels respectively. The sample period is from 11th January 2018 to 11th May 2018.

Panel A: results based on set 1 groups

-	$VarianceRatio_{i,t}$	$Predict_{i,t}$	$Autocorrelation_{i,t}$	$VarianceRatio_{i,t}$	$Predict_{i,t}$	$Autocorrelation_{i,t}$
	(1)	(2)	(3)	(1)	(2)	(3)
DVC_t	-1.348** (-2.08)	-0.874*** (-4.38)	-0.004 (-0.17)	-0.617* (-1.78)	-0.618*** (-2.59)	-0.015 (-0.71)
$TRET_i$	-11.882*** (-4.25)	-1.763*** (-2.60)	-0.267*** (-10.48)	-1.151 (-0.79)	-2.078*** (-2.89)	-0.089 (-1.43)
DVC_t*$TRET_i$	1.376** (2.12)	0.819*** (4.06)	-0.007 (-0.32)	0.584** (2.10)	0.801*** (3.93)	-0.015 (-0.64)
$Time_t$	12.117*** (4.34)	2.569*** (4.34)	0.343*** (13.79)	0.002 (0.35)	-0.005 (-1.34)	0.000 (0.82)
$MktCap_{i,t}$				0.140 (1.15)	0.058 (0.88)	-0.002 (-0.41)
$Volatility_{i,t}$				887.021*** (38.49)	-8.630*** (-2.83)	-0.051*** (-2.75)
$return_{i,t}$				-8.866* (-1.89)	-0.137 (-0.05)	-0.050 (-0.35)
Constant	11.632*** (4.17)	2.689*** (4.55)	0.298*** (20.12)	-2.692 (-0.80)	1.451 (0.84)	1.506*** (3.70)

Firm fixed effects	YES	YES	YES	YES	YES	YES
Observations	12970	12970	12970	12970	12970	12970
$\overline{R^2}$	33.67%	35.56%	4.86%	88.93%	35.62%	4.98%

Panel B: results based on set 2 groups

-	$VarianceRatio_{i,t}$	$Predict_{i,t}$	$Autocorrelation_{i,t}$	$VarianceRatio_{i,t}$	$Predict_{i,t}$	$Autocorrelation_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
DVC_t	-2.284*** (-2.99)	-1.020*** (-4.75)	0.185 (0.47)	-0.446 (-1.14)	-0.678** (-2.49)	0.308 (0.54)
$TRET_i$	-11.214*** (-3.99)	-1.634*** (-2.69)	-16.076*** (-6.82)	0.128 (0.09)	-1.729*** (-2.83)	-15.225*** (-6.56)
DVC_t*$TRET_i$	1.667** (2.11)	0.944*** (4.26)	-0.515 (-1.06)	0.331 (1.13)	0.957*** (4.33)	-0.581 (-1.20)
$Time_t$				-0.002 (-0.39)	-0.009* (-1.79)	0.000 (0.05)
$MktCap_{i,t}$				0.054 (0.76)	-0.014 (-0.49)	-0.076 (-0.78)
$Volatility_{i,t}$				927.885*** (58.77)	-8.756*** (-3.12)	-1.564*** (-5.58)
$return_{i,t}$				-5.412 (-1.22)	0.956 (0.35)	-13.660 (-1.60)
$Constant$	-1.120 (-0.500)	3.362*** (3.64)	69.054*** (10.18)	-1.120 (-0.503)	3.362*** (3.64)	69.054*** (10.17)
Firm fixed effects	YES	YES	YES	YES	YES	YES
Observations	12970	12970	12970	12970	12970	12970
$\overline{R^2}$	33.67%	27.35%	2.09%	88.93%	35.62%	4.98%

Table 8. Placebo test

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

$$MKTQuality_{i,t} = a_1 + \beta_1 DVC_t + \beta_2 TRET_i + \beta_3 DVC_t \times TRET_i + \beta_4 Time_t + \delta^{\prime} X_{i,t} + FE_i + \varepsilon_{i,t}$$

DVC_t is a dummy variable equalling one if the trading day is 12th March 2018 or afterwards, and otherwise zero. $TRET_i$ is a dummy variable that equals to one if the stock belongs to the treatment group, and otherwise zero. $MKTQuality_{i,t}$ corresponds to one of the following market quality variables of $RelativeSpread_{i,t}$, $EffectiveSpread_{i,t}$, $RealizedSpread_{i,t}$, $Amihud_{i,t}$, $Depth_{i,t}$, $VarianceRatio_{i,t}$, $Predict_{i,t}$, $Autocorrelation_{i,t}$, $Resilience\_ES_{i,t}$, $Resilience\_RS_{i,t}$ or $Resilience\_depth_{i,t}$. $RelativeSpread_{i,t}$, is the stock-day time-weighted relative spread for lit venues. $EffectiveSpread_{i,t}$ and $RealizedSpread_{i,t}$ are as defined in Equations (3) and (4) and are volume-weighted. $Amihud_{i,t}$ is the stock-day's return divided by daily volume in billion shares. $Depth_{i,t}$ is the natural log of daily pound volume of the total order submitted at the best bid and ask price for stock *i* on day *t*. $VarianceRatio_{i,t}$ is computed as defined in Equation (8) using ten and one second time intervals. $Predict_{i,t}$ is the stock-day predictability of one-minute mid-quote returns using lagged order imbalance, and is computed by estimating Equation (9) and obtaining the $\overline{R^2}$ value stock i on day t. $Autocorrelation_{i,t}$ is defined as the absolute value of the stock-day's 10-second mid-quote return autocorrelations. $Time_t$ is a trend variable that starts at zero at the beginning of the sample period and increases by one every trading day. $MktCap_{i,t}$ is the log of closing market capitalisation for stock *i* on day *t*. $Volatility_{i,t}$ is the daily standard deviation of mid-quote return. $return_{i,t}$ measures the daily return for stock *i* on day *t*. $Resilience\_ES_{i,t}$ and $Resilience\_RS_{i,t}$ are computed in relation to $EffectiveSpread_{i,t}$ and $RealizedSpread_{i,t}$ respectively using Equation (5) with a time interval of five minutes. $Resilience\_depth_{i,t}$ is computed in relation to $Depth_{i,t}$ using Equation (5) with a time interval of five minutes. FE_i denotes firm fixed effects. Panels A and B report the estimation results on liquidity and informational efficiency. Standard errors are clustered both by stock and date, t -statistics are reported in parentheses. *, ** and *** correspond to statistical significance at the 0.1, 0.05 and 0.01 levels respectively. The sample period is from 11th January 2018 to 11th May 2018.

Panel A: results based on liquidity

	$RelativeSpread_{i,}$	$EffectiveSpread_i$	$RealizedSpread_{i,t}$	$Amihud_{i,t}$	$Depth_{i,t}$	$RelativeSprea$	$EffectiveSpread$	$RealizedSpreaa$	$Amihud_{i,t}$	$Depth_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DVC_t	-0.164 (-1.64)	0.001 (0.86)	-0.036 (-0.25)	-1.655** (-2.27)	0.059*** (4.53)	-0.072 (-0.43)	-0.001** (-2.48)	-0.982** (-2.42)	4.120 (0.66)	0.123*** (6.28)
$TRET_i$	-0.237** (-2.39)	-0.002*** (-2.97)	0.086 (0.49)	-0.575 (-1.35)	-2.671*** (-27.54)	1.381* (1.87)	-0.008 (-0.77)	-0.495 (-0.90)	-31.216** (-2.28)	-2.505*** (-24.24)
DVC_t* $TRET_i$	0.115 (1.10)	-0.001 (-0.87)	0.400 (1.36)	1.123 (1.32)	0.021 (1.18)	0.191 (1.31)	-0.001 (-1.51)	0.408 (1.53)	3.792 (0.64)	0.016 (0.87)
$Time_t$						-0.003 (-0.94)	0.000** (2.56)	0.020** (2.27)	-0.322*** (-3.08)	-0.001*** (-3.49)
$MktCap_{i,t}$						0.157* (1.88)	-0.001 (-0.88)	-0.006 (-0.10)	-3.490** (-2.28)	0.023*** (4.36)

$Volatility_{i,t}$						71.123*** (13.74)	0.312*** (6.36)	-49.014*** (-8.43)	-45.942 (-1.12)	-1.363*** (-5.43)
$return_{i,t}$						-0.032*** (-5.95)	-0.000*** (-3.34)	-0.073* (-1.70)	-0.204 (-1.58)	-0.018*** (-4.19)
Constant	0.492*** (5.07)	0.003*** (3.65)	-0.264** (-2.05)	0.925** (2.46)	21.611*** (243.19)	-3.774* (-1.84)	0.027 (0.82)	-0.045 (-0.03)	97.483** (2.53)	21.126*** (135.77)
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	11,370	11,370	11,370	11,370	11,370	11,370	11,370	11,370	11,348	11,370
$\overline{R^2}$	17.79%	3.21%	2.08%	18.19%	86.75%	57.41%	7.67%	4.37%	19.74%	96.78%

Panel B: results based on LOB resilience

	$Resilience\_ES_{i,t}$	$Resilience\_RS_{i,t}$	$Resilience\_depth_{i,t}$	$Resilience\_ES_{i,t}$	$Resilience\_RS_{i,t}$	$Resilience\_depth_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
DVC_t	0.007* (1.77)	-0.013 (-1.51)	0.051*** (4.68)	0.013 (1.64)	0.018 (1.58)	0.022 (1.20)
$TRET_i$	0.148 (1.43)	-0.426*** (-2.64)	0.840*** (12.72)	0.170 (1.63)	-0.087 (-1.44)	0.822*** (10.81)
DVC_t*$TRET_i$	-0.005 (-0.45)	-0.032 (-1.61)	-0.025 (-1.38)	-0.007 (-0.55)	0.011 (1.01)	-0.026 (-1.43)
$Time_t$				-0.000 (-0.70)	-0.001** (-2.31)	0.001* (1.94)
$MktCap_{i,t}$				0.003** (2.13)	-0.005* (-1.94)	-0.003 (-0.58)
$Volatility_{i,t}$				0.098 (1.49)	0.293* (1.79)	-0.073 (-0.35)
$return_{i,t}$				-0.001* (-1.85)	0.001 (0.87)	-0.005*** (-4.93)

Constant	-0.978*** (-55.87)	0.897*** (26.56)	0.577*** (10.58)	-1.043*** (-26.75)	1.012*** (13.82)	0.619*** (5.14)
Firm fixed effects	YES	YES	YES	YES	YES	YES
Observations	9,654	9,654	11,370	9654	9654	11,370
$\overline{R^2}$	35.64%	8.86%	48.58%	35.63%	8.92%	48.59%

Panel C: results based on informational efficiency

	$VarianceRatio_{i,t}$	$Predict_{i,t}$	$Autocorrelation_{i,t}$	$VarianceRatio_{i,t}$	$Predict_{i,t}$	$Autocorrelation_{i,t}$
	(1)	(2)	(3)	(4)	(5)	(6)
DVC_t	-0.007 (-1.54)	-0.015 (-0.69)	0.002 (0.09)	-0.005 (-1.15)	-0.040* (-1.80)	0.004 (0.62)
$TRET_i$	-0.037*** (-2.58)	-0.169*** (-6.40)	-0.167*** (-5.90)	0.001 (0.08)	-0.141*** (-5.65)	-0.152*** (-6.56)
DVC_t*$TRET_i$	0.004 (0.77)	0.012 (0.57)	-0.004 (-0.17)	0.003 (1.18)	0.010 (0.47)	-0.007 (-1.36)
$Time_t$				-0.000 (-0.44)	0.001 (1.43)	0.000 (0.14)
$MktCap_{i,t}$				0.001 (0.77)	-0.004 (-0.89)	-0.001 (-0.74)
$Volatility_{i,t}$				9.278*** (58.77)	1.881*** (3.41)	-0.015*** (-5.37)
$return_{i,t}$				-0.054 (-1.23)	-0.171 (-1.29)	-0.132 (-1.55)
Constant	0.046*** (3.197)	0.345*** (14.885)	0.340*** (13.214)	-0.011 (-0.50)	0.411*** (3.21)	0.671*** (10.00)
Firm fixed effects	YES	YES	YES	YES	YES	YES
Observations	12,777	12,777	12,777	12,777	12,777	12,777
$\overline{R^2}$	28.52%	2.71%	2.09%	90.97%	3.15%	30.67%