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Volatility, dark trading and market quality: evidence from the 2020 COVID-19 pandemic-driven market volatility

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JEL classification: G12, G14, G15, G18

Keywords: COVID-19, dark pools, volatility, liquidity, informational efficiency, market quality.

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1. Introduction

At the heart of the debate on the effects of trading in non-transparent downstairs-type markets – the so-called dark pools – are the dynamics of venue selection[1] by both informed and uninformed traders. Theory suggests that dark trading dynamics are driven by volatility in the lit market (see Zhu, 2014); however, the endogenous determination of volatility makes it challenging to test this prediction. In this paper, we avoid this empirical issue by exploiting the novel coronavirus (COVID-19) crisis as an excess market volatility-inducing exogenous event to investigate the role of volatility in venue selection by informed and uninformed traders in today's financial markets. Understanding the dynamics of venue selection is critical for the determination of the effects of dark trading on market quality characteristics, especially as the volume of trading activity credited to dark pools continues to reach new levels around the world. For example, the volume of trading executed in dark pools accounted for 9.1% and 9.6% of all on-exchange activity in April and July 2019, respectively. These are the largest shares in the MiFID II era, which already imposes an 8% cap on dark trading in European financial markets over any 12-month period.[2] Furthermore, in the US, dark pools and other off-exchange trading venues executed 38.6% of US equity volume in April 2019.[3]

Indeed, the less than adequate understanding of dark trading dynamics in an empirical sense may be driving the mixed evidence on the impact of dark trading on market quality characteristics. For example, Buti *et al.* (2011) find no supporting evidence that dark trading is harmful to market liquidity. Based on their analyses of FTSE data, Aquilina *et al.* (2017) and Brugler (2015) show that dark trading leads to improved liquidity in the aggregate and the primary exchange respectively. However, Nimalendran and Ray (2014) investigate trading data

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[1] Reference to traders' venue selection or choice implies their preference between dark and lit venues.
[2] https://www.thetradenews.com/dark-pool-trading-volumes-surge-pre-mifid-ii-levels/ and https://www.thetradenews.com/dark-trading-volumes-reach-highest-level-mifid-ii/
[3] https://www.wsj.com/articles/dark-pools-draw-more-trading-amid-low-volatility-11556886916

from one of the 32 US dark venues and find that dark trading is associated with increased price impact on quoting exchanges. This is consistent with the findings of Degryse *et al.* (2015); using data from the Dutch market, they show that dark trading has a detrimental effect on market liquidity. Adding complexity to the question is the increasingly popular view that the effects of dark trading on market quality characteristics are non-linear (see Comerton-Forde & Putniņš, 2015; Aquilina *et al.,* 2017).

Zhu (2014) is increasingly recognised as one of the influential theoretical contributions on dark trading. Zhu's (2014) model predicts a non-linear relationship between volatility and dark market share; specifically, for sufficiently small volatility, dark market share increases with volatility. However, for an excessive level of volatility, dark market share decreases with volatility. In the model, the addition of a dark pool to a market with a lit exchange results in an asymetric self selection involving informed and uninformed traders. Specifically, uninfomed traders gravitate towards the dark pool because they face lower adverse selection risk there, while infomed traders concentrate on the lit exchange due to the higher probability of non-execution they face in the dark pool, since their orders typically bunch on one end of the limit order book. This self selection is linked to an improvement in informational efficiency in the aggregate market, comprising of the lit exchange and the dark pool (see Aquilina *et al.,* 2017). If all informed traders hold similar types of information sets (for example, fundamental information about the value of an instrument) as modelled by Zhu (2014), the self-selection induced by dark trading can improve the efficiency of the price discovery process. This is because a reduction in the number of informed trades due to fewer uninformed traders in the lit market (informed orders execute against uninformed orders as in Glosten & Milgrom (1985), Kyle (1985) and many others) results in a lowering of competition on the same private information set held by informed traders.

Zhu's (2014) model establishes volatility as a key driver in the overall dynamics of self-selection. As informed trader concentration increases in the lit market, volatility widens the exchange spread and encourages more uninformed (liquidity) traders to migrate to the dark pool – this is the natural state of things when volatility is moderate. Informed traders stay at the lit exchange because when volatility is at a moderate level, the exchange spread is not excessive, and thus the cost of execution risk is greater than the benefit of potential price improvements a dark pool may offer (for example, in Australia and Canada, price improvement is required to trade regular sizes in dark pools).[4] However, when volatility in the exchange exceeds the maximum level needed for informed traders to avoid the dark pool, informed traders start to migrate to the dark pool in search of uninformed counterparties to trade with and in a bid to avoid the widening exchange spread. Thus, liquidity constraints in the lit market can result in informed traders entering into non-transparent/dark venues in order to reduce their transaction costs and increase their profits, as already reported by some empirical studies (see Hendershott & Mendelson, 2000; Nimalendran & Ray, 2014). The informed traders' migration consequently results in uninformed traders leaving the erstwhile safety of the dark pool for the lit exchange.

Two studies have empirically examined the links between volatility and dark trading.[5] Buti *et al.* (2011) find that dark market share is higher on days with lower volatility, and Ye (2010) finds that stocks with lower volatility have higher dark market shares. Our study differs from Buti *et al.* (2011) and Ye (2010) for at least two reasons. Firstly, our motivation differs from the aforementioned studies. Specifically, Buti *et al.*'s (2011) motivation is investigating the effects of dark trading on market quality, and Ye (2010) aims to study transaction costs in crossing networks and the competition between exchanges and crossing networks. However, we focus on the role of volatility in traders' venue choice in times of stress. As already

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[4] See https://www.cfainstitute.org/-/media/documents/issue-brief/policy-brief-trade-at-rules.ashx.

[5] At least one other study examines the effects of dark trading on volatility (see Foley *et al.* 2012) but not vice versa.

discussed, an important motivation for addressing this question is offered by Zhu (2014). Specifically, Zhu (2014) shows that the relationship between volatility and venue choice is not linear, and while the impact of lit market volatility on dark market share is positive for sufficiently low levels of volatility, it becomes negative during excessive volatility/market stress periods. Secondly, the general endogenous determination of volatility makes it challenging to disentangle whether volatility informs the self-selection dynamics often reported in the finance media.[6] Although Buti *et al.* (2011) and Ye (2010) employ an instrumental variable approach to address endogeneity, further questions regarding the effectiveness of this approach remain.[7] One issue is that the two studies only introduce instruments for dark market activity, since their focus is not the investigation of the effects of volatility on traders' venue choice. Addressing this methodological challenge requires the identification of a truly exogenous volatility-inducing shock event. Hence, by contrast, we employ the onset of the COVID-19 pandemic impact on financial markets, which is clearly exogeneous and is not driven by any market determinants, for this purpose. The exogenous event we use in this study is driven by the spread of a virus that arguably has no comprehension of modern market structures nor directly responds to them.

For clarity, we exploit both the excessive volatility-inducing COVID-19 pandemic, as a shock, and the Markets in Financial Instruments Directive II (MiFID II) double volume cap (DVC) dark trading restrictions in force in the case of 55 European stocks during our sample period, to investigate the role of volatility in the evolution of dark market share and the decision of where to trade in the cases of informed and uninformed traders. We find that, consistent with the theoretical literature (see Zhu 2014), excessive volatility at lit venues is linked with the

[6] See as examples, https://www.wsj.com/articles/dark-pools-draw-more-trading-amid-low-volatility-11556886916 and https://blogs.wsj.com/marketbeat/2011/09/02/investors-flee-dark-pools-as-market-volatility-erupts/

[7] Buti *et al.* (2011) employ the method developed by Hasbrouck and Saar (2013) and use other stocks' dark trading activity during the same time period as an instrument for dark trading activity in a particular stock. Ye (2010) uses the total trading volume as an instrument for total number of shares submitted to a crossing network.

economically significant shift of informed trading activity from lit venues to dark pools. We also show that this move by informed traders drives the migration of uninformed traders, who are wary of being adversely selected, from dark pools to lit venues. The net effect of the cross-migration is a loss of market share by dark pools and an increase in lit venues' market share. We extend our analysis to examine the effects of these dynamics on market quality, and find that lit market liquidity improves (i.e. spreads narrow) during the volatile trading period, while price discovery deteriorates on account of informed traders migrating to the dark pools. Thus, it appears that volatility is a market regulating mechanism driving the share of trading activity in dark pools. Regulators should account for this when designing regulatory mechanisms, such as dark trading caps and waivers.

2. Institutional background

The enactment of the Markets in Financial Instruments Directive (MiFID) in November 2007 introduced alternative high-tech trading venues known as multilateral trading platforms (MTFs). MTFs operate as intermediaries facilitating the exchange of financial instruments between a number of market participants. Concurrently, under MiFID, pre-trade and post-trade transparency requirements are imposed on all trading venues in order to reduce potential adverse selection costs linked to market 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 current bid and ask price. NTW allows two parties to formalise negotiated transactions. LIS offers block traders the right to hide their trading intention when transaction size is larger than the prevailing normal market size. OMF allows orders to be held by exchanges in an order management facility pending disclosure.

Since the commencement of MiFID, trades in dark pools operated by MTFs have benefited mainly 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, concerned by the potential negative influence of dark liquidity on the price discovery process, enacted a second iteration of MiFID, the so-called MiFID II, and the Market in Financial Instruments Regulation (MiFIR), 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 and relates to average daily trading volume over the preceding 12-month period. According to the first DVC-related 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 subjected to six-month trading suspensions from 12th March 2018. As of September 2018, six months after the implementation of the DVC, more than 1200 instruments, mainly equities, were under dark trading suspensions. The affected instruments corresponded to about 35% of the most liquid European stocks. For our sample period, spanning 24th January and 24th March 2020, ESMA data shows that 62 instruments'[8] (55 out of which are European stocks) are under DVC dark trading suspensions; their suspensions are from 14th November 2019 until 13th May 2020.

It is worth noting that an enforcement of the DVC in a stock does not fully preclude some form of dark trading in the stock. Large block trades are still allowed to trade in dark

[8] https://www.esma.europa.eu/double-volume-cap-mechanism

pools if the trade size is large enough to qualify for the LIS waiver. The LIS wavier threshold is based on the average daily volume (ADV) for each instrument. For small-cap stocks with ADV of less than €50,000, the LIS waiver threshold is €15,000 and for large-cap stocks with ADVs greater than €100 million, the LIS waiver threshold can be up to €650,000. In any case, market data shows that the dark trading volumes recorded once the DVC is enforced for a stock is zero to negligible.

3. Sample selection and variables

3.1. Sample Selection

Investigating the role of volatility in venue choice is challenging because of the often-endogenous determination of volatility by the venue selection decisions taken by both informed and uninformed traders. For example, uninformed traders deciding to migrate from lit to dark venues will induce volatility on the lit exchange; if the volatility level rises enough, it will force informed traders to move to dark venues in search of liquidity. In addition, it is also very likely that the venue choice process and volatility are determined by common factors, some of which cannot be observed directly. The above issues make identifying a volatility-inducing exogenous shock useful in being able to adequately estimate the impact of volatility on venue choice. Such a shock should satisfy two important criteria: 1) it should have an impact on volatility and 2) it should not be determined by market conditions of dark pool trading. We argue that the market crisis induced by the spreading of COVID-19 is a potential candidate that satisfies these two criteria. Firstly, Baker *et al.* (2020) show that indeed stock market volatility in global markets increases significantly during this period. Secondly, it is obvious that the crisis caused by the pandemic has no direct connection to dark trading, or to any organised trading in financial markets for that matter – the virus is unaware of the existence of market structures. Motivated by this, we investigate the effects of stock price volatility on traders' venue choice by employing

COVID-19-induced volatility within a natural experimental difference-in-differences (DiD) framework. Our data covers a two-month period from 24th January to 24th March 2020, spanning the period prior to and the period defined by the market crisis occasioned by the rapid spreading of COVID-19. This is because Baker *et al.* (2020) show that the COVID-19-induced excessive volatility in global markets started on 24th February 2020, when the virus started to quickly spread in the US and Europe.

Employing a DiD framework requires the identification of control and treated groups of stocks. Since we study the dynamics of venue choice between dark and lit venues, our treated group includes stocks that trade on both dark and lit venues. By contrast, the control group of stocks are restricted from trading on dark venues during our sample period; this is due to the imposition of a dark trading cap under the MiFID II provisions. This approach allows us to isolate the impact of COVID-19-induced volatility on trading activity in stocks eligible for dark trading from its market-wide effects, and is only possible because of the identification of stocks with dark trading restrictions. The implementation of the DVC creates a very good opportunity to identify our control group of stocks. Specifically, the stocks with suspended dark trading privileges during our sample are ideal candidates for the control group. Thus, we select the 55 European equities serving dark trading suspensions between 14th November 2019 and 13th May 2020, a period inclusive of our sample period (24th January to 24th March 2020).

We use the method described in Shkilko and Sokolov (2020) to create a matched treated sample of stocks; hence, our total sample size equals 110 European stocks. Specifically, we compute the matching error for three metrics commonly used for this purpose: size, price and volume. Then, the 55 stocks with the corresponding lower matching errors for each of the 55 stocks in the control group are included in the treated group. The method works well, because our key metrics do not differ economically and statistically between groups.

3.2. Variable construction

For every stock in the treated and control groups, we obtain intraday data from the Thomson Reuters Tick History (TRTH) v2 database. We collect data from the main venues where our selected stocks are traded: 1) the main market where stocks are listed (for example, London Stock Exchange (LSE) for the UK stocks, Xetra for the German stocks, etc.); 2) Cboe Europe, which hosts the most liquid pan-European limit order books and dark pools, including BXE and CXE; and 3) Turquoise, hosting one of the most liquid dark pools in Europe, Turquoise Plato (formerly Turquoise Midpoint Dark). According to market data from Cboe Europe, the venues included in our dataset account for a daily minimum of 93% of the currency trading value for the stocks in our sample; hence, our data is representative in the cases of the stocks in the sample. The dataset contains standard transaction-level variables such as date, exchange time, transaction price, volume, bid price, ask price, bid size and ask size. Using the obtained dataset, we compute daily estimates of trading activity, liquidity, order imbalance, high-frequency trading (HFT) and volatility.

As stated, the main aim of this study is to examine the dynamics of traders' venue selection. We proxy venue choice by using dark market share and trading volume in lit markets, because they embody aggregate trader venue selection. The dark market share, $DMS_{i,d}$, is computed as the dark trading volume divided by the total trading volume for stock *i* on day *d*. Trading volume, $Volume_{i,d}$, is the number of shares traded in lit venues for stock *i* on day *d*.[9] Within our framework, we aim to control for general market dynamics by including a number of relevant variables. We measure liquidity using relative quoted spread ($Rspread_{i,d}$) and depth ($Depth_{i,d}$). $Rspread_{i,d}$ is the relative quoted spread for stock *i* on day *d* and is computed as a time-weighted average of the difference between ask and bid prices divided by the mid-price

[9] Throughout this paper, trading volume refers to trading volume in lit markets. Trading volume in dark markets is stated as dark trading volume.

(mid-price is the average of ask and bid prices) corresponding to each transaction. $Depth_{i,d}$ is the top-of-book depth and computed as the natural logarithm of the sum of the best bid and ask sizes corresponding to each transaction for stock i on day d.

$Volatility_{i,d}$ is a proxy for volatility and computed as the standard deviation of hourly mid-price returns for stock *i* on day d (see Malceniece *et al.* 2019). $OIB_{i,d}$ is the order imbalance metric described in Chordia *et al.* (2008) and is computed as the absolute value of the buyer-initiated volume minus the number of seller-initiated volume divided by total volume stock *i* on day d. $HFT_{i,d}$ is the proxy for HFT and computed as the number of messages divided by the number of transactions for stock *i* on day d (see Malceniece *et al.* 2019). Table 1 provides an overview of the different variables used in this paper.

INSERT TABLE 1 ABOUT HERE

3.3. Descriptive Statistics

Table 2 provides descriptive statistics for the 110 stocks, i.e. 55 treated and 55 control stocks, in the sample. Panel A reports summary statistics for the pre-event period (from 24th January 2020 to 23rd February 2020), whereas Panel B presents summary statistics for the post-event period (from 24th February 2020 to 24th March 2020). In both panels, we provide statistics for the treated and control groups of stocks separately and compute the statistical differences in our model variables in order to observe the differences in market dynamics for these groups; standard errors of the mean estimates are used for statistical inferences.

INSERT TABLE 2 ABOUT HERE

Panel A shows that the stock-day averages of all variables between the two stock groups, with the exception of $DMS_{i,d}$, in the treated group are not statistically different from each other. This underscores the relevance of our matching procedure and evidences that both groups have similar market dynamics prior to the COVID-19-induced market volatility event. There are some important points to note when comparing the evolution of variables during the post-event periods. Firstly, as evident in Panel B, the average values of all variables change substantially during the post-event period, which indicates that market conditions are different after the onset of the COVID-19-induced market volatility event. For example, the average $Volume_{i,d}$ increases by 2.5 (2.2) times for the treated (control) group. Moreover, $Rspread_{i,d}$ widens by more than 40% for both groups, indicating liquidity constraints. Secondly, while the average $Volume_{i,d}$ of the control group is marginally higher than the average $Volume_{i,d}$ of the treated group prior to the event, a substantial switch occurs following the onset of the excessive volatility period with the treated group's average $Volume_{i,d}$ suddenly outstripping the control group's by 14%. This is consistent with our argument that excessive volatility contributes to the market dynamics of stocks traded simultaneously on both dark and lit venues. The observed 16% decline in $DMS_{i,d}$ for the treated group of stocks suggests that some traders move to lit venues during excessive volatility periods. However, these traders could have also just exited the market altogether; we formally test this in the next section. Linked to the second point, thirdly, we also observe (in Panel B) statistically and economically significant differences in the estimated variables' values for both groups of stocks during the excessively volatile sample interval, thus evidencing the significance of the impact of the COVID-19-induced excessive volatility/instability on stock characteristics.

The findings presented in Table 2 raise an interesting question about why excessive market-wide volatility affects stocks differently depending on whether they are traded in a relatively unfettered manner in both dark and lit venues. We argue that this phenomenon is linked to dark venue trading availability. This is because when we compare the general market conditions (dark trading, liquidity, volatility, order-book dynamics and HFT activities) of the treated and control groups during the pre-event period, only $DMS_{i,d}$ differs significantly prior to the onset of excessively volatile trading conditions (see Panel A of Table 2). The significant (both economically and statistically) difference in $DMS_{i,d}$ is expected as the control group's stocks have been suspended from dark trading, whereas the treated group's stocks are available for trading in dark pools. This is further confirmed by the number of dark trading transactions in the treated and control groups during the sample period. Specifically, the treated group's stocks have a total of 223,438 transactions in dark pools, while this number is 142 for the control group's stocks. Thus, relatively unrestricted trading in dark venues appears as a strong indicator of the post-event differences between the control and treated groups' market determinants. In the next section, we formally test our arguments driven from descriptive statistics analysis.

4. Analyses, results and discussions

4.1. Volatility analysis

The main limitation of the existing empirical papers reporting on the volatility-dark trading relationship (see as an example, Buti *et al.* 2011) is that they ignore the non-linear relationship predicted by Zhu (2014) and, in their frameworks, volatility is endogenously-determined. Excessive volatility and dark market share/venue choice are jointly endogenous as there may be a reverse causality between volatility and dark market share/venue choice. In order to address potential endogeneity concerns, we use the COVID-19-induced excessive volatility as an exogenous shock to investigate the relationship between excessive volatility and traders' venue choice. Baker *et al.* (2020) show that from 24th February to 24th March 2020, US financial markets were dramatically volatile. More explicitly, the authors find that there are 18 market jumps in these 22 trading days and this number is the highest in financial markets history. This finding is strong evidence of the excessive market volatility extensively reported in the media during these periods. Although Baker *et al.*'s (2020) analysis is based on the US financial markets, and we focus on European markets, the volatility trend is consistent as shown in Figure 1.

INSERT FIGURE 1 ABOUT HERE

Figure 1 shows the impact of the COVID-19 pandemic on volatility in the 110 stocks in our sample. The volatility proxy is the daily cross-sectional average, $Volatility_{i,d}$, as defined in Section 3.2 and Table 1. Consistent with Baker *et al.* (2020), there is a substantial increase in volatility from 24th February 2020. Specifically, $Volatility_{i,d}$ increases by about 3 times between 24th February and 24th March 2020 in comparison with the month before. This implies that, like US markets, COVID-19 induces excessive volatility in European markets too. The COVID-19-linked excessive volatility observed between 24th February and 24th March 2020 allows us to employ this pandemic as an exogenous shock to investigate the role of volatility in traders' venue choice.

4.2. Venue choice analysis

4.2.1. Dark Market Share analysis

Zhu (2014) shows that excessive volatility increases (reduces) lit (dark) market share. We test this by first conducting a univariate analysis, followed by estimating a multivariate regression model. For the univariate analysis, we compute the evolution of dark market share during our sample period, and then test the null hypothesis that there is no difference between dark pool share during the pre- and excessive volatility periods. It is important to note that this part of the analysis is strictly based on the treated group of stocks, because the control group of stocks are under dark trading suspension during the sample period.

INSERT FIGURE 2 AND TABLE 3 ABOUT HERE

Figure 2 and Table 3 present the evolution of dark trading volume and dark market share during pre- and event periods. Although, dark trading volume in the treated stocks doubles during the excessive volatility period, this is only reflective of the overall increase in trading activity driven by the market response to the COVID-19 pandemic (see Figure 3 and Table 4).

Indeed, dark market share declines from 2.5% to 2.1% (about 15.6% = (2.5-2.1)/2.5) which implies that the magnitude of the increase in trading activity is higher in the lit venue (the difference between pre-and the excessive market volatility periods is statistically significant at 0.01 level for both dark volume and dark market share). This is consistent with the predictions of Zhu (2014). Nevertheless, the insights are based on univariate analysis and should be backed up by a more robust analysis. Hence, we next conduct a multivariate analysis to further examine the trends described above. Specifically, we estimate the following model:

$$DMS_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_{i,d} + \gamma_2 Volume_{i,d} + \gamma_3 Rspread_{i,d} + \gamma_4 Depth_{i,d} + \gamma_5 Volatility_{i,d} + \gamma_6 OIB_{i,d} + \gamma_7 HFT_{i,d} + \varepsilon_{i,d} \qquad (1)$$

where $Event_{i,d}$ is a dummy variable that equals one for the days between 24th February and 24th March 2020 inclusive and zero otherwise. α_i and β_d are stock and time fixed effects. Standard errors are robust to heteroscedasticity and autocorrelation.[10] All other variables are as defined in Section 3.2 and Table 1.

INSERT TABLE 4 ABOUT HERE

Table 4 reports the estimation results for the Equation (1). The estimates suggest a negative and statistically significant relationship (at 0.05 level) between $Event_{i,d}$ and $DMS_{i,d}$. Specifically, $DMS_{i,d}$ declines by 1.3% following the onset of the COVID-19-induced excess volatility in European markets. This implies that, consistent with Zhu (2014), dark market share decreases during periods of excessively high volatility. The result is consistent with the univariate analysis we present in Table 3 and shows that the relationship is still significant after controlling for important market dynamics/variables. The economic significance of the decrease as estimated with the multivariate analysis is even bigger than estimated with the univariate analysis. Explicitly, while in the univariate analysis we find a 15.6% (0.4/2.5)

[10] Standard errors are robust to heteroscedasticity and autocorrelation in all models estimated in the paper.

reduction in dark market share, it is about 52% (1.3/2.5) in the multivariate analysis – effectively, more than half of the dark trading share of the market is lost during periods of market stress/volatility. Another important point to note is that, statistically, $Volatility_{i,d}$ is not significantly related to $DMS_{i,d}$. This is expected since $Event_{i,d}$ captures excessive volatility in the stocks examined, and therefore the significance of $Volatility_{i,d}$ disappears after controlling for $Event_{i,d}$ in the model. It implies that, consistent with Zhu (2014), excessive volatility is a more important factor than general volatility when explaining the impact of volatility on traders' venue selection. This further underscores the distinction between this study and the existing literature on volatility and dark trading, which focuses only on endogenous general volatility (see Ye, 2010; Buti *et al.,* 2011).

The findings presented in Figure 2, Tables 3 and 4 allow us to speculate that, indeed, some fraction of dark market share moves to lit venues. However, this is not the only interpretation. Specifically, one may argue that dark traders delay their trading rather than moving to lit venues, and therefore the reduction in dark market share reported in Table 3 and 4 is the result of this delay. We consider this argument by conducting some volume analysis in the next section.

4.2.2. Volume Analysis

The decrease in dark market share reported in Section 4.2.1 could potentially be explained by two mechanisms: 1) traders that use dark pools move to lit venues during periods of excessive volatility; and 2) these traders may delay their trading activity, in which case they are not migrating to lit venues. We employ a DiD framework in order to formally test which of these mechanisms explain our earlier finding.

We demonstrate in Section 3.2 and Table 2 that the two groups of treated and control stocks we employ in this paper have very similar market dynamics prior to the onset of excessive market volatility driven by the COVID-19 pandemic. Specifically, both groups' liquidity, volatility, order-book dynamics and HFT levels do not significantly differ from each before the event (see Table 2). The only identified difference between these groups is the availability of dark trading privileges for the treated group of stocks, with the control group of stocks restricted from dark trading due to their having breached the DVC under MiFID II provisions. Therefore, it is logical to expect that any difference between the impact of COVID-19-induced volatility on treated and control groups' market activities is linked to differences in dark trading privileges for both groups of stocks. In order to test whether this expectation holds, we estimate the following DiD model where the dependent variable is lit volume, $Volume_{i,d}$:

$$Volume_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_{i,d} + \gamma_2 Treated_{i,d} + \gamma_3 Event_{i,d} * Treated_{i,d} + \gamma_4 Rspread_{i,d} + \gamma_5 Depth_{i,d} + \gamma_6 Volatility_{i,d} + \gamma_7 OIB_{i,d} + \gamma_8 HFT_{i,d} + \varepsilon_{i,d} \quad (2)$$

and where $Treated_{i,d}$ is a dummy equalling one for the treated group of stocks and zero for the stocks in the control group. α_i and β_d are stock and time fixed effects, and all other variables are as previously defined. $Event_{i,d} * Treated_{i,d}$ is a key variable, encapsulating the difference between the impact of the COVID-19 crisis on treated and control groups. Specifically, if traders delay their trading in dark pools because of excessive volatility in lit markets, then the impact of COVID-19-sourced excessive volatility should be the same for both treated and control groups' lit volume. This implies that the coefficient of $Event_{i,d} * Treated_{i,d}$ would not be statistically significant, because dark market availability is the only difference between the control and treated groups' market dynamics during the pre-event period (see Table 2) and that difference should disappear if traders that are using dark pools delay their trading. However, if traders that are active in dark pools before the event move to lit venues, then $Event_{i,d} * Treated_{i,d}$ would be statistically significant because it captures the excess lit venues trading activity impact of traders with access to both lit and dark venues, and it could then be argued that they are shifting some of their trading from dark to lit venues.

Before estimating the Equation (2), it is useful to conduct some univariate analysis aimed at guiding our thinking on what to expect from the multivariate analysis.

INSERT FIGURE 3 AND TABLE 5 ABOUT HERE

Panel A of Figure 3 presents the evolution of total trading volume, whereas Panel B presents the evolution of treated and control groups' volume separately. It is important to note that this is the evolution of the day-by-day total volume for all stocks. As evident in Panel A, total daily trading volume increases during the post-event periods. This is not unusual as everyone is trading in an attempt to exploit information or hedge risks during excessive volatility periods. Panel B of Figure 3 offers us a more nuanced view of the impact of the COVID-19 crisis on the trading activity of investors with respect to the treated and control groups of stocks. Specifically, the control groups' volume is slightly higher than the treated group's volume before the event (the difference is not statistically significant). However, the situation changes drastically following the onset of the excessive volatility period and the treated group's volume rises above the control group's (see Table 5 for more details). Another important point to note in Panel B is the correlation between the evolution of the control and treated groups' volume during the pre-event period. It is seen that $Volume_{i,d}$ for both groups have parallel trends in the absence of an event. It implies that the parallel trend assumption – which is vital for the empirical relevance of DiD framework – holds. Indeed, the break in the evolution of volume between the two groups is underscored by the differences in their level of volume increases after 24th February 2020. Table 5 shows that while the control group's average daily lit volume increases by about 112% between 24th February and 24th March 2020, this increase is about 147% for the treated group, which indicates that the magnitude of increase is about 35% higher for the treated group. This is indeed a huge economic impact and consistent with our main argument regarding the move of traders from dark to lit venues. It is also consistent with estimates in Table 4 indicating significant falls in dark trading market share for our sample of stocks between 24th February and 24th March 2020.

INSERT TABLE 6 ABOUT HERE

We now shift our attention to the outcome of the estimation of Equation (2) as reported in Table 6. There are some important points to note. Firstly, $Event_{i,d}$ is statistically significantly (at 0.01 level) and positively related to $Volume_{i,t}$ implying that indeed there is a substantial increase in lit volume during the COVID-19-driven market volatility period, when compared to the month before. Economically this implies that the number of shares traded daily during the post-event periods increases by about 1.2 million or, on average, 92% (= 1.2/1.3) for the 110 stocks in our sample.[11] This is a significant economic effect and shows that the pandemic crisis has unmistakable impacts on financial markets. Secondly, and most importantly, the interaction coefficient (γ_3) suggests that COVID-19-induced volatility is linked with average daily increases of about 460,000 shares for each of the treated stocks when compared to the control group of stocks; the coefficient is statistically significant at 0.05 level. The economic significance of this relative increase in lit trading activity is obvious. The average $Volume_{i,d}$ for the control group of stocks is about 2 million shares during our sample period. Thus, the magnitude of increases in trading volume is about 23% (=0.46/2) higher for the treated group compared with the control group. This is indeed a substantial change in economic terms. Thus, there is compelling evidence that, although traders increase their lit venue trading activity for all stocks during the COVID-19-induced market volatility period, they do so on a larger scale for stocks with trading privileges in both lit and dark venues. Taken together with the estimates in Table 4 these estimates support the argument that, in times of excessive market volatility and widening lit market spreads, informed traders, who traditionally constitute a small proportion of traders, migrate to dark pools, and thus in turn induce the migration of uninformed

[11] The stock-day average trading volume during the pre-event period is 1.3 million shares (see Table 2).

traders to lit venues as the latter seek to avoid being adversely selected by the former (see Zhu 2014). Uninformed traders typically constitute the majority share of active market participants; therefore, the net effect of these dynamics is an increase in the lit trading activity of traders in the stocks eligible for trading in both lit and dark venues.

4.3. How volatility drives venue choice by informed traders

Zhu (2014) identifies adverse selection risk as a key driver of the venue selection decisions made by traders, especially in the case of uninformed traders (see also Aquilina *et al.* 2017). Specifically, the study suggests that informed traders stay on the lit exchange under "normal" market conditions, i.e. "normal" conditions means lower volatility and exchange spread. This is because under these conditions exchange spread is not excessive, and thus the cost of execution risk is higher than the price-improvements benefit. However, when there is excessive volatility in financial markets, then informed traders start to move to dark pools to avoid the higher exchange spread. This implies that excessive volatility in lit markets introduces additional adverse selection cost to dark pools. This "new" adverse selection cost forces uninformed\liquidity traders to exit from dark pools. In this scenario, dark pool liquidity traders have two options, either to delay their trading, which can be quite costly when markets are especially volatile as observed in this case, or move to lit exchanges. The results reported in Table 6 show that traders select the second option and move to lit exchanges. In this section, we investigate whether the adverse selection channel proposed by Zhu (2014) explains our finding.

We proxy adverse selection cost by using the method developed by Lin *et al.* (1995).[12] Specifically, we compute the daily adverse selection component, $ASC_{i,d}$, of the relative spread,

[12] For robustness, we estimate the adverse selection component of the spread by using the approach of Stoll (1989) and obtain qualitatively similar results.

$Rspread_{i,d}$, by using intraday high frequency data as obtained from the TRTH database. Then, as in Section 4.2, we compare the adverse selection costs of treated and control groups of stocks. When informed traders move to dark venues during excessive volatility periods, there is a difference between the evolution of $ASC_{i,d}$ (after controlling for the general trend in $Rspread_{i,d}$) in the treated and control groups, as only the treated group's stocks have an unfettered dark pool access option. This is linked to dark pools in Europe executing against the prices displayed by lit venues; they are, hence, essential passive price takers and are less informative than lit venues. As informed traders migrate to the dark pools, their ability to signal information will be curtailed given that midpoint dark pools execute with lit venues' prices as references.

INSERT FIGURE 4 AND TABLE 7 ABOUT HERE

Panel A of Figure 4 presents the evolution of treated and control $ASC_{i,d}$ during the sample period. There are two essential points to note here. Firstly, $ASC_{i,d}$ increases for both groups, indicating that informed traders are more active during the post-event period. This is expected as $Rspread_{i,d}$ increases for both groups too. Thus, an increase in $ASC_{i,d}$ is not very informative by itself. In order to investigate whether adverse selection cost increases or not, we need to compute the percentage of $Rspread_{i,d}$ driven by adverse selection cost and compare its values for before and after the onset of the COVID-19-induced market volatility. For this, we divide $ASC_{i,d}$ by $Rspread_{i,d}$ and then multiply the outcome by 100 to obtain the adverse selection component weighted by $Rspread_{i,d}$, $ASW_{i,d}$. The estimates reported in Panel B of Table 7 show that, for the treated group, the average $ASW_{i,d}$ is 21% (=(13.14/61.14)*100) in the pre-event period, reducing to 19% (=(20.19/87.95)*100) during the COVID-19-induced market volatility period. For the control group, the average $ASW_{i,d}$ is 25% (=(15.69/61.39)*100) during the pre-event period, increasing to 37% (=(35.22/94.25)*100) during the COVID-19-induced market volatility period. Thus, while the control group's adverse selection cost increases by 12%, the treated group's adverse selection cost declines by about 2%. This clearly shows that the COVID-19 crisis does not have the same impact on the adverse selection costs of treated and control groups.

The above finding is further strengthened by the evolution of the difference between control and treated groups' $ASC_{i,d}$, shown in Panel B of Figure 5. It is evident that the difference is relatively stable and close to 0 before the event. However, it increases and becomes more unstable after the event, which indicates both the reduction in proportion of information-driven trading activity in the treated stocks and the magnitude of the $ASC_{i,d}$ increases for the control group of stocks during the COVID-19-induced market volatility period. The difference is also found to be statistically significant when we use the standard error of the mean difference for statistical inference as shown in Panel A of Table 7. The estimates presented suggest that the difference between the control and treated groups' $ASC_{i,d}$ prior to the COVID-19 crisis is 2.55 bps and not statistically significant. However, the difference increases to 18.41 bps and becomes statistically significant at the 0.01 level following the onset of the crisis period. The same results hold for $ASW_{i,d}$ (see Panel B). This finding is consistent with Zhu (2014) and our argument that informed traders migrate to dark pools when volatility in lit venues becomes excessive. To formally test the argument in the multivariate framework, we estimate the following model; all variables are as previously defined:

$$ASW_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_{i,d} + \gamma_2 Treated_{i,d} + \gamma_3 Event_{i,d} * Treated_{i,d}$$
$$+ \gamma_4 Depth_{i,d} + \gamma_5 Volatility_{i,d} + \gamma_6 OIB_{i,d} + \gamma_7 HFT_{i,d} + \gamma_8 Volume_{i,d} + \varepsilon_{i,d} \qquad (3)$$

INSERT TABLE 8 ABOUT HERE

Table 8 reports the estimation results for Equation (3). $Event_{i,d}$ is positive and statistically significantly (at 0.05 level), which implies that overall $ASW_{i,d}$ increases during the post-event period.[13] However, the interaction coefficient (γ_3) is negative and statistically significant (at 0.05 level) implying that the treated group's $ASW_{i,d}$ reduces over the same period when we compare it with the control group's $ASW_{i,d}$. The magnitude of the association is also economically meaningful. Specifically, $ASW_{i,d}$ of the treated group reduces by 3.08% during the post-event period when we compare it with the control group. The economic significance of this estimate is put into some perspective when we consider that the stock-day average $ASW_{i,d}$ is about 29% for the control group in our sample period. The implication here is that information-based trading activity in stocks with dark trading privileges declines by about 10% (=3.08/29) during the most volatile period of the COVID-19-induced market turmoil in comparison with stocks without this privilege. This is consistent with the predictions of Zhu (2014) and the results presented in Figure 4 and Table 7 and suggests that indeed informed traders move their trading activity to dark pools during periods of excessive volatility. The move in turn drives the exit of uninformed traders from dark pools to lit venues, and this switch causes reductions in dark market share as reported in Table 4 and increases in lit market volume as shown in Table 6. One may argue that informed traders may stop trading, and therefore the reduction in $ASW_{i,d}$ of the treated group is related to this. However, if this is the case, we would expect to see the same effects in the control group; it is implausible that a different factor other than the opportunity to trade in an unfettered manner in dark pools is driving the differential in the evolution of $ASW_{i,d}$ during the COVID-19-induced market volatility period. Thus, our DiD framework allows as to interpret this result as informed traders moving from lit to dark venues.

4.4. Market quality implications

Empirical findings reported in Section 4.2 show that, overall, traders are shifting significant proportions of their trading from dark to lit venues during excessive volatility

[13] As reported in Table 7, this positive relationship is driven by the control group.

(market stress) periods. More explicitly, we find that in times of excessive market volatility, informed traders migrate to dark pools in order to avoid the higher exchange spread, and this increases adverse selection risk in these markets. Thereafter, increased adverse selection forces uninformed traders to move from lit venues to dark ones (see Section 4.3). While reporting on these dynamics is of academic, and arguably practical, interest, the bottom-line should ultimately be what they mean for market quality. Therefore, in this section, we examine the market quality implications of this cross-migration.

Price discovery and liquidity are generally considered to be two of the most important market quality characteristics (see O'Hara 2003). Hence, we examine the effects of the reported dynamics on both the efficiency of the price discovery process/informational efficiency and liquidity by using a DiD framework similar to those used in Sections 4.2 and 4.3 above. We estimate the following models with market quality metrics on the left-hand side.

$$Rspead_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_{i,d} + \gamma_2 Treated_{i,d} + \gamma_3 Event_{i,d} * Treated_{i,d} + \gamma_4 Depth_{i,d} + \gamma_5 Volatility_{i,d} + \gamma_6 OIB_{i,d} + \gamma_7 HFT_{i,d} + \gamma_8 Volume_{i,d} + \varepsilon_{i,d} \quad (4)$$

$$Corr_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_{i,d} + \gamma_2 Treated_{i,d} + \gamma_3 Event_{i,d} * Treated_{i,d} + \gamma_4 Rspread_{i,d} + \gamma_5 Depth_{i,d} + \gamma_6 Volatility_{i,d} + \gamma_7 OIB_{i,d} + \gamma_8 HFT_{i,d} + \gamma_9 Volume_{i,d} + \varepsilon_{i,d} \quad (5)$$

where the proxy for informational efficiency, $Corr_{i,d}$, is the absolute value of first order return autocorrelation for each stock *i* on day *d,* expressed in basis points (bps). It is computed by first estimating 30 seconds' returns within each stock-day ($ret_{i,t,d}$) and then computing $Corr_{i,d}$ as $Corr_{i,d} = |Correlation(ret_{i,t,d}, ret_{i,t-1,d})|$. We employ the absolute value of the correlation coefficients as this captures both the under- and over-reaction of returns to information, with smaller values indicating greater efficiency. The empirical relevance of this metric is underscored by its wide use in the literature (see as examples, Hendershott & Jones, 2005;

Comerton-Forde & Putniņš, 2015). All other variables are as previously defined. The first model, Equation (4), is used to estimate the impact of the dark trading dynamics in the treated stocks during the volatile period on lit market liquidity, with relative spread as the proxy for liquidity, whereas the second model, Equation (5), examines the role of the dark trading dynamics in the treated stocks during the volatile period in price discovery.

INSERT TABLES 9 AND 10 ABOUT HERE

Table 9 reports estimation results for the Equation (4). The interaction variable's coefficient, γ_3, is negative and statistically significant (at 0.05 level) implying that the treated group's $Rspead_{i,d}$ decreases during the excessive volatility periods when compared to the control group's $Rspead_{i,d}$. $Rspead_{i,d}$ is the inverse measure of liquidity, which means that the treated group's liquidity improves over the same period in comparison with the control group's liquidity. This is consistent with earlier reported estimates in this paper, as well as the predictions of Zhu (2014), supporting the notion that the migration of informed traders' to dark pools unleashes an exodus of uninformed (liquidity) traders from dark pools to lit venues. This ultimately results in lit venues increasing their share of liquidity-providing traders and executed orders. The magnitude of the narrowing observed in the treated stocks' $Rspead_{i,d}$ during the COVID-19 impact period is also economically meaningful. Specifically, the spread of stocks with dark trading privileges narrows by about 9% (=7.25/81) during the post-event period when compared with the control group.[14]

Table 10 shows the estimated coefficients for Equation (5). The interaction variable, $Event_{i,d} * Treated_{i,d}$, is positively related to $Corr_{i,d}$; the relationship is statistically significant at the 0.10 level. The first observation here is that the informational efficiency impact of dark trading is not as powerful as its liquidity effects. The asymmetric effects of dark

[14] The average $Rspead_{i,d}$ for the control group is 81 bps.

trading dynamics on market quality characteristics is in line with the literature. For example, Zhu (2014) shows that the addition of a dark pool to a lit exchange decreases liquidity on the lit exchange and improves price discovery (see also Buti *et al.*, 2011; Comerton-Forde & Putniņš, 2015). Nevertheless, the significance of the informational efficiency effects is obvious, with the implication that the treated group's informational efficiency deteriorates in response to the volatile trading conditions spurred by the COVID-19 pandemic, when compared to the control group's informational efficiency. The change in informational efficiency is also economically meaningful. The average $Corr_{i,d}$ for the control group is 1082 bps, which suggests that the treated group's information efficiency deteriorates by about 2.8% (=31.34/1082) as a result of the COVID-19 pandemic market turmoil, in comparison with that of the control group. This finding is not surprising and is what we would expect to find given the migration of informed traders to dark pools as a result of increased volatility on the lit exchange. Estimates in Table 8 show that, consistent with the theoretical literature (see Zhu, 2014), informed traders migrate from the lit to dark venues during the COVID-19-induced excessive market volatility period. The consequence of this is a delay in the incorporation of information held by the migrating informed traders, since dark pools do now offer pre-trade transparency. Under normal conditions, when trading in a lit venue via the limit order book, information held by informed traders is more likely to be observed earlier than when they trade in dark pools, where they are also more susceptible to non-execution risk. Ultimately, although the (negative) informational efficiency effect of the COVID-19-triggered dark trading dynamics is economically meaningful, it pales in comparison to the liquidity effects.

5. Conclusion

The most obvious impact of the 2019-20 COVID-19 pandemic on financial markets is the injection of an unprecedented level of price volatility, especially in the cases of developed markets in the US and Europe. In February 2020, the pandemic-driven volatility held European markets in its vice-like grip for weeks, and in the process has induced a series of interesting market dynamics. One of these dynamics is a sharp loss of market share by dark pools as widely reported in the financial media.[15] In this paper, we exploit the exogenous nature of the volatility induced by the pandemic and the existing dark trading caps policy in force in European markets as part of MiFID II provisions to investigate how volatility drives dark market share and the dynamics of venue selection by informed and uninformed traders.

Through a series of univariate and multivariate analyses we show that, in line with the theoretical literature (see Zhu 2014), excessive volatility at lit venues is linked with the migration of informed traders from those venues to dark pools, which in turn drives the migration of adverse selection-wary uninformed traders from dark pools to lit venues. The net effect of the cross-migration is a loss of market share by dark pools and an increase in lit venues' market share. The market quality implications of these dynamics, although mixed, are economically meaningful and statistically significant. While stocks with dark trading privileges experience higher levels of liquidity, i.e. narrower spreads, during the COVID-19-driven market volatility period, the informational efficiency of their prices reduces in comparison to the stocks under dark trading restrictions.

This contribution is timely and has implications for dark trading regulation, given the increasingly intense regulatory constraints being considered for the use of dark pools across the world, and already implemented in Europe. Seemingly appealing and uncomplicated policies aimed at addressing the complex issues in financial markets, such as algorithmic trading, market fragmentation and dark trading, are often inadequate, mainly because they are seldom driven by a full understanding of the factors driving such phenomena. With respect to dark trading, what our results show is the need for regulatory interventions to be flexible and account for

[15] See as an example the coverage by Financial Times: https://www.ft.com/content/11c4b4d8-ff8a-49d3-817b-09de8266479a

changes in market conditions, such as periods of exogenously driven high volatility. This is because provisions designed for normal trading conditions (e.g. dark trading caps and waivers) become irrelevant when markets are impacted by events such as a pandemic.

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Figure 1. Volatility

The figure plots the day-by-day evolution of the cross-sectional average of $Volatility_{i,d}$ for 110 European stocks employed in the study. $Volatility_{i,d}$ is computed as the standard deviation of hourly mid-price returns for stock i on day d. The sample period covers from 24th January to 24th March 2020. The vertical bar indicates 24th February 2020, when the COVID-19-induced excessive volatility is adjudged to have commenced in global financial markets.

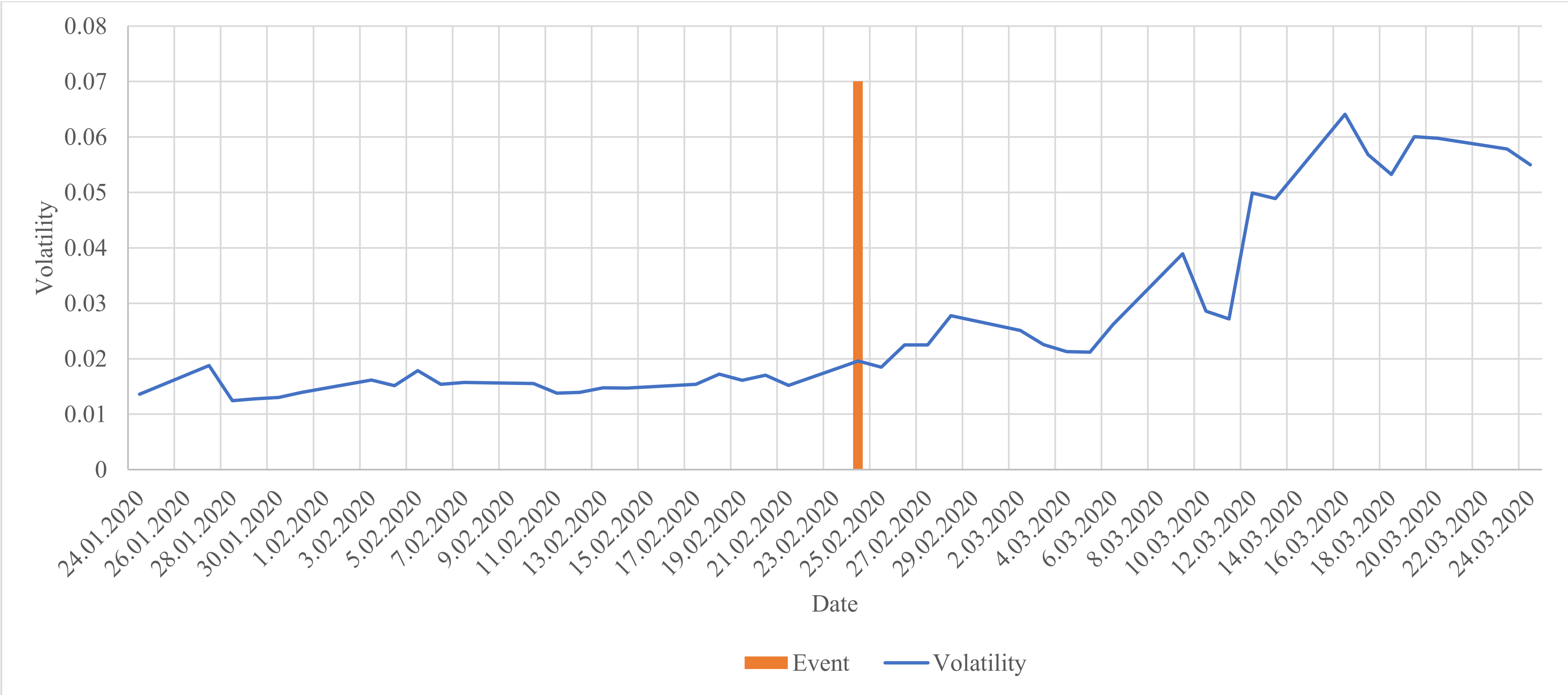


Figure 2. Dark trading

The figure plots the day-by-day evolution of the dark volume and dark market share for 55 European stocks that could be traded at both lit and dark venues. Dark market share is computed as the dark trading volume for a given day divided by the total trading volume on the same day. The sample period covers from 24th January to 24th March 2020. The vertical bar indicates 24th February 2020, when the COVID-19-induced excessive volatility is adjudged to have commenced in global financial markets.

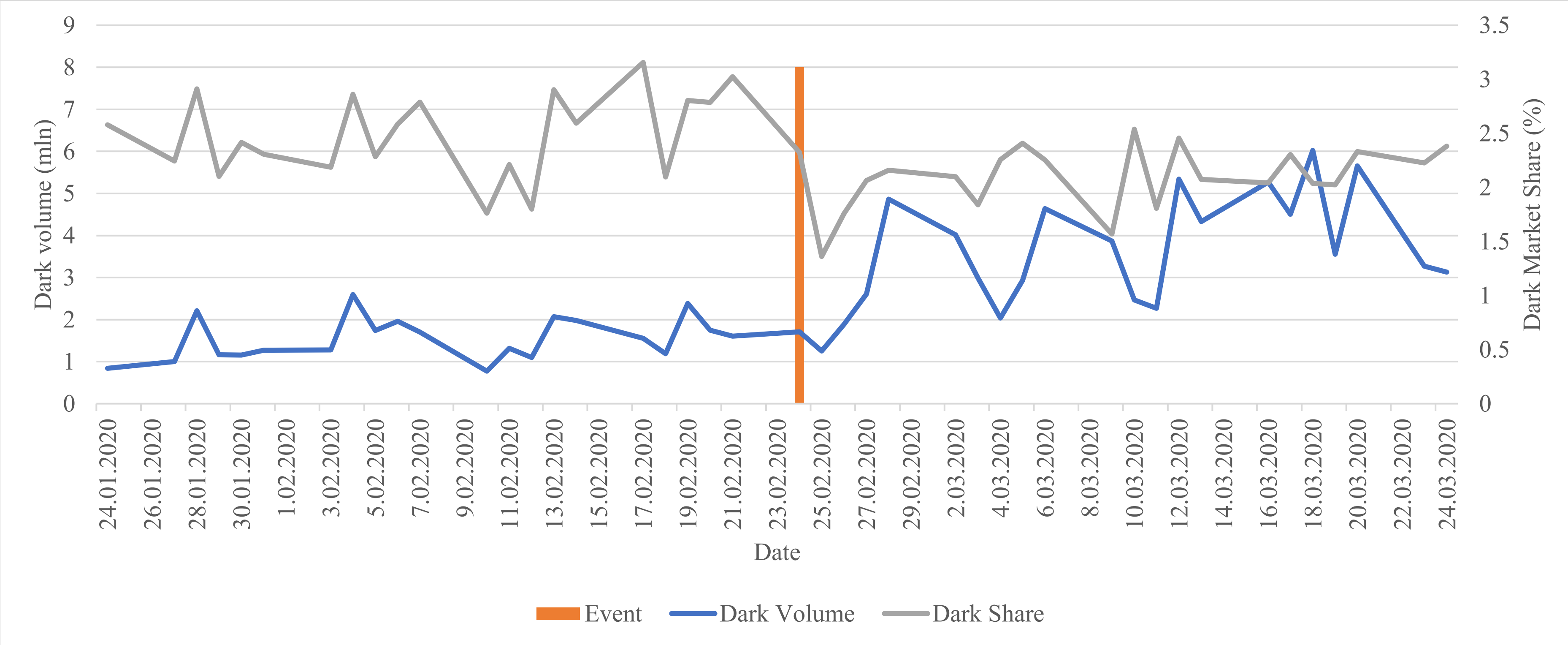
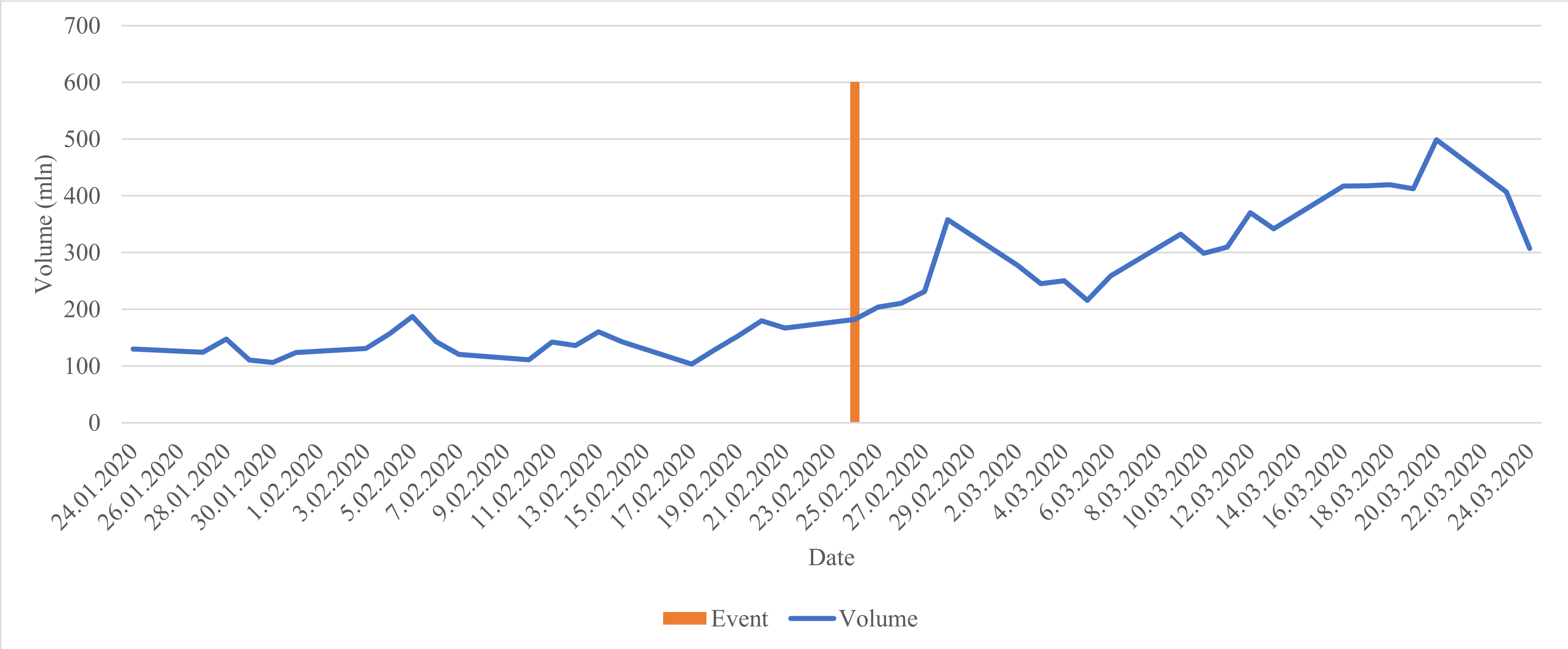


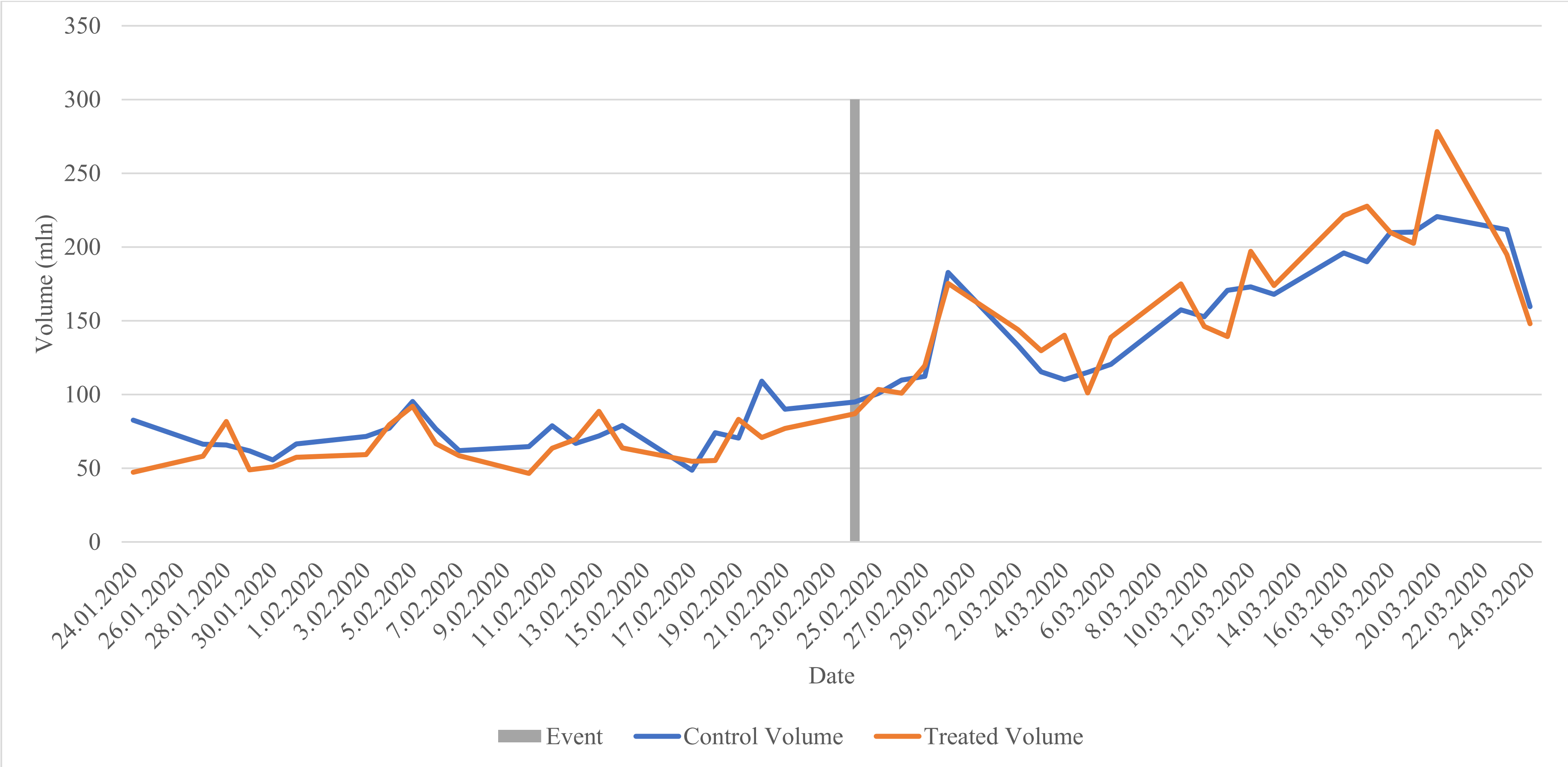
Figure 3. Trading volume

The figure presents the day-by-day evolution of lit volume for 110 European stocks; Panel A presents the day-by-day evolution of lit volume for the full sample (both the 55 stocks that could be traded at both lit and dark venues, i.e. treated stocks, and the 55 stocks with dark venue restrictions, i.e. control stocks), while Panel B shows the day-by-day evolution of lit volume for the control and treated groups separately. The sample period covers from 24th January to 24th March 2020. The vertical bar indicates 24th February 2020, when the COVID-19-induced excessive volatility is adjudged to have commenced in global financial markets.

Panel A



Panel B

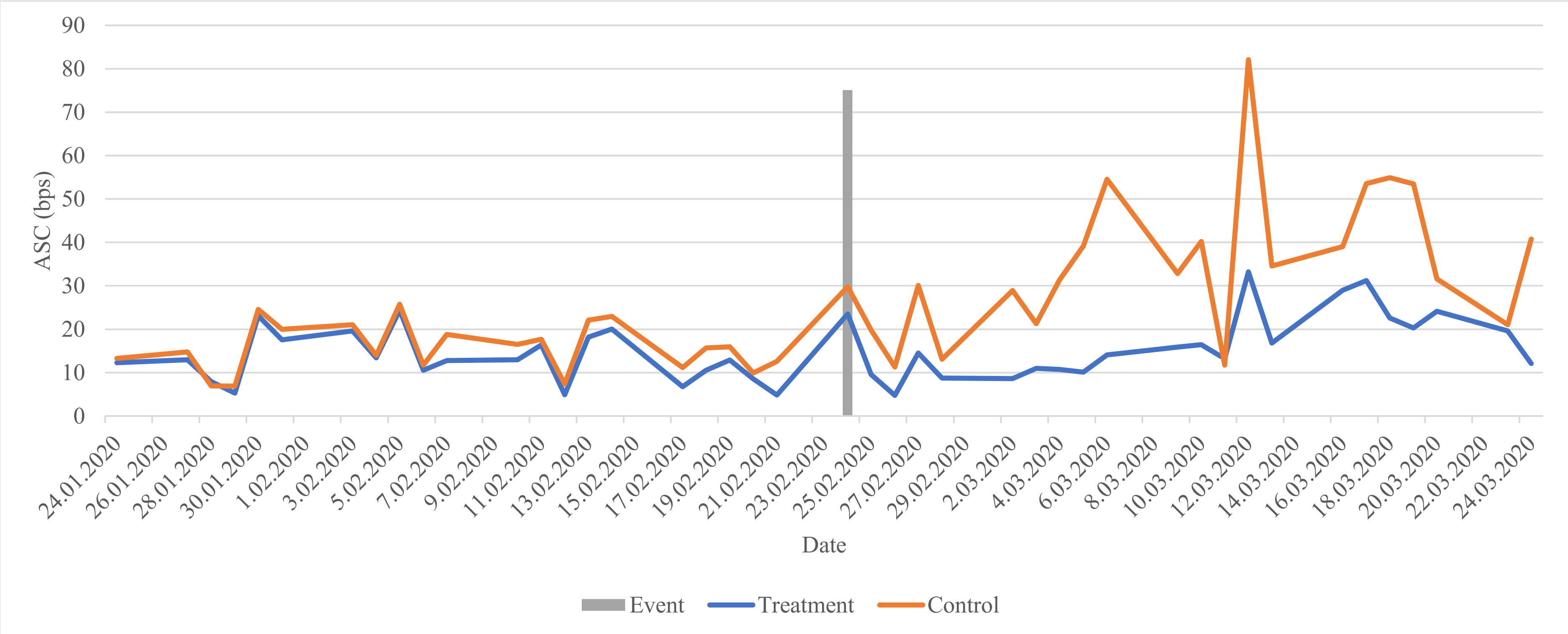


Volume (mln)
350
300
250
200
150
100
50
0
24.01.2020
26.01.2020
28.01.2020
30.01.2020
1.02.2020
3.02.2020
5.02.2020
7.02.2020
9.02.2020
11.02.2020
13.02.2020
15.02.2020
17.02.2020
19.02.2020
21.02.2020
23.02.2020
25.02.2020
27.02.2020
29.02.2020
2.03.2020
4.03.2020
6.03.2020
8.03.2020
10.03.2020
12.03.2020
14.03.2020
16.03.2020
18.03.2020
20.03.2020
22.03.2020
24.03.2020
Date
Event
Control Volume
Treated Volume

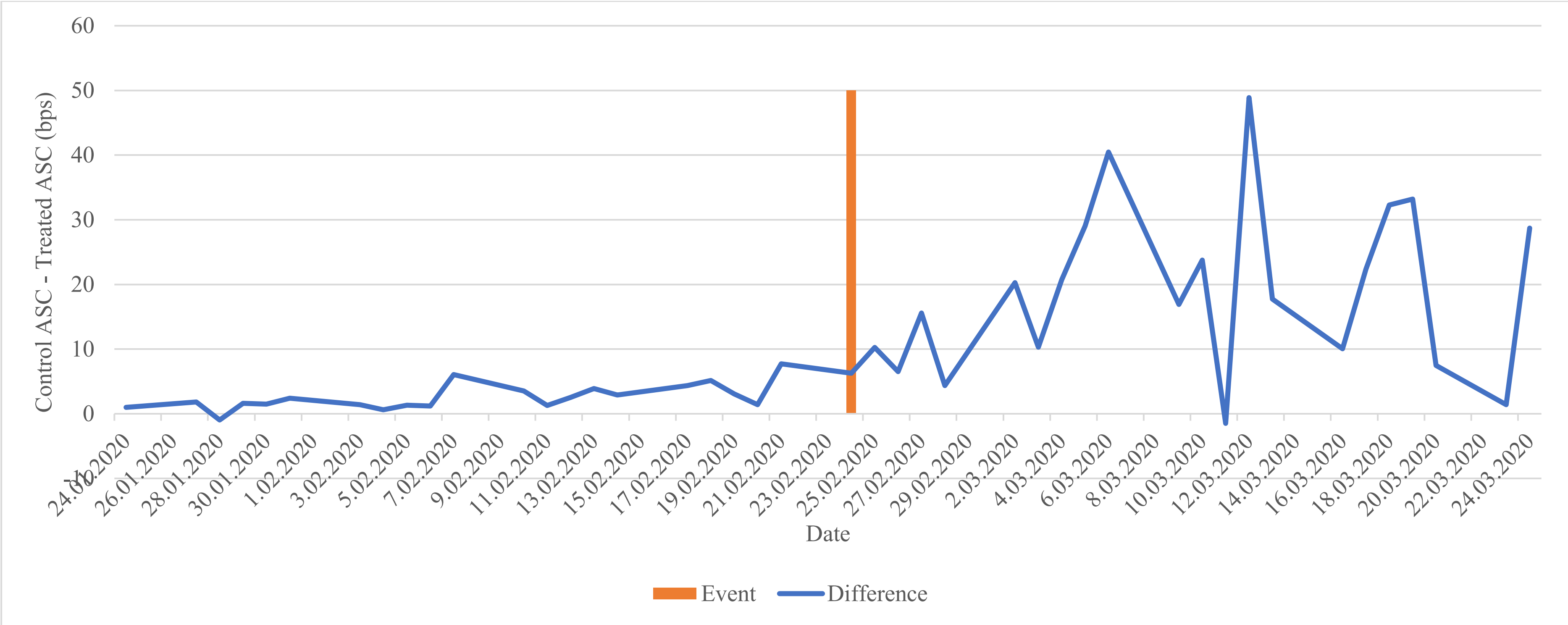
Figure 4. Adverse selection component

Panel A presents the day-by-day evolution of the cross-sectional average of $ASC_{i,d}$ for 55 European stocks that could be traded at both lit and dark venues, i.e. treated stocks, and for 55 European stocks with dark venue restrictions, i.e. control stocks. Panel B shows the evolution of the difference between the control group's $ASC_{i,d}$ and the treated group's $ASC_{i,d}$. $ASC_{i,d}$ is the adverse selection component of relative spread $Rspread_{i,d}$ for stock i on day d and is computed by using the method developed by Lin *et al.* (1995). The sample period covers from 24th January to 24th March 2020. The vertical bar indicates 24th February 2020, when the COVID-19-induced excessive volatility is adjudged to have commenced in global financial markets.

Panel A



Panel B



Control ASC - Treated ASC (bps)
60
50
40
30
20
10
0
-10
24.01.2020
26.01.2020
28.01.2020
30.01.2020
1.02.2020
3.02.2020
5.02.2020
7.02.2020
9.02.2020
11.02.2020
13.02.2020
15.02.2020
17.02.2020
19.02.2020
21.02.2020
23.02.2020
25.02.2020
27.02.2020
29.02.2020
2.03.2020
4.03.2020
6.03.2020
8.03.2020
10.03.2020
12.03.2020
14.03.2020
16.03.2020
18.03.2020
20.03.2020
22.03.2020
24.03.2020
Date
Event
Difference

Table 1. Variable definitions

This table defines the variables used in this study. *Unit* is the unit of measurement; *Market* is the market for which a variable is computed; and *Definition* provides a short definition and computation method.

Variable	Unit	Market	Definition
$DMS_{i,d}$	%	Dark, Lit	Dark market share; computed as dark trading volume divided by the total trading volume for stock *i* on day *d*
$Volume_{i,d}$	Millions	Lit	Number of shares traded in stock *i* on day *d*
$Rspread_{i,d}$	bps	Lit	Relative quoted spread for stock *i* on day *d*; computed as a time-weighted average of the difference between ask and bid prices divided by the mid-price (mid-price is the average of ask and bid prices) corresponding to each transaction
$Depth_{i,d}$	ln	Lit	The top-of-book depth; computed as the natural logarithm of the sum of the best bid and ask sizes for stock *i* on day *d*.
$Volatility_{i,d}$		Lit	A proxy for volatility; computed as a standard deviation of hourly mid-price returns for stock *i* on day *d*
$OIB_{i,d}$		Lit	Order imbalance defined in Chordia *et al.* (2008); computed as the absolute value of the buyer-initiated volume minus the number of seller-initiated volume divided by total volume stock *i* on day *d*
$HFT_{i,d}$		Lit	A proxy for HFT and computed as the number of messages divided by the number of transactions for stock *i* on day *d*

Table 2. Descriptive statistics

This table contains the pre- (Panel A) and event (Panel B) periods stock-day mean and standard deviation estimates for variables using data for 55 European stocks that could be traded at both lit and dark venues, i.e. treated stocks, and for 55 European stocks with dark venue restrictions, i.e. control stocks. The final column presents the t-statistics of two-sample t-tests of differences between the treated group's and the control group's variables. $DMS_{i,d}$ is the dark market share and is computed as the dark trading volume divided by the total trading volume for stock i on day d, $Volume_{i,d}$ is the number of shares traded for stock i on day d, $Rspread_{i,d}$ is the relative quoted spread for stock i on day d and is computed as a time-weighted average of the difference between ask and bid prices divided by the mid-price (mid-price is the average of ask and bid prices) corresponding to each transaction, $Depth_{i,d}$ is the top-of-book depth and is computed as the natural logarithm of the sum of the best bid and ask sizes for stock i on day d, $Volatility_{i,d}$ is a proxy for volatility and is computed as the standard deviation of hourly mid-price returns for stock i on day d, $OIB_{i,d}$ is the order imbalance for stock i on day d and is computed as the absolute value of the buyer-initiated volume minus the number of seller-initiated volume divided by the total volume of stock i on day d, $HFT_{i,d}$ is a proxy for HFT and is computed as the number of messages divided by the number of transactions for stock i on day d. The sample period is from 24th January to 24th March 2020. The event start date is 24th February 2020, when the COVID-19-induced excessive volatility is adjudged to have commenced in global financial markets. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

Panel A. Pre-event period

Variable	Treated group		Control group		Difference between means (t-statistic)
	Mean	Std. dev	Mean	Std. dev	Treated - control
$DMS_{i,d}$	2.5%	0.023	0.009%	0.001	2.45%*** (37.69)
$Volume_{i,d}$	1.328	0.261	1.332	0.109	-0.004 (-0.491)
$Rspread_{i,d}$	61.142	7.813	61.386	5.231	-0.244 (-0.902)
$Depth_{i,d}$	13.778	1.305	13.724	0.464	0.054 (1.356)
$Volatility_{i,d}$	0.0151	0.002	0.0152	0.001	-0.0001 (-1.551)
$OIB_{i,d}$	0.321	0.091	0.325	0.013	-0.004 (-1.513)
$HFT_{i,d}$	17.704	6.752	17.931	2.315	-0.227 (-1.106)

Panel B. Event period

Variable	Treated group		Control group		Difference between means (t-statistic)
	Mean	Std. dev	Mean	Std. dev	Treated - Control
$DMS_{i,d}$	2.1%	0.029	0.009%	0.002	2.095%*** (25.071)
$Volume_{i,d}$	3.275	4.115	2.874	2.631	0.401*** (2.855)
$Rspread_{i,d}$	87.952	11.146	94.253	7.705	-6.301*** (-16.176)

$Depth_{i,d}$	14.840	1.331	14.394	0.493	0.446*** (10.930)
$Volatility_{i,d}$	0.0338	0.004	0.0418	0.002	-0.008*** (-62.225)
$OIB_{i,d}$	0.337	0.107	0.394	0.022	-0.057*** (-18.151)
$HFT_{i,d}$	19.979	5.721	18.493	2.317	1.486*** (8.374)

Table 3. Dark volume

This table presents average daily dark trading volume and dark market share for the treated group during pre- and event periods along with t-statistics of the two-sample t-tests of differences between pre- and event periods' dark volume statistics. The sample period is from 24th January to 24th March 2020. The event start date is 24th February 2020, when the COVID-19-induced excessive volatility is adjudged to have commenced in global financial markets. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

	Dark volume (mln)	Dark market share (%)
Pre-event period	1,77	2.5
Event period	3.57	2.1
Difference (Event – pre)	1.80	-0.4
Percentage change and t-statistic	101%*** (6.42)	-15.6%*** (-3.65)

Table 4. The role of COVID-19 induced excessive volatility in dark market share

This table reports the coefficient estimates from the following regression model:

$$DMS_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_{i,d} + \gamma_2 Volume_{i,d} + \gamma_3 Rspread_{i,d} + \gamma_4 Depth_{i,d} + \gamma_5 Volatility_{i,d} + \gamma_6 OIB_{i,d} + \gamma_7 HFT_{i,d} + \varepsilon_{i,d}$$

where $DMS_{i,d}$ is a dark market share and is computed as the dark trading volume divided by the total trading volume for stock i on day d, α_i and β_d are stock and time fixed effects respectively, $Event_{i,d}$ is a dummy equalling 1 from 24th February to 24th March 2020 and 0 from 24th January to 23rd February 2020. $Volume_{i,d}$ is the number of shares traded for stock i on day d, $Rspread_{i,d}$ is the relative quoted spread for stock i on day d and is computed as a time-weighted average of the difference between ask and bid prices divided by the mid-price (mid-price is the average of ask and bid prices) corresponding to each transaction, $Depth_{i,d}$ is the top-of-book depth and is computed as the natural logarithm of the sum of the best bid and ask sizes for stock i on day d, $Volatility_{i,d}$ is a proxy for volatility and is computed as the standard deviation of hourly mid-price returns for stock i on day d, $OIB_{i,d}$ is the order imbalance for stock i on day d and is computed as the absolute value of the buyer-initiated volume minus the number of seller-initiated volume divided by the total volume of stock i on day d, $HFT_{i,d}$ is a proxy for HFT and is computed as the number of messages divided by the number of transactions for stock i on day d. The sample period is from 24th January to 24th March 2020. The sample includes 55 European stocks that could be traded at both lit and dark venues, i.e. treated stocks, and 55 European stocks with dark venue restrictions, i.e. control stocks. Standard errors are robust to heteroscedasticity and autocorrelation. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

Variable	Coefficient	*t*-statistic
$Event_{i,t}$	-1.3**	-2.54
$Rspread_{i,t}$	-0.0008**	-2.21
$Depth_{i,t}$	1.02***	19.14
$Volatility_{i,t}$	-0.0	-0.46
$OIB_{i,t}$	0.07***	3.08
$HFT_{i,t}$	0. 01***	3.14
Stock fixed effects	Yes	
Time fixed effects	Yes	
$\overline{R^2}$	56.2 %	

Table 5. Trading volume

This table contains the pre- and event average daily volume estimates for 55 European stocks that could be traded at both lit and dark venues, i.e. treated stocks, and for 55 European stocks with dark venue restrictions, i.e. control stocks. The estimates are reported separately for the treated and control groups along with t-statistics of the two-sample t-tests of differences between pre- and event periods average daily volumes. The sample period is from 24th January to 24th March 2020. The event start date is 24th February 2020, when the COVID-19-induced excessive volatility is adjudged to have commenced in global financial markets. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

	Control group (mln)	Treated group (mln)
Pre-event period	73.04	69.96
Event period	155.15	161.52
Difference (event – pre)	82.11	91.56
Percentage change (*t*-statistic)	112.4%*** (6.78)	147.2%*** (7.72)

Table 6. The role of COVID-19 induced excessive volatility in lit volume

This table reports the coefficient estimates from the following regression model, estimated using data for 55 European stocks that could be traded at both lit and dark venues, i.e. treated stocks, and for 55 European stocks with dark venue restrictions, i.e. control stocks:

$$Volume_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_{i,d} + \gamma_2 Treated_{i,d} + \gamma_3 Event_{i,d} * Treated_{i,d} + \gamma_4 Rspread_{i,d} + \gamma_5 Depth_{i,d} + \gamma_6 Volatility_{i,d} + \gamma_7 OIB_{i,d} + \gamma_8 HFT_{i,d} + \varepsilon_{i,d}$$

where $Volume_{i,d}$ is the number of shares traded for stock *i* on day d, α_i and β_d are stock and time fixed effects respectively, $Event_{i,d}$ is a dummy equalling 1 from 24th February to 24th March 2020 and 0 from 24th January to 23rd February 2020. $Treated_{i,d}$ is a dummy, which equals 1 for the treated group of stocks and 0 for the control group of stocks. $Rspread_{i,d}$ is the relative quoted spread for stock i on day *d* and is computed as a time-weighted average of the difference between ask and bid prices divided by the mid-price (mid-price is the average of ask and bid prices) corresponding to each transaction, $Depth_{i,d}$ is the top-of-book depth and is computed as the natural logarithm of the sum of the best bid and ask sizes for stock *i* on day d, $Volatility_{i,d}$ is a proxy for volatility and is computed as the standard deviation of hourly mid-price returns for stock i on day d, $OIB_{i,d}$ is the order imbalance for stock *i* on day *d* and is computed as the absolute value of the buyer-initiated volume minus the number of seller-initiated volume divided by the total volume of stock *i* on day *d*, $HFT_{i,d}$ is a proxy for HFT and is computed as the number of messages divided by the number of transactions for stock *i* on day *d*. The sample period is from 24th January to 24th March 2020. Standard errors are robust to heteroscedasticity and autocorrelation. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

Variable	Coefficient	*t*-statistic
$Event_{i,t}$	1.22***	2.65
$Treated_{i,t}$	-0.15	-1.5
$Event_{i,t} * Treated_{i,t}$	0.460**	2.37
$Rspread_{i,t}$	-0.005***	-4.72
$Depth_{i,t}$	0.93***	10.85
$Volatility_{i,t}$	10.49***	6.34
$OIB_{i,t}$	1.09***	4.33
$HFT_{i,t}$	0.0004	0.24
Stock fixed effects	YES	
Time fixed effects	YES	
$\overline{R^2}$	67.5%	

Table 7. Adverse selection component

This table contains the pre- and event stock-day averages of $ASC_{i,d}$ and $ASW_{i,d}$, for 55 European stocks that could be traded at both lit and dark venues, i.e. treated stocks, and for 55 European stocks with dark venue restrictions, i.e. control stocks. The estimates are reported separately for the treated and control groups along with t-statistics of the two-sample t-tests of differences between treated and control groups. $ASC_{i,d}$ is the adverse selection component of $Rspread_{i,d}$ and is computed using the method developed by Lin *et al.* (1995), while $ASW_{i,d}$ is the weight of $ASC_{i,d}$ in $Rspread_{i,d}$, calculated by dividing $ASC_{i,d}$ by $Rspread_{i,d}$ and then multiplying by 100. The sample period is from 24th January to 24th March 2020. The event date is 24th February 2020, when the COVID-19-induced excessive volatility is adjudged to have commenced in global financial markets. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

Panel A

	Pre-event	Event
Treated $ASC_{i,d}$	13.14	16.81
Control $ASC_{i,d}$	15.69	35.22
Difference (control – treated)	2.55 (1.61)	18.41***(3.63)

Panel B

	Pre-event	Event
Treated $ASW_{i,d}$	21%	19%
Control $ASW_{i,d}$	25%	37%
Difference (control – treated)	4% (1.58)	18%***(5.75)

Table 8. The role of COVID-19 induced excessive volatility in adverse selection cost

This table reports the coefficient estimates from the following regression model, estimated using data for 55 European stocks that could be traded at both lit and dark venues, i.e. treated stocks, and for 55 European stocks with dark venue restrictions, i.e. control stocks:

$$ASW_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_{i,d} + \gamma_2 Treated_{i,d} + \gamma_3 Event_{i,d} * Treated_{i,d}$$
$$+ \gamma_4 Depth_{i,d} + \gamma_5 Volatility_{i,d} + \gamma_6 OIB_{i,d} + \gamma_7 HFT_{i,d} + \gamma_8 Volume_{i,d} + \varepsilon_{i,d}$$

where $ASW_{i,d}$ is the weight of $ASC_{i,d}$ in $Rspread_{i,d}$, calculated by dividing $ASC_{i,d}$ by $Rspread_{i,d}$ and then multiplying by 100, $ASC_{i,d}$ is the adverse selection component of $Rspread_{i,d}$ and is computed by using the method developed in Lin *et al.* (1995), $Rspread_{i,d}$ is the relative quoted spread for stock i on day d and is computed as time-weighted average of the difference between ask and bid prices divided by the mid-price (mid-price is the average of ask and bid prices) corresponding to each transaction. α_i and β_d are stock and time fixed effects respectively, $Event_{i,d}$ is a dummy equal 1 from 24th February to 24th March 2020 and 0 from 24th January to 23rd February 2020, $Treated_{i,d}$ is a dummy equalling 1 for the treated group of stocks and 0 for the control group of stocks. $Depth_{i,d}$ is the top-of-book depth and is computed as the natural logarithm of the sum of the best bid and ask sizes for stock i on day d, $Volatility_{i,d}$ is a proxy for volatility and is computed as the standard deviation of hourly mid-price returns for stock i on day d, $OIB_{i,d}$ is the order imbalance for stock i on day d and is computed as the absolute value of the buyer-initiated volume minus the number of seller-initiated volume divided by the total volume of stock i on day d, $HFT_{i,d}$ is a proxy for HFT and is computed as the number of messages divided by the number of transactions for stock i on day d. The sample period is from 24th January to 24th March 2020. Standard errors are robust to heteroscedasticity and autocorrelation. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

Variable	Coefficient	*t*-statistic
$Event_{i,t}$	2.23**	2.17
$Treated_{i,t}$	-1.59	-1.40
$Event_{i,t} * Treated_{i,t}$	-3.08**	-2.03
$Depth_{i,t}$	-0.91***	-3.85
$Volatility_{i,t}$	3.53*	1.71
$OIB_{i,t}$	3.85***	5.53
$HFT_{i,t}$	0.306	0.66
$Volume_{i,t}$	0.54	1.35
Stock fixed effects	YES	
Time fixed effects	YES	
$\overline{R^2}$	33.2%	

Table 9. The role of COVID-19 induced excessive volatility in liquidity

This table reports the coefficient estimates from the following regression model, estimated using data for 55 European stocks that could be traded at both lit and dark venues, i.e. treated stocks, and for 55 European stocks with dark venue restrictions, i.e. control stocks:

$$Rspread_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_{i,d} + \gamma_2 Treated_{i,d} + \gamma_3 Event_{i,d} * Treated_{i,d}$$
$$+ \gamma_4 Depth_{i,d} + \gamma_5 Volatility_{i,d} + \gamma_6 OIB_{i,d} + \gamma_7 HFT_{i,d} + \gamma_8 Volume_{i,d} + \varepsilon_{i,d}$$

where $Rspread_{i,d}$ is the relative quoted spread for stock *i* on day d and computed as time-weighted average of the difference between ask and bid prices divided by the mid-price (mid-price is the average of ask and bid prices) corresponding to each transaction. α_i and β_d are stock and time fixed effects respectively, $Event_{i,d}$ is a dummy equal 1 from 24th February to 24th March 2020 and 0 from 24 January to 23 February 2020, $Treated_{i,d}$ is a dummy equalling 1 for the treated group of stocks and 0 for the control group of stocks. $Depth_{i,d}$ is the top-of-book depth and is computed as the natural logarithm of the sum of the best bid and ask sizes for stock *i* on day *d*, $Volatility_{i,d}$ is a proxy for volatility and is computed as the standard deviation of hourly mid-price returns for stock *i* on day d, $OIB_{i,d}$ is the order imbalance for stock i on day d and is computed as the absolute value of the buyer-initiated volume minus the number of seller-initiated volume divided by the total volume of stock *i* on day d, $HFT_{i,d}$ is a proxy for HFT and is computed as the number of messages divided by the number of transactions for stock *i* on day *d*. The sample period is from 24th January to 24th March 2020. Standard errors are robust to heteroscedasticity and autocorrelation. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

Variable	Coefficient	*t*-statistic
$Event_{i,t}$	21.88***	3.21
$Treated_{i,t}$	-1.14	-0.53
$Event_{i,t} * Treated_{i,t}$	-7.25**	-2.54
$Depth_{i,t}$	-6.92***	-5.41
$Volatility_{i,t}$	15.72***	6.46
$OIB_{i,t}$	4.54*	1.72
$HFT_{i,t}$	0.04	1.59
$Volume_{i,t}$	-1.03***	-4.60
Stock fixed effects	YES	
Time fixed effects	YES	
$\overline{R^2}$	75.8%	

Table 10. The role of COVID-19 induced excessive volatility in price discovery/informational efficiency

This table reports the coefficient estimates from the following regression model, estimated using data for 55 European stocks that could be traded at both lit and dark venues, i.e. treated stocks, and for 55 European stocks with dark venue restrictions, i.e. control stocks:

$$Corr_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_{i,d} + \gamma_2 Treated_{i,d} + \gamma_3 Event_{i,d} * Treated_{i,d} + \gamma_4 Rspread_{i,d} + \gamma_5 Depth_{i,d} + \gamma_6 Volatility_{i,d} + \gamma_7 OIB_{i,d} + \gamma_8 HFT_{i,d} + \gamma_9 Volume_{i,d} + \varepsilon_{i,d}$$

where $Corr_{i,d}$ is first-order return autocorrelations for each stock *i* on day *d* at 30 seconds frequency. α_i and β_d are stock and time fixed effects respectively, $Event_{i,d}$ is a dummy equalling1 from 24th February to 24th March 2020 and 0 from 24th January to 23rd February 2020, $Treated_{i,d}$ is a dummy equalling 1 for the treated group of stocks and 0 for the control group of stocks. $Rspread_{i,d}$ is the relative quoted spread for stock *i* on day *d* and computed as time-weighted average of the difference between ask and bid prices divided by the mid-price (mid-price is the average of ask and bid prices) corresponding to each transaction. $Depth_{i,d}$ is the top-of-book depth and is computed as the natural logarithm of the sum of the best bid and ask sizes for stock *i* on day *d*, $Volatility_{i,d}$ is a proxy for volatility and is computed as the standard deviation of hourly mid-price returns for stock *i* on day *d*, $OIB_{i,d}$ is the order imbalance for stock *i* on day *d* and is computed as the absolute value of the buyer-initiated volume minus the number of seller-initiated volume divided by the total volume of stock *i* on day *d*, $HFT_{i,d}$ is a proxy for HFT and is computed as the number of messages divided by the number of transactions for stock *i* on day *d*. The sample period is from 24th January to 24th March 2020. Standard errors are robust to heteroscedasticity and autocorrelation. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

Variable	Coefficient	*t*-statistic
$Event_{i,t}$	60.41	0.36
$Treated_{i,t}$	-3.33	-0.47
$Event_{i,t} * Treated_{i,t}$	31.34*	1.71
$Rspread_{i,t}$	-2.06***	-7.19
$Depth_{i,t}$	-5.41***	-13.39
$Volatility_{i,t}$	-26.41***	-3.88
$OIB_{i,t}$	-4.39***	-3.94
$HFT_{i,t}$	-0.26	-0.64
$Volume_{i,t}$	1.98	0.41
Stock fixed effects	YES	
Time fixed effects	YES	
$\overline{R^2}$	24.1%	

Appendix A

This appendix lists the stocks included in the stock sample. The stocks are listed alphabetically using the ISINs.

ISIN	**Company Name**	**Country**
BE0003755692	Agfa-Gevaert Nv	Belgium
BMG671801022	Odfjell Drilling Ltd.	Norway
CH0001341608	Hypothekarbank Lenzburg Ag	Switzerland
CH0003390066	Mikron Holding Ag	Switzerland
CH0010754924	Schweiter Technologies Ag	Switzerland
CH0239518779	Hiag Immobilien Holding Ag	Switzerland
CH0386200239	Medartis Holding Ag	Switzerland
CH0406705126	Sensirion Holding Ag	Switzerland
DE0006219934	Jungheinrich Ag	Germany
DE0006569908	Mlp Ag	Germany
DE000A1DAHH0	Brenntag AG	Germany
DK0016188733	Nykredit Invest Balance Defensiv	Denmark
DK0016188816	Nykredit Invest Balance Moderat	Denmark
DK0060010841	Danske Inv Mix Akk Kl	Denmark
DK0060642726	Maj Invest Value Aktier Akkumulerende	Denmark
DK0060738599	Demant	Denmark
ES0171996095	Grifols, S.A.	Spain
FI0009003727	Wärtsilä Oyj Abp	Finland
FI0009010854	Lassila & Tikanoja Oyj	Finland
FI4000074984	Valmet Oyj	Finland
FR0000073298	Ipsos	France
FR0010112524	Nexity	France
GB0001110096	Boot (Henry)	United Kingdom
GB0002018363	Clarkson	United Kingdom
GB0002634946	Bae Systems	United Kingdom
GB0004161021	Hays Plc	United Kingdom
GB0009633180	Dechra Pharmaceuticals	United Kingdom

GB00B05M6465	Numis Corp	United Kingdom
GB00B0LCW083	Hikma Pharmaceuticals	United Kingdom
GB00B1JQDM80	Marston's Plc	United Kingdom
GB00B1ZBKY84	Moneysupermarket.Com Group Plc	United Kingdom
GB00B63H8491	Rolls-Royce Hldgs Plc	United Kingdom
GB00BF4HYT85	Bank Of Georgia Group Plc	United Kingdom
GB00BG0TPX62	Funding Circle Holdings Plc	United Kingdom
GB00BG12Y042	Energean Oil & Gas Plc	United Kingdom
GB00BGLP8L22	Imi	United Kingdom
GB00BJTNFH41	Ao World Plc	United Kingdom
GB00BMSKPJ95	Aa	United Kingdom
GB00BYSS4K11	Georgia Healthcare Group Plc	United Kingdom
GB00BYYW3C20	Forterra Plc	United Kingdom
GB00BZ1G4322	Melrose Industries	United Kingdom
GB00BZ6STL67	Metro Bank	United Kingdom
GB00BZBX0P70	Gym Group Plc	United Kingdom
GG00B4L84979	Burford Capital Ltd	United Kingdom
IE00BD5B1Y92	Bank Of Cyprus Holdings Public Limited Company	Ireland
IE00BDQYWQ65	Ishares	Ireland
IT0005331019	Carel Industries	Italy
JE00B2419D89	Breedon Group Plc	United Kingdom
JE00BG6L7297	Boohoo.Com Plc	United Kingdom
NO0010663669	Magseis	Norway
SE0000103699	Hexagon Aktiebolag	Sweden
SE0000163628	Elekta Ab (Publ)	Sweden
SE0005468717	Ferronordic Machines Ab	Sweden
SE0010468116	Arjo Ab B	Sweden
SE0010948588	Bygghemma Group First Registered	Sweden
AT0000KTMI02	Pierer Mobility Ag	Austria
BE0003766806	Ion Beam Applications Sa Iba	Belgium

CH0044781141	Gam Precious Metals - Physical Gold	Switzerland
DE0005103006	Adva Optical Networking Se	Germany
DE0006047004	Heidelbergcement AG	Germany
DK0060027142	ALK-Abello A/S	Denmark
DK0060580512	Nnit	Denmark
DK0060946788	Ambu	Denmark
ES0177542018	International Airlines Group	Spain
FI0009005870	Konecranes Abp	Finland
FI0009009377	Capman	Finland
FI0009800643	Yit Oyj	Finland
FI4000312251	Kojamo Oyj	Finland
FR0000050353	Lisi	France
FR0000066672	Gl Events	France
FR0010221234	Eutelsat Communications	France
FR0010908533	Edenred	France
FR0011471135	Erytech Pharma	France
GB0000163088	Speedy Hire	United Kingdom
GB0000904986	Bellway	United Kingdom
GB0004082847	Standard Chartered	United Kingdom
GB0004270301	Hill & Smith Hldgs	United Kingdom
GB0006043169	Morrison(Wm.)Supermarkets	United Kingdom
GB0009465807	Weir Group	United Kingdom
GB0033195214	Kingfisher	United Kingdom
GB00B0HZPV38	Kaz Minerals Plc	United Kingdom
GB00B17BBQ50	Investec Plc	United Kingdom
GB00B17WCR61	Connect Group Plc	United Kingdom
GB00B4Y7R145	Dixons Carphone Plc	United Kingdom
GB00B7KR2P84	Easyjet	United Kingdom
GB00BJGTLF51	Target Healthcare Reit Plc	United Kingdom
GB00BZ3CNK81	Torm Plc	United Kingdom
IM00B5VQMV65	Gvc Holdings Plc	United Kingdom

IT0000076502	Danieli & C. Officine Meccaniche Spa	Italy
IT0001447348	Mittel	Italy
IT0003007728	Tod S Spa	Italy
IT0004053440	Datalogic	Italy
IT0004056880	Amplifon Spa	Italy
JE00BJVNSS43	Ferguson Plc	United Kingdom
LI0315487269	Vpb Vaduz	Liechtenstein
LU0569974404	Aperam S.A	Luxembourg
NL0000339703	Beter Bed Holding Nv	Netherlands
NL0010733960	Lastminute.Com	Netherlands
NL0011832936	Cosmo Pharmaceuticals N.V.	Netherlands
NO0003053605	Storebrand Asa	Norway
NO0010593544	Insr Insurance Group	Norway
SE0000105199	Haldex	Sweden
SE0000379497	Semcon	Sweden
SE0000426546	New Wave	Sweden
SE0006593919	Klovern	Sweden
SE0009921588	Bilia	Sweden
GB0006640972	4imprint Group Plc	United Kingdom
GB0008085614	Morgan Sindall Group Plc	United Kingdom
GB00B8460Z43	Gcp Student Living	United Kingdom
GB00B1V9NW54	Hilton Food Group Plc	United Kingdom

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