Frequent batch auctions under liquidity constraints

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Abstract We exploit European regulatory interventions to investigate the effects of sub-second periodic auctions on market quality under dark trading restrictions. The restrictions are linked to an observable increase in periodic auctions and an economically meaningful loss of liquidity. While periodic auctions ameliorate illiquidity, their effects are significantly less than those of the restrictions; therefore, the combined effects of periodic auctions' increases and the restrictions are general declines in liquidity and informational efficiency. However, consistent with theory, periodic auctions are linked to reductions in adverse selection costs, thereby underscoring their potential to address latency arbitrage and the technological arms race.

Keywords: Frequent batch auctions; dark trading; MiFID II; latency arbitrage; liquidity; informational efficiency.

JEL Classification: G14; G15; G18

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...stop this nonsense by moving from continuous trading to frequent batch auctions. To human eyes trading will be essentially continuous, but the robots will effectively gather in a room every second (or 100ms, if that seems too glacial for the financial terminators) for a brief blind auction

Financial Times, 21st February, 2014

1. Introduction

While a large number of market microstructure studies suggest that algorithmic and high frequency trading (AT and HFT) benefit market quality (see as examples, Brogaard et al., 2014; Harris, 2013; Hasbrouck and Saar, 2013; Hendershott et al., 2011; Ibikunle, 2018), several others report their tendency to induce extreme and destabilizing events, such as "flash crashes" (see as examples, Easley et al., 2011; Kirilenko et al., 2017; Ibikunle and Rzayev, 2020). Others note their propensity to induce a greater price impact on large institutional orders (see Putnins and Barbara, 2016). Raman et al. (2014) and Anand and Venkataraman (2016) also find that endogenous HFT liquidity providers destabilise markets during stressful periods. Two additional consequences of trading at high speeds are latency arbitrage, involving the exploitation of a trading time disparity between fast and slow traders (see Rzayev and Ibikunle, 2019), and the technological arms race (see Diaz-Rainey et al., 2015), a negative externality-inducing development (see Menkveld, 2014).

Budish et al. (2015) argue that the technological arms race is a symptom of a flawed market design and they propose the *frequent batch auctions* (FBA)/*sub-second periodic auctions* mechanism (hereafter referred to as periodic auctions), which divides trading into intervals of very short lengths, for example, every tenth of a second, as an antidote. In effect, this treats time as discrete instead of continuous and orders are processed in a batch auction rather than serially. While frequent batch auctions are not yet widely used globally, according to the UK's Financial Conduct Authority (FCA), periodic auctions have recently experienced two significant spurts of growth due to the implementation of the provisions of the EU's Markets in Financial Instruments Directive (MiFID) II. Although periodic auctions account for less than 5% of the average trading volume in UK markets during the MiFID II era, the mechanism's significance has recently become apparent. This results from the commencement of the double volume cap (DVC) measure, a MiFID II provision designed to restrict dark trading in European markets (see Ibikunle et al., 2019 for a detailed discussion of the DVC), in place since early

2018. Evidence suggests that a non-negligible portion of volumes, otherwise destined for dark pools in stocks under the DVC restriction, are executed through periodic auctions and other non-continuous trading mechanisms, the so-called 'quasi-dark' mechanisms (see Johann et al., 2019).

In recognition of their relevance, the European Securities and Markets Authority (ESMA) called for evidence of the effects of periodic auctions on market quality.[1] However, there have been very limited attempts to investigate the direct market quality effects of periodic auctions as a trading mechanism thus far. In addition, if periodic auctions are to serve as a means of addressing the twin issues of latency arbitrage and the technological arms race, they must be shown to, at a minimum, have a benign or positive effect on market quality. Therefore, in this study, we investigate the effects of periodic auctions on market quality characteristics in Europe's most active equity market, the UK market.

In line with Johann et al. (2019), we find that stocks experiencing DVC-imposed dark trading restrictions experience higher periodic auctions volumes and that the overall market quality effects of periodic auctions on the market are limited and mixed. Specifically, we find that periodic auctions have a generally positive effect on liquidity and a largely benign effect on adverse selection costs, except in the case of the most liquid stocks, where adverse selection declines with the use of periodic auctions. The adverse selection costs effect is explained by the predictions of Budish et al. (2015): periodic auctions offer a safe haven for slower traders who are susceptible to the latency arbitrage strategies deployed by faster traders. Thus, increasing use of periodic auctions lowers the incidence of slower traders being adversely selected, especially through the latency arbitrage strategy typically deployed by HFTs. The mixed nature of the evidence uncovered is underscored by the estimated impact of periodic auctions on informational efficiency. The overall effect of periodic auctions trading, especially during the DVC window, is a deviation from a random walk or reduction in informational efficiency. This finding is consistent with periodic auctions slowing down the price discovery process. While trading in dark pools implies a degree of delay (as in Menkveld et al., 2017;

[1] The ESMA report calling for evidence can be accessed here: https://www.esma.europa.eu/sites/default/files/library/esma70-156-785_call_for_evidence_periodic_auctions_for_equity_instruments.pdf

Zhu, 2014), periodic auctions in an otherwise high frequency trading environment will inevitably slow down trading.

To the best of our knowledge, this is the first study to provide empirical evidence on the market quality implications of periodic auctions in European markets. Although Johann et al. (2019) include periodic auctions in their list of 'quasi-dark' trading mechanisms, the identification of periodic auctions mechanisms as quasi-dark is slightly problematic given that a key feature of auctions is transparency – specifically, the fact that all orders are reflected in the observable indicative auction price and volume as they arrive in the market and prior to uncrossing. European exchanges, such as Cboe, also claim that the orders submitted to their periodic auctions mechanisms are sent to lit order books as they arrive. Our paper also isolates the effects of periodic auctions on market quality characteristics, while controlling for volumes attributed to other trading mechanisms.

In general, deploying latency arbitrage-based trading strategies is more suited to a fragmented market environment given the likelihood of disparities in reaction times among different venues (Wah and Wellman, 2013). However, HFT makes these viable strategies within a single venue because it allows for a significant difference in the trading speeds of slow and fast traders (Menkveld, 2014; Wah and Wellman, 2016). By doing so, according to Aquilina et al. (2017b), HFT imposes adverse selection costs on slower traders (see also Rzayev and Ibikunle, 2019). The quest for faster trading speeds has resulted in the technological arms race, a competition driven by investment in hardware and software (see Biais and Woolley, 2011). Both are sustained by fast traders' need for the retention of their speed advantage over slow traders and the pursuit of parity or the eclipsing of fast traders by the slow traders. Menkveld (2014) argues that the arms race raises the spectre of negative externality and waste in financial markets. Thus, if the importance of speed is reduced, the activities driving the arms race and latency arbitrage should decline, consequently leading to a reduction in both phenomena. The FBA, as proposed by Budish et al. (2015), could significantly reduce the influence of speed on the price discovery process. This could shift investor focus from the acquisition of speed-enabling transactions to obtaining better prices, implying that the introduction of an FBA-type mechanism could offer price efficiency (see Madhavan, 1992).

Cboe's periodic auction mechanism, which was introduced on 19th October 2015 and currently accounts for about 70% of the periodic auction volume in Europe, is largely consistent with the structure of the FBA proposed by Budish et al. (2015). Its auction book provides both pre-trade and post-trade transparency, thus meeting MiFID II's regulatory technical standards (RTS). Although periodic auctions have been the subject of some academic studies, they have only focused on long interval auction lengths and not the FBA-type periodic auctions we examine in the context of AT/HFT. For example, Madhavan (1992) argues that periodic auctions offer greater price efficiency than the more common continuous order-driven trading mechanism. This is due to the pooling effect of the periodic auctioning system, allowing for simultaneous execution. The pooling of orders for simultaneous execution addresses the problem of information asymmetry that the sequential trading system of the continuous order-driven trading mechanism induces (see also Barclay et al., 2008). The simultaneous executions in classical auctions could also positively affect the pricing process when they are deployed in conjunction with continuous order-driven trading. Amihud et al. (1997) show that an iterated continuous trading process preceded by a call auction on the Tel Aviv Stock Exchange is linked to improvements in the price discovery process.

Evidence from other studies that broadly examine the implications of call auctions for market quality characteristics is more nuanced. Sarkar (2016) investigates midday auctions at the London Stock Exchange (LSE) and reports that the use of the mechanism is linked to a larger spread and increased price volatility. However, the most common use of call auctions in financial markets is as market opening or closing mechanisms, and this has been the focus of a stream of literature (see as examples, Bellia et al., 2020; Chang et al., 2008; Cordi et al., 2015; Ibikunle, 2015). For example, Barclay et al. (2008) and Chang et al. (2008) report on the positive effects of the use of the opening call auction for market opening. Opening call auctions can help market participants build a consensus on an opening price ahead of the continuous trading phase, and thus offer informational efficiency benefits. The work of Barclay et al. (2008) and Chang et al. (2008) nevertheless contrasts with the findings of Ibikunle (2015), who reports a high rate of failure to open, and low levels of informational efficiency for low volume stocks on the LSE when compared to the levels of informational efficiency recorded for the continuous trading period. The study also finds that although the closing call auction offers higher informational efficiency levels than the opening call auction, it is still lower than the continuous trading phase attains. This finding is linked to the fact that the advantages of transparency and liquidity the call auction offers cannot necessarily be regarded as such in an era where HFT guarantees high levels of trading activity during the continuous trading phase of the market.

Cordi et al. (2015) find positive links between market quality characteristics and the use of the closing call auction, while Comerton-Forde et al. (2007) argue that the use of the closing call auction could reduce price manipulation. Chelley-Steeley (2008) and Chelley-Steeley (2009) in turn investigate the market quality impact of the introduction of the closing auction on the LSE. Both studies report market quality improvements. These findings are consistent with those of Pagano and Schwartz (2003) and Comerton-Forde et al. (2007), who examine the introduction of the closing auction on the Paris Bourse and the Singapore Stock Exchange respectively. Thus, with the exception of the evidence from the LSE (for smaller stocks), there appears to be a consensus in the literature on the links between the deployment of the call auctions and market quality characteristics. This may have implications for the use of periodic auctions at high frequency.

Finally, more recently, using data from the Taiwan Stock Exchange (TWSE) Indriawan et al. (2020) investigate a transition from batch auctions to continuous trading and find that the move is linked to an increase in adverse selection and a liquidity decline. Our study differs from theirs in at least two respects. The first relates to significant market structure differences: while they focus on a transition from batch auctions to continuous trading, we investigate an event that should lead to an increased use of periodic auctions within a hybrid trading system. Second, TWSE's batch auctions are distinct from the periodic auctions we examine in that the former operates five-second interval auctions, while the periodic auctions systems we examine operate maximum intervals of 100 milliseconds.

2. Background

2.1. Periodic auctions and market quality: the literature and hypotheses

Although periodic auctions are mainly discussed in the context of addressing the technological arms race and its potential welfare externalities (see Menkveld, 2014), its deployment should first be viewed in less ambitious terms. This is because the overriding question when designing markets is that of the system of exchange, specifically, how the decision could either enhance or hinder the evolution of market quality characteristics, such as liquidity and informational efficiency. Periodic auction trading systems are structurally distinct from the other auction types that have been studied extensively in the literature. Firstly, periodic auctions have smaller intervals; Budish et al. (2015) suggest that the interval should be smaller than one second and, in line with this, the leading global system operated by Cboe provides 100ms-level auction intervals. Secondly, periodic auctions are typically conducted alongside continuous trading, and currently the volume of periodic auctions only captures a small amount of the total volume in the market. Therefore, trading in periodic auctions might be more influenced by the market's main trading system than vice versa. Thirdly, the main aim of periodic auctions has thus far been to de-emphasise the influence of speed in trading, i.e. the activities of HFT, while opening and closing call auctions aim to provide more efficient prices.

There are limited existing studies on periodic auctions. An FCA (2018) investigation of the growth of periodic auctions in UK stocks finds little difference in growth between stocks experiencing dark trading caps and those that are not. Johann et al. (2019) investigate the shift of dark pool volume to other non-continuous trading mechanisms following the imposition of dark trading restrictions on some stocks. They find that only a small proportion of the hitherto dark volume shift into such markets, including periodic auctions. They also find limited changes in overall market quality. Aquilina et al. (2017b) investigation of the impact of periodic auctions on adverse selection costs is limited by the fact that it is based on a small pre-MiFID II sample and volume. Thus, the effects of periodic auctions remain largely unexplored and unclear in the empirical literature, which underscores the ESMA call for more evidence given the concerns of various stakeholders (see McDowell, 2019).

INSERT FIGURE 1 AND FIGURE 2 ABOUT HERE

Figure 1 provides clear evidence of the above-noted spurts of growth in periodic auctions volume (Panel A), currency volume (Panel B) and transactions (Panel C) in UK stocks since the start of the MiFID II regulatory era. The growth also appears to be due to the migration of trading from other trading mechanisms (see Figure 2). However, the overall picture presented in Figure 1 and by the FCA (2018) fails to account for the differences in the growth of periodic auctions in stocks experiencing dark trading restrictions and those that are not. Nevertheless, it is logical to expect that there would be a difference in the periodic auctions volume growth trajectories for stocks facing dark trading restrictions and those that are not. Therefore, we propose the following hypothesis:

Hypothesis 1: *Following the implementation of the DVC, stocks with DVC-imposed dark trading restrictions will experience a higher periodic auctions volume when compared to those with no DVC-related restrictions.*

The implementation of the DVC might lead to the shift of hitherto dark trading volume to quasi-dark markets, including the periodic auction book (see Johann et al., 2019).

Our next few hypotheses relate to the market quality effects of periodic auctions. The call auction is widely employed as an opening and closing mechanism in financial markets, with implications for market quality during the continuous trading period. Indeed, Ibikunle (2015) identifies distinctions in the effects of the call auction depending on its positioning relative to the continuous trading period and the activeness of the stocks (see also Cao et al., 2000; Jiang et al., 2012; Chang et al., 2008; Cordi et al., 2015). Therefore, it is rational to expect that periodic auctions interact with the continuous trading mechanism when deployed concurrently, and that this has implications for market quality. However, since market quality characteristics, such as liquidity, are functions of trading activity (see Chordia et al., 2001; Chordia et al., 2008), these implications are likely linked to periodic auctions volume. Although periodic auctions were deployed in European markets prior to the MiFID II era, as shown in Figure 2, they captured only a very small percentage of the overall daily market volume before the implementation of MiFID II, less than 0.1% of the total trading volume (see FCA, 2018; Cboe, 2020). The implementation of MiFID II provisions, especially the imposition of the DVC dark trading restrictions, changed this, leading to a substantial growth in period auctions volume, as seen in Figure 1.

The above suggests that the potential effects of periodic auctions on market quality characteristics are more likely to be empirically evidenced following the implementation of MiFID II provisions, i.e. a period with relatively sufficient volumes. The crucial question here is whether more periodic auctions enhances or impairs market quality characteristics. Given the evolution of periodic auctions around the DVC implementation, the market quality effects of any changes in the volume of periodic auctions could be linked to the effects of dark trading restrictions. Ibikunle et al. (2019) find that MiFID II dark trading halts are linked to a general decline in market quality, while Johann et al. (2019) find that the market quality effects of any MiFID-II-induced shift in trading volume from dark to other venues is negligible. Therefore, it is useful to employ a framework that distinguishes the effects of periodic auctions on market quality characteristics while controlling for the effects of the DVC. Liquidity and informational efficiency are crucial characteristics that indicate the quality of the trading process. While an implementation of the DVC is expected to adversely impact liquidity in the affected stocks (Ibikunle et al., 2019), periodic auctions should alleviate some of the liquidity constraints the DVC's implementation imposes. Information might also be released in a timelier manner when traders migrate from dark pools to more transparent trading mechanisms, such as periodic auctions. An improvement in transparency could inform an improvement in the price discovery process through the formation of more efficient prices, which in turn could encourage the submission of more orders and liquidity improvements in the aggregate market (see Amihud et al., 1997; Madhavan, 1992; Bloomfield et al., 2015). Therefore, we propose the following hypotheses:

Hypothesis 2: *The implementation of the DVC impairs liquidity for stocks with dark trading restrictions.*

Hypothesis 3: *An increase in periodic auctions alleviates the liquidity constraints induced by DVC implementation.*

The argument with regard to the effects of periodic auction on liquidity related to DVC implementation is linked to transparency, i.e. the dynamics of a component of the spread and adverse selection costs. In the classical call auctions literature, congregating all available market liquidity at a single point for price determination purposes is a central theoretical argument. Schwartz (2012) asserts that doing so enhances the accuracy of the price discovery process, while Madhavan (1992) argues that since all traders are given access to the same prices at the same time, call auctions reduce information asymmetry. Schnitzlein (1996) also finds that there is a reduction in adverse selection costs incurred by uninformed traders under a call auction. Therefore, the structural similarities between the periodic auction and the call auction lead us to expect periodic auctions to be negatively related to adverse selection costs:

Hypothesis 4: *Periodic auctions are negatively linked to adverse selection costs.*

With respect to the DVC itself, the implementation of a dark trading halt in stocks will force a transfer of slow traders from dark pools to more transparent ones using trading mechanisms, such as continuous and periodic auctions (see Johann et al., 2019). An increase in the volume of slow (uninformed) traders in lit venues, or at least less dark venues, will lessen the concentration of informed traders in these venues, resulting in lower risk of uninformed traders being adversely selected by informed or faster ones at more transparent venues:

Hypothesis 5: *The implementation of the DVC leads to a reduction in adverse selection costs.*

Although the implementation of the DVC implies a shift of trading activity from dark to more transparent venues, the overall impact of periodic auctions on informational efficiency is likely to be a weakness. This is because, while trading in dark pools signifies a degree of delay due to informed traders facing higher non-execution risk (see Zhu, 2014) and execution delays (see Menkveld et al., 2017) than in more transparent venues, periodic auctions are intentionally designed to slow down trading, and often to counter the effects of speed in trading. Therefore, one anticipated effect of an increased use of periodic auctions on the price discovery process is making it less efficient, i.e. the price formation process becomes slower:

Hypothesis 6: *Periodic auctions are negatively linked to informational efficiency.*

2.2. Periodic auctions in Europe

Cboe launched its periodic auctions trading mechanism in October 2015, using both the BXE and DXE order books. The stated aim of the periodic auctions book is to provide a trading environment with reduced emphasis on speed, instead enhancing the importance of price. Periodic auctions orders at Cboe are accepted from 08:00 to 16:30 London time during trading days. Combined orders are not allowed in the submitting processes, meaning that orders in different directions must be submitted separately. Auctions are also conducted continuously and consecutively throughout the trading day. Traders are able to submit market, limit and pegged orders in the books accepting periodic auctions orders. Orders with the so-called minimum acceptable quantity (MAQ) rule are also accepted. MAQ orders are only executable when the referenced MAQ size is fulfilled. In contrast to the FBA design envisaged by Budish et al. (2015), the duration of each auction is randomized, however, it is less than the maximum limit, which is 100ms. Each auction is split into two stages. The first is the price determination stage, when the auction price is formed; the second is the execution allocation stage. To determine the auction prices, four criteria must be met: naming maximum executable volume, minimum surplus, market pressure and reference price. The most important point here is ensuring that, for each auction, the mechanism selects the equilibrium price where the executed volume is maximised. The basis of 'price/size/time' is followed during the price determination process; this means that the importance of price is directly enhanced in the auctions. Furthermore, in order to ensure an orderly price formation process, the EBBO (European best bid and offer) collar is introduced. By ensuring that the auction prices fall within the collar, this move protects against the auction prices, leading to best execution issues.

During the order allocation process, orders in Cboe periodic auctions, the allocation priority order is 'broker (optional)/price/size/time'. The broker preference feature is optional and refers to single broker paired transactions. The feature supports attracting broker trading activity; according to Cboe data, broker priority orders have been contributing about 20% of total periodic auction volumes since 2018 Q2.[2] In order to ensure that this feature does not interfere with price formation, it is only available at the execution stage. In line with MiFID II requirements, the Cboe periodic auctions book offers pre-trade transparency.[3]

The London Stock Exchange Group (LSEG) also recently introduced its own periodic auctions book called Turquoise Plato Lit Auctions, which has been in operation since 2017 Q4. Although the Turquoise periodic auctions book came into the market later than Cboe, it has a lot of the same features as the former, including order type, member/price priority,[4] allocation, and price formation. However, the Turquoise auction interval is slightly different from that of Cboe. In Turquoise, the interval is divided into two parts: a 50-millisecond fixed interval and a randomized interval with a maximum 50-millisecond duration. Hence, the interval durations vary from 50 to 100 milliseconds.

3. Data, variable construction, and descriptive statistics

3.1. Sample, matching process, and data

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[2] Data obtained from Cboe shows that broker priority allocations account for 33.7%, 20.7%, 19.7%, 21.8%, 22.1%, 24.8%, 22.4%, and 20.7% of the exchange's periodic auctions volume for the eight quarters from 2018 Q1 to 2019 Q4.

[3] See https://ec.europa.eu/finance/securities/docs/isd/mifid/rts/160714-rts-1-annex_en.pdf

[4] The Turquoise member priority has features similar to Cboe's broker priority in allocation.

We employ the constituents of the FTSE 250 index of stocks, which includes 250 of the largest 350 UK firms' stocks as listed on the LSE. The decision to use the FTSE 250 stocks is driven by our empirical framework, which involves deploying two estimation approaches. The first is a difference-in-differences (DiD) framework used to estimate the relative evolution in periodic auctions trading activity in stocks affected by the DVC relative to those not affected. This approach requires the matching of the affected (treated) stocks with those that are unaffected (control stocks). The selection of the larger FTSE 100 stocks would have made pairing for a sufficient number of stocks impossible – given that a significant proportion of FTSE 100 stocks ran afoul of the DVC during our sample period – leading to unbalanced pairing. The second estimation approach is a standard panel estimation with stock and time fixed effects, and this is deployed to estimate the effects of the expected DVC-induced periodic auctions dynamics on market quality variables. For this part of the analysis, we expand the sample to include all DVC-affected FTSE 250 stocks during the sample period: 158 stocks. The sample period covers 3rd January 2018 to 29th June 2018, which includes a period of dark trading suspensions in a large number of FTSE 250 stocks in the first half of 2018 – the first round of suspensions under MiFID II was on 12th March 2018.

For the DiD estimation, we first match the sample of DVC-affected stocks with those that are unaffected. Consistent with Shkilko and Sokolov (2020), we match every stock in the treated group with a stock with dark trading privileges using total volume, a liquidity proxy (relative spread) and information efficiency proxy (5-second autocorrelation of intraday stock returns) for the first empirical framework. We compute matching error for a given number of pairs as follows:

$$matchingerror_{ij} = \sum_{k=1}^{3} \left(\frac{c_k^i - c_k^j}{c_k^i + c_k^j} \right)^2 \qquad (1)$$

where c_k corresponds to the matching criteria, including stock price, currency volume and market value, and i and j represent a pair of stocks. Variables are sampled no later than a month prior to announcement of the DVC suspensions in order to ensure that they are not directly influenced by the shock. The matching process yields 57 control stocks and 57 treated stocks. The success of the matching approach is underscored by the observation that the control and treated group of stocks are not economically or significantly (in statistical terms) different from one another with respect to the variables employed in the matching prior to implementation of the DVC (see Panel B of Table 2).

Transactions in the periodic auctions of FTSE 250 stocks mainly occur at Turquoise and Cboe, with the two exchanges capturing more than 85% of the periodic auctions transactions in the market. Therefore, the intraday data we obtain for our sample of stocks includes trading activity recorded for the LSE, Turquoise and Cboe, containing data for all the trading mechanisms deployed on all three exchanges over the sample period. We also note that, based on aggregate trading data from Cboe, the three venues account for more than 95% of all trading activity in the FTSE 350 stocks.

We obtain intraday time and sales tick data from the Thomson Reuters Tick History (TRTH) version 2 database. The dataset includes variables such as the Reuters Identification Code (RIC), qualifiers (identifying trade/order type/unique characteristics, such as whether a trade is executed in the dark or not), date, TRTH timestamp, exchange timestamp, price, volume, bid price, ask price, bid volume, ask volume, and bid and ask quotes. The exchange timestamp is critical given that we aim to aggregate data across different venues. This timestamp is different from the TRTH timestamp and is provided as part of the TRTH version 2 database. It allows us to observe the exact time each trading activity observation was recorded at each trading venue using the London local time; the local time is the same for all the exchanges represented in the data since all three venues are based in the same geographical location (London). We allocate each trade a pair of corresponding prevailing best bid and ask quotes based on the quotes submission information available in the TRTH database. We then merge the order book-level data for the three trading venues in order to create a single 'global' order book/venue for the London market. The 36.12 million transactions are valued at 203 billion British Pounds Sterling and executed in 215 stocks over the sample period. The full sample of stocks is listed in Appendix A.

3.2. *Market quality metrics*

In this section, we discuss our estimation of the market quality variables. All market quality variables are estimated using data from the continuous trading mechanism deployed by the main market for FTSE 250 stocks, the LSE's Stock Exchange Electronic Trading Service

(SETS).[5] We proxy liquidity with relative spread for stock i at time τ estimated as follows:

$$Relative\ \ spread_{i,\tau} = \frac{ask\ \ price_{i,\tau} - bid\ \ price_{i,\tau}}{mid\ \ price_{i,\tau}} \tag{2}$$

where the $mid\ \ price_{i,\tau}$ is the average of $ask\ \ price_{i,\tau}$ and $bid\ \ price_{i,\tau}$ for stock i at time τ, and $ask\ \ price_{i,\tau}$ and $bid\ \ price_{i,\tau}$ correspond to the ask and bid prices for stock i at time τ. $RelativeSpread_{i,d}$ is then computed as the daily volume-weighted value of $Relative\ \ spread_{i,\tau}$ for stock i on each day d.

In addition to liquidity, we also proxy adverse selection cost as a component of the bid-ask spread. Adverse selection cost reflects the level of latency arbitrage in the market, and it is also employed by related studies, such as Aquilina et al. (2017b) and Shkilko and Sokolov (2020). The entrance of fast traders could potentially lead to losses for the liquidity supplier, because fast traders can react more rapidly to new information, thereby inducing latency arbitrage. In this situation, irrespective of their analytical abilities, faster traders will be the informed traders and slower traders will be the uninformed traders. In response to this exposure, liquidity suppliers are likely to expand the spread by imposing higher adverse selection costs, thereby protecting themselves from being adversely selected. This is in line with Budish et al. (2015) and Rzayev and Ibikunle (2019), who argue that latency arbitrage is a form of adverse selection. Therefore, the evolution of adverse selection in the market could be an indicator of changes in the use of latency arbitrage as a trading strategy caused by fast traders. We estimate adverse selection costs for stock i in time τ as:

$$Adverse\ \ selection_{i,\tau} = \frac{q_{i,\tau}(m_{i,\tau+15s} - m_{i,\tau})}{m_{i,\tau}} \tag{3}$$

where $m_{i,\tau}$ is the midpoint price for stock i at time τ and $m_{i,\tau+15s}$ is the midpoint price for stock i at time $\tau + 15$ seconds; the 15-second window is in line with existing studies, such as Conrad and Wahal (2020) and Shkilko and Sokolov (2020). $q_{i,\tau}$ indicates the trade direction for stock i at time τ and corresponds to +1 for buyer-initiated trades and -1 for seller-initiated ones; we use the Lee and Ready (1991) algorithm to determine $q_{i,\tau}$, setting the interval at 15-seconds. In the regression models, we employ daily volume-weighted estimates

[5] Employing concatenated real-time transactions and price data across the three venues in our sample does not yield qualitatively different estimates.

of $Adverse\ \ selection_{i,\tau}$ for stock i at day d; this is denoted as $AdverseSeletcion_{i,d}$.

Informational efficiency is an important market quality characteristic because it indicates the level of efficient incorporation of information into instrument prices. Therefore, we follow Boehmer et al. (2018), Ibikunle et al. (2019), and Foley and Putniņš (2016) in employing the absolute value of the autocorrelation of midpoint (average of the ask and bid prices) returns as a proxy for the test of informational efficiency. We estimate this proxy at the 5-second frequency and then aggregate across the day as a measure of short-term informational efficiency. Estimates close to zero indicate that the pricing process follows a random walk; hence, the market has a higher level of informational efficiency:

$$Autocorrelation_{i,d} = |Corr(return_{i,d,n}, return_{i,d,n-1})| \tag{4}$$

$Autocorrelation_{i,d}$ is the absolute value for the 5-second midpoint return autocorrelation for stock i on day d. In the formula, $return_{i,d,n}$ is the nth of the 5-second length midpoint return of stock i on day d, and $return_{i,d,n-1}$ is the $(n-1)$th of the 5-second length midpoint return of stock i on day d. Utilizing the absolute value of autocorrelation allows for easier capturing of both the under- and over-reaction of returns to information, with higher values suggesting lower efficiency.

For robustness, we also employ an additional proxy for informational efficiency: variance ratio. According to Chordia et al. (2008) and Comerton-Forde and Putniņš (2015), markets with higher levels of pricing efficiency should generate prices that follow the random walk, which suggests that variance should have a linear relation to return frequency. We estimate the measure, as outlined in Equation (5):

$$VarianceRatio_{i,d} = \left|1 - \frac{\sigma^2_{i,d,5-minute}}{5*\sigma^2_{i,d,1-minute}}\right| \tag{5}$$

where $VarianceRatio_{i,d}$ is the variance ratio for stock i on day d, and $\sigma^2_{i,d,1-minute}$ and $\sigma^2_{i,d,5-minute}$ are the variance estimates of midpoint stock returns over 1 minute and 5 minutes respectively. In an efficient market, $\sigma^2_{i,d,5-minute}$ should be about five times the value of $\sigma^2_{i,d,1-minute}$. As an absolute value, $VarianceRatio_{i,d}$ is equal to or larger than zero; higher values imply worse informational efficiency.

3.3. Other variables

The other variables work as proxies for periodic auctions and variables employed as controls in our models. Periodic auctions proxies include $PAVolume_{i,d}$, $PACurrencyVolume_{i,d}$ and $PATransaction_{i,d}$ and they are defined as trading volume, currency value of traded volume and transactions of periodic auction books for stock i on day d respectively. The constructed control variables include $Volume_{i,d}$, which is defined as the volume of all transactions using all non-periodic auctions trading mechanisms across exchanges where stock i is traded on day d. $ClosePrice_{i,d}$ is the end-of-day close price of stock i on day d, and $MarketValue_{i,d}$ is the end-of-day market value of stock i on day d. $OrderImbalance_{i,d}$ is the proxy for order imbalance for stock i on day d, computed as defined in Chordia et al. (2008), i.e. as the absolute value of the buyer-initiated volume for stock i on day d minus the amount of seller-initiated volume for stock i on day d divided by the sum of buyer and seller-initiated volume for stock i on day d. $Volatility_{i,d}$ is the proxy for return volatility for stock i on day d, and this is calculated as the variance of 1-minute intervals mid-price returns. $Momentum_{i,d}$ is a proxy for momentum for stock i on day d, and this is estimated as the 3-day cumulative abnormal return on closing price. Table 1 defines all the variables employed in our study.

INSERT TABLE 1 HERE

3.4 Descriptive statistics

Panel A of Table 2 presents the summary statistics for all the variables employed in the study. Mean and standard deviation estimates are presented for the full sample of stocks and stock terciles in terms of trading activity. A few estimates are of particular interest. Firstly, over the sample, the most active stocks appear to be more liquid. This is consistent with the literature on the links between trading activity and liquidity (see as an example, Chordia et al., 2001). Interestingly, however, the more active stocks appear to perform worse in terms of informational efficiency. This is perhaps linked to the fact that these stocks are also more likely to be traded via periodic auctions, which would suggest a measure of delay in order execution since batching needs to precede uncrossing during the auctions process. Secondly, the tendency for the more active stocks to be more likely to be traded via periodic auctions than the less active stocks is explained by the former being more likely to be traded via other off-main exchange trading facilities, such as dark pools, due to the need to avoid queues (see Ibikunle et al., 2019).

Panel B of Table 2 reports the pre-DVC comparative estimates of the microstructure variables used in matching the stocks included in the DiD estimations (see Section 4.1). The estimates and statistical tests show minimal differences for all the variables and none of these differences are statistically significant at conventional levels.

INSERT TABLE 2 HERE

4. Analysis, results and discussion

4.1. Effects of dark trading bans on periodic auctions

Our starting hypothesis is that the imposition of the DVC will lead to an increase in the volume of transactions executed via a periodic auction mechanism. Therefore, we begin by testing whether this dynamic is observed in the data. Our first examination of this question employs univariate analysis testing for differences in trading activity on either side of the DVC coming into effect. The results presented in Table 3 include estimates for nominal stock volume, currency volume and the number of transactions. The estimates are presented separately for the control and treated groups of stocks. In all cases there are statistically significant increases in trading activity following the DVC; however, the increases are far more pronounced for the treated stocks. This is unsurprising given that following the DVC, the treated stocks lose the opportunity to trade in dark pools – an increasingly popular trading mechanism. This is also consistent with the FCA (2018) and Johann et al. (2019)

INSERT TABLE 3 HERE

While this univariate investigation is useful, it is important to control for the myriad of factors that could be driving the evolution of periodic auction volume. Hence, we construct the following DiD model to estimate how the imposition of DVC drives period auction trading activity in the affected stocks relative to the stocks that are directly unaffected by the DVC:

$$PA_{i,d} = \alpha + \beta_1 DVC_d + \beta_2 Treated_i + \beta_3 DVC_d \times Treated_i + \beta_4 Control_{i,d} + \gamma_d d + \delta_i i + \epsilon_{i,d} \quad (6)$$

where $PA_{i,d}$ corresponds to one of the log-formal periodic auctions proxies, i.e. $PAVolume_{i,d}$, $PACurrencyVolume_{i,d}$ and $PATransaction_{i,d}$, for stock i on day d.

$Treated_i$ and DVC_d are dummy variables. $Treated_i$ is a proxy for whether stock i is banned from dark trading or not; if yes, it takes the value of one, otherwise it is zero. DVC_d is a proxy for whether DVC is deployed in the market or not on day d; it takes the value of one for 12th March 2018 and subsequent days in the sample, and zero otherwise. $Control_{i,d}$ contains a series of control variables for stock i on day d, including $Volume_{i,d}$, $ClosePrice_{i,d}$, $Volatility_{i,d}$, $OrderImbalance_{i,d}$, $Momentum_{i,d}$, $RelativeSpread_{i,d}$ and $MarketValue_{i,d}$, all of which are as previously defined. Volume, which captures the trading volume from other trading mechanisms, is included because there is an expectation of interactions among the various trading mechanisms available to traders in the FTSE 250 stocks. Johann et al. (2019) report a shifting effect involving the continuous market and the so-called quasi-dark markets. $\delta_i i$ and $\gamma_d d$ are stock and time fixed effects. The standard errors are robust to autocorrelation and heteroscedasticity.

Finally, it is essential that the parallel trend assumption holds in the case of the dependent variables, i.e. $PAVolume_{i,d}$, $PACurrencyVolume_{i,d}$ and $PATransaction_{i,d}$. In particular, the three variables need to have parallel trends in the treatment and control groups in the absence of an event.

INSERT FIGURE 3 HERE

Panels A, B and C in Figure 3 clearly show that the three variables employed in Equation (6) exhibit similar trends during the pre-treatment period and this is also confirmed by statistical tests. This implies that our treatment and control groups can be used in the DiD framework and our modeling approach satisfies the parallel trend assumption requirement.

INSERT TABLE 4 HERE

Table 4 reports the regression results of Equation (6). Panels A, B and C present the results for models where the log of $PAVolume_{i,d}$, $PACurrencyVolume_{i,d}$ and $PATransaction_{i,d}$ correspond to $PA_{i,d}$ in Equation (5) respectively. Each panel presents full sample estimates as well as estimates by terciles. β_1, the DVC coefficient, is positive and statistically significant in all the panels with respect to each tercile and full sample estimations. The coefficient estimates are also economically meaningful; for example, the estimates for the full sample for trading volume, currency volume and number of transactions are 2.36, 3.38 and 1.23 respectively and they are all statistically significant at the 0.01 level. These estimates indicate

236%, 338% and 123% increases in periodic auctions trading volume, currency volume and number of transactions respectively for the event period relative to the period preceding the imposition of the DVC. The significance of these estimates is underscored by the fact that the volume of trading occurring via trading mechanisms other than periodic auctions is controlled for and highly statistically significant in each of the regression estimations. The estimates also suggest a rise in the average execution sizes of period auctions transactions. This is because, while the number of periodic auctions transactions increases during the event period, the relative increase is much lower than that observed for trading volume and currency trading volume. These observations are consistent in the cases of the terciles as well.

However, there is an area of inconsistency when considering the terciles, and this affects the β_2 estimates. While for the full sample and the highest and lowest terciles, the treated group of stocks are generally traded more via periodic auctions than the control stocks, this is not the case for the middle tercile. There is no obvious or theoretically relevant explanation for this. What is interesting and theoretically relevant, however, is that once the $Treated_i$ coefficient has interacted with the DVC_d coefficient, the deficit is eliminated. This is in line with our expectation that the imposition of the DVC would increase the use of periodic auctions for the stocks it affects. Indeed, the β_3 estimates are positive and statistically significant for both the full sample of stocks and for the terciles in all the three panels. This suggests that, on average, there are statistically significant increases in the use of periodic auctions as a trading mechanism in treated stocks following the imposition of the DVC when compared with the control stocks. These estimates are consistent with Johann et al. (2019), who find that the DVC induces migration of trading to quasi-dark venues.

There is another interesting observation to be noted here. β_3 estimates are generally higher for the terciles than for the full sample, except in one notable, and consistent, instance – the largest group of stocks. This suggests that the effect of the DVC is weakest in large stocks. This phenomenon could be linked to the much higher proportions of dark trading activity typically observed among smaller stocks in the London market. In the London market, lower trading stocks are known to be frequently traded away from the downstairs continuous (lit) market, with most of their trades by value taking place in the 'dark' LSE-operated (upstairs) broker-dealer market (see Armitage and Ibikunle, 2015). In the LSE's broker-dealer market, publishing of orders is not mandatory and executed orders can go unreported for up to three minutes, with only the order submitters and attending broker-dealers aware of their existence until reported. Thus, it appears that small UK stocks are mainly traded in opaque venues. For example, Armitage and Ibikunle (2015) find that more than 62% of the orders executed by value in the smallest FTSE 250 stocks are in the LSE's broker-dealer market. This 'dark' trading facility can only remain an option for such stocks following DVC in the cases of disproportionately large orders. Therefore, when dark trading privileges are halted in small stocks, they are more likely than large stocks to pivot to using periodic auctions, a quasi-dark option. This explains the monotonic decline by stock size grouping in β_3s observed in Table 4. The estimates are larger in all three panels for the smallest stocks and lowest for the largest stocks.

4.2. Periodic auctions and market quality

4.2.1 Liquidity analysis

We now investigate how changes in the levels of periodic auctions in stock affects its market quality-related characteristics, such as liquidity and informational efficiency. Since our focus is on estimating the effects of the increase in periodic auctions trading on market quality characteristics, rather than the comparative effects between stocks experiencing dark trading restrictions and those that are not, we estimate a fixed effects panel regression model. This also allows us to expand our sample size to 158 stocks with varying levels of periodic auction trading over the full sample period.

The multivariate regression model we estimate is as follows:

$$RelativeSpread_{i,d} = \alpha + \beta_1 DVC_d + \beta_2 PATransaction_{i,d} + \beta_3 DVC_d \times PATransaction_{i,d} + \beta_4 Control_{i,d} + \gamma_d d + \delta_i i + \epsilon_{i,d} \quad (7)$$

where all variables are as previously defined. The main variable of interest is the interaction variable, $DVC_d \times PATransaction_{i,d}$, which is introduced to capture the effects of the reported increase in periodic auctions following the DVC's implementation of the liquidity proxy, $RelativeSpread_{i,d}$. The standard errors are robust to autocorrelation and heteroscedasticity.

INSERT TABLE 5 HERE

Table 5 reports the estimation results for Equation (7). The estimates are presented for the full sample of stocks and by liquidity terciles. Consistent with our hypothesis on the impact of increased use of periodic auctions on liquidity (Hypothesis 2), all of the β_1 estimates are positive and the two most liquid stock terciles' coefficients are statistically significant at the 0.01 level. These estimates indicate that the implementation of the DVC is linked to a widening spread and thus a loss of liquidity. This is consistent with the findings of Ibikunle et al. (2019) on the effects of the DVC on liquidity, and this is driven by a number of factors, including the reduction of order flow competition between lit and dark venues when the dark trading halt is restricted. The reduction in order flow competition enables market-makers in lit venues to exploit their new-found power to set spreads for trading. This increased leverage or power inevitably leads to larger transaction costs and wealth transfer from liquidity-takers to liquidity-providers (see for example Foucault and Menkveld, 2008; Zhu, 2014; Kwan et al., 2015; Gresse, 2017).

A second potential driver is that dark trading restrictions imply the loss of a potential trading mechanism, which then leads to counterparties having to queue for liquidity. However, in line with Hypothesis 3, the negative and statistically significant β_2 estimates for all but one of the regressions reported in the table suggest that liquidity constraints during the sample period are alleviated by the opportunity to increase the use of periodic auctions as a trading outlet. These estimates apply to the entire sample time series and so they cannot be completely disentangled from the effects of the DVC-induced increases in periodic auctions activity despite controlling for the DVC. A theoretical explanation for the estimates is that more information is released when traders migrate from dark pools to more transparent venues due to the improvement of transparency, which in turn triggers more efficient prices and further liquidity improvements in the aggregate market (see Amihud et al., 1997; Madhavan, 1992; Bloomfield et al., 2015).

Nevertheless, the improvement in liquidity appears to be less pronounced than the loss of liquidity induced by the DVC. For example, the middle and lowest terciles' β_1 (β_2) estimates are 0.020 (-0.001) and 0.015 (-0.004) respectively and they are all statistically significant at the 0.01 level. The estimates show that exploiting periodic auctions only ameliorates the liquidity constraints to a small degree. Therefore, it is unsurprising that the β_3 estimate for the full sample is positive (0.002) and statistically significant at the 0.01 level, indicating that the combined effects of the DVC and the increase in periodic auctions during the dark trading restrictions period reflects, on average, a worsening of liquidity for the full sample of stocks. The only stocks to buck this trend are the most liquid tercile stocks. This can be explained by the fact that the most liquid stocks are usually the most active ones and therefore they are likely to be more affected by restrictions on dark trading. Periodic auctions thus provide an opportunity to shift unfulfilled hitherto dark orders.

A similar argument can be made with regard to the effect of trading using the other non-periodic auctions trading mechanisms captured by the volume variable: the coefficient estimates, although generally negative and statistically significant at the 0.01 level, are very small in comparison to the liquidity constraining effects of the DVC. Taken together, the estimates presented in Table 5 are consistent with the submissions of Johann et al. (2019), who find that the introduction of MiFID II regulations, i.e. the DVC, has a negligible impact on market liquidity.

4.2.2. Adverse selection analysis

We next investigate how the periodic auctions dynamics around the DVC impact adverse selection costs, a component of the spread. Periodic auctions are often touted as a countermeasure against the technological arms race for speed (see Budish et al., 2015; Cboe, 2018). The arms race in itself has given rise to adverse selection-inducing latency arbitrage (see Shkilko and Sokolov, 2020; Ibikunle and Rzayev, 2020; Indriawan et al., 2020), which suggests that, consistent with improving liquidity (as shown in Section 4.2.1), a rise in periodic auctions across the full sample period could be linked to a reduction in adverse selection costs. In order to test this, we estimate the following panel regression model:

$$AdverseSelection_{i,d} = \alpha + \beta_1 DVC_d + \beta_2 PATransaction_{i,d} + \beta_3 DVC_d \times PATransaction_{i,d} + \beta_4 Control_{i,d} + \gamma_d d + \delta_i i + \epsilon_{i,d} \quad (8)$$

where $AdverseSelection_{i,d}$ is the daily volume-weighted adverse selection in stock i on day d. All other variables are as previously defined, and standard errors are robust to autocorrelation and heteroscedasticity.

INSERT TABLE 6 HERE

Table 6 reports the estimated coefficients for Equation (8). The first main observation is that, in line with Hypothesis 5, the DVC decreases the adverse selection in the full sample of stocks and terciles; all the coefficient estimates, with the exception of the lowest liquidity tercile, are statistically significant at the 0.01 level. Although this appears counter-intuitive based on the earlier reported results for the liquidity model estimation, the results are consistent with the expectation that the implementation of a dark trading halt in stocks will force a transfer of slow traders from dark pools to other more transparent venues, such as the continuous (lit) market (see Johann et al., 2019). An increase in the number of slow (uninformed) traders in lit venues, or at least in less dark venues, will dilute the concentration of informed traders in these venues and result in a lowering of the risk of being adversely selected. Furthermore, the impact of the DVC on liquidity provision is driven by reduction in order flow competition, which allows lit market-makers to set spreads that favor them more, rather than through any increase in adverse selection costs.

The β_2 coefficient estimates indicate that the effects of periodic auctions on adverse selection costs are generally weak, with only the most liquid tercile's coefficient returning a statistically significant estimate (-0.01% at a 0.01 level of statistical significance). Although this effect, which suggests that Hypothesis 4 is upheld, is likely only relevant to very liquid stocks, it is in line with the extensive stream of literature on how call auctions affect the price discovery process. There is a clear theoretical argument for congregating all available market liquidity at a single point in order to determine the fair price of an instrument. Schwartz (2012) asserts that this enhances the accuracy of the price discovery process, while Madhavan (1992) argues that since all traders are given access to the same prices at the same time, call auctions reduce information asymmetry. Schnitzlein (1996) also finds that there is a reduction in adverse selection costs incurred by uninformed traders under a call auction. Although periodic auctions occur at much smaller intervals and higher speeds, the theoretical arguments stand given the structural similarities between the traditional call auction generally deployed in modern financial markets and periodic auctions.

The interaction term's coefficient estimates paint a different picture from those offered by the β_1 and β_2 estimates, especially for the most liquid tercile stocks. The full sample and most liquid tercile β_3 estimates are positive and statistically significant at the 0.01 level, a complete reversal of the most liquid tercile's β_1 and β_2 estimates. This suggests that the increase in the volume of periodic auction trades observed during the DVC period reverses the ameliorating effect of periodic auctions and the DVC on adverse selection costs, thereby indicating a nonlinear effect of periodic auctions on adverse selection. The suggestion that trading in dark/quasi-dark venues has a nonlinear effect on market quality characteristics is not unusual; for example, Comerton-Forde and Putniņš (2015) and Aquilina et al. (2017a) report nonlinear effects of dark trading on market quality variables. The positive β_3 estimates could be linked to hitherto dark trading activity migrating to quasi-dark venues instead of lit venues during the DVC window, as Johann et al. (2019) report. This could explain the positive relationship between adverse selection and periodic auctions during the DVC, a development that is typically associated with a significant reduction in the proportion of transactions executed in lit markets (see Aquilina et al., 2017b). The nonlinear effect is also consistent with Eom et al. (2007) argument that market quality is an increasing concave function of transparency. It is important to note that this effect is not observed in the least liquid stocks tercile, with its β_3 estimate returning a negative value of -0.03% (significant at a 0.1 level). This is also in line with Aquilina et al. (2017b) reporting a much higher inflection point where the negative relationship between adverse selection risk and dark trading in lower volume stocks turns positive.

4.2.3. Information efficiency analysis

We now address the question of how the evolution of periodic auctions related to dark trading halts can drive the efficiency of the price discovery process. Evidence on the direct effects of periodic auctions on informational efficiency is sparse. However, the extensive body of research on the effects of the longer duration call auctions offers some indication of what we might expect. In particular, both theoretical and empirical studies (Amihud et al., 1997; Madhavan, 1992; Chang et al., 2008; Comerton-Forde et al., 2007) suggest that call auctions improve the efficiency of the price discovery process. In order to ascertain how periodic auctions impact informational efficiency, we estimate the following panel regression model:

$$InformationalEfficiency_{i,d} = \alpha + \beta_1 DVC_d + \beta_2 PATransaction_{i,d} + \beta_3 DVC_d \times PATransaction_{i,d} + \beta_4 Control_{i,d} + \gamma_d d + \delta_i i + \epsilon_{i,d} \quad (9)$$

where $InformationalEfficiency_{i,d}$ corresponds to one of $Autocorrelation_{i,d}$ or $VarianceRatio_{i,d}$. All other variables are as previously defined, and the standard errors are robust to autocorrelation and heteroscedasticity.

INSERT TABLE 7 HERE

Table 7 reports the regression results for Equation (9). For the sake of clarity, we examine the results presented in both panels of the table in tandem. The first observation is that all but two of the eight β_1 coefficient estimates in both panels are negative and statistically significant at conventional levels; the full sample estimates in Panels A and B are -4.50% and -10% respectively, and both are statistically significant at the 0.01 level. This suggests that, contrary to its effects on liquidity, the imposition of the DVC appears to improve the efficiency of the price discovery process. This is likely to be linked to informed traders' reactions to the increased level of transparency induced by the forced migration of hitherto dark order flow to more transparent venues. In contrast to the arguments of Chowdhry and Nanda (1991) and Madhavan (1995) that informed traders trade more slowly in transparent markets, the increased transparency in the aggregate market is linked to improvements in market efficiency. One factor that makes the arguments of Chowdhry and Nanda (1991) and Madhavan (1995) rather invalid in this case is that informed traders generally face a higher risk of non-execution (see Zhu, 2014) and delays in darker/less-transparent markets (see Menkveld et al., 2017). Hence, any caution informed traders may exhibit in markets that are more transparent is less of an impediment to the price discovery process than the non-execution risk and delay associated with trading in dark pools. The economic significance of the coefficient estimates is also notable, with the full sample's results suggesting a 10% improvement in the estimated measure of informational efficiency. This finding is inconsistent with the ambiguous picture Johann et al. (2019) analysis provides. This deviation could be linked to the sample focus: our analysis examines only the case for Europe's most active market across all venue types – the UK – while Johann et al. (2019) pan-European focus could potentially contribute to a more internally inconsistent observation across various EU member states.

However, our estimates of the direct effects of periodic auctions on informational efficiency present a more ambiguous view that is in keeping with the findings of Johann et al. (2019). In Panel B, none of the β_2 estimates are statistically significant at conventional levels, indicating that the effect of periodic auctions on informational efficiency is benign at best; hence, the β_3 coefficients reflect the effects of the DVC on $VarianceRatio_{i,d}$. Another theoretical explanation is that more information is released when orders are shifted from dark pools to more transparent venues, thereby increasing transparency (see Amihud et al., 1997; Madhavan, 1992; Bloomfield et al., 2015). In contrast, in Panel A, which shows the results based on $Autocorrelation_{i,d}$ as an informational efficiency proxy, the full sample and most liquid tercile's β_2 estimates are positive and statistically significant at the 0.01 and 0.05 levels respectively. The interaction term's coefficients in Panel A are also positive and statistically significant for the full sample and the two upper liquidity terciles. Taken together, the estimates in Panel A suggest that the overall effect of periodic auctions trading during the DVC window for the stocks it affects is a deviation from a random walk or reductions in informational efficiency. Thus, while trading in other (non-dark pool) venues improves price efficiency (as shown by the generally negative and statistically significant $Volume_{i,d}$ coefficient estimates), the periodic auctions appear to have the opposite effect. This result can be explained by the speed of trading in periodic auctions (even at 100ms intervals). While trading in dark pools suggests a degree of delay (as in Menkveld et al., 2017; Zhu, 2014), periodic auctions are deliberately designed as mechanisms to make HFT less threatening and slow down trading. It is therefore unsurprising that their main effect on the price discovery process is making it less efficient, and Hypothesis 6 is upheld.

5. Conclusion

According to Budish et al. (2015), frequently batching orders and auctioning instruments offers an effective solution to address the latency arbitrage and the technological arms race in financial markets, as well as the externalities they induce (see Menkveld, 2014). The question of how frequently batching and uncrossing needs to take place to maintain or enhance market quality remains largely unanswered. In this paper, we exploit recent regulatory developments in Europe to investigate the effects of sub-second periodic auctions on market quality characteristics in UK-listed stocks. The UK financial markets – the most active trading environment in Europe – offer a unique opportunity to assess the direct effects of a shift of trading volume towards periodic auctions following the imposition of dark trading restrictions on the market. This is crucial because frequent auctioning remains uncommon in financial markets.

Consistent with Johann et al. (2019), we observe that stocks that have had their dark trading privileges withdrawn experience higher periodic auctions volumes than matched stocks with dark trading privileges. However, the overall market quality effects of periodic auctions are at best limited and mixed. We find that for stocks experiencing dark trading halts, periodic auctions are linked to a statistically significant reduction in overall market liquidity and an increase in adverse selection costs when the DVC is in effect. Controlling for the dark trading restrictions suggests that periodic auctions have a generally positive effect on liquidity and a largely benign effect on adverse selection costs, except in the case of the most liquid stocks, where adverse selection declines in line with periodic auctions. This is consistent with the predictions of Budish et al. (2015): that periodic auctions offer a safe haven for slower traders who are susceptible to the latency arbitrage trading of faster traders. Thus, a rise in the use of periodic auctions lowers the incidence of slower traders being adversely selected.

The evidence of the impact of periodic auctions on informational efficiency is also mixed. Periodic auctions, especially during the DVC window, are linked to a deviation from a random walk or reduction in informational efficiency. This finding is in line with periodic auctions slowing down the price discovery process. While trading in dark pools implies delays relative to trading in lit venues (as in Menkveld et al., 2017; Zhu, 2014), periodic auctions often deliberately design a mechanism to slow down trading, i.e. in response to the technological arms race or latency arbitrage.

The mixed nature of the evidence on frequent discrete trading systems is underscored by the rise in periodic auctions in Europe, while in Taiwan the TWSE has replaced its discrete system with a continuous one (see Indriawan et al., 2020). Therefore, the insights on a new breed of discrete trading systems that this study presents demand attention. Indeed, this is also a valuable early reference for regulators when considering the trade-offs between continuous and discrete trading mechanisms, especially given that the debate on the societal welfare effects of technological arms race speed in financial markets continues unabated. Our study offers some tentative evidence of the relevance of periodic auctions as a mechanism for addressing latency arbitrage and, by extension, the technological arms race.

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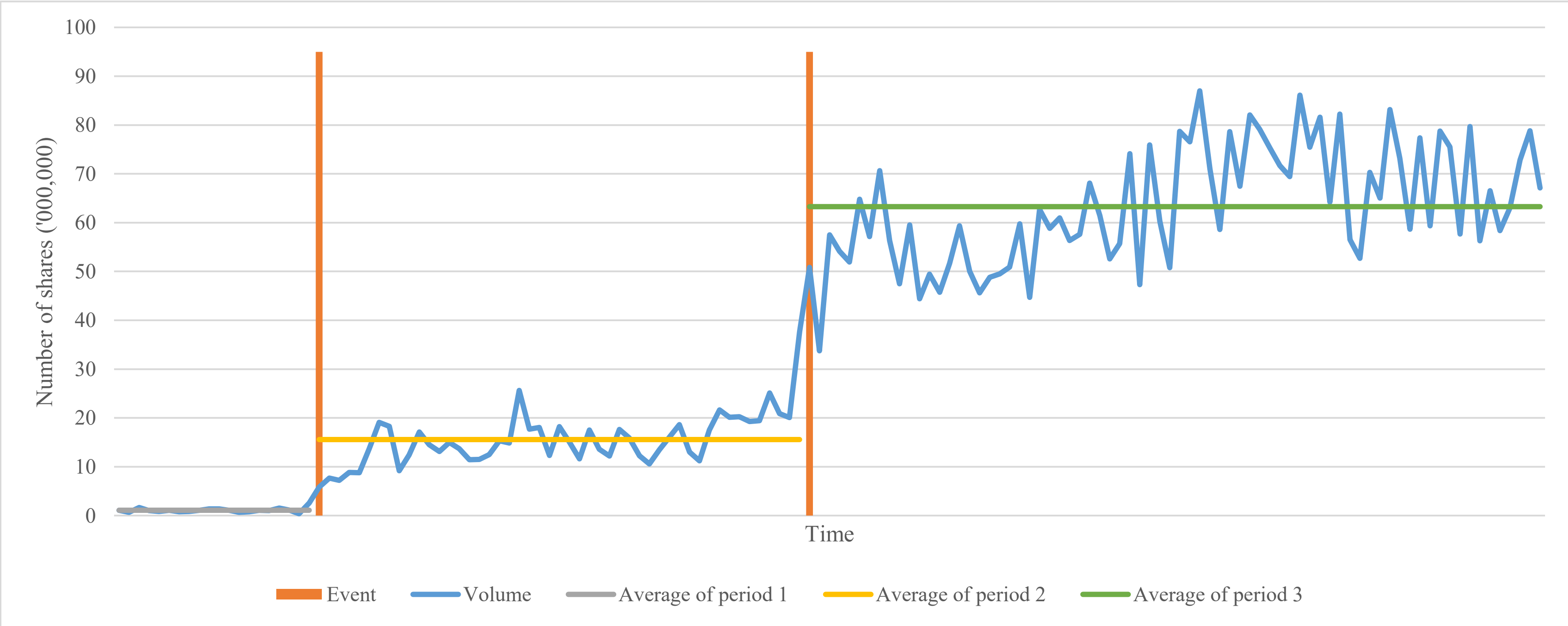
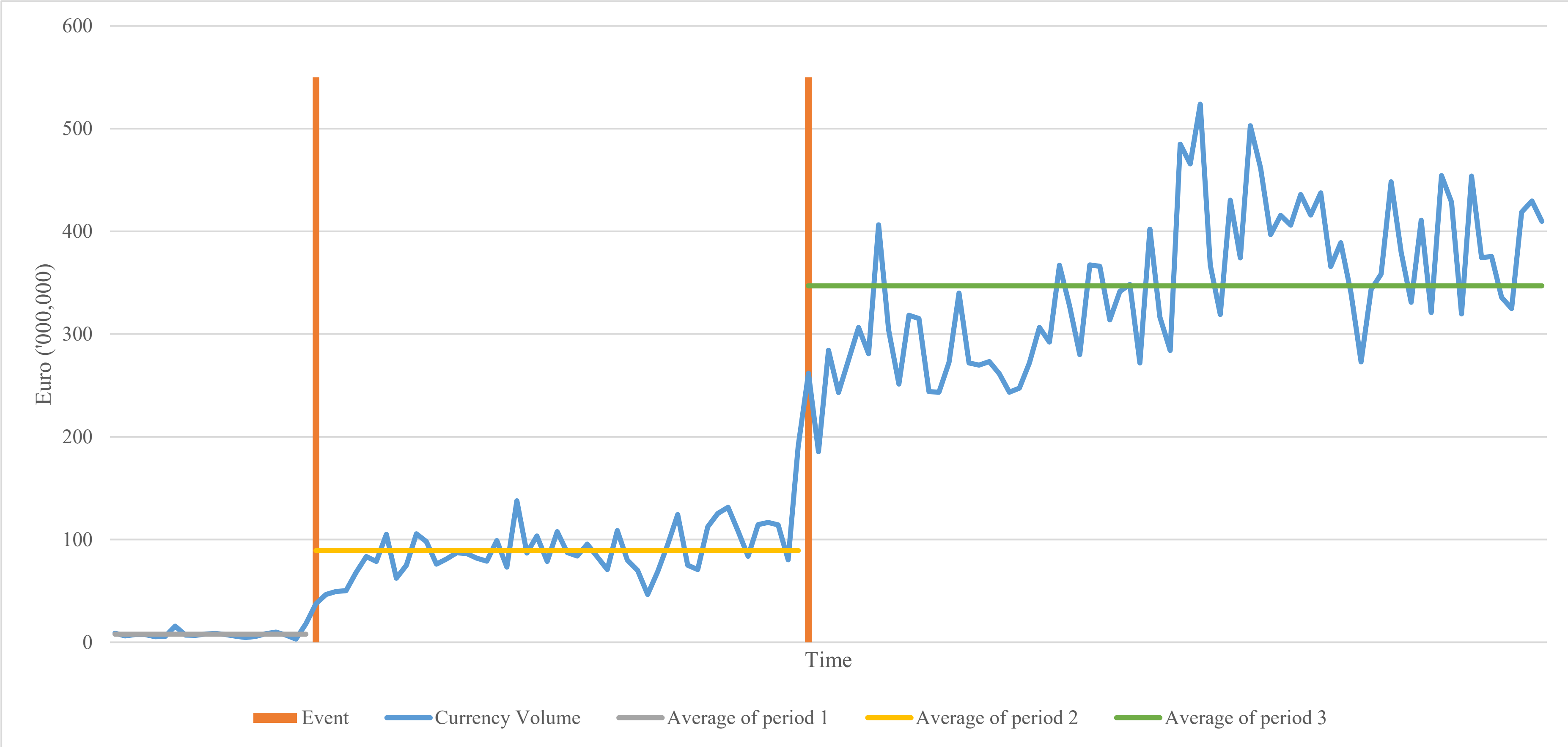
Figure 1. Trading in periodic auctions books and the implementation of the double volume cap

The figure plots the trading volume, currency volume and number of transactions in European periodic auctions books in relation to the implementation of the first double volume cap (DVC) for London Stock Exchange-listed stocks. The orange vertical bars correspond to two events: when MiFID II came into force on 3rd January 2018 and when the first DVC suspensions commenced on 12th March 2018. The horizontal plots represent the average stock-level estimates for three periods; grey, yellow and green correspond to pre-MiFID II (1st December 2017 to 2nd January 2018), pre-DVC (3rd January to 9th March 2018, a Friday) and DVC periods (12th March to 29th June 2018) respectively.

Panel A. Periodic auctions volume



Panel B. Periodic auctions volume in currency



Panel C. Periodic auctions transactions

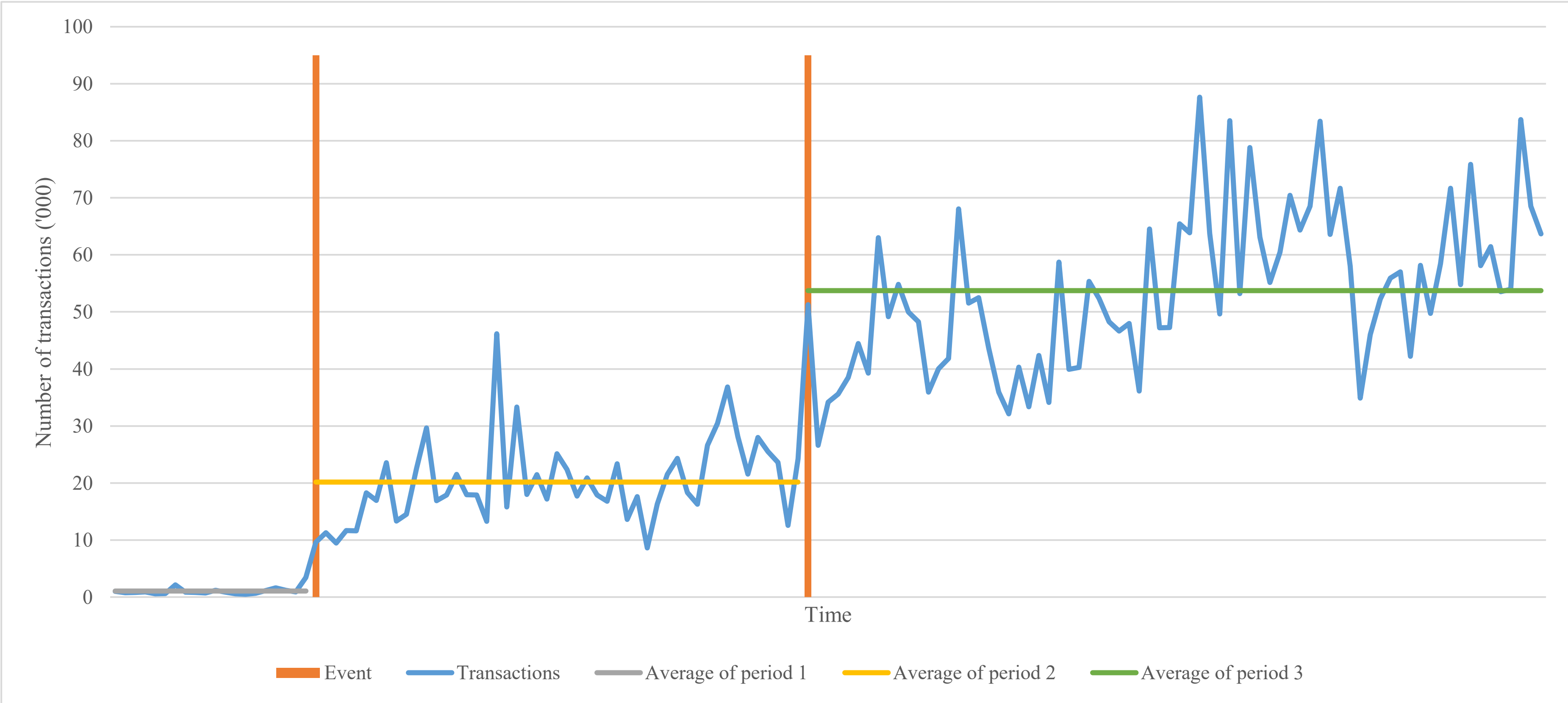
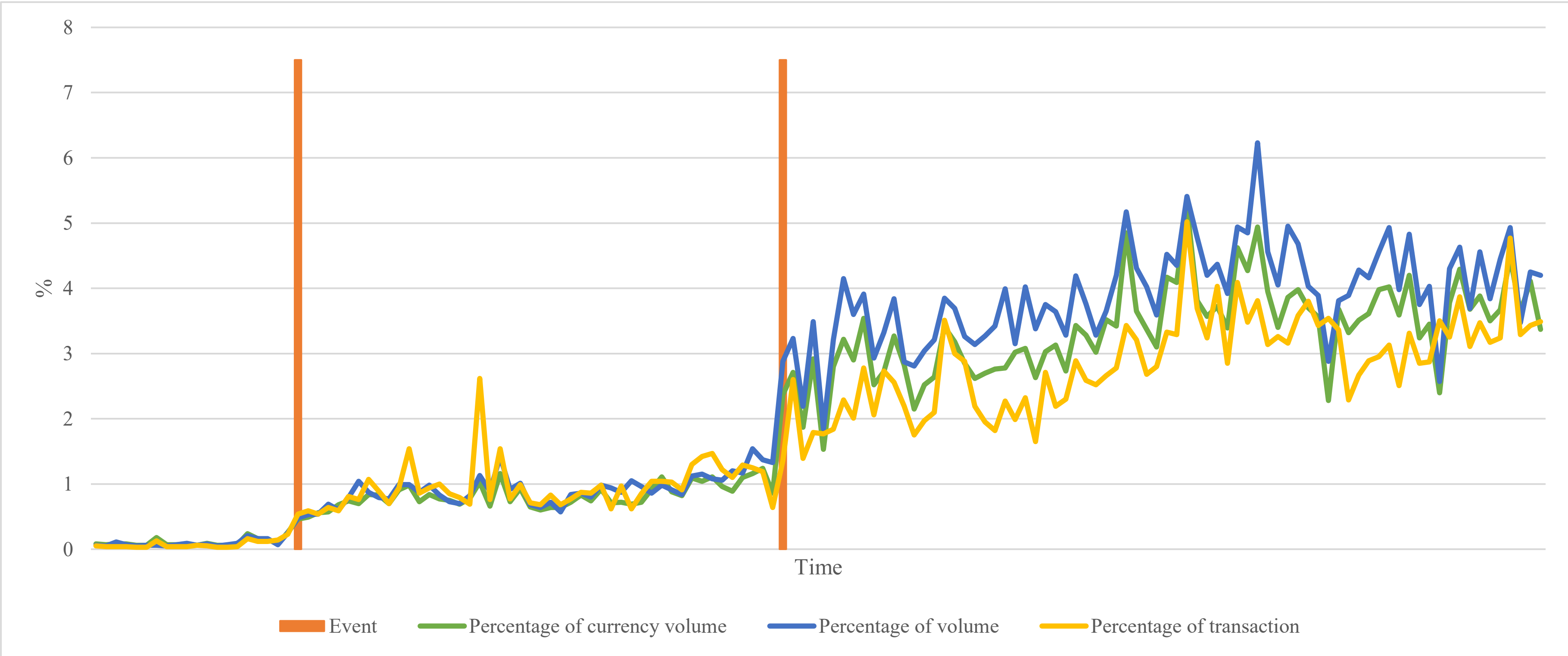


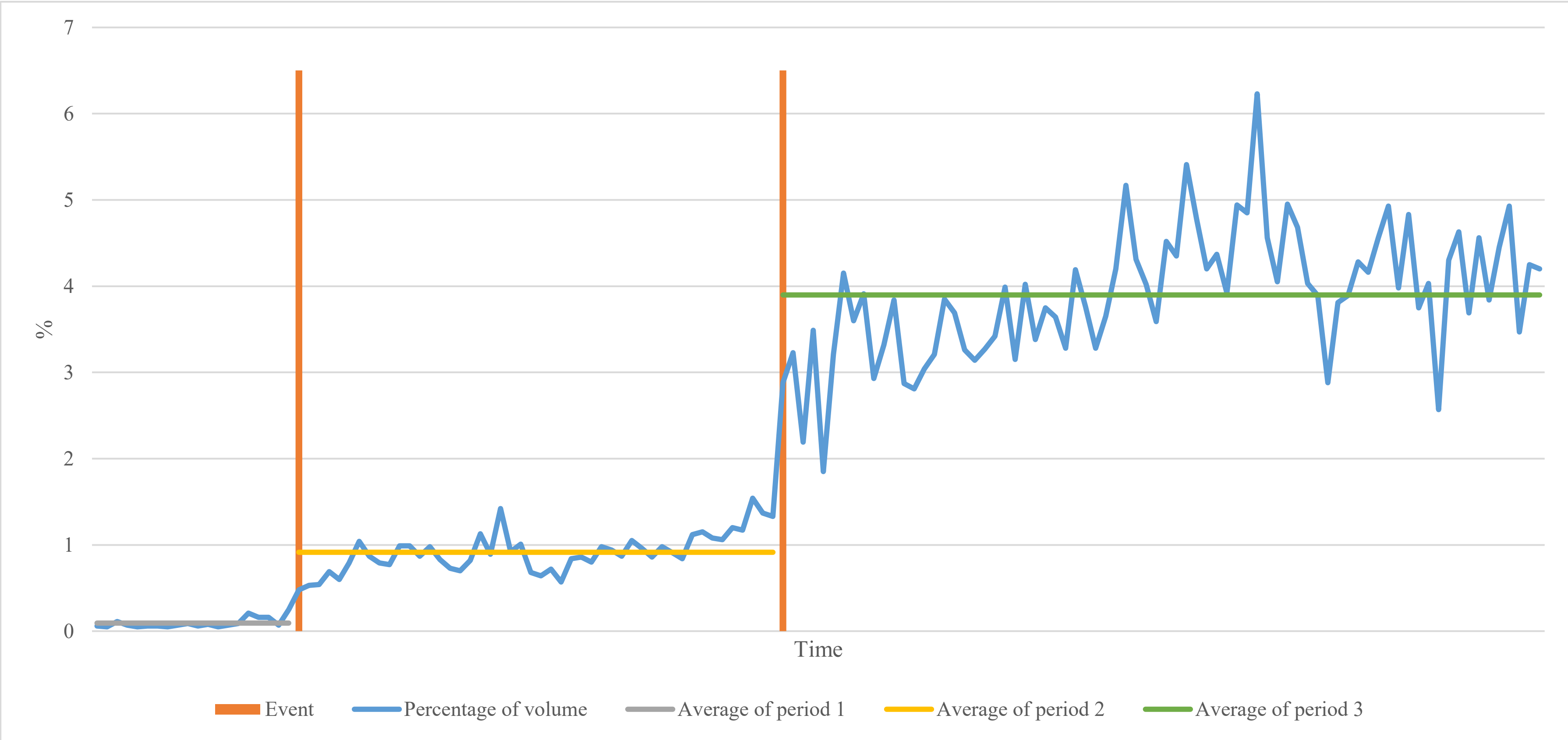
Figure 2. Periodic auctions activity as a percentage of total market activity

The figure plots the volume, currency volume and transactions of periodic auctions relative to the total market volume for London Stock Exchange-listed stocks and the implementation of the first double volume cap (DVC). The orange vertical bars correspond to two events: when MiFID II came into force on 3rd January 2018 and when the first DVC suspensions commenced on 12th March 2018. The horizontal plots represent the average periodic overall estimates; grey, yellow and green correspond to pre-MiFID II (1st December 2017 to 2nd January 2018), pre-DVC (3rd January to 9th March 2018, a Friday) and DVC periods (12th March to 29th June 2018) respectively.

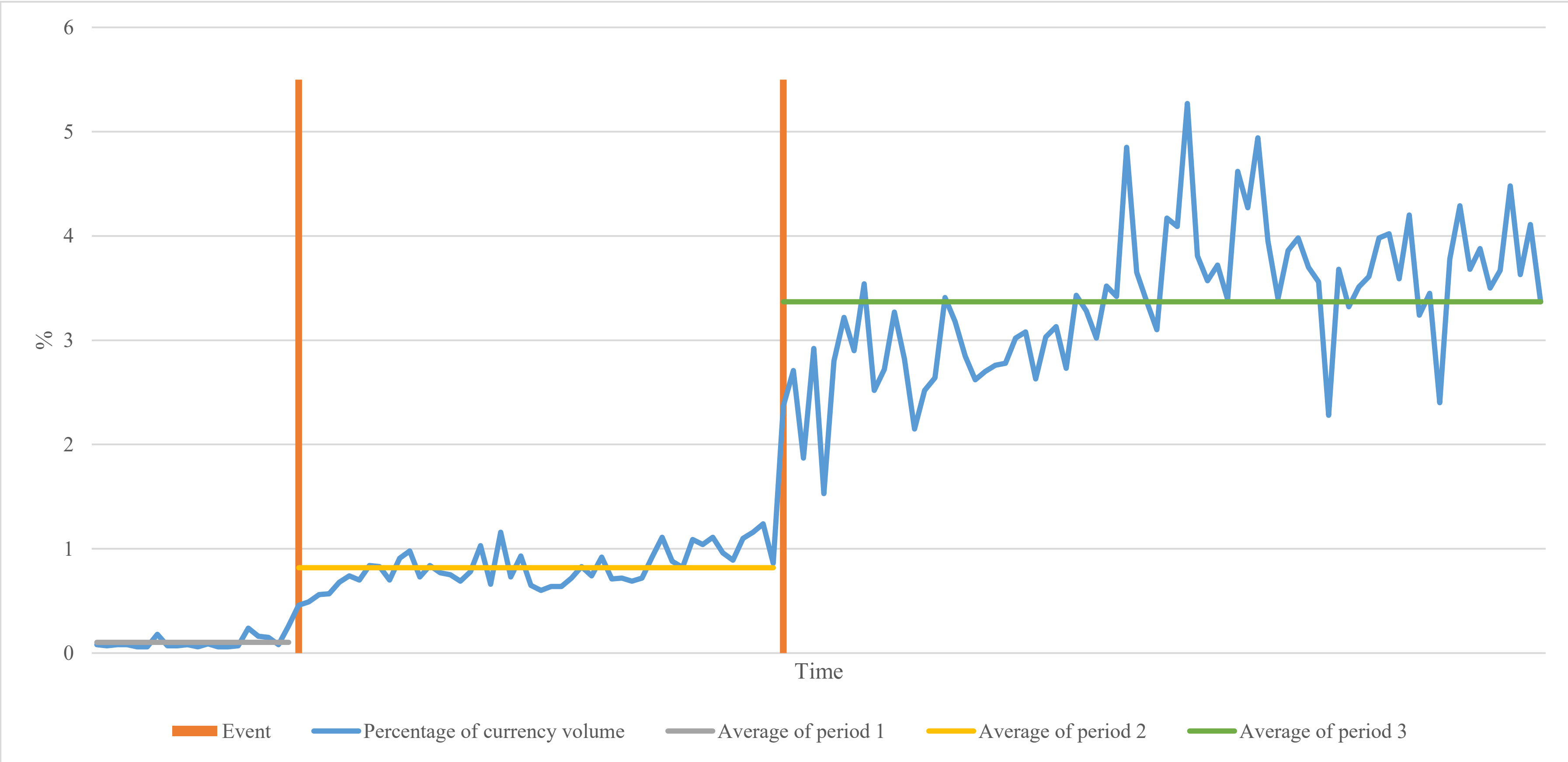
Panel A. Periodic auctions percentages of volume, currency volume and transactions in the entire market



Panel B. Periodic auctions percentages of volume



Panel C. Periodic auctions percentages of currency volume



Panel D. Periodic auctions percentages of transactions

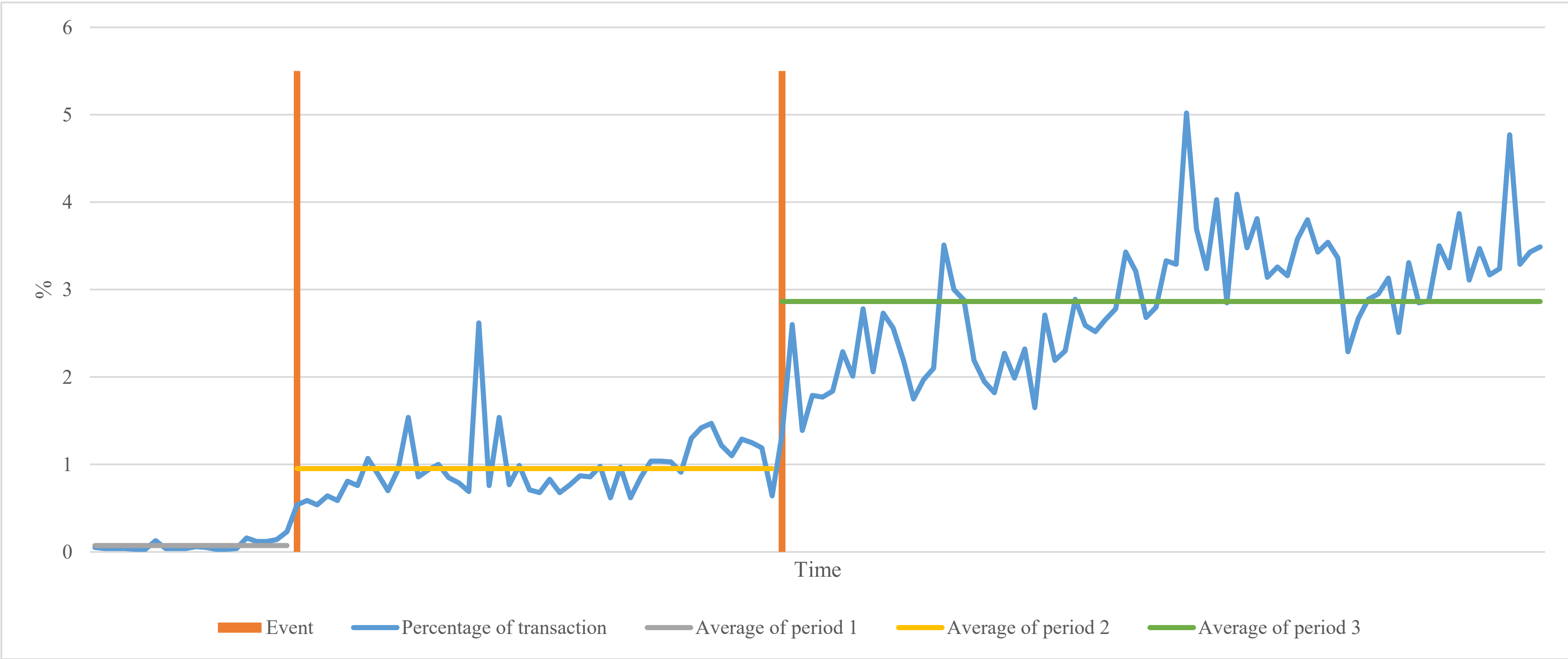
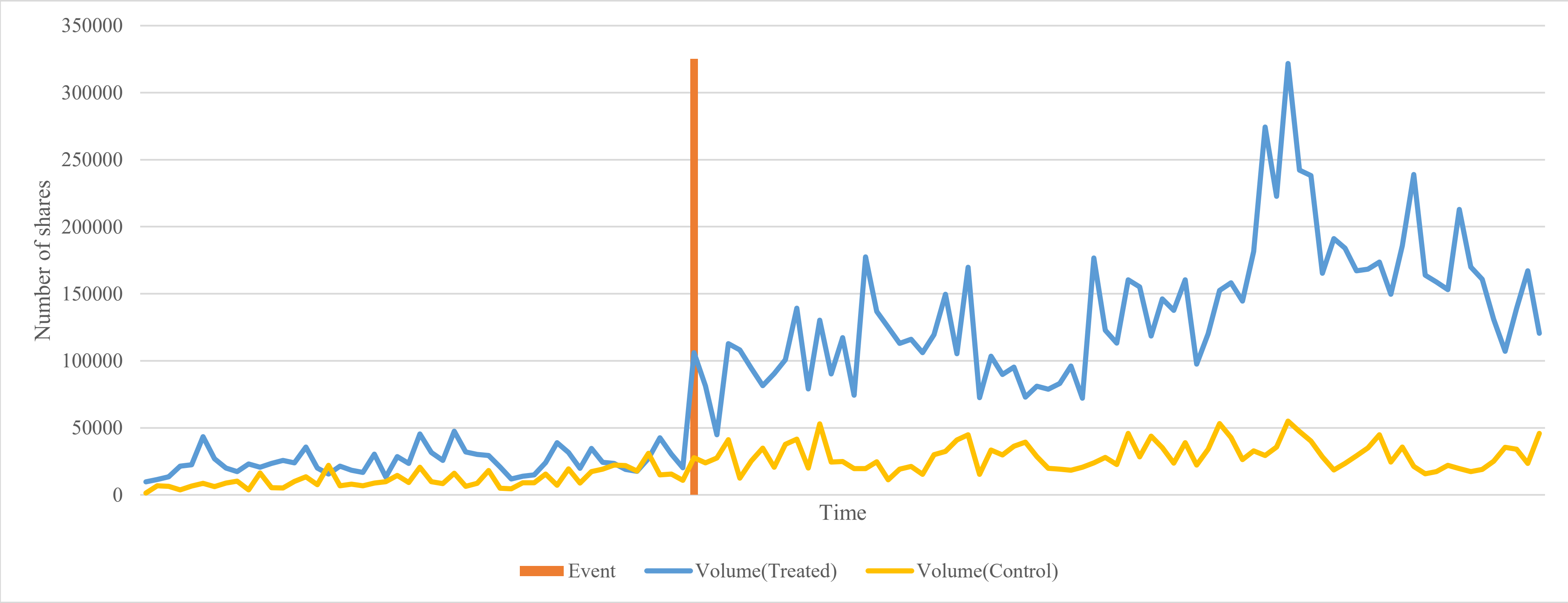


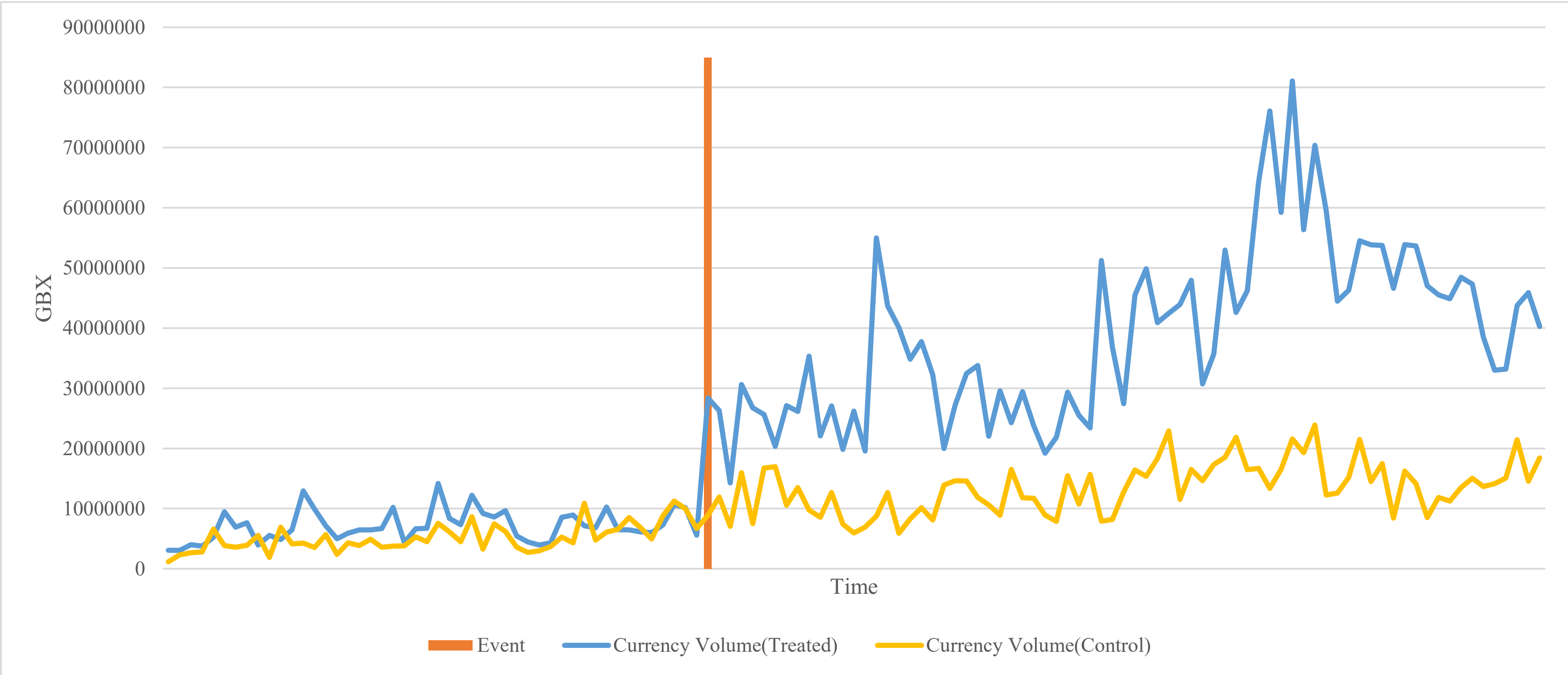
Figure 3. Evolution of outcome variables for treated and control groups

The figures plot the evolution of three outcome variables ($PAVolume_{i,d}$, $PACurrencyVolume_{i,d}$ and $PATransaction_{i,d}$) prior to and following the implementation of the double volume cap (DVC) mechanism. $PAVolume_{i,d}$, $PACurrencyVolume_{i,d}$ and $PATransaction_{i,d}$ are as defined in Table 1. The sample period covers [-2.5; +3.5 months] intervals around the DVC. The vertical bar indicates the date of the DVC implementation, 12th March 2019. The treatment group consists of the 57 FTSE 250 stocks with DVC restrictions and the control group includes the 57 FTSE 250 stocks with no DVC restrictions.

Panel A. Evolution of $PAVolume_{i,d}$ in relation to the DVC



Panel B. Evolution of $PACurrencyVolume_{i,d}$ in relation to the DVC



Panel C. Evolution of $PATransaction_{i,d}$ in relation to the DVC

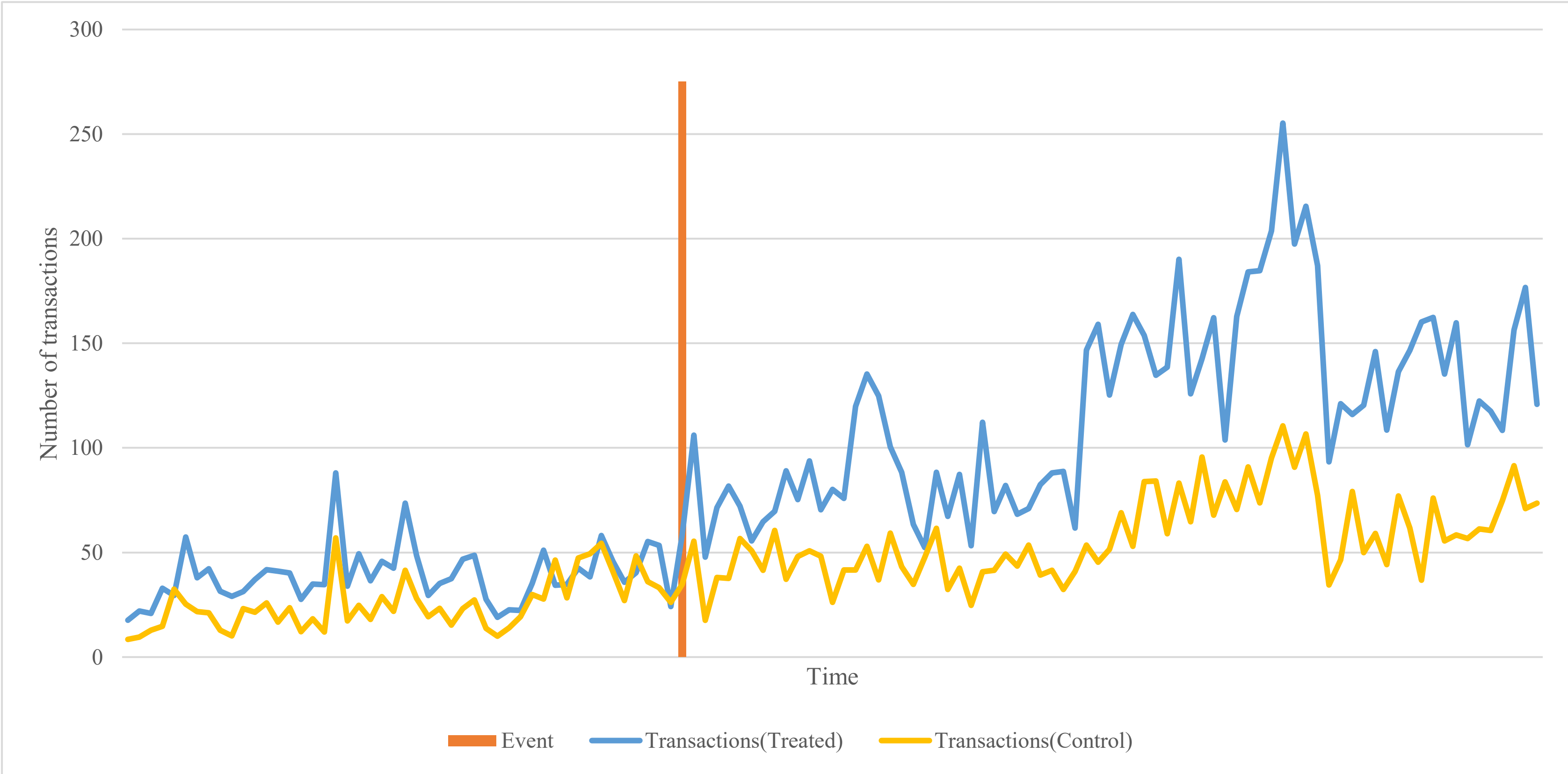


Table 1. Variable definitions

The table defines the variables employed in this study.

Variable	*Unit*	*Definition*
		Periodic auctions variables
$PAVolume_{i,d}$	Shares	Number of shares traded in periodic auctions order books for stock i on day d.
$PACurrencyVolume_{i,d}$	GBX	Currency (in GBX) value of the shares traded in periodic auctions order books for stock i on day d.
$PATransactions_{i,d}$		Number of transactions recorded in periodic auctions order books for stock i on day d.
		Dependent variables
$RelativeSpread_{i,d}$	%	Relative quoted spread for stock i on day d, computed as the volume-weighted average of the difference between bid prices and ask prices divided by the average of both prices.
$AdverseSelection_{i,d}$	%	Adverse selection costs for stock i on day d, computed as the volume-weighted average of the difference between the effective spread and the realized spread divided by the average of bid and ask prices. Trade direction is estimated using the Lee and Ready (1991) classification algorithm.
$VarianceRatio_{i,d}$		Variance ratio for stock i on day d, and a proxy for informational efficiency. Computed by taking the absolute value of 1 minus a long-term midpoint return variance (5 minutes) divided by a short-term midpoint return variance (1 minute) multiplied by five, which is the quotient between the long-term and the short-term. Midpoint is the average of bid and ask prices.
$Autocorrelation_{i,d}$		Autocorrelation for stock i on day d, and a proxy for informational efficiency. This is estimated by taking the absolute value of the autocorrelation for 5-second midpoint returns on day d.
		Control variables
$Volume_{i,d}$	‘000	Volume traded in all exchanges (excluding the periodic auctions mechanism) for stock i on day d.
$MarketValue_{i,d}$	£’000,000	End-of-day market value of stock i on day d.
$ClosePrice_{i,d}$	GBX	Close price for stock i on day d.

$OrderImbalance_{i,d}$	Order imbalance for stock i on day d, computed as the absolute value of the buyer-initiated volume minus the seller-initiated volume divided by total volume in stock i on day d.
$Volatility_{i,d}$	A proxy for volatility, computed as the variance of one-minute intervals midpoint returns for stock i on day d.
$Momentum_{i,d}$	A proxy for momentum, computed as the 3-day cumulative abnormal return on close price for stock i on day d.

Table 2. Statistics

In this table, Panel A reports the summary statistics (mean and standard deviation) for all the variables employed in the study, while Panel B presents the results of a statistical comparison of the matching criteria for stocks employed in a difference-in-differences estimation. $PAVolume_{i,d}$, $PACurrencyVolume_{i,d}$ and $PATransaction_{i,d}$ are proxies for periodic auctions activities and are the volume, currency volume and number of transactions in periodic auctions for stock i on day d. $ClosePrice_{i,d}$ is the end-of-day close price of stock i on day d. $Volatility_{i,d}$ is the midpoint return volatility for stock i on day d. $OrderImbalance_{i,d}$ proxies order imbalance for stock i on day d. $Volume_{i,d}$ is the volume of trading (excluding periodic auctions) in stock i on day d. $MarketValue_{i,d}$ is the end-of-day market value of stock i on day d. $Momentum_{i,d}$ is the three-day cumulative abnormal return on closing price for stock i on day d. $RelativeSpread_{i,d}$ is the daily volume-weighted average of relative quoted spread for stock i on day d. $AdverseSelection_{i,d}$ is the daily volume-weighted average of adverse selection costs for stock i on day d. $VarianceRatio_{i,d}$ is the variance ratio for stock i on day d, and $Autocorrelation_{i,d}$ is the autocorrelation for stock i on day d. The sample consists of 215 FTSE 250 stocks trading in London's trading venues between 3rd January and 29th June 2018. The stocks are divided into terciles using currency volume in GBX.

Panel A. Summary statistics

Variables	Full sample		Largest tercile		Median tercile		Smallest tercile	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
$PAVolume_{i,d}$	87,155.45	239,122.10	47,904.49	185,442.30	71,104.87	191,317.30	141,413.00	308,842.80
$PACurrencyVolume_{i,d}$ (GBX)	37,455,557	84,829,696	10,051,155	40,604,182	22,688,090	39,854,284	78,938,863	124,795,051
$PATransaction_{i,d}$	126.824	226.196	33.783	97.326	78.484	121.195	265.846	313.65
$ClosePrice_{i,d}$ (GBX)	1,072.95	2,857.64	1,124.52	4,666.98	747.460	926.17	1,352.15	1,477.17
$Volatility_{i,d}$	0.046	0.274	0.059	0.355	0.036	0.200	0.044	0.246
$OrderImbalance_{i,d}$	-0.373	26.963	-1.366	36.061	0.265	23.857	-0.055	18.161
$MarketValue_{i,d}$ (£'000,000)	1,968.23	1,573.13	956.067	447.842	1,609.82	802.663	3,311.24	1,898.23
$Volume_{i,d}$ ('000)	1,501.03	2,953.16	616.46	1,377.22	1,206.57	2,057.38	2,655.77	4,206.45
$Momentum_{i,d}$	-0.002	0.065	-0.002	0.068	-0.002	0.059	-0.0003	0.046

$RelativeSpread_{i,d}$	0.189	0.169	0.298	0.237	0.165	0.081	0.107	0.076
$AdverseSelection_{i,d}$	0.003	0.01	0.005	0.015	0.003	0.008	0.002	0.006
$VarianceRatio_{i,d}$	0.572	0.322	0.511	0.348	0.601	0.313	0.603	0.297
$Autocorrelation_{i,d}$	0.06	0.104	0.043	0.075	0.057	0.1	0.08	0.126

Panel B. Comparative analysis for matched sample of stocks

Variables	Treated group	Control group	Difference	*t*-statistics
$Autocorrelation_{i,d}$	0.049111	0.047691	0.00142	0.624
$RelativeSpread_{i,d}$	0.257	0.216	0.041	-1.531
$Volume_{i,d}$ (‘000)	1,222.827	1,276.462	-53.635	-0.912

Table 3. Trading activity in periodic auctions order books

This table presents estimates of trading activity in periodic auctions order books. $PAVolume_{i,d}$, $PACurrencyVolume_{i,d}$ and $PATransaction_{i,d}$ are proxies for periodic auctions' trading activities and are the volume, currency volume and number of transactions in periodic auctions for stock i on day d. t-statistics for two-sample tests of differences between average trading activity of the pre- and post-event periods are also presented. The sample period is from 3rd January to 29th June 2018 and the event date is 12th March 2018, when the double volume cap mechanism was implemented in European markets. The sample consists of 114 FTSE 250 stocks trading in London's trading venues between 3rd January and 29th June 2018; the control and treated groups of stocks each have 57 stocks. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

	Control group			Treated group		
Variables	$PAVolume_{i,d}$	$PACurrencyVolume_{i,d}$	$PATransaction_{i,d}$	$PAVolume_{i,d}$	$PACurrencyVolume_{i,d}$	$PATransaction_{i,d}$
Pre-event	11,528.13	5,232,510	25.882	24,880.91	7,158,572	39.245
Post-event	29,854.03	13,668,073	58.122	139,855.60	39,351,537	118.906
Difference	18,325.9***	8,435,563***	32.24***	114,974.69***	32,192,965***	79.661***
t-statistic	10.94	10.84	9.00	22.76	23.99	20.64

Table 4. Trading activity in periodic auctions around the DVC

This table reports the estimated coefficients for the following difference-in-differences regression model:

$$PA_{i,d} = \alpha + \beta_1 DVC_d + \beta_2 Treated_i + \beta_3 DVC_d \times Treated_i + \beta_4 Control_{i,d} + \gamma_d d + \delta_i i + \epsilon_{i,d}$$

where $PA_{i,d}$ corresponds to one of the log of periodic auctions proxies, i.e. $PAVolume_{i,d}$ (Panel A), $PACurrencyVolume_{i,d}$ (Panel B) and $PATransaction_{i,d}$ (Panel C), for stock i on day d. $Treated_i$ and DVC_d are dummy variables. $Treated_i$ takes the value of one if stock i is under the double volume cap (DVC)-linked dark trading restrictions and zero otherwise. DVC_d takes the value of one for 12th March 2018 and subsequent days in the sample and zero otherwise. $Control_{i,d}$ contains a series of control variables for stock i on day d. The variables include the log of $Volume_{i,d}$, which is the volume of trading (excluding periodic auctions) in stock i on day d, log of $MarketValue_{i,d}$, the end-of-day market value of stock i in day d, $OrderImbalance_{i,d}$, which proxies order imbalance for stock i on day d, $Volatility_{i,d}$, the midpoint return volatility for stock i in day d, and $Momentum_{i,d}$, the three-day cumulative abnormal return on closing price for stock i on day d. The others include the log of $ClosePrice_{i,d}$, the end-of-day closing price for stock i on day d and $RelativeSpread_{i,d}$, a proxy for the level of liquidity in stock i on day d. The sample consists of 114 FTSE 250 stocks trading in London's trading venues between 3rd January and 29th June 2018; the control and treated groups of stocks each have 57 stocks. The stocks are divided into terciles using currency volume in GBX. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

Panel A

	Dependent variable: $\log(PAVolume_{i,d})$			
	Full sample	Largest tercile	Median tercile	Smallest tercile
DVC_d	2.359***	3.133***	2.389***	1.437*
	(5.332)	(4.537)	(2.865)	(1.880)
$Treated_i$	7.134***	7.073***	-3.548***	1.241×10^{1}***
	(6.981)	(7.867)	(-3.503)	(8.427)
$DVC_d \times Treated_i$	1.999***	8.672×10^{-1}***	2.444***	2.725***
	(17.337)	(4.791)	(11.059)	(13.528)
$\log(Volume_{i,d})$	8.817×10^{-1}***	9.695×10^{-1}***	8.809×10^{-1}***	8.393×10^{-1}***
	(19.385)	(11.933)	(9.447)	(12.301)
$\log(ClosePrice_{i,d})$	-7.802×10^{-1}***	-7.355×10^{-1}*	-9.477×10^{-1}***	-3.099***
	(-3.109)	(-1.658)	(-2.740)	(-2.996)

$\log(MarketValue_{i,d})$	1.217*** (3.734)	5.609×10^{-1} (1.325)	1.688** (2.467)	4.048*** (3.827)
$RelativeSpread_{i,d}$	-1.066*** (-4.152)	-2.968*** (-4.004)	-1.469*** (-2.585)	-6.568×10^{-1}** (-1.993)
$Volatility_{i,d}$	3.051×10^{-3}** (2.204)	-5.171×10^{-3} (-1.085)	1.133×10^{-2}* (1.854)	4.685×10^{-3}*** (2.834)
$OrderImbalance_{i,d}$	-1.027×10^{-1} (-1.173)	-2.206×10^{-1} (-1.272)	-1.370×10^{-1} (-0.817)	-2.886×10^{-2} (-0.222)
$Momentum_{i,d}$	3.188×10^{-1} (0.772)	4.894×10^{-1} (0.859)	-3.841×10^{-1} (-0.475)	4.066×10^{-1} (0.486)
Constant	-9.322*** (-3.651)	-5.581 (-1.529)	-4.811 (-0.892)	-1.637×10^{1}*** (-3.596)
Observations	13,822	4,657	4,585	4,580
$\overline{R^2}$	0.72	0.742	0.658	0.649
Stock and time fixed effects	Yes	Yes	Yes	Yes

Panel B

Dependent variable: $\log(PACurrencyVolume_{i,d})$				
	Full sample	Largest tercile	Median tercile	Smallest tercile
DVC_d	3.378*** (5.067)	4.448*** (4.515)	3.312*** (2.754)	2.135* 1.704
$Treated_i$	1.126×10^{1}*** (7.314)	9.394*** (7.324)	-6.148*** (-4.210)	1.895×10^{1}*** 7.851
$DVC_d \times Treated_i$	2.579*** (14.845)	8.375×10^{-1}*** (3.243)	3.202*** (10.047)	3.837*** 11.627

$\log(Volume_{i,d})$	1.157*** (16.891)	1.118*** (9.647)	1.116*** (8.297)	1.222*** 10.933
$\log(ClosePrice_{i,d})$	-5.411×10^{-1} (-1.431)	3.360×10^{-1} (0.531)	-1.367*** (-2.741)	-3.796** -2.240
$\log(MarketValue_{i,d})$	2.347*** (4.781)	6.034×10^{-1} (0.999)	3.051*** (3.091)	6.645*** 3.834
$RelativeSpread_{i,d}$	-1.598*** (-4.132)	-4.879*** (-4.614)	-2.070** (-2.525)	-9.064×10^{-1}* -1.678
$Volatility_{i,d}$	3.939×10^{-3}* (1.888)	-1.088×10^{-2} (-1.600)	1.622×10^{-2}* (1.841)	5.808×10^{-3}** (2.144)
$OrderImbalance_{i,d}$	-1.850×10^{-1} (-1.402)	-3.618×10^{-1} (-1.463)	-1.918×10^{-1} (-0.793)	-7.361×10^{-2} (-0.345)
$Momentum_{i,d}$	2.467×10^{-1} (0.397)	3.511×10^{-1} (0.432)	-5.091×10^{-1} (-0.436)	2.466×10^{-1} (0.180)
Constant	-1.943×10^{1}*** (-5.049)	-1.028×10^{1}** (-1.974)	-8.413 (-1.081)	-3.177×10^{1}*** (-4.259)
Observations	13,822	4,657	4,585	4,580
$\overline{R^2}$	0.704	0.735	0.667	0.635
Stock and time fixed effects	Yes	Yes	Yes	Yes

Panel C

Dependent variable: $\log(PATransaction_{i,d})$				
	Full sample	Largest tercile	Median tercile	Smallest tercile
DVC_d	1.228*** (5.943)	1.773*** (5.305)	1.213*** (3.351)	6.199×10^{-1}* (1.654)

$Treated_i$	4.524*** (9.482)	4.844*** (11.134)	-3.481*** (-7.915)	5.727*** (7.930)
$DVC_d \times Treated_i$	9.756×10^{-1}*** (18.123)	4.627×10^{-1}*** (5.282)	1.102*** (11.481)	1.285*** (13.009)
$\log(Volume_{i,d})$	4.850×10^{-1}*** (22.843)	5.916×10^{-1}*** (15.048)	4.481×10^{-1}*** (11.066)	4.552×10^{-1}*** (13.607)
$\log(ClosePrice_{i,d})$	-2.446×10^{-1}** (-2.088)	-5.030×10^{-1}** (-2.343)	-2.897×10^{-1}* (-1.929)	-7.272×10^{-1} (-1.434)
$\log(MarketValue_{i,d})$	7.420×10^{-1}*** (4.878)	6.458×10^{-1}*** (3.153)	3.566×10^{-1} (1.200)	2.401*** (4.629)
$RelativeSpread_{i,d}$	-3.892×10^{-1}*** (-3.249)	-1.361*** (-3.795)	-5.724×10^{-1}** (-2.319)	-2.491×10^{-1} (-1.541)
$Volatility_{i,d}$	3.649×10^{-4} (0.565)	-9.789×10^{-4} (-0.424)	3.971×10^{-3} (1.497)	9.999×10^{-4} (1.233)
$OrderImbalance_{i,d}$	-1.440×10^{-2} (-0.352)	-3.040×10^{-2} (-0.362)	-2.202×10^{-2} (-0.302)	-9.062×10^{-3} (-0.142)
$Momentum_{i,d}$	1.198×10^{-1} (0.622)	1.593×10^{-1} (0.578)	-1.973×10^{-1} (-0.562)	1.967×10^{-1} (0.479)
Constant	-8.889*** (-7.457)	-8.064*** (-4.566)	-5.349×10^{-1} (-0.228)	-1.658×10^{1}*** (-7.429)
Observations	13,822	4,657	4,585	4,580
$\overline{R^2}$	0.767	0.788	0.737	0.672
Stock and time fixed effects	Yes	Yes	Yes	Yes

Table 5. The effects of periodic auctions on liquidity

This table reports the estimated coefficients for the following regression model:

$$RelativeSpread_{i,d} = \alpha + \beta_1 DVC_d + \beta_2 \log(PATransaction_{i,d}) + \beta_3 DVC_d \times \log(PATransaction_{i,d}) + \beta_4 Control_{i,d} + \gamma_d d + \delta_i i + \epsilon_{i,d}$$

where $RelativeSpread_{i,d}$ is the daily volume-weighted average relative quoted spread for stock i on day d, $PATransaction_{i,d}$ is the number of periodic auctions transactions in stock i on day d. DVC_d takes the value of one for 12th March 2018 and subsequent days in the sample and zero otherwise, and i and d are stock and time fixed effects variables respectively. $Control_{i,d}$ contains a series of control variables for stock i on day d. The variables include the log of $Volume_{i,d}$, which is the volume of trading (excluding periodic auctions) in stock i on day d, log of $MarketValue_{i,d}$, the end-of-day market value of stock i on day d, $OrderImbalance_{i,d}$, which proxies order imbalance for stock i on day d, $Volatility_{i,d}$, the midpoint return volatility for stock i on day d, $Momentum_{i,d}$, the three-day cumulative abnormal return on closing price for stock i on day d, and the log of $ClosePrice_{i,d}$, the end-of-day closing price for stock i on day d. The sample consists of 158 FTSE 250 stocks trading in London's trading venues between 3rd January and 29th June 2018 that are affected by the double volume cap mechanism triggered on 12th March 2018. The stocks are divided into terciles using currency volume in GBX. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

Dependent variable: $RelativeSpread_{i,d}$				
	Full sample	Largest tercile	Median tercile	Smallest tercile
DVC_d	1.120×10^{-2}	1.512×10^{-2}***	1.952×10^{-2}***	1.542×10^{-2}
	(1.370)	(5.326)	(3.974)	(0.647)
$\log(PATransaction_{i,d})$	-2.752×10^{-3}***	-8.929×10^{-5}	-7.747×10^{-4}***	-3.645×10^{-3}***
	(-6.839)	(-0.455)	(-3.208)	(-3.381)
$DVC_d \times \log(PATransacation_{i,d})$	2.149×10^{-3}***	-7.341×10^{-4}***	-9.128×10^{-5}	2.192×10^{-3}*
	(4.714)	(-2.730)	(-0.275)	(1.700)
$\log(Volume_{i,d})$	-4.963×10^{-3}***	4.911×10^{-4}	-2.378×10^{-3}***	-7.797×10^{-3}***
	(-5.404)	(1.411)	(-3.864)	(-3.536)
$\log(ClosePrice_{i,d})$	-3.396×10^{-2}***	5.189×10^{-3}	-1.448×10^{-3}	1.352×10^{-2}
	(-4.804)	(1.620)	(-0.380)	(0.539)

$\log(MarketValue_{i,d})$	-7.827×10^{-2}***	-2.110×10^{-2}***	-3.241×10^{-2}***	-1.875×10^{-1}***
	(-11.661)	(-5.866)	(-10.200)	(-7.568)
$OrderImbalance_{i,d}$	3.083×10^{-3}	-2.474×10^{-3}**	2.743×10^{-4}	7.013×10^{-3}
	(1.231)	(-2.276)	(0.163)	(1.236)
$Momentum_{i,d}$	-2.700×10^{-2}***	2.926×10^{-3}	-1.075×10^{-2}*	-6.043×10^{-2}***
	(-3.475)	(1.150)	(-1.721)	(-3.237)
$Volatility_{i,d}$	-1.175×10^{-4}***	1.469×10^{-6}	-1.499×10^{-5}	-2.610×10^{-4}***
	(-5.654)	(0.130)	(-1.008)	(-5.439)
Constant	9.327×10^{-1}***	2.391×10^{-3}***	3.600×10^{-1}***	1.391***
	(22.926)	(8.001)	(11.393)	(14.234)
Observations	19,165	6,331	6,519	6,315
$\overline{R^2}$	0.767	0.694	0.534	0.649
Stock and time fixed effects	Yes	Yes	Yes	Yes

Table 6. The effects of periodic auctions on adverse selection

The table reports the estimated coefficients for the following regression model:

$$AdverseSelection_{i,d} = \alpha + \beta_1 DVC_d + \beta_2 \log(PATransaction_{i,d}) + \beta_3 DVC_d \times \log(PATransaction_{i,d}) + \beta_4 Control_{i,d} + \gamma_d d + \delta_i i + \epsilon_{i,d}$$

where $AdverseSelection_{i,d}$ is the daily volume-weighted average of adverse selection costs for stock i on day d, $PATransaction_{i,d}$ is the number of periodic auctions transactions in stock i on day d. DVC_d takes the value of one for 12th March 2018 and subsequent days in the sample and zero otherwise, and i and d are stock and time fixed effects variables respectively. $Control_{i,d}$ contains a series of control variables for stock i on day d. The variables include the log of $Volume_{i,d}$, which is the volume of trading (excluding periodic auctions) in stock i on day d, log of $MarketValue_{i,d}$, the end-of-day market value of stock i on day d, $OrderImbalance_{i,d}$, which proxies order imbalance for stock i on day d, $Volatility_{i,d}$, the midpoint return volatility for stock i on day d, and $Momentum_{i,d}$, the three-day cumulative abnormal return on closing price for stock i on day d. The others include the log of $ClosePrice_{i,d}$, the end-of-day closing price for stock i on day d, and $RelativeSpread_{i,d}$, a proxy for the level of liquidity in stock i on day d. The sample consists of 158 FTSE 250 stocks trading in London's trading venues between 3rd January and 29th June 2018 that are affected by the double volume cap mechanism triggered on 12th March 2018. The stocks are divided into terciles using currency volume in GBX. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

Dependent variable: $AdverseSelection_{i,d}$				
	Full sample	Largest tercile	Median tercile	Smallest tercile
DVC_d	-3.844×10^{-3}***	-2.676×10^{-3}***	-5.629×10^{-3}***	-2.546×10^{-3}
	(-3.510)	(-4.384)	(-5.597)	(-0.828)
$\log(PATransaction_{i,d})$	-3.991×10^{-5}	-1.176×10^{-4}***	5.689×10^{-5}	2.218×10^{-4}
	(-0.740)	(-2.792)	(1.151)	(1.593)
$DVC_d \times \log(PATransaction_{i,d})$	1.769×10^{-4}***	2.217×10^{-4}***	7.780×10^{-5}	-2.966×10^{-4}*
	(2.896)	(3.840)	(1.145)	(-1.782)
$RelativeSpread_{i,d}$	6.516×10^{-3}***	6.794×10^{-3}**	1.406×10^{-2}***	6.178×10^{-3}***
	(6.686)	(2.483)	(5.469)	(3.750)
$\log(Volume_{i,d})$	2.771×10^{-4}**	1.280×10^{-4}*	2.422×10^{-4}*	4.677×10^{-4}
	(2.251)	(1.715)	(1.922)	(1.642)

$\log(ClosePrice_{i,d})$	-1.489×10^{-3} (-1.571)	1.066×10^{-3} (1.552)	-6.514×10^{-4} (-0.835)	-3.408×10^{-3} (-1.054)
$\log(MarketValue_{i,d})$	-2.422×10^{-4} (-0.269)	-2.999×10^{-3}*** (-3.874)	-1.117×10^{-3}* (-1.705)	2.220×10^{-3} (0.691)
$OrderImbalance_{i,d}$	3.809×10^{-4} (1.135)	-7.378×10^{-5} (-0.316)	-2.534×10^{-5} (-0.073)	5.150×10^{-4} (0.703)
$Momentum_{i,d}$	-4.600×10^{-3}*** (-4.420)	-9.647×10^{-4}* (-1.767)	-1.063×10^{-3} (-0.832)	-7.275×10^{-3}*** (-3.018)
$Volatility_{i,d}$	-1.622×10^{-5}*** (-5.939)	4.196×10^{-6}* (1.727)	-4.004×10^{-6} (-1.317)	-1.883×10^{-5}*** (-3.033)
Constant	1.297×10^{-2}** (2.349)	5.157×10^{-3}*** (3.948)	1.217×10^{-2}* (1.863)	4.644×10^{-3} (0.362)
Observations	19,165	6,331	6,519	6,315
$\overline{R^2}$	0.13	0.19	0.146	0.103
Stock and time fixed effects	Yes	Yes	Yes	Yes

Table 7. The effects of periodic auctions on informational efficiency

The table reports the estimated coefficients for the following regression model:

$$Informationefficiency_{i,d} = \alpha + \beta_1 DVC_d + \beta_2 \log(PATransaction_{i,d}) + \beta_3 DVC_d \times \log(PATransaction_{i,d}) + \beta_4 Control_{i,d} + \gamma_d d + \delta_i i + \epsilon_{i,d}$$

where $InformationEfficency_{i,d}$ corresponds to one of two proxies for informational efficiency for stock i on day d; the two proxies are $Autocorrelation_{i,d}$ (Panel A) and $VarianceRatio_{i,d}$ (Panel B). $PATransaction_{i,d}$ is the number of periodic auctions transactions in stock i on day d. DVC_d takes the value of one for 12th March 2018 and subsequent days in the sample and zero otherwise, and i and d are stock and time fixed effects variables respectively. $Control_{i,d}$ contains a series of control variables for stock i on day d. The variables include the log of $Volume_{i,d}$, which is the volume of trading (excluding periodic auctions) in stock i on day d, log of $MarketValue_{i,d}$, the end-of-day market value of stock i on day d, $OrderImbalance_{i,d}$, which proxies order imbalance for stock i on day d, $Volatility_{i,d}$, the midpoint return volatility for stock i on day d and $Momentum_{i,d}$, the three-day cumulative abnormal return on closing price for stock i on day d. The others include the log of $ClosePrice_{i,d}$, the end-of-day closing price for stock i on day d and $RelativeSpread_{i,d}$, a proxy for the level of liquidity in stock i on day d. The sample consists of 158 FTSE 250 stocks trading in London's trading venues between 3rd January and 29th June 2018 that are affected by the double volume cap mechanism triggered on 12th March 2018. The stocks are divided into terciles using currency volume in GBX. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

Panel A

Dependent variable: $Autocorrelation_{i,d}$				
	Full sample	Largest tercile	Median tercile	Smallest tercile
DVC_d	-4.456×10^{-2}***	-9.552×10^{-2}***	-4.628×10^{-2}**	-2.386×10^{-2}
	(-3.609)	(-3.252)	(-2.214)	(-1.500)
$\log(PATransaction_{i,d})$	1.803×10^{-3}***	4.885×10^{-3}**	7.571×10^{-4}	8.161×10^{-4}
	(2.964)	(2.410)	(0.737)	(1.134)
$DVC_d \times \log(PATransacation_{i,d})$	1.477×10^{-3}**	4.966×10^{-3}*	4.952×10^{-3}***	-2.934×10^{-4}
	(2.145)	(1.788)	(3.508)	(-0.341)
$RelativeSpread_{i,d}$	8.812×10^{-3}	-1.468×10^{-1}	2.469×10^{-2}	1.010×10^{-2}
	(0.802)	(-1.116)	(0.462)	(1.185)
$\log(Volume_{i,d})$	-3.347×10^{-3}**	-7.791×10^{-3}**	-4.673×10^{-3}*	-1.979×10^{-4}
	(-2.412)	(-2.169)	(-1.784)	(-0.134)

$\log(ClosePrice_{i,d})$	-2.175×10^{-2}**	-7.827×10^{-2}**	2.912×10^{-3}	-2.123×10^{-2}
	(-2.036)	(-2.367)	(0.180)	(-1.270)
$\log(MarketValue_{i,d})$	9.714×10^{-4}	5.203×10^{-2}	1.821×10^{-4}	-5.852×10^{-3}
	(0.096)	(1.397)	(0.013)	(-0.352)
$OrderImbalance_{i,d}$	-6.932×10^{-3}*	-9.789×10^{-3}	-4.947×10^{-3}	-8.207×10^{-3}**
	(-1.833)	(-0.872)	(-0.690)	(-2.168)
$Momentum_{i,d}$	-1.434×10^{-2}	-4.539×10^{-2}*	5.604×10^{-3}	-3.092×10^{-3}
	(-1.223)	(-1.728)	(0.211)	(-0.248)
$Volatility_{i,d}$	4.116×10^{-5}	-4.849×10^{-5}	1.188×10^{-4}*	1.955×10^{-5}
	(1.310)	(-0.415)	(1.881)	(0.609)
Constant	1.754×10^{-1}***	1.471×10^{-1}	5.376×10^{-2}	1.985×10^{-1}***
	(2.817)	(0.593)	(0.396)	(2.995)
Observations	19,165	6,331	6,519	6,315
$\overline{R^2}$	0.097	0.104	0.08	0.041
Stock and time fixed effects	Yes	Yes	Yes	Yes

Panel B

Dependent variable: $VarianceRatio_{i,d}$				
	Full sample	Largest tercile	Median tercile	Smallest tercile
DVC_d	-9.977×10^{-2}***	8.828×10^{-2}	-1.183×10^{-1}**	-1.062×10^{-1}*
	(-2.979)	(1.420)	(-2.001)	(-1.789)
$\log(PATransaction_{i,d})$	-1.971×10^{-4}	-6.052×10^{-4}	1.536×10^{-4}	1.418×10^{-4}
	(-0.119)	(-0.141)	(0.053)	(0.053)
$DVC_d \times \log(PATransacation_{i,d})$	-5.546×10^{-3}***	-2.692×10^{-2}***	-1.073×10^{-2}***	1.115×10^{-3}
	(-2.970)	(-4.579)	(-2.688)	(0.347)

$RelativeSpread_{i,d}$	-2.093×10^{-1}*** (-7.025)	-1.441*** (-5.171)	-8.155×10^{-1}*** (-5.397)	-1.782×10^{-1}*** (-5.602)
$\log(Volume_{i,d})$	-3.308×10^{-2}*** (-8.792)	-3.798×10^{-2}*** (-4.996)	-3.881×10^{-2}*** (-5.238)	-2.808×10^{-2}*** (-5.108)
$\log(ClosePrice_{i,d})$	5.021×10^{-2}* (1.734)	9.768×10^{-2} (1.396)	-3.237×10^{-2} (-0.706)	2.089×10^{-1}*** (3.346)
$\log(MarketValue_{i,d})$	3.429×10^{-2} (1.244)	4.606×10^{-2} (0.584)	5.756×10^{-2} (1.494)	-1.307×10^{-1}** (-2.109)
$OrderImbalance_{i,d}$	6.549×10^{-4} (0.064)	1.805×10^{-2} (0.760)	9.074×10^{-3} (0.448)	-1.942×10^{-3} (-0.137)
$Momentum_{i,d}$	2.127×10^{-2} (0.669)	3.700×10^{-2} (0.665)	-4.059×10^{-2} (-0.540)	1.790×10^{-2} (0.385)
$Volatility_{i,d}$	-9.132×10^{-5} (-1.072)	-4.766×10^{-4}* (-1.926)	1.063×10^{-4} (0.594)	-2.356×10^{-4}** (-1.967)
Constant	3.635×10^{-1}** (2.153)	5.252×10^{-1} (0.287)	8.416×10^{-1}** (2.192)	6.312×10^{-1}** (2.551)
Observations	19,165	6,331	6,519	6,315
$\overline{R^2}$	0.087	0.08	0.063	0.084
Stock and time fixed effects	Yes	Yes	Yes	Yes

Appendix A. Stocks employed in this study

This appendix presents the stocks included in the stock sample, including information of ISINs, tickers and company names.

A1. Unrestricted stocks

Ticker	Company Name	ISIN
3IN	3i Infrastructure	JE00BF5FX167
ACA	Acacia Mining	GB00BYWF9Y76
ASL	Aberforth Smaller Companies Trust	GB0000066554
ATST	Alliance Trust	GB00B11V7W98
BGEO	Bank of Georgia	GB00BF4HYT85
BGFD	Baillie Gifford Japan Trust	GB0000485838
BRWM	BlackRock World Mining Trust	GB0005774855
BTEM	British Empire Securities & General Trust	GB0001335081
CLDN	Caledonia Investments	GB0001639920
CTY	City of London Inv Trust	GB0001990497
EDIN	Edinburgh Inv Trust	GB0003052338
ELTA	Electra Private Equity	GB0003085445
BNKR	Bankers Investment Trust Plc	GB0000767003
FCSS	Fidelity China Special Situations	GB00B62Z3C74
FGT	Finsbury Growth & Income Trust	GB0007816068
FXPO	Ferrexpo	GB00B1XH2C03
GCP	GCP Infrastructure Investments Ltd	JE00B6173J15
GFRD	Galliford Try	GB00BKY40Q38
GFTU	Grafton Group	IE00B00MZ448
GPOR	Great Portland Estates	GB00BF5H9P87
HICL	HICL Infrastructure Company Ltd	GB00BJLP1Y77
INPP	International Public Partnership Ltd	GB00B188SR50
INVP	Investec Plc	GB00B17BBQ50
JII	JPMorgan Indian Inv Trust	GB0003450359
JLIF	John Laing Infrastructure Fund Ltd	GG00B4ZWPH08
JMG	JPMorgan Emerging Markets Inv Trust	GB0003418950
MCRO	Micro Focus International	GB00BJ1F4N75
MNKS	Monks Inv Trust	GB0030517261
MRC	Mercantile Investment Trust (The)	GB00BF4JDH58
MYI	Murray International Trust	GB0006111909
NBLS	NB Global Floating Rate Income Fund	GG00B3KX4Q34
NESF	NextEnergy Solar Fund	GG00BJ0JVY01
PCT	Polar Capital Technology Trust	GB0004220025
PHNX	Phoenix Group Holdings (DI)	GB00BGXQNP29
PLI	Perpetual Income & Growth Inv Trust	GB0006798424
PNL	Personal Assets Trust	GB0006827546
PSH	Pershing Square Holdings	GG00BPFJTF46

RCP	Rit Capital Partners	GB0007366395
RDI	Redefine International	IM00BH3JLY32
RDW	Redrow	GB00BG11K365
RHIM	RHI Magnesita	NL0012650360
RMV	Rightmove	GB00BGDT3G23
RSE	Riverstone Energy Limited	GG00BBHXCL35
SCIN	Scottish Inv Trust	GB0007826091
SDP	Schroder AsiaPacific Fund	GB0007918872
SEQI	Sequoia Economic Infrastructure	GG00BV54HY67
HGT	HGCapital Trust	GB00BJ0LT190
SSPG	SSP Group	GB00BGBN7C04
TMPL	Temple Bar Inv Trust	GB0008825324
TRY	TR Property Inv Trust	GB0009064097
UKW	Greencoat UK Wind	GB00B8SC6K54
VEC	Vectura Group	GB00BKM2MW97
VEIL	Vietnam Enterprise Investments	KYG9361H1092
VOF	Vinacapital Vietnam Opportunity	GG00BYXVT888
WPCT	Woodford Patient Capital Trust	GB00BVG1CF25
WTAN	Witan Inv Trust	GB00BJTRSD38
WWH	Worldwide Healthcare Trust	GB0003385308

A2. restricted stocks

Ticker	**Company Name**	**ISIN**
AA	AA	GB00BMSKPJ95
AGK	Aggreko	GB00BK1PTB77
AGR	Assura	GB00BVGBWW93
ALM	Allied Minds	GB00BLRLH124
ASCL	Ascential	GB00BYM8GJ06
ASHM	Ashmore Group	GB00B132NW22
AVV	Aveva Group	GB00BBG9VN75
BAB	Babcock International Group	GB0009697037
BAG	Barr (A.G.)	GB00B6XZKY75
BBA	BBA Aviation	GB00B1FP8915
BBOX	Tritax Big Box Reit	GB00BG49KP99
BBY	Balfour Beatty	GB0000961622
BCA	BCA Marketplace	GB00BP0S1D85
BEZ	Beazley	GB00BYQ0JC66
BME	B&M European Value Retail S.A.	LU1072616219
BOY	Bodycote	GB00B3FLWH99
BRW	Brewin Dolphin Holdings	GB0001765816
BTG	BTG	GB0001001592
BVIC	Britvic	GB00B0N8QD54
BWNG	Brown (N.) Group	GB00B1P6ZR11

BWY	Bellway	GB0000904986
BYG	Big Yellow Group	GB0002869419
CAPC	Capital & Counties Properties	GB00B62G9D36
CARD	Card Factory	GB00BLY2F708
CBG	Close Brothers Group	GB0007668071
CCC	Computacenter	GB00BV9FP302
CEY	Centamin (DI)	JE00B5TT1872
CINE	Cineworld Group	GB00B15FWH70
CNE	Cairn Energy	GB00B74CDH82
CRST	Crest Nicholson Holdings	GB00B8VZXT93
CTEC	Convatec	GB00BD3VFW73
CTEC	Convatec Group Plc	GB00BD3VFW73
CWK	Cranswick	GB0002318888
DCC	DCC	IE0002424939
DCG	Dairy Crest Group	GB0002502812
DLG	Direct Line Insurance Group	GB00BY9D0Y18
DLN	Derwent London	GB0002652740
DNLM	Dunelm Group	GB00B1CKQ739
DOM	Domino's Pizza Group	GB00BYN59130
DPH	Dechra Pharmaceuticals	GB0009633180
DPLM	Diploma	GB0001826634
DRX	Drax Group	GB00B1VNSX38
DTY	Dignity	GB00BRB37M78
ECM	Electrocomponents	GB0003096442
ELM	Elementis	GB0002418548
EMG	Man Group	GB00B83VD954
EQN	Equiniti Group	GB00BYWWHR75
ERM	Euromoney Institutional Investor	GB0006886666
ESNT	Essentra	GB00B0744359
ESUR	Esure Group	GB00B8KJH563
ETO	Entertainment One Limited	CA29382B1022
FDSA	Fidessa Group	GB0007590234
FGP	FirstGroup	GB0003452173
FRCL	Foreign and Colonial Inv Trust	GB0003466074
GFS	G4S	GB00B01FLG62
GNC	Greencore Group	IE0003864109
GNK	Greene King	GB00B0HZP136
GNS	Genus	GB0002074580
GOG	Go-Ahead Group	GB0003753778
GRG	Greggs	GB00B63QSB39
GRI	Grainger	GB00B04V1276
GVC	GVC Holdings	IM00B5VQMV65
HAS	Hays	GB0004161021
HFD	Halfords Group	GB00B012TP20

HMSO	Hammerson	GB0004065016
HOC	Hochschild Mining	GB00B1FW5029
HSV	Homeserve	GB00BYYTFB60
HSX	Hiscox Limited (DI)	BMG4593F1389
HTG	Hunting	GB0004478896
HWDN	Howden Joinery Group	GB0005576813
IBST	Ibstock	GB00BYXJC278
ICP	Intermediate Capital Group	GB00BYT1DJ19
IGG	IG Group Holdings	GB00B06QFB75
IMI	IMI Plc	GB00BGLP8L22
INCH	Inchcape	GB00B61TVQ02
INDV	Indivior	GB00BRS65X63
IPF	International Personal Finance	GB00B1YKG049
IPO	IP Group	GB00B128J450
ISAT	Inmarsat	GB00B09LSH68
JAM	JPMorgan American Inv Trust	GB00BKZGVH64
JDW	Wetherspoon (J.D.)	GB0001638955
JLG	John Laing Group	GB00BVC3CB83
JLT	Jardine Lloyd Thompson Group	GB0005203376
JUP	Jupiter Fund Management	GB00B53P2009
KAZ	Kaz Minerals	GB00B0HZPV38
KIE	Kier Group	GB0004915632
LMP	London Metric Property	GB00B4WFW713
LRD	Laird	GB00B1VNST91
LRE	Lancashire Holdings Ltd.	BMG5361W1047
MAB	Mitchells & Butlers	GB00B1FP6H53
MARS	Marston's	GB00B1JQDM80
MCS	Mccarthy & Stone	GB00BYNVD082
MERL	Merlin Entertainments	GB00BDZT6P94
MGAM	Morgan Advanced Materials	GB0006027295
MGGT	Meggitt	GB0005758098
MLC	Millennium & Copthorne Hotels	GB0005622542
MONY	Moneysupermarket.com Group	GB00B1ZBKY84
MSLH	Marshalls	GB00B012BV22
MTO	Mitie Group	GB0004657408
NEX	National Express Group	GB0006215205
OCDO	Ocado Group	GB00B3MBS747
OSB	OneSavings Bank	GB00BM7S7K96
PAG	Paragon Group Of Companies	GB00B2NGPM57
PAY	PayPoint	GB00B02QND93
PDL	Petra Diamonds Ltd.(DI)	BMG702781094
PETS	Pets at Home Group	GB00BJ62K685
PFC	Petrofac Ltd.	GB00B0H2K534
PFG	Provident Financial	GB00B1Z4ST84

PMO	Premier Oil	GB00B43G0577
PNN	PENNON GROUP	GB00B18V8630
PTEC	Playtech	IM00B7S9G985
PZC	PZ Cussons	GB00B19Z1432
QQ	QinetiQ Group	GB00B0WMWD03
RMG	Royal Mail	GB00BDVZYZ77
RNK	Rank Group	GB00B1L5QH97
ROR	Rotork	GB00BVFNZH21
RPC	RPC Group	GB0007197378
RRS	Randgold Resources Ltd.	GB00B01C3S32
RSW	Renishaw	GB0007323586
RTN	Restaurant Group	GB00B0YG1K06
SAFE	Safestore Holding	GB00B1N7Z094
SAGA	Saga	GB00BLT1Y088
SCT	Softcat	GB00BYZDVK82
SGC	Stagecoach Group	GB00B6YTLS95
SHB	Shaftesbury	GB0007990962
SHI	SIG	GB0008025412
SHP	Shire Plc	JE00B2QKY057
SKY	Sky	GB0008220112
SMP	St. Modwen Properties	GB0007291015
SMWH	WH Smith	GB00B2PDGW16
SNR	Senior	GB0007958233
SPI	Spire Healthcare Group	GB00BNLPYF73
SPX	Spirax-Sarco Engineering	GB00BWFGQN14
SRP	Serco Group	GB0007973794
STJ	St James's Place	GB0007669376
SVS	Savills	GB00B135BJ46
SXS	Spectris	GB0003308607
SYNT	Synthomer	GB0009887422
TALK	TalkTalk Telecom Group	GB00B4YCDF59
TATE	Tate & Lyle	GB0008754136
TCG	Thomas Cook Group	GB00B1VYCH82
TED	Ted Baker	GB0001048619
TEP	Telecom Plus	GB0008794710
TLW	Tullow Oil	GB0001500809
TPK	Travis Perkins	GB0007739609
UDG	UDG Healthcare Public Ltd.	IE0033024807
ULE	Ultra Electronics Holdings	GB0009123323
UTG	Unite Group	GB0006928617
VCT	Victrex plc	GB0009292243
VED	Vedanta Resources	GB0033277061
VM	Virgin Money Holdings (UK)	GB00BD6GN030
VSVS	Vesuvius	GB00B82YXW83

WEIR	Weir Group	GB0009465807
WG	Wood Group (John)	GB00B5N0P849
WIZZ	Wizz Air Holdings	JE00BN574F90
WKP	Workspace Group	GB00B67G5X01
WMH	William Hill	GB0031698896