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The market quality effects of *sub-second* frequent batch auctions: Evidence from dark trading restrictions

Zeyu Zhang [a], Gbenga Ibikunle [a,b,c,*]

[a] The University of Edinburgh, United Kingdom
[b] European Capital Markets Cooperative Research Centre, Pescara, Italy
[c] RoZetta Institute, Sydney, Australia

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ABSTRACT

Recent European regulatory restrictions on dark trading induced an increase in sub-second frequent batch/periodic auctions (PA). We exploit this development to investigate the effects of PA on market quality. The restrictions are linked to an observable increase in PA and an economically meaningful loss of liquidity. PA is also associated with a significant decline in liquidity and informational efficiency. However, consistent with Budish et al. (2015 – *The Quarterly Journal of Economics, 130, 1547*), increased execution via PA leads to a decline in adverse selection costs, which underscores its potential as a trading mechanism for addressing latency arbitrage and the technological arms race.

> *…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 100 ms, if that seems too glacial for the financial terminators) for a brief blind auction*
>
> Financial Times, 21st February 2014

1. Introduction

While market microstructure studies increasingly suggest that algorithmic/high frequency trading (AT/HFT) benefits market quality (see as examples, Brogaard, Hendershott, & Riordan, 2014; Harris, 2013; Hasbrouck & Saar, 2013; Hendershott, Jones, & Menkveld, 2011), several others report its tendency to induce extreme and destabilizing events, such as "flash crashes" (see as examples, Easley, De Prado, & O'hara, M., 2011; Kirilenko, Kyle, Samadi, & Tuzun, 2017). Others note its propensity to induce a greater price impact on large institutional orders (see Putnins & Barbara, 2016). Raman, Robe, and Yadav (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, and the technological arms race, 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. They propose the *sub-second frequent batch auctioning* (FBA) mechanism, also often called *periodic auctioning* (PA) (hereafter referred to as PA), which divides trading into intervals of very short lengths (e.g., every tenth of a second) as an 'antidote'. In effect, this treats time discretely instead of as a continuous construct, and orders are processed in batches of auctions rather than serially. While frequent batch auctions are not yet widely used globally, according to the UK's Financial Conduct Authority (FCA), PA has 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 PA accounts 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 in place since early 2018. Evidence suggests that a non-negligible portion of volumes, otherwise destined for dark pools in stocks under

* Corresponding author at: University of Edinburgh Business School, 29 Buccleuch Place, Edinburgh EH8 8BA, United Kingdom.
E-mail address: Gbenga.Ibikunle@ed.ac.uk (G. Ibikunle).

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the DVC restriction, are executed through PA and other non-continuous trading mechanisms, the so-called 'quasi-dark' mechanisms (see Johann, Putniņš, Sagade, & Westheide, 2019).

In recognition of their relevance, the European Securities and Markets Authority (ESMA) called for evidence on the effects of PA on market quality.[1] However, there have been limited attempts to investigate the direct market quality effects of PA as a trading mechanism thus far. In addition, if PA is 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 PA on market quality characteristics in Europe's most active equity market, the UK market.

Consistent with Johann et al. (2019), we find that stocks undergoing DVC-imposed dark trading restrictions also experience higher PA volumes, and that the overall market quality effects of PA on the market are limited and mixed. Specifically, we find that PA has a generally negative effect on liquidity but is linked to a decline in adverse selection costs. The adverse selection costs effect is explained by the predictions of Budish et al. (2015): PA offers a safe haven for slower traders who are susceptible to the latency arbitrage strategies deployed by faster traders. Thus, increasing the use of PA lowers the incidence of slower traders being adversely selected through the latency arbitrage-based strategies typically deployed by HFTs. The seemingly contradictory effects of PA on liquidity and adverse selection is explained by the findings of Brogaard, Hagströmer, and Xu (2021), who show that call auctions are attractive to traders who do not prioritize immediacy, but require the certainty of the depth that the simultaneous execution in call auctions offer, and that short-term informed traders are likely to use such mechanisms. These findings imply that PA extracts liquidity from continuous markets. The extraction may, perversely, result in would-be informed traders being dis-incentivized to acquire new information to exploit in the continuous market. The mixed nature of the evidence on liquidity and adverse selection is underscored by the estimated impact of PA on informational efficiency. The overall effect of PA, especially during the DVC window, is a deviation from a random walk or reduction in informational efficiency. This finding is consistent with PA slowing down the pace of the price discovery process. While trading in dark pools implies a degree of delay (as in Menkveld, Yueshen, & Zhu, 2017; Zhu, 2014), PA in an otherwise high frequency trading environment will, inevitably, slow down trading, thus delaying the incorporation of new information into price. The dis-incentivizing of would-be informed traders from acquiring new information linked to PA also explains the links between a reduction in informational efficiency and an increase in PA activity.

To the best of our knowledge, this is the first study to provide empirical evidence on the market quality implications of PA deployed in parallel with continuous trading in European markets. Although Johann et al. (2019) include PA in their list of 'quasi-dark' trading mechanisms, the identification of PA mechanisms as quasi-dark is slightly problematic given that a key feature of auctions is transparency. Specifically, 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 PA mechanisms are sent to lit order books as they arrive.

The reminder of this paper is set out as follows. Section 2 discusses the related literature, Section 3 outlines our hypotheses and offers a background on the evolution of PA in Europe, and Section 4 discusses the data and variables. Sections 5 and 6 present the empirical framework and a discussion of the results respectively, while Section 7 concludes.

2. Related literature

By their nature, latency arbitrage trading strategies are more suited to a fragmented market environment due to the likelihood of disparities in reaction times among different venues (see Foucault, Kozhan, & Tham, 2017; Wah & Wellman, 2013). However, HFT makes these strategies viable within a single venue as well, because it facilitates the occurrence of speed differentials between slow and fast traders (see Menkveld, 2014; Wah & Wellman, 2016). By doing so, according to Foley, O'neill, Aquilina, and Ruf (2022), HFT imposes adverse selection costs on slower traders. The quest for faster trading speeds has thus resulted in the technological arms race, a competition driven by significant investment in computing and communications infrastructure (see Biais & Woolley, 2011). Investment in speed-inducing technologies is 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. It could also shift investor focus from the acquisition of speed-enabling transactions to obtaining better prices, implying that the introduction of FBA-type trading mechanisms could enhance price efficiency (see Madhavan, 1992).

Cboe's PA mechanism, which was introduced on 19th October 2015 and currently accounts for about 70% of the PA 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 trading through auctions has been the subject of some academic studies, those studies have only focused on long interval auction lengths and not the FBA-type PA we examine in the context of AT/HFT. For example, Madhavan (1992) argues that auctions offer greater price efficiency than the more common continuous order-driven trading mechanism. This is due to the pooling effect of the 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, Hendershott, & Jones, 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, Mendelson, and Lauterbach (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 examining 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, while Brogaard et al. (2021), presenting evidence based on Copenhagen and Helsinki midday auctions, show that price impact is reduced during auctions.

However, the most common use of call auctions in financial markets is as market opening or closing mechanisms – a focus of an expansive stream of the literature (see as examples, Bellia, Pelizzon, Subrahmanyam, Uno, & Yuferova, 2020; Chang, Rhee, Stone, & Tang, 2008; Cordi, Foley, & Putniņš, 2015; Ibikunle, 2015). 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

[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

volume stocks on the LSE when compared to the levels of informational efficiency recorded for the continuous trading period. The study also finds that while 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 connected 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.

Furthermore, studies, such as Cordi et al. (2015) and Comerton-Forde, Lau, and Mcinish (2007), find positive links between market quality characteristics and the use of the closing call auction; Comerton-Forde et al. (2007) also 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, which are similar to the findings of Pagano and Schwartz (2003), who examine the introduction of the closing auction on the Paris Bourse. Thus, apart from the evidence from the LSE (for smaller stocks) presented by Ibikunle (2015), there appears to be a consensus in the literature on the association between the deployment of the call auctions and market quality characteristics. The findings discussed above may have implications for the use of PA at a high frequency.

Finally, more recently, using data from the Taiwan Stock Exchange (TWSE) Indriawan, Roberto, and Shkilko (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. First, while they focus on a transition from batch auctions to continuous trading, we investigate an event that should lead to an increased use of PA within a hybrid trading system. Second, TWSE's batch auctions are distinct from the PA we examine in that the former operates five-second interval auctions, while the PA systems we investigate operate maximum intervals of 100 milliseconds – a tenth of a second.

3. Background

3.1. Periodic auctions and market quality: hypotheses development

Although PA is 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. PA trading systems are structurally distinct from the other auction types that have been studied extensively in the literature. Firstly, PA has smaller intervals; Budish et al. (2015) suggest that the interval should be smaller than one second and, in line with their suggestion, the leading global system, operated by Cboe, provides 100 ms auction intervals. Secondly, PA is typically conducted alongside continuous trading, and currently the volume of PA only captures a small amount of the total volume in the market. Therefore, trading in PA might be more influenced by the market's main trading system than vice versa. Thirdly, the main aim of using PA as a trading mechanism 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 PA trading mechanisms. An investigation into the growth of PA in UK stocks by the FCA (2018) 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 PA. They also find limited changes in overall market quality. Foley et al.'s (2022) investigation of the impact of PA 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 PA 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).

Fig. 1 provides clear evidence of the above-noted spurts of growth in PA 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 Fig. 2). However, the overall picture presented in Fig. 1 and by the FCA (2018) fails to account for the differences in the growth of PA 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 PA 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 PA

Table 1
Variable definitions.

Variable	*Unit*	*Definition*
$PAVolume_{i,d}$	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*.
$RelativeSpread_{i,d}$	bp	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.
$AdverseSelection_{i,d}$	bp	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 min) divided by a short-term midpoint return variance (1 min) 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-s midpoint returns on day *d*.
$Volume_{i,d}$	'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*.

The table defines the variables employed in this study.

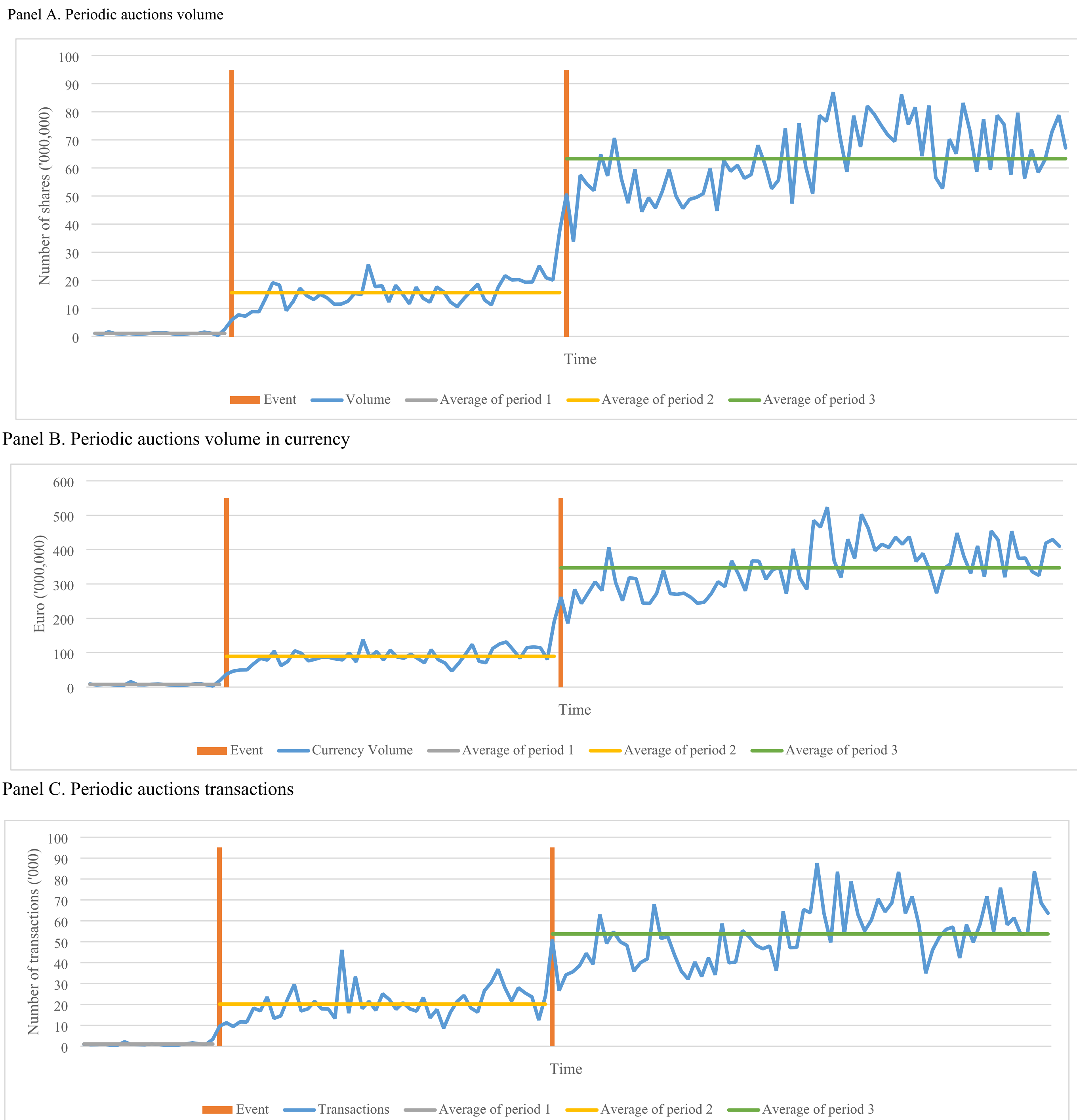


Fig. 1. Trading in periodic auctions books and the implementation of the double volume cap.
The figure plots the trading volume, currency volume and number of transactions in European periodic auctions books in relation to the implementation of the first double volume cap (DVC) for London Stock Exchange-listed 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. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

volume when compared to those with no DVC-related restrictions.

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, Ghysels, & Hatheway, 2000; Chang et al., 2008; Cordi et al., 2015; Jiang, Likitapiwat, & Mcinish, 2012). Therefore, it is

Panel A. Periodic auctions as a percentage of total volume, currency volume and transactions

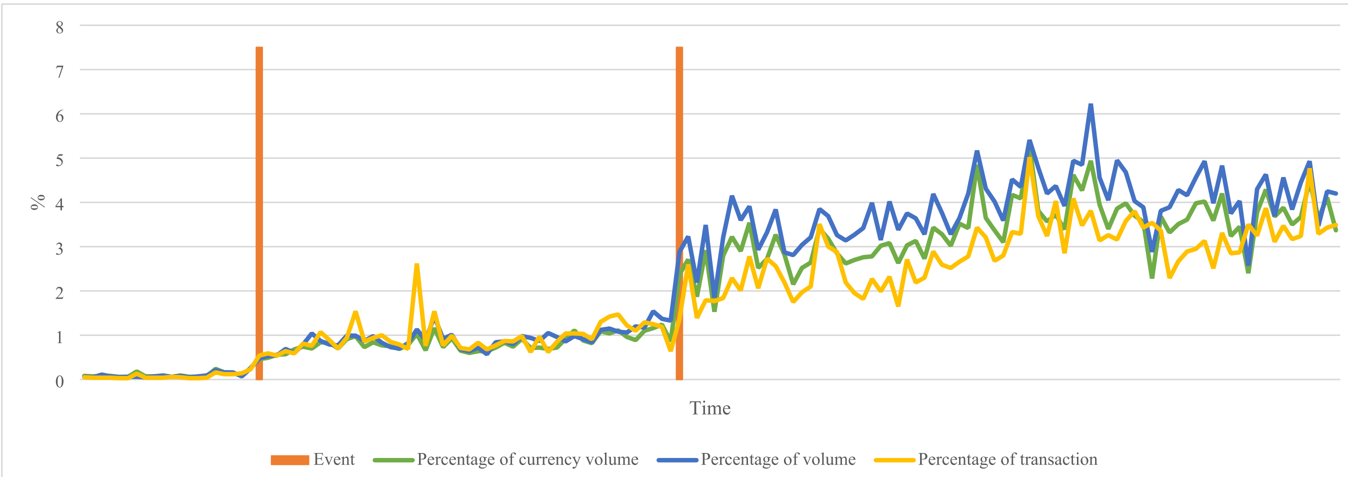


Fig. 2. Periodic auctions activity as a percentage of total market activity.
The figure plots the volume, currency volume and transactions of periodic auctions relative to the total market volume for London Stock Exchange-listed stocks and the implementation of the first double volume cap (DVC). The 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 as a percentage of total volume, currency volume and transactions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

rational to expect that PA interacts 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, Roll, & Subrahmanyam, 2001; Chordia, Roll, & Subrahmanyam, 2008), these implications are likely linked to PA volume. Although PA is deployed in European markets prior to the MiFID II era, as shown in Fig. 2, it 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 Cboe, 2020; FCA, 2018). The implementation of MiFID II provisions, especially the imposition of the DVC dark trading restrictions, changed this, leading to a substantial growth in PA volume, as seen in Fig. 1.

The above suggests that the potential effects of PA 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 an increased use of PA enhances or impairs market quality characteristics. Given the evolution of PA around the DVC implementation, the market quality effects of any changes in the volume of its could be linked to the effects of dark trading restrictions. Ibikunle, Li, Mare, and Sun (2021) 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 PA 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 may be expected to adversely impact liquidity in the affected stocks, PA should alleviate some of the liquidity constraints the DVC's implementation imposes. However, controlling for the effects of the DVC to cleanly test for the market quality effects of PA may yield a different outcome. Extrapolating from Kalay, Wei, and Wohl (2002), who show that PA is linked to a lower level of liquidity when compared with continuous trading, we should expect that an increase in PA relative to trading in the (transparent) continuous market will impair liquidity. Furthermore, according to Amihud et al. (1997), introducing continuous trading to a hitherto auctions-based market enhances liquidity; hence, we should expect that an increase in PA relative to continuous trading will lead to a deterioration in liquidity. Finally, that PA may restrict market making HFT competition, which Brogaard and Garriott (2019) show improves market quality implies that PA may impair liquidity. 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 PA impairs liquidity.

The argument regarding the effects of PA 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 PA and call auctions suggest that PA will be negatively related to adverse selection costs:

Hypothesis 4. PA is inversely 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 PA (see Johann et al., 2019). An increase in the volume of slow (uninformed) traders in lit venues, or at least fewer 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 PA on informational efficiency is likely to be to impair it. 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, PA is intentionally designed to slow down trading and counter the effects of speed in trading. Even at frequencies of 100 ms, price discovery may be impaired given that information transmission latency between two main financial centers in Europe (London and Frankfurt) that are furthest apart is a mere 2.3 ms (4.6 ms for a round trip).[2] Therefore, one anticipated effect of an increased use of PA on the price discovery process is making it less efficient, i.e., the price formation process becomes slower:

Hypothesis 6. PA is negatively linked to informational efficiency.

3.2. Periodic auctions in Europe

Cboe launched its PA trading mechanism in October 2015, using both the BXE and DXE order books. The stated aim of the PA book is to provide a trading environment with reduced emphasis on speed, instead enhancing the importance of price. PA 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 PA 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 100 ms. 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, 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 on Cboe, 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 PA volumes since 2018 Q2.[3] 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 PA book offers pre-trade transparency.[4]

The London Stock Exchange Group (LSEG) also subsequently introduced its own PA book called Turquoise Plato Lit Auctions, which has been in operation since 2017 Q4. Although the Turquoise PA 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,[5] 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.

4. Data, variable construction, and descriptive statistics

4.1. Sample, matching process, and data

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 PA trading activity in stocks affected by the DVC relative to those not affected; the framework itself exploits the DVC. This approach requires the matching of the affected (treatment) 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 PA 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 many 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, this process identifies a set of control and treatment stocks to employ in our DiD framework. To ascertain that deviations in the evolution of the market microstructure/quality characteristics of interest are linked to the evolution of dark trading, we must ensure that both the control and treatment groups of stocks have similar market microstructure properties to begin with. We conduct this matching in line with Shkilko and Sokolov (2020); we match every stock in the treatment group with a stock with dark trading privileges using total volume, a liquidity proxy (relative spread) and information efficiency proxy (5-s autocorrelation of intraday stock returns) for the first empirical framework. We compute matching error for a given number of pairs as follows:

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

where c_k corresponds to the matching criteria, including $Volume_{i,d}$, $RelativeSpread_{i,d}$ and $Autocorrelation_{i,d}$, and i and j represent a pair of stocks. $Volume_{i,d}$, $RelativeSpread_{i,d}$ and $Autocorrelation_{i,d}$ are formally defined in 3.2 below. Variables are sampled no later than a month prior to announcement of the DVC suspensions to ensure that they are not directly influenced by the shock. The matching process yields 57 control stocks and 57 treatment stocks. The success of the matching approach is underscored by the observation that the control and treatment 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).

PA transactions in FTSE 250 stocks mainly occur at Turquoise and

[2] https://www.reuters.com/article/us-highfrequency-microwave/lasers-microwave-deployed-in-high-speed-trading-arms-race-idUSBRE9400L920130501

[3] 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.

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

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

Table 2
Descriptive statistics.

Panel A. Summary statistics

Variables	Full sample		Smallest tercile		Median tercile		Largest 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
$PATransactions_{i,d}$	126.824	226.196	33.783	97.326	78.484	121.195	265.846	313.65
$ClosePrice_{i,d}$ (GBX)	1072.95	2857.64	1124.52	4666.98	747.460	926.17	1352.15	1477.17
$Volatility_{i,d}$	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)	1968.23	1573.13	956.067	447.842	1609.82	802.663	3311.24	1898.23
$Volume_{i,d}$ ('000)	1501.03	2953.16	616.46	1377.22	1206.57	2057.38	2655.77	4206.45
$Momentum_{i,d}$	−0.002	0.065	−0.002	0.068	−0.002	0.059	−0.0003	0.046
$RelativeSpread_{i,d}$	18.920	16.945	29.864	23.753	16.508	8.115	10.699	7.627
$AdverseSelection_{i,d}$	0.322	0.106	0.531	1.589	0.287	0.848	0.151	0.609
$VarianceRatio_{i,d}$	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	Treatment group	Control group	Difference	*t*-statistics
$Autocorrelation_{i,d}$	0.049111	0.047691	0.00142	0.624
$RelativeSpread_{i,d}$	25.7	21.6	4.1	−1.531
$Volume_{i,d}$ ('000)	1222.827	1276.462	−53.635	−0.912

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 $PATransactions_{i,d}$ 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 (in basis points) for stock *i* on day *d*. $AdverseSelection_{i,d}$ is the daily volume-weighted average of adverse selection cost (in basis points) 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.

Cboe, with the two exchanges capturing more than 85% of the PA 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 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.

4.2. 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).[6] 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. $RelativeSpread_{i,d}$ (expressed in basis points) 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 Foley et al. (2022) 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

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

adverse selection costs, thereby protecting themselves from being adversely selected. 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:

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

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-s 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-s. In the regression models, we employ daily volume-weighted estimates of $Adverse\ selection_{i,\tau}$ for stock i at day d in basis points; this is denoted as $AdverseSeletcion_{i,d}$.

Informational efficiency is an important market quality characteristic because it indicates the extent to which instruments' prices reflect information. Therefore, we follow Boehmer, Fong, and Wu (2021) 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-s 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:

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

$Autocorrelation_{i,d}$ is the absolute value for the 5-s midpoint return autocorrelation for stock i on day d. In the formula, $return_{i,d,n}$ is the nth of the 5-s length midpoint return of stock i on day d, and $return_{i,d,n-1}$ is the $(n-1)$th of the 5-s 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 Eq. (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 min and 5 min 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.

4.3. Other variables

Several other variables are also estimated as proxies for PA trading activity and those employed as controls in our models. PA proxies include $PAVolume_{i,d}$, $PACurrencyVolume_{i,d}$ and $PATransactions_{i,d}$ and they are defined as trading volume, currency value of traded volume and transactions of PA 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-PA 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-min 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.

4.4. 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. Reporting in trading activity terciles recognises the theoretical (and empirical) links between trading activity and market quality characteristics, and thus may allow for the observation of additional interesting insights linked to variations in trading activity in the sub-samples. 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 PA, 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 PA 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., 2021).

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.

5. Empirical framework

5.1. Tracking the 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 PA. 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 treatment groups of stocks. In all cases there are statistically significant increases in PA trading activity following the DVC; however, the increases are far more pronounced for the treatment stocks. As can be observed in Table 3, while the magnitude of increase in the control group's PA trading activity metrics are 2.59, 2.61 and 2.25 for $PAVolume_{i,d}$,$PACurrencyVolume_{i,d}$ and $PATransactions_{i,d}$ respectively, the corresponding estimates for the treatment group of stocks are 5.62, 5.50 and 3.03. This is unsurprising given that following the DVC, the treatment stocks lose the opportunity to trade in dark pools – an increasingly popular trading mechanism. Hence, the implication of the estimates is that the imposition of dark trading restrictions induced a migration of dark trading volume in the treatment group of stocks to PA.

While this univariate investigation is useful, it is important to control for the myriad of factors that could be driving the evolution of PA vol-

Table 3
Trading activity in periodic auctions order books.

	Control group			Treatment group		
Variables	$PAVolume_{i,d}$	$PACurrencyVolume_{i,d}$	$PATransactions_{i,d}$	$PAVolume_{i,d}$	$PACurrencyVolume_{i,d}$	$PATransactions_{i,d}$
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
Difference factor	2.59	2.61	2.25	5.62	5.50	3.03

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 treatment groups of stocks each have 57 stocks. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

ume. Hence, we construct the following DiD model to estimate how the imposition of DVC drives PA 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 PA proxies, i.e. $PAVolume_{i,d}$,$PACurrencyVolume_{i,d}$ and $PATransactions_{i,d}$, 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 respectively. The standard errors are double-clustered by stock and time, and are robust to autocorrelation and heteroscedasticity. The key coefficient of interest here is β_3, a positive and statistically significant coefficient estimate would indicate a statistically significant increase in the use of PA as a trading mechanism in treatment stocks following the imposition of the DVC when compared with the control group of stocks.

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 $PATransactions_{i,d}$. In particular, the three variables need to have parallel trends in the treatment and control groups in the absence of an event.

Panels A, B and C in Fig. 3 clearly show that the three variables employed in Eq. (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.

5.2. Periodic auctions and market quality

5.2.1. Liquidity analysis

Since we focus on estimating the effects of the increase in PA trading activity 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 stock-day panel regression model. This also allows us to expand our sample size to 158 stocks with varying levels of PA trading activity over the full sample period.

The multivariate regression model we estimate is as follows:

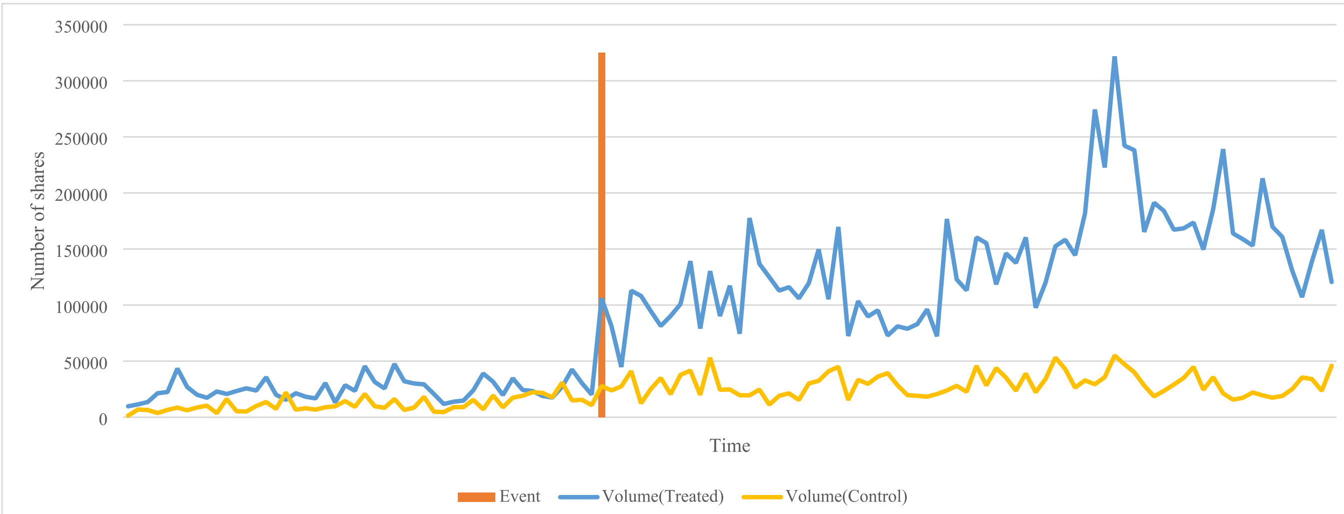
$$RelativeSpread_{i,d} = \alpha + \beta_1 PATransactions_{i,d} + \beta_2 DVC_d + \beta_3 Control_{i,d} + \delta_i i + \epsilon_{i,d} \quad (7)$$

where all variables are as previously defined. The main variable of interest is $PATransactions_{i,d}$, introduced to capture the effects of the evolution of PA on the liquidity proxy, $RelativeSpread_{i,d}$. DVC_d is added to the model to control for the effects dark trading restriction occurring during the sample period. β_1 is the key coefficient of interest here. A positive (negative) estimate would suggest a widening (narrowing) of the spread and hence a corresponding loss (enhancement) of liquidity with a greater use of PA as a trading mechanism.

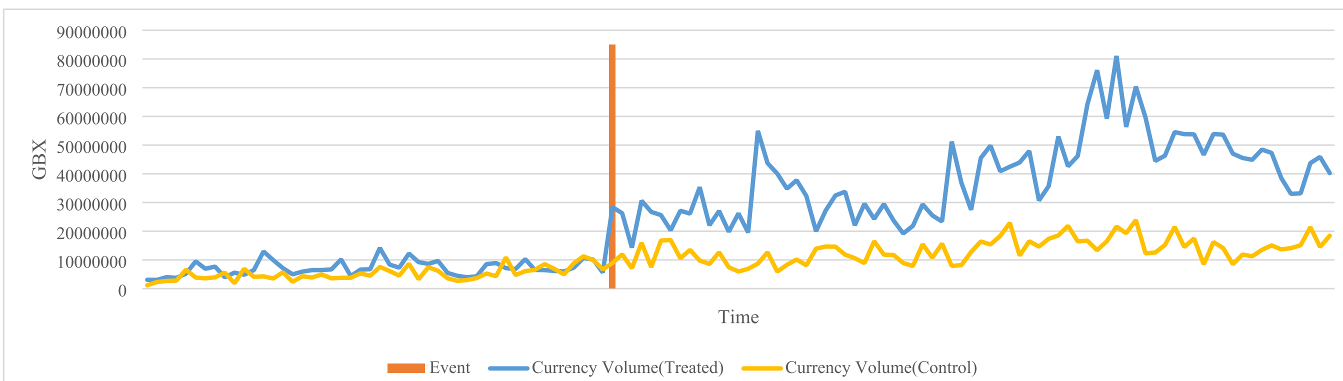
Eq. (7) is estimated using an instrumental variable setting to account for the likelihood of the endogenous determination of PA trading activity. The crucial challenge in employing an instrumental variable framework is the identification of a suitable instrument for $PATransactions_{i,d}$. It would be preferable to exploit a natural event in developing an experiment that would allow us to account for endogeneity issues; however, no such event occurs during our sample period. Therefore, we look to the existing literature to devise instruments that meet the usual conditions for good instrument candidates, i.e., the need for instruments to be highly correlated with the variable to be instrumented, and largely uncorrelated with $\epsilon_{i,d}$ in Eq. (7). We identify and employ two sets of IVs. The first IV approach is the one first proposed by Hasbrouck and Saar (2013) and thereafter used by several others such as Buti, Rindi, and Werner (2011), Comerton-Forde and Putniņš (2015) and Degryse, De Jong, and Kervel (2015). It involves instrumenting the variables using the average level of $PATransactions_{i,d}$ in stocks of similar market capitalisation. In this paper, we use stocks in the same average daily trading value (in pounds sterling) decile for instrumenting a stock's $PATransactions_{i,d}$ value.

The second IVs construction approach aims to maximise the potential for instrument-disturbance orthogonality by extending the Hasbrouck and Saar (2013) approach. It entails firstly using the initial averages of the trading variables across stocks in the same decile in a panel least squares framework, which regresses $PATransactions_{i,d}$ on its corresponding decile cross-sectional stock average and the other control variables. The residuals from this step are then employed as IVs. The expected lack of correlation between the IVs and Eq. (7)'s error term is that the common cross-sectional components in the stock averages would have been 'exhausted' in explaining the changes in the endogenous variable, thus leaving only the stock-dependent factors not explained by the cross-sectional average. In the first stage regressions, we regress $PATransactions_{i,d}$ on the instrumental variable and control variables as described above, for each stock. The first-stage *F-statistics*, testing the null of weak instruments, show that our models do not suffer weak instruments issues, with only four test statistics falling below the

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 $PATransactions_{i,d}$ in relation to the DVC

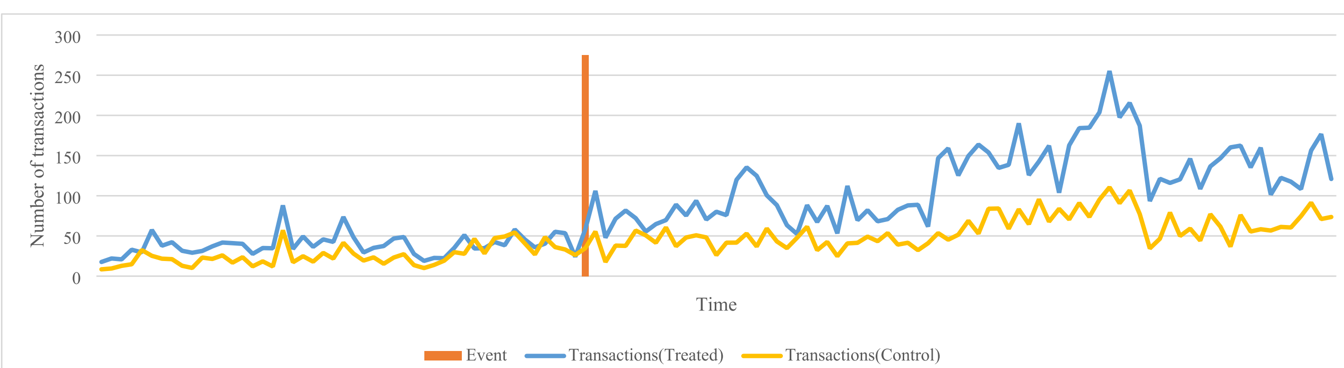


Fig. 3. Evolution of outcome variables for treatment and control groups.

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 $PATransactions_{i,d}$ in relation to the DVC.

threshold of 10, which Stock, Wright, and Yogo (2002)suggest is required for 2SLS inferences to be reliable. The values of the four F-statistics are 8.47, 9.05, 9.05 and 9.59. Furthermore, in all the regressions, Cragg and Donald (1993) and Kleibergen-Paap LM statistics reject the nulls of weak instruments and under-identification, based on the critical values, respectively.

Results based on both IV approaches are broadly consistent; hence, we present and discuss only the results for the second IV approach in the main text, while those based on the first are available on an online appendix for reference. Standard errors are double clustered to account for dependencies in the data and are robust to autocorrelation and heteroscedasticity.

5.2.2. Adverse selection analysis

We next investigate how the PA dynamics around the DVC impact adverse selection costs, a component of the spread. PA is 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 Indriawan et al., 2020; Shkilko & Sokolov, 2020), which suggests that a rise in PA across the full sample period could be linked to a reduction in adverse selection costs. To test this, we estimate the following stock-day panel regression model:

$$AdverseSelection_{i,d} = \alpha + \beta_1 PATransactions_{i,d} + \beta_2 DVC_d + +\beta_3 Control_{i,d} + \delta_i i + \epsilon_{i,d} \tag{8}$$

where $AdverseSelection_{i,d}$ is the daily volume-weighted adverse selection cost in stock *i* on day *d*. All other variables are as previously defined, and the equation is estimated using the same set of IV frameworks described in Section 4.2.1. Standard errors are double clustered to account for dependencies in the data and are robust to autocorrelation and heteroscedasticity. As in Eq. (7) β_1 is the key coefficient of interest in Eq. (8). A positive (negative) estimate would suggest an increase (decrease) in adverse selection costs with an increase in the use of PA as a trading mechanism. Since PA mechanisms are often intentionally designed to slow down trading and counter HFT strategies, it is logical to expect some impairment of the price discovery process through a delay in the incorporation of information into prices. A negative β_1 would support this expectation.

5.2.3. Informational efficiency analysis

We now address the question of how the evolution of PA relates to the efficiency of the price discovery process. Evidence on the direct effects of PA 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. Both theoretical and empirical studies (see Amihud et al., 1997; Chang et al., 2008; Comerton-Forde et al., 2007; Madhavan, 1992) suggest that call auctions improve the efficiency of the price discovery process. In order to ascertain how PA impacts informational efficiency, we estimate the following stock-day panel regression model using the same IV framework earlier described:

$$\begin{aligned} InformationalEfficiency_{i,d} = \alpha + \beta_1 PATransactions_{i,d} + \beta_2 DVC_d + \beta_3 Control_{i,d} \\ + \gamma_d d + \delta_i i + \epsilon_{i,d} \end{aligned} \tag{9}$$

where $InformationalEfficiency_{i,d}$ corresponds to one of $Autocorrelation_{i,d}$ or $VarianceRatio_{i,d}$. All other variables are as previously defined, and standard errors are double clustered to account for dependencies in the data and are robust to autocorrelation and heteroscedasticity. β_1 remains the key coefficient of interest. A positive (negative) β_1 estimate would suggest an impairment (enhancement) of informational efficiency as the use of PA as a trading mechanism increases. As PA slows down trading and counter HFT strategies, we should expect some impairment of informational efficiency through a delay in the incorporation of information into prices. Thus, we expect a positive β_1 estimates.

6. Results and discussions

6.1. The effects of dark trading bans on periodic auctions

Table 4 reports the regression results of Eq. (6). Panels A, B and C present the results for models where the log of $PAVolume_{i,d}$, $PACurrencyVolume_{i,d}$ and $PATransactions_{i,d}$ correspond to $PA_{i,d}$ in Eq. (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 PA 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 PA 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 PA transactions. This is because, while the number of PA 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 treatment group of stocks are generally traded more via PA 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 PA 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 PA as a trading mechanism in treatment 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. 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 with more than 60% of the orders executed by value in the smallest FTSE 250 stocks being executed 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 PA, 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.

6.2. Periodic auctions and liquidity

Table 5 reports the estimation results for Eq. (7). The parameters are presented for the full sample of stocks and by trading activity terciles. All the β_1 estimates are positive with three out of four statistically significant at conventional levels. This suggests that an increase in the use of PA during our sample period is harmful to liquidity. Considering that we control for the, admittedly, liquidity impairing effect of the DVC, this

Table 4
Trading activity in periodic auctions around the DVC.

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***	5.609×10^{-1}	1.688**	4.048***
	(3.734)	(1.325)	(2.467)	(3.827)
$RelativeSpread_{i,d}$	-1.066×10^{-2}***	-2.968×10^{-2}***	-1.469×10^{-2}***	-6.568×10^{-3}**
	(−4.152)	(−4.004)	(−2.585)	(−1.993)
$Volatility_{i,d}$	3.051×10^{-3}**	-5.171×10^{-3}	1.133×10^{-2}*	4.685×10^{-3}***
	(2.204)	(−1.085)	(1.854)	(2.834)
$OrderImbalance_{i,d}$	-1.027×10^{-1}	-2.206×10^{-1}	-1.370×10^{-1}	-2.886×10^{-2}
	(−1.173)	(−1.272)	(−0.817)	(−0.222)
$Momentum_{i,d}$	3.188×10^{-1}	4.894×10^{-1}	-3.841×10^{-1}	4.066×10^{-1}
	(0.772)	(0.859)	(−0.475)	(0.486)
Constant	−9.322***	−5.581	−4.811	-1.637×10^{1}***
	(−3.651)	(−1.529)	(−0.892)	(−3.596)
Observations	13,822	4657	4585	4580
$\overline{R^2}$	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***	4.448***	3.312***	2.135*
	(5.067)	(4.515)	(2.754)	1.704
$Treated_i$	1.126×10^{1}***	9.394***	−6.148***	1.895×10^{1}***
	(7.314)	(7.324)	(−4.210)	7.851
$DVC_d \times Treated_i$	2.579***	8.375×10^{-1}***	3.202***	3.837***
	(14.845)	(3.243)	(10.047)	11.627
$log(Volume_{i,d})$	1.157***	1.118***	1.116***	1.222***
	(16.891)	(9.647)	(8.297)	10.933
$log(ClosePrice_{i,d})$	-5.411×10^{-1}	3.360×10^{-1}	−1.367***	−3.796**
	(−1.431)	(0.531)	(−2.741)	−2.240
$log(MarketValue_{i,d})$	2.347***	6.034×10^{-1}	3.051***	6.645***
	(4.781)	(0.999)	(3.091)	3.834
$RelativeSpread_{i,d}$	-1.598×10^{-2}***	-4.879×10^{-2}***	-2.070×10^{-2}**	-9.064×10^{-3}*
	(−4.132)	(−4.614)	(−2.525)	−1.678
$Volatility_{i,d}$	3.939×10^{-3}*	-1.088×10^{-2}	1.622×10^{-2}*	5.808×10^{-3}**
	(1.888)	(−1.600)	(1.841)	(2.144)
$OrderImbalance_{i,d}$	-1.850×10^{-1}	-3.618×10^{-1}	-1.918×10^{-1}	-7.361×10^{-2}
	(−1.402)	(−1.463)	(−0.793)	(−0.345)
$Momentum_{i,d}$	2.467×10^{-1}	3.511×10^{-1}	-5.091×10^{-1}	2.466×10^{-1}
	(0.397)	(0.432)	(−0.436)	(0.180)
Constant	-1.943×10^{1}***	-1.028×10^{1}**	−8.413	-3.177×10^{1}***
	(−5.049)	(−1.974)	(−1.081)	(−4.259)
Observations	13,822	4657	4585	4580
$\overline{R^2}$	0.704	0.735	0.667	0.635
Stock and time fixed effects	Yes	Yes	Yes	Yes

Panel C

Dependent variable: $log(PATransactions_{i,d})$

	Full sample	Largest tercile	Median tercile	Smallest tercile
DVC_d	1.228***	1.773***	1.213***	6.199×10^{-1}*
	(5.943)	(5.305)	(3.351)	(1.654)
$Treated_i$	4.524***	4.844***	−3.481***	5.727***
	(9.482)	(11.134)	(−7.915)	(7.930)
$DVC_d \times Treated_i$	9.756×10^{-1}***	4.627×10^{-1}***	1.102***	1.285***
	(18.123)	(5.282)	(11.481)	(13.009)
$log(Volume_{i,d})$	4.850×10^{-1}***	5.916×10^{-1}***	4.481×10^{-1}***	4.552×10^{-1}***
	(22.843)	(15.048)	(11.066)	(13.607)

(continued on next page)

Table 4 (*continued*)

Panel C				
Dependent variable: $log(PATransactions_{i,d})$				
	Full sample	Largest tercile	Median tercile	Smallest tercile
$log(ClosePrice_{i,d})$	-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^{-3}*** (−3.249)	-1.361×10^{-2}*** (−3.795)	-5.724×10^{-3}** (−2.319)	-2.491×10^{-3} (−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	4657	4585	4580
$\overline{R^2}$	0.767	0.788	0.737	0.672
Stock and time fixed effects	Yes	Yes	Yes	Yes

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 $PATransactions_{i,d}$ (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 treatment groups of stocks each have 57 stocks. The stocks are divided into terciles using currency volume in GBX. The t-statistics are presented in parentheses and derived from standard errors clustered by stock and date. ***, ** and * correspond to statistical significance at the 0.01, 0.05 and 0.1 levels respectively.

finding is meaningful, and economically so as well. The parameter estimates show that a one unit increase in PA transactions is linked with increases in relative spread of about 0.237, 0.087, 0.040 and 0.411 bps for the full sample, largest, median and smallest terciles of stocks respectively.[7] Compared with the mean relative spread, these estimates suggest respective increases of 1.25%, 0.81%, 0.24% and 1.38% in the relative spread, thus underscoring the economic significance of the effects of PA activity. This finding is consistent with Kalay et al. (2002), who find that call auctions are linked to a lower level of liquidity in comparison with continuous trading, thus implying that an increase in PA at the expense of trading in the continuous market may harm the liquidity. Amihud et al. (1997) also suggest that liquidity is enhanced by the addition of a continuous mechanism to call auctions; hence, our results showing that liquidity deteriorates in line with PA is consistent with the extant literature. Furthermore, Brogaard and Garriott (2019) show that HFT arbitrageur competition improves liquidity, and PA, as a mechanism are designed to address latency arbitrages ensuing from HFT arbitrageur activity. Hence, as PA usage increases, we should expect a reduction in the HFT arbitrageur competition and by consequence a deterioration in liquidity.

The DVC_d coefficient estimates (the β_2s) are also of interest. However, the corresponding coefficient estimates are generally not statistically significant, except for the largest tercile of stocks estimates. In line with Ibikunle et al. (2021), we would expect that the imposition of the dark trading restriction during our sample period is generally linked with a loss of liquidity; however, the largest tercile's coefficient estimate is −0.329 statistically significant at 0.05 level, implying that the DVC imposition is linked with an improvement in liquidity. A plausible explanation for this contradictory result is that, as argued by Comerton-Forde and Putniņš (2015), there is a threshold at which an increase in dark trading volume impairs market quality characteristics, such as liquidity. Hence, if the threshold is much lower for large stocks than for other stock categories, and the level of dark trading in large stocks had already reached a level where dark trading impairs liquidity, a dark trading halt should elicit some liquidity improvements, at least in the short-term.

Nevertheless, the seeming inconsistency of the DVC coefficient estimate for the largest tercile of stocks in Table 5 is underlined by a contradictory corresponding estimate of 0.295 obtained from the alternative IV specification.

6.3. Periodic auctions and adverse selection costs

Table 6 reports the estimated coefficients for Eq. (8). The negative β_1 coefficient estimates indicate that the effects of PA on adverse selection costs are consistent across all terciles and the full sample, and statistically significant at conventional levels, except for the smallest tercile. The estimates support Hypothesis 5. The result also suggests that the wider spreads observed as being linked to increasing PA activity in

[7] The corresponding coefficients are 0.32, 0.08, 0.07 and 0.46 bps for the panel least squares estimation as reported in Panel A of Table B1 in the online appendix, implying that a one unit increase in periodic auctions transactions is linked with increases of about 0.186, 0.048, 0.039 and 0.266 bps in relative spreads for the full sample, largest, median, and smallest terciles of stocks respectively. The estimates are 0.42, 0.22, 0.44 and 0.32 bps for the 2SLS alternative IV estimations reported in Panel B of Table B1 in the online appendix, thus showing that a one unit increase in periodic auctions transactions is linked with increases of 0.243, 0.126, 0.257 and 0.186 bps in relative spreads for full sample, largest, median, and smallest terciles of stocks respectively.

Table 5
The effects of periodic auctions on liquidity.

Dependent variable: $RelativeSpread_{i,d}$				
	Full sample	Largest tercile	Median tercile	Smallest tercile
$log(PATransactions_{i,d})$	4.007×10^{-1}**	1.488×10^{-1}***	6.812×10^{-2}	7.066×10^{-1}**
	(2.556)	(2.745)	(0.536)	(2.481)
DVC_d	-1.166×10^{-1}	-3.286×10^{-1}**	-2.089×10^{-1}	-4.795×10^{-1}
	(−0.377)	(−2.494)	(−0.536)	(−0.636)
$log(Volume_{i,d})$	-5.035×10^{-1}***	2.396×10^{-1}***	-9.898×10^{-2}	-7.728×10^{-1}**
	(−2.639)	(3.472)	(−1.196)	(−2.520)
$1/ClosePrice_{i,d}$	5.460×10^{2}	-2.708×10^{2}	4.679	2.634×10^{2}
	(1.057)	(−1.515)	(0.018)	(0.410)
$log(MarketValue_{i,d})$	−7.458**	−3.858***	−3.292	-2.047×10^{1}**
	(−2.396)	(−5.745)	(−1.549)	(−2.212)
$OrderImbalance_{i,d}$	8.103×10^{-2}	-6.291×10^{-2}	-5.000×10^{-1}	3.988×10^{-1}
	(0.135)	(−0.311)	(−1.672)	(0.431)
$Momentum_{i,d}$	−2.551	3.209×10^{-2}	-1.241×10^{-1}	−7.048*
	(−1.605)	(0.067)	(−0.132)	(−1.776)
$Volatility_{i,d}$	−1.047	-6.294×10^{-4}	5.976×10^{-3}*	-3.422×10^{-2}
	(−0.414)	(−0.450)	(2.054)	(−0.913)
Observations	19,122	6368	6439	6315
$\overline{R^2}$	0.765	0.761	0.662	0.675
Within R^2	0.024	0.069	0.019	0.042
Fixed Effects	Stock	Stock	Stock	Stock
Kleibergen-Paap LM	5360.326***	1017.597***	831.906***	835.235***
Cragg-Donald	7444.728***	1209.422***	953.998***	961.171***

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

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

where $RelativeSpread_{i,d}$ is the daily volume-weighted average relative quoted spread for stock *i* on day *d*, $PATransactions_{i,d}$ 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*. $PATransactions_{i,d}$ is instrumented for stock *i* by first collecting its stock decile $PATransactions_{i,d}$ cross-sectional averages. $PATransactions_{i,d}$ is then regressed on the corresponding cross-sectional stock averages and the other control variables in a panel least squares framework; the residuals yielded by this estimation are each employed as the IV for $PATransactions_{i,d}$. The t-statistics are presented in parentheses and derived from standard errors clustered by stock and date. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. 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.

Section 4.2.1 are not due to an increase in adverse selection costs. Hence, it appears that the impairment in liquidity in the wake of increasing PA volumes is likely linked to longer queues and an increase in order processions costs. The effects of a one unit increase in PA transactions are −0.019, −0.021, −0.038 and − 0.014 bps for the full sample, largest, median, and smallest terciles of stocks respectively.[8] These estimates imply that the effects are economically significant when compared with the mean of adverse selection cost estimates. A one unit increase in PA transactions is linked with reductions of about −6.2%, −10.7%, −12.6% and − 2.76% in adverse selection costs for the full sample, largest, median, and smallest terciles of stocks respectively. This is a further indication that PA may be relevant to addressing the toxic latency arbitrage problem associated with the technological arms race.

The finding that increasing PA volumes is linked with a reduction in adverse selection in the continuous market is in line with the stream of the literature, e.g., Brogaard et al. (2021) and Amihud et al. (1997), that suggests that call auctions generate lower price impacts or information asymmetry relative to continuous trading mechanisms. Brogaard et al. (2021) also show that the call auction is attractive to traders who do not require immediacy but need greater depth, and that short-term informed traders may be keener to use such mechanisms. The implication of these is that PA extracts liquidity from continuous markets, leading to hitherto informed traders being dis-incentivized to acquire new information to trade with in the continuous market. This argument reconciles the finding that increasing PA volume is linked with both a reduction in liquidity and adverse selection cost in the continuous market.

In a related theoretical study, Economides and Schwartz (1995) demonstrate that call auctions can reduce information asymmetry due to their facilitation of simultaneous execution, which alleviates the effects of information asymmetry. Schwartz (2012) also 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 auctioning in PA occurs 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

[8] The coefficients are −0.02, −0.03, −0.50 and − 0.01 bps for the panel least squares estimation as reported in Panel A of Table B2 in the online appendix, implying that a one unit increase in periodic auctions transactions is linked with decreases of about −0.014, −0.015, −0.291 and − 0.006 bps in adverse selection costs for the full sample, largest, median, and smallest terciles of stocks respectively. The estimates are −0.12, −0.10, −0.20 and − 0.05 bps for the 2SLS alternative IV estimations reported in Panel B of Table B2 in the online appendix, thus showing that a one unit increase in periodic auctions transactions is linked with decreases of about −0.243, −0.126, −0.257 and − 0.187 bps in adverse selection costs for full sample, largest, median, and smallest terciles of stocks respectively.

Table 6
The effects of periodic auctions on adverse selection.

Dependent variable: $AdverseSelection_{i,d}$

	Full sample	Largest tercile	Median tercile	Smallest tercile
$log(PATransactions_{i,d})$	-3.213×10^{-2}**	-3.668×10^{-2}***	-6.471×10^{-2}***	-2.372×10^{-2}
	(−2.540)	(−3.328)	(−5.663)	(−0.949)
DVC_d	-1.755×10^{-1}***	-8.062×10^{-2}***	-1.759×10^{-1}***	-2.782×10^{-1}***
	(−4.671)	(−4.646)	(−5.709)	(−3.349)
$RelativeSpread_{i,d}$	5.198×10^{-3}	3.671×10^{-3}	1.380×10^{-2}***	4.003×10^{-3}
	(1.448)	(0.664)	(3.797)	(1.062)
$log(Volume_{i,d})$	2.431×10^{-2}*	3.289×10^{-2}**	6.364×10^{-2}***	1.833×10^{-2}
	(1.721)	(2.227)	(5.495)	(0.742)
$1/ClosePrice_{i,d}$	-1.858×10^{1}	3.084×10^{1}	9.201×10^{1}***	-4.486×10^{1}*
	(−0.616)	(0.960)	(4.318)	(−1.939)
$log(MarketValue_{i,d})$	-5.251×10^{-1}***	-4.051×10^{-1}***	-3.370×10^{-1}***	-7.887×10^{-1}*
	(−3.626)	(−4.315)	(−2.749)	(−1.801)
$OrderImbalance_{i,d}$	5.142×10^{-2}	-2.390×10^{-2}	7.929×10^{-2}	5.144×10^{-2}
	(0.976)	(−0.879)	(1.488)	(0.654)
$Momentum_{i,d}$	-5.048×10^{-1}**	-1.192×10^{-1}**	-9.190×10^{-2}	−1.060*
	(−2.169)	(−2.099)	(−0.735)	(−1.876)
$Volatility_{i,d}$	-2.238×10^{-3}***	-5.408×10^{-4}**	-9.141×10^{-4}	-3.889×10^{-3}***
	(−2.693)	(−2.011)	(−1.567)	(−5.486)
Observations	19,122	6368	6439	6315
$\overline{R^2}$	0.106	0.126	0.132	0.081
Within R^2	0.025	0.076	0.081	0.023
Fixed Effects	Stock	Stock	Stock	Stock
Kleibergen-Paap LM	5633.375***	1004.678***	844.799***	838.026***
Cragg-Donald	7981.915***	1191.005***	970.865***	964.722***

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

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

where $AdverseSelection_{i,d}$ is the daily volume-weighted average of adverse selection costs for stock *i* on day *d*, $PATransactions_{i,d}$ 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*. $PATransactions_{i,d}$ is instrumented for stock *i* by first collecting its stock decile $PATransactions_{i,d}$ cross-sectional averages. $PATransactions_{i,d}$ is then regressed on the corresponding cross-sectional stock averages and the other control variables in a panel least squares framework; the residuals yielded by this estimation are each employed as the IV for $PATransactions_{i,d}$. The t-statistics are presented in parentheses and derived from standard errors clustered by stock and date. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. 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 PA mechanisms. Results here support our Hypothesis 4 that an increase in PA is linked with a reduction in adverse selection costs.

In addition, the β_2 estimates show that the DVC is associated with a reduction in adverse selection in the full sample of stocks and terciles; all the coefficient estimates are statistically significant at the 0.01 level. The estimates suggest that after the introduction of the DVC, adverse selection costs decline, on average, by about 0.19%, 0.09%, 0.20% and 0.29% for the full, largest, median, and smallest stock terciles respectively. 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 a 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.

6.4. Periodic auctions and informational efficiency

Table 7 reports the regression results for Eq. (9), estimates for regression modeling based on $VarianceRatio_{i,d}$ and $Autocorrelation_{i,d}$ are presented in Panels A and B respectively. In Panel A, all β_1 estimates are negative, with the full sample and the largest tercile estimates statistically significant at the 0.01 level. The β_1 estimates indicate that a one unit increase in PA transactions improves informational efficiency, as measured using variance ratios, by 63.7, 130.2, 27.3 and 5.6 bps for the full sample, largest, median and smallest terciles of stocks respectively.[9] In economic terms, when compared with the mean variance ratio estimates, this implies that, on average, a unit increase in PA transactions improves informational efficiency by 1.12% and 2.16% in the cases of the full sample of largest tercile of stocks respectively. The

[9] The corresponding coefficients are −125, −258, −73 and − 7 bps for the panel least squares estimation as reported in Panel A of Table B3 in the online appendix, implying that a one unit increase in periodic auctions transactions is linked with decreases of about −72.63, −150.33, −42.75 and − 4.20 bps in the variance ratios for the full sample, largest, median, and smallest terciles of stocks respectively. The estimates are −16, −137, −4 and − 58 bps for the 2SLS alternative IV estimations reported in Panel B of Table B3 in the online appendix, thus showing that a one unit increase in periodic auctions transactions is linked with decreases of −9.58, −79.96, −2.52 and − 33.66 bps in the variance ratios for full sample, largest, median and smallest terciles of stocks respectively.

Table 7
The effects of periodic auctions on informational efficiency.

Panel A

Dependent variable: $VarianceRatio_{i,d}$

	Full sample	Largest tercile	Median tercile	Smallest tercile
$log(PATransactions_{i,d})$	-1.095×10^{-2}***	-2.237×10^{-2}**	-4.689×10^{-3}	-9.544×10^{-4}
	(−3.070)	(−2.629)	(−0.819)	(−0.138)
DVC_d	7.984×10^{-4}	1.295×10^{-2}	5.807×10^{-3}	9.771×10^{-3}
	(0.101)	(1.066)	(−0.499)	(0.812)
$RelativeSpread_{i,d}$	-2.050×10^{-3}***	-1.798×10^{-2}***	-6.514×10^{-3}***	-1.519×10^{-3}***
	(−3.074)	(−5.082)	(−2.857)	(−3.100)
$log(Volume_{i,d})$	-8.408×10^{-3}***	1.585×10^{-2}	1.072×10^{-3}	-1.242×10^{-3}
	(2.663)	(1.419)	(0.205)	(−0.215)
$1/ClosePrice_{i,d}$	−1.190	-2.098×10^{1}*	7.282×10^{-1}	−2.847
	(−0.319)	(−1.771)	(0.073)	(−0.602)
$log(MarketValue_{i,d})$	1.142×10^{-1}***	1.382×10^{-1}***	3.733×10^{-2}	1.186×10^{-1}***
	(3.856)	(2.856)	(0.647)	(2.792)
$OrderImbalance_{i,d}$	-1.551×10^{-4}	9.915×10^{-3}	3.671×10^{-3}	-3.122×10^{-3}
	(−0.013)	(0.396)	(0.167)	(−0.186)
$Momentum_{i,d}$	3.539×10^{-2}	1.338×10^{-2}	1.315×10^{-1}**	-9.470×10^{-3}
	(1.098)	(0.233)	(2.500)	(−0.218)
$Volatility_{i,d}$	-3.872×10^{-5}	-1.346×10^{-4}	-4.150×10^{-5}	1.390×10^{-5}
	(−0.615)	(−0.800)	(−0.625)	(0.182)
Observations	19,122	6368	6439	6315
$\overline{R^2}$	0.073	0.066	0.058	0.089
Within R^2	0.006	0.019	0.007	0.006
Fixed Effects	Stock	Stock	Stock	Stock
Kleibergen-Paap LM	5633.375***	1004.678***	844.799***	838.026***
Cragg-Donald	7981.915***	1191.005***	970.865***	964.722***

Panel B

Dependent variable: $Autocorrelation_{i,d}$

	Full sample	Largest tercile	Median tercile	Smallest tercile
$log(PATransactions_{i,d})$	7.567×10^{-3}***	1.500×10^{-2}***	7.526×10^{-3}***	4.805×10^{-3}***
	(3.446)	(3.182)	(2.994)	(3.410)
DVC_d	5.882×10^{-4}	-3.297×10^{-3}	7.281×10^{-3}	-1.719×10^{-3}
	(0.159)	(−0.495)	(1.610)	(−0.622)
$RelativeSpread_{i,d}$	5.544×10^{-5}	-2.011×10^{-3}*	-3.599×10^{-5}	1.126×10^{-4}***
	(1.190)	(−2.004)	(−0.087)	(3.607)
$log(Volume_{i,d})$	-6.593×10^{-3}***	-1.685×10^{-2}***	-7.348×10^{-3}***	-3.818×10^{-3}***
	(−3.346)	(−2.820)	(−3.097)	(−3.026)
$1/ClosePrice_{i,d}$	1.732	1.564×10^{1}**	5.679	3.521×10^{-1}
	(1.445)	(2.201)	(1.115)	(0.433)
$log(MarketValue_{i,d})$	-1.910×10^{-2}*	-2.424×10^{-2}	-6.724×10^{-3}	-2.659×10^{-2}**
	(−1.763)	(−1.195)	(−0.593)	(−2.468)
$OrderImbalance_{i,d}$	-7.347×10^{-3}**	1.106×10^{-3}	-1.655×10^{-2}**	-6.112×10^{-3}*
	(−2.284)	(0.092)	(−2.196)	(−1.788)
$Momentum_{i,d}$	-2.282×10^{-2}**	-5.306×10^{-2}**	-1.091×10^{-3}	-1.087×10^{-2}
	(−2.144)	(−2.079)	(−0.067)	(−1.172)
$Volatility_{i,d}$	1.157×10^{-5}	3.992×10^{-5}	-3.677×10^{-5}	2.105×10^{-5}
	(0.327)	(0.531)	(−0.623)	(1.055)
Observations	19,122	6368	6439	6315
$\overline{R^2}$	0.054	0.028	0.016	0.019
Within R^2	0.005	0.007	0.008	0.005
Fixed Effects	Stock	Stock	Stock	Stock
Kleibergen-Paap LM	5633.375***	1004.678***	844.799***	838.026***
Cragg-Donald	7981.915***	1191.005***	970.865***	964.722***

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

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

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). $PATransactions_{i,d}$ 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*. Others include log of $ClosePrice_{i,d}$, closing price for stock *i* on day *d* and $RelativeSpread_{i,d}$, a proxy for stock-day liquidity. $PATransactions_{i,d}$ is instrumented for stock *i* by first collecting its stock decile $PATransactions_{i,d}$ cross-sectional averages. $PATransactions_{i,d}$ is then regressed on the corresponding cross-sectional stock averages and the other control variables in a panel least squares framework; the residuals yielded by this estimation are each employed as the IV for $PATransactions_{i,d}$. The t-statistics are presented in parentheses and derived from standard errors clustered by stock and date. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. 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.

corresponding estimates are 0.45% and 0.11% for the median and smallest stock terciles respectively, implying a weaker effect linked to trading activity. These estimates are consistent with the arguments of Economides and Schwartz (1995) suggesting that PA can reduce the information asymmetry and enhance the price discovery process (see also, Amihud et al., 1997; Kalay et al., 2002; Madhavan, 1992).

However, in contrast, all the β_1 coefficient estimates in Panel B are positive and statistically significant at 0.01 level, thus strongly indicating that an increase in PA volumes is linked with a reduction in informational efficiency. Specifically, the coefficient estimates are 76, 150, 75 and 5 bps for the full sample, largest, median, and smallest terciles of stock respectively.[10] Results suggest a one unit increase in PA is linked with increases of about 42.76, 84.64, 42.56 and 27.11 bps in the autocorrelation of short-horizon returns. These estimates indicate respective corresponding increases of about 7.12%. 10.58%, 7.47% and 6.30% on average, which is economically significant.

We also note that the results presented in Panel B are on the whole much stronger than those obtained in Panel A. The Panel B estimates indicate a deviation of prices from the random and a loss of informational efficiency in response to higher levels of trading via PA. This finding is more in keeping with Menkveld et al.'s (2017) pecking order hypothesis, which argues that traders that value immediacy are more likely to trade in the (transparent) continuous markets, and these traders are more likely to be informed. The implication is therefore that as the increasing use of PA reduces the volume of uninformed traders in the continuous market, informed traders are, at a minimum, less able to quickly exploit their information sets in the continuous market. In an extreme case, we may also expect them to become dis-incentivized to acquire new information with which to trade (see Glosten & Milgrom, 1985; Kyle, 1985), thus resulting in reduced informational efficiency. Furthermore, given that PA is, by design, a slower trading mechanism than continuous trading, we should expect an increase in their use to lead to a slowing down of the price discovery process. This would imply an impairment of the informational efficiency. Overall, this ambiguity observed in the results presented in Table 7, when both panels are taken together, mirrors that of Johann et al. (2019), and is largely consistent with our Hypothesis 6, which states that PA is linked to a reduction in informational efficiency.

7. Conclusion

According to Budish et al. (2015), frequently batch auctioning offers an effective solution for addressing the twin challenges of latency arbitrage and the technological arms race in financial markets, as well as the externalities they induce (see Menkveld, 2014). However, the question of how frequently batching and uncrossing need 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 PA on market quality characteristics in UK-listed stocks. The UK financial markets – the most active trading environment in Europe during our sample period – offer a unique opportunity to assess the direct effects of a shift in trading volume towards PA 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 PA volumes than matched stocks with dark trading privileges. However, the overall market quality effects of PA are, for now, at best limited and mixed.

Controlling for the dark trading restrictions in place during our sample period, we find that, although PA trading activity is linked with a statistically significant and economically meaningful reduction in overall market liquidity, they are also linked with a decrease in adverse selection costs. This finding is consistent with the predictions of Budish et al. (2015): that PA offers a safe haven for slower traders who are susceptible to the latency arbitrage trading of faster traders. Thus, a rise in the use of PA lowers the incidence of slower traders being adversely selected. The illiquidity-inducing effect of PA also implies that trading in the continuous market becomes less attractive given lower volume of uninformed traders for informed traders to adversely select (see Brogaard et al., 2021).

The evidence of the impact of PA on informational efficiency is mixed, with variance ratio and autocorrelation of short-term returns, as informational efficiency proxies, yielding contrasting insights. This ambiguous view is in line with the recent literature (see Johann et al., 2019). Taken together, however, the overall weight of the results leans towards PA being linked with a deviation from the random walk and a reduction in informational efficiency. This finding is in line with PA 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), PA IS often deliberately designed as a mechanism to slow down trading, for example 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 PA in Europe, while in Taiwan the TWSE has recently replaced its discrete system with a continuous one (see Indriawan et al., 2020). Therefore, the insights on the market quality effects induced by 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 and speed in financial markets continues unabated. Our study offers evidence of the relevance of PA as a mechanism for addressing latency arbitrage and, by extension, the technological arms race.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.irfa.2023.102737.

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[10] The corresponding coefficients are 93, 80, 83 and 5 bps for the panel least squares estimation as reported in Panel C of Table B3, implying that a one unit increase in periodic auctions transactions is linked with increases of about 53.98, 104.93, 48.46 and 3.02 bps in the autocorrelation coefficients for the full sample, largest, median, and smallest terciles of stocks respectively. The estimates are 61, 91, 118 and 17 bps for the 2SLS alternative IV estimations reported in Panel D of Table B3, thus showing that a one unit increase in periodic auctions transactions is linked with increases of 35.65, 52.90, 68.44 and 9.83 bps in the autocorrelation coefficients for full sample, largest, median, and smallest terciles of stocks respectively.

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