Latency arbitrage and frequent batch auctions

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Abstract

We investigate the relationship between latency arbitrage and trading via frequent batch auctions (FBA). We show that increases in single and cross-market latency arbitrage opportunities (LAOs) are linked to an economically meaningful increase in FBA activity, which implies that slower traders view trading in FBA as an effective strategy to avoid being adversely selected on speed by high-frequency trading snipers. This effect is consistent irrespective of whether LAOs are toxic or not; however, they vary in their magnitude by LAO duration. Shorter durations are linked to progressively more severe shifts in trading activity from continuous lit trading to FBA.

Keywords: Frequent batch auctions; latency arbitrage; high-frequency trading; high-frequency market-making, endogenous liquidity supply.

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

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1. Introduction

In classical market microstructure models (for example, Kyle, 1985; Glosten, 1989; Glosten and Milgrom, 1985; Easley and O'hara, 1987), adverse selection risk is driven by private information or information asymmetry; thus, market-makers tend to widen their bid-ask spreads when confronted with this risk. Adverse selection risk is traditionally linked to more skilled investors/traders acquiring and exploiting information at the expense of the so-called uninformed traders. However, in today's high-frequency trading (HFT)-dominated financial markets, informed traders need not be skilled at acquiring private information; they simply need to be faster at trading on what may already be public information. Although public information may be observable by all traders at the same time, faster traders react and complete their trading with slower traders before the latter can defensively update their orders or issue cancelations. This is latency arbitrage, which is essentially the HFT version of adverse selection (Aquilina et al., 2020; Budish et al., 2015; Foucault et al., 2017). Hence, the speed of reaction to new information ends up contributing to the adverse selection cost faced by uninformed/slower traders (Budish et al., 2015; Easley et al., 2012). Although this form of adverse selection cost is somewhat different from the classic view of private information, the logic remains the same – some traders exploit new information ahead of other traders, thereby putting slower traders at a disadvantage. The fact that high-frequency traders (HFTs) can anticipate the trading pressure of slower traders (Hirschey, 2020; Foucault et al., 2016) has further reduced the reliance of sophisticated traders on classic information acquisition approaches in favor of significant investment in speed (see Budish et al., 2015; Rzayev et al., 2019). Consequently, the trading speed differential in financial markets has emerged as a critical factor in profit acquisition due to adverse selection.

Latency arbitrage opportunities can arise from single platform (Aquilina et al., 2020; Budish et al., 2015; Rzayev et al., 2019), or multi-platform (Hollifield et al., 2017; Foucault et al., 2017; Wah, 2016) strategies deployed by aggressive 'sniping' HFTs. Beyond increasing spreads to counter the potential loss, endogenous liquidity suppliers may also invest in HFT technologies to avoid being adversely selected (Menkveld and Zoican, 2017). This further intensifies the search for faster trading speeds and increasing competition among HFTs – both aggressive sniping and market-making liquidity-supplying ones. Rzayev et al. (2019) show that the effect of this increasing use of speed-enabling technology is dependent on the type of HFT that dominates the market. When endogenous liquidity suppliers are fast they can use their speed to avoid adverse selection and inventory management risks and thus they are more likely to supply liquidity, while aggressive HFTs adversely select slower traders, and thus induce illiquidity when the slower traders are forced to stop trading or seek shelter in less transparent mechanisms, such as dark pools. The competition among the different types of HFTs can also be problematic because it may result in a welfare-reducing technological arms race given the need for participants to maintain their speed differential to the competition (see Biais et al., 2015; Bongaerts et al., 2016). Unsurprisingly, these developments have been the focus of regulatory interventions in recent years, and some exchanges have sought to differentiate themselves as anathema to what HFT represents. For example, in 2016, IEX successfully lobbied the Securities and Exchange Commission (SEC) to introduce a 350 microsecond delay 'speed bump' in a bid to reduce HFTs' speed advantage; other exchanges, such as NYSE, have since offered speed bumps of their own (see Khapko and Zoican, 2020; Baldauf and Mollner, 2020). Another increasingly prevalent 'solution' to the latency arbitrage faced by slower traders is trading via frequent batch auctions (FBA), as proposed by Budish et al. (2015). This basically involves the transfer of volume from continuous to discrete markets, where order execution occurs in short intermittent millisecond-long bursts. The latter prioritizes price instead of speed.

Discrete mechanisms are well-established price-setting tools that are often used to determine opening and closing market prices (see Bellia et al., 2020; Chang et al., 2008; Cordi et al., 2015; Ibikunle, 2015). Madhavan (1992) argues that the pooling effect of the periodic auctioning system, which allows for simultaneous execution of periodic auctions, offers greater price efficiency than the continuous order-driven trading mechanism. 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 is not well-suited to addressing (see also Barclay et al., 2008). The simultaneous execution in classical auctions also enhances price discovery when deployed to complement continuous trading. Amihud et al. (1997) show that an iterated continuous trading process preceded by a call auction on the Tel Aviv Stock Exchange enhances price discovery. However, the modern iteration of periodic auctions, as deployed on European exchanges such as Cboe, are very different and more in keeping with the sub-second frequent batch auction mechanism advocated by Budish et al. (2015). The emergence of these mechanisms and their recent growth in trading activity therefore presents an opportunity to examine their interrelations with crucial market characteristics and phenomena, and to test some of the theoretical arguments already advanced regarding their role in curbing the technological arms race or addressing the exposure of slower traders to latency arbitrage. Early results are rather mixed. Although Zhang and Ibikunle (2020) show that the effects of FBA on market quality in the case of UK stocks is mostly benign, they also find that, under dark trading restrictions, FBA is linked to a deterioration in liquidity. They nevertheless show that, consistent with the theory, FBA is linked to reductions in adverse selection costs, thereby underscoring its potential to address latency arbitrage.

In this study, in a direct examination of the theoretical arguments advanced by Budish et al. (2015), we investigate the relationship between the evolution of FBA and latency arbitrage. Evidence obtained from our analysis shows that trading via FBA is an effective approach for slower traders to avoid being adversely selected by HFT snipers. Firstly, consistent with the existing research showing that market-making and endogenous liquidity-supplying HFTs constitute a larger proportion of HFTs than snipers in European markets (see, as an example, Hagströmer and Nordén, 2013), we show that a rise in HFT activity does not necessarily imply an increase in latency arbitrage activity; therefore, HFT is not a reliable gauge of the exposure of slow traders to sniping activity. Secondly, we find that, in line Budish et al.'s (2015) arguments, a general increase in single and cross-market latency arbitrage is linked to a rise in FBA volume, which implies that slower traders are avoiding being adversely selected on speed by faster sniping HFTs by escaping to the relative safety of the FBA. Thirdly, and as an extension of this finding, we show that, although non-toxic latency arbitrage is not harmful to slower traders, it nevertheless induces an economically meaningful shift in trading volume from continuous trading to FBA. Specifically, irrespective of whether latency arbitrage opportunities are toxic or not, their effect on FBA is consistent in that they instigate a rise in FBA trading activity. The implication of this finding is that slower traders at risk of being sniped are not sophisticated enough to distinguish between toxic latency arbitrage and non-toxic latency arbitrage. In conclusion, we find that the FBA volume-engendering effect of latency arbitrage is linked to how long the opportunities endure. Shorter duration latency arbitrage opportunities are linked to a general increase in FBA volume. Shorter duration latency arbitrage opportunities also imply a higher level of sniping activity because snipers are faster and more focused on identifying and exploiting these opportunities. This in turn induces a retreat from continuous lit market trading by slower traders. We show that as the duration of latency arbitrage opportunities increases, their effect on FBA declines along the duration curve.

Understanding the relationship between latency arbitrage opportunities and FBA/periodic auctions is not only crucial to validating Budish et al.'s (2015) theoretical predictions; it also has critical policy and asset allocation implications (see also Baldauf and Mollner, 2020). However, to the best of our knowledge this current study is the first to directly investigate this relationship. Related studies have, for example, offered evidence on how adverse selection risk and/or immediacy may drive trading decisions in markets where mechanisms with varying levels of transparency options exist (see Ibikunle et al., 2021; Menkveld et al., 2017; Zhang and Ibikunle, 2020; Zhu, 2014). However, while estimating adverse selection is a possible approach to proxying for latency arbitrage activity, doing so would capture significantly more than latency arbitrage and could be shown to include other forms of information asymmetry (Aquilina et al., 2020).

2. Institutional Background

Discrete market mechanisms have been extensively examined in the market microstructure literature, with relevant works including Madhavan (1992), Amihud et al. (1997), Comerton-Forde et al. (2007), Barclay and Hendershott (2008) and Ibikunle (2015). However, until recently, discrete trading mechanisms, such as open and closing call auctions, have mainly been employed for price-setting following a lull or a price discovery-impacting event. Budish et al. (2015) are the first to propose frequent batch auctions or high-frequency periodic auctions as a potential solution to the technological arms race and latency arbitrage in financial markets. Cboe's periodic auction mechanism, which was introduced in October 2015 is similar in structure to the FBA proposed by Budish et al. (2015). Its auction book, which currently accounts for more than 70% of the periodic auction volume in Europe, offers both pre-trade and post-trade transparency, thus meeting MiFID II's regulatory technical standards (RTS). Using data from the Cboe, FCA (2018) and Zhang and Ibikunle (2020) have mapped two waves of significant growth spurts in the FBA in Europe, one of which coincides with the first implementation of MiFID II's double volume cap (DVC) mechanism (Johann et al., 2019; Zhang and Ibikunle, 2020). However, the current trading environment is still quite different from the theoretical abstraction envisaged by Budish et al. (2015), given that their model outlines a market where FBA is the only medium of instrument exchange. Currently in Europe only about 5% of the market volume is exchanged via FBA-type mechanisms (Cboe, 2020). This is much higher than the pre-MiFiD II era – less than 1% – and it offers an empirical setting for investigating Budish et al.'s (2015) predictions. Furthermore, the volume of executions via the FBA is growing in Europe, with the focus of exchanges, consistent with Budish et al. (2015), being on providing a trading environment with reduced emphasis on speed, while prioritizing price.

The FBA orders at Cboe are accepted between 08:00 and 16:30hrs London time. Orders in different directions must be submitted separately since combined orders are not allowed in the submitting process. Auctions are conducted continuously and consecutively throughout the trading day. Traders can submit market, limit and pegged orders in the BXE and DXE order books. 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 under the maximum limit of 100ms. Each auction is split into two stages. In the first, the price determination stage, the auction price is formed, while, in the second, execution allocation is completed. Four criteria must be met to determine the auction prices: identifying maximum executable volume, minimum surplus, market pressure and reference price. The crucial issue here is ensuring that, for each auction, the mechanism selects the equilibrium price where the executed volume is maximized. For the price determination, a 'price/size/time' priority is set, underscoring the value of price in the auctions. In addition, the EBBO (European best bid and offer) collar has been introduced to ensure an orderly price formation process; requiring that the auction prices fall within the collar protects against the emergence of best execution issues.

In 2017, the London Stock Exchange Group (LSEG) also introduced its own FBA book called Turquoise Plato Lit Auctions (TPLA). The TPLA shares some features with the Cboe FBA, including order type, price priority, allocation, and price formation. However, the TPLA auction interval differs slightly from that of Cboe. In TPLA, the interval is divided into two parts: a 50-millisecond fixed interval, and a randomized interval with a maximum 50-millisecond duration. Hence, the interval durations vary from 50 to 100 milliseconds.

3. Hypothesis Development

Although there is a valid theoretical case for viewing the FBA as a viable tool to address latency arbitrage, the existing trading environment across markets is different from the theoretical abstractions of Easley et al. (2012) and Budish et al. (2015), and arguably more complex. This is especially the case given that HFT-enabling technologies are not employed by HFT snipers only. Endogenous liquidity providers, including market-makers and uninformed traders, may deploy HFT technologies to counter HFT snipers (Menkveld and Zoican, 2017), and empirical evidence suggests that they do so (see Rzayev et al., 2019). Therefore, it is also reasonable to consider whether estimating the level of HFT activity in a market can yield a reasonably accurate view of the rate of deployment of latency arbitrage strategies by HFT snipers. Indeed, Aquilina et al. (2020), Baldauf and Mollner (2020), and Menkveld and Zoican (2017) suggest that only treating HFTs as snipers can be misleading. Bernales (2019) also notes that HFTs tend to use limit orders rather than market orders when posting orders for large stocks, which underscores both the cautious behavior of HFT snipers and the need for caution in abrogating a rise in HFT activity to sniping HFT activity. HFT snipers only need to submit sniping orders or cancel these orders if they fail to turn a profit, while HFT market-makers need to update their orders by cancelling existing and/or submitting new ones more often, thus potentially triggering more HFT activity and a higher level of market-making HFT activity. Moreover, as market-making or endogenous liquidity-supplying HFTs do not necessarily need to leave the continuous market given their ability to avoid being adversely selected by latency arbitrageurs because of their fast-trading ability, they are unlikely to seek shelter in FBA-type mechanisms that may offer protection against the latency arbitrage strategies of HFT snipers. This also suggests that HFT activity in continuous markets is inversely related to FBA/periodic auctions. Thus, investing in HFT-enabling technologies, a trend documented by Rzayev et al. (2019) in the European markets, not only reduces reliance on FBA, but may also contribute to the offsetting effects of HFT on FBA/periodic auctions. Specifically, we would expect to see a reduced demand for trading via FBA following an increase in HFT activity. Therefore, we test the following preliminary hypothesis to investigate the evolution of the relationship between HFT and FBA.

Hypothesis 1: HFT is inversely related to FBA.

While an increase in aggregate HFT activity may be linked with a reduced demand for FBA, it is nevertheless plausible to expect that should the increase in aggregate HFT activity be predominantly driven by the activities of HFT snipers who deploy latency arbitrage strategies, the relationship between HFT and FBA will be positive. Therefore, we would expect increasing levels of market-making HFT to lead to a reduction in the use of FBA. Therefore, we test the following hypothesis:

Hypothesis 2: An increase in market-making HFT activity is linked with a reduction in FBA.

Next, we examine the case for the effects of latency arbitrage opportunities, which we argue is the crucial factor for FBA. This is because FBA has been depicted in the extant literature as a means of addressing latency arbitrage and the technological arms race in financial markets (Baldauf and Mollner, 2020; Budish et al., 2015). The ability of agents to compete on speed underpins latency arbitrage opportunities, while FBA devalues the relevance of speed and prioritizes price. Slower traders have the choice to take part in FBA, which can eliminate their speed disadvantage. Lack of an active trading environment may not be critical for some slower traders when compared to the risk of being sniped, especially for traders who do not prioritize immediacy in trading.

The emergence of latency arbitrage opportunities is linked to the availability of new information, and this may alert traders who have trading intentions regarding the onset of information asymmetry (Foucault et al., 2017; Hollifield et al., 2017; Aquilina et al., 2020). Uninformed trading at this point may lead to losses, especially for traders who lack the HFT infrastructure to infer the flow of information in the order flow, e.g., by observing order imbalance at high frequency. For this type of trader, the FBA offers some safety that continuous trading lacks with respect to latency arbitrage. Therefore, if the FBA is effective, after the onset of latency arbitrage there should be an increase in the volume of orders executed via FBA in response to the potential risk of being sniped. A rise in latency arbitrage opportunities should induce an increase in the volume of trading via FBA and other more opaque mechanisms because slower traders will likely shift their orders to avoid being sniped. Hence our third hypothesis:

Hypothesis 3: An increase in latency arbitrage opportunities leads to a rise in FBA volume.

According to the literature (Aquilina et al., 2020; Foucault et al., 2017; Hollifield et al., 2017; Budish et al., 2015), latency arbitrages can arise from both cross-market and single-market strategies/activities, and cross-market latency arbitrage opportunities can be further sorted into toxic and non-toxic types. All arbitrage opportunities or activities contribute to the price discovery processes in the market, but differ in their informational impacts (Foucault et al., 2017; Hollifield et al., 2017). According to Aquilina et al. (2020) and Budish et al. (2015), single-market latency arbitrage opportunities are related to informational impacts in the market due to the jump in prices caused by new information arriving in the market. However, for cross-market latency arbitrage opportunities, only the toxic types are related, while non-toxic latency arbitrage opportunities are caused by temporary liquidity shocks (Foucault et al., 2017). For liquidity suppliers, the existence of non-toxic cross-market arbitrage opportunities does not present a challenge with respect to being sniped, and, according to Foucault et al. (2017), these can even be profitable for liquidity suppliers. However, in both the cross-market and single-market the toxic latency arbitrage opportunities adversely impact liquidity suppliers. According to Aquilina et al. (2020), Budish et al. (2015), Hollifield et al. (2017), and Foucault et al. (2017), both toxic cross-market and single-market latency arbitrage opportunities imply the difference of speed in reaction to new information among arbitragers (snipers) and endogenous liquidity suppliers. Facing these opportunities, it is necessary for liquidity suppliers to consider strategies that avoid the losses arising from being sniped by the faster traders. Menkveld and Zoican (2017) state that some liquidity suppliers also employ HFT and take part in competing on speed, but for slow liquidity suppliers, hybrid markets with FBA-type mechanisms provide further (welcome) trading options for these traders. In such a case, more toxic cross-market opportunities and single-market latency arbitrage opportunities may induce an increase in FBA volume.[1] Based on the above, we test the following hypothesis:

Hypothesis 4: The effect of an increase in latency arbitrage opportunities on FBA volume is dependent on whether the opportunities are toxic or non-toxic. Toxic latency arbitrage opportunities induce an increase in FBA volume, while the effect of non-toxic latency arbitrage opportunities is benign.

Finally, we consider an important feature of latency arbitrage opportunities, which is the duration of latency arbitrage opportunities. Wah (2016), Hollifield et al. (2017), Foucault et al. (2017), and Aquilina et al. (2020) state that latency arbitrage opportunities differ in terms of duration, and suggest that this is the defining feature of their effect on market quality characteristics. Furthermore, according to Aquilina et al. (2020) and Budish et al. (2015), HFT snipers tend to have the fastest speeds in the market and win a large proportion of the competition in latency arbitrage exchanges. Hence, if HFT snipers win most of the latency arbitrage exchanges they engage in, the durations of different opportunities should be mostly decided by snipers' reactions because the strategy of snipers is to capture as much potential profit as fast as possible. They tend to submit orders satisfying the entire potential volume offered by an arbitrage opportunity with the 'sniping price', which indicates that opportunities are generally closed by snipers. Therefore, it is logical to expect that different durations may impact FBA volume differently. Shorter durations may suggest that snipers are more active and can thus make profits more rapidly during such opportunities, which in turn would imply a riskier situation for slower traders. This may encourage traders who do not

[1] We note the argument that slow traders may be ill-equipped to ascertain whether latency arbitrage opportunities are toxic or non-toxic. They may also be too risk-averse, and therefore reroute orders in the face of a general increase in latency arbitrage opportunities. Hence, their pattern of FBA activity, or even whether they employ FBA when facing different types of latency arbitrage opportunities, remains unclear.

want to be sniped to choose to trade via FBA, and to forego competing with HFT snipers, especially in the case of traders who can employ both approaches to protect themselves. Conversely, longer durations may suggest that snipers are not active enough to effectively snipe slower traders, and slower traders may therefore have more latitude to avoid being sniped. The other possibility for longer durations is that, in this scenario, HFT competition could still be beneficial for market-makers due to the slower reactions of snipers. This also means that traders who have the option of both trading using FBA and competing on speed with snipers may choose to employ the latter strategy given its lower risk profile. Therefore, our final hypothesis is as follows:

Hypothesis 5: The effect of latency arbitrage opportunities on the FBA is dependent on the duration of the opportunities.

4. Data and Empirical Framework

4.1. Data

We collect tick-by-tick data for FTSE 100 stocks from the Refinitiv Datascope (formerly Thomson Reuter Tick History version 2/TRTHv2) database, which provides data based on intraday message information at the nanosecond level. The dataset collected includes variables stocks' Reuters Identification Code (RIC), message type (identifying transaction/order), date, timestamp, transaction price and volume, bid price, ask price, bid size and ask size. The specific auction data collected includes RIC, types, date, timestamp, price and volume. Data is collected for the two largest exchanges facilitating the execution of FTSE 100 stocks in London – the London Stock Exchange (LSE) and Cboe; these two exchanges account for a combined 84% of the entire executed volume in FTSE 100 stocks during our sample period. The location of both venues in London avoids any potential concatenation issues as they relate to the times of exchange order submission and execution. We also employ the exact exchange times submitted to Refinitiv; hence the timestamps in our dataset captures are consistent with exchange records and not when messages are relayed to Refinitiv. The dataset covers all trading days for the two-year period spanning 2nd January 2019 to 31st December 2020, and includes all transactions recorded during the regular trading hours of 09:00 to 16:30hrs London local time. The LSE-specific intraday auction period of

12:00 to 12:02hrs is excluded; indeed, we exclude all messages between 12:00 and 12:03 to account for the random end of the LSE intraday auction.

Our data includes 100 stocks; however, four of the stocks experienced a change in their RICs during our sample period – GVC, LSE, RBS and JE changed to ENT, LSEG, NWG and JETJ respectively.[2] All of these stocks are retained as they are, and firm fixed effects are not changed on account of the RIC changes. The full, cleaned dataset contains 26,550,873 stock-minutes, 324.5 million transactions and 258.8 billion pounds volume for the exchanges included. This includes 12.24 billion pounds worth of stocks in FBA trading volume, executed over 23.79 million transactions completed via auction.

4.2. *Metrics and descriptive statistics*

4.2.1. High-frequency trading activity metrics

We estimate HFT using two measures. The first is the negative trading volume divided by the number of quote messages and then scaled 100, while the second is the number of messages divided by the number of transactions; the calculation of messages is defined as in Equation (1):

$$Message_{i,t} = Transactions_{i,t} + BestQuoteUpdate_{i,t} \tag{1}$$

$$HFTVolume_{i,t} = -\frac{Volume_{i,t}}{100Messages_{i,t}} \tag{2}$$

$$HFTTransactions_{i,t} = \frac{Message_{i,t}}{Transactions_{i,t}} \tag{3}$$

The $BestQuoteUpdate_{i,t}$ in Equation (1) is the total number of best quote updates for stock i at time t. The $Volume_{i,t}$ in Equation (2) is the total currency volume for stock i at time t, and the $Transactions_{i,t}$ in Equation (1) and (3) is the total number of transactions for stock i at time t. t corresponds to one minute. The idea of these proxies is to normalize the message traffic by trading volume or number of transactions (Malceniece et al., 2019).

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[2] RBS (Royal Bank of Scotland plc.) and GVC (GVC Holdings plc.) changed their symbols (names) to NWG (NatWest Group plc.) and ENT (Entain plc.) respectively. JE (Just Eat plc.) merged with Takeaway.com in February 2020, leading to a change in symbol to JETJ. On 29 January 2021, LSE (London Stock Exchange plc.) simply changed its ticker to LSEG to be in keeping with its parent company name: London Stock Exchange Group plc. following its acquisition of Refinitiv. Refinitiv Datascope changed LSE's RIC to LSEG ahead of 2021 and a technical change. Removing these stocks from our sample does not yield any material or consequential difference in the results.

4.2.2. Proxies for proportions of HFT market-makers

Estimating the proportion of HFT activity driven by market-makers is critical to testing our second hypothesis; however, directly capturing this value is impossible due to a lack of trader-specific data. Therefore, we compute a proxy based on trading data. According to Hagströmer and Nordén (2013), HFT market-makers tend to submit more orders than HFT snipers, which leads to higher order-to-transaction ratios. One possible reason for this is that HFT market-makers update their orders more frequently when there are price movements/information updates, which further contribute more orders in the market. They also suggest that the high order-to-transaction ratio (OTR) may imply a high proportion of HFT market-makers. However, if observations are constructed based on the minute level, one potential problem is that some intervals may suffer non-trading episodes, which provides problematic infinite values. Therefore, we estimate transaction-to-order ratio (TOR), which can effectively address this problem. According to Comerton-Forde et al. (2019), the transaction-to-order ratio can be employed as a proxy for HFT activity; however, they do not identify the possibility of detecting HFT market-making activities using the same proxy. We define the $TOR_{i,t}$ as the transaction-to-order ratio for stock i at time t as follows:

$$TOR_{i,t} = \frac{TotalTransactionsVolume_{i,t}}{TotalBestPriceOrderVolume_{i,t}} \quad (4)$$

where $TotalTransactionsVolume_{i,t}$ is the total volume of transactions for stock i at time t, and $TotalBestPriceOrderVolume_{i,t}$ is the total volume of orders at the best price for stock i at time *t*. Hagströmer and Nordén (2013) argue that HFT market-makers tend to have higher OTR, so, inversely, higher $TOR_{i,t}$ should imply lower HFT market-making activity.

4.2.3. Latency arbitrage opportunities

Latency arbitrage opportunities can be broadly sorted into single-market opportunities (Aquilina et al., 2020; Budish et al., 2015) and cross-market opportunities (Foucault et al., 2017; Wah, 2016; Hollifield et al., 2017). Attempts at capturing both types include the works of Aquilina et al. (2020), Dewhurst et al. (2019), Foucault et al. (2017), Hollifield et al. (2017) and Wah (2016). We build on some of these approaches for our analysis.

Estimating cross-market arbitrage opportunities is quite well developed at present due to contributions by Foucault et al. (2017), Hollifield et al. (2017) and Wah (2016), while the work on estimating single-market equivalents is still limited. Of the studies estimating single-market latency arbitrages mentioned above, Aquilina et al. (2020) provide the most precise measurement based on HFT order placement; however, their work is based on a novel/unique dataset that is, at present, publicly unavailable. Hollifield et al. (2017) also employ the correlation of prices among different markets with the same security to detect all possible opportunities, which contains both cross- and single-market latency arbitrage opportunities. One potential drawback of this approach is that measurements may include unexploited opportunities and the observed correlations are unable to distinguish single- and cross-market opportunities. Therefore, for cross-market arbitrages, we employ a modified approach borrowing from both Hollifield et al. (2017) and Wah's (2016) approaches in that we employ different exchange prices for a cross-traded security across platforms to detect the cross-market latency arbitrage opportunities. In theory, for the same security, when the bid price from one market is higher than the ask price from another, there is an opportunity for latency arbitrage, but other costs such as transaction costs are considered, as in Foucault et al. (2017). Therefore, we treat the following instance as an opportunity: when the bid price from one market is 2bps or more higher than the ask price from the other market. Then, in line with Foucault et al. (2017), we sort the opportunities into $TCLAO_{i,t}$, toxic cross-market latency arbitrage opportunity, and $NCLAO_{i,t}$, non-toxic cross-market latency arbitrage opportunity. A cross-market opportunity is $TCLAO_{i,t}$ for stock i at time t when the resulting spread is larger than the spread before the opportunity appears. The enlarging of the spread is deemed to be linked to permanent information-induced movements due to sniping activity. Conversely, a cross-market latency arbitrage opportunity $NCLAO_{i,t}$ for stock i at time t occurs when the resulting spread is not larger than prior to the onset of the opportunity. This suggests that the opportunity is linked to short-term liquidity shocks rather than information. We then combine $NCLAO_{i,t}$ and $TCLAO_{i,t}$ to obtain $CLAO_{i,t}$ as the sum of all cross-market latency arbitrage opportunities for stock i at time t.

Detection of single-market latency arbitrage is much more challenging. With Aquilina et al. (2020), their access to a unique proprietary dataset simplifies the problem – we do not have this option. Therefore, we infer single-market opportunities by following the predictions of Budish et al. (2015); they state that the midpoint jumping higher than half of the bid-ask spread is indicative of a potential single-market latency arbitrage opportunity. Thus, when there is a jump on the midpoint higher than the current half spread, we count this as one opportunity, and set $SLAO_{i,t}$ as a single-market opportunity for stock i at time t. According to Budish et al. (2015), single-market opportunities are directly related to information impact, and thus our measurements, following Budish et al. (2015), focus on identifying information-defined latency arbitrage opportunities. The opportunities are not further separated into toxic and non-toxic categories. Finally, all types of opportunities are summed to yield an estimate of all latency arbitrage opportunities per stock-minute, $LAO_{i,t}$. Also, because there are often stock-minutes with more than one latency arbitrage opportunity and some extreme ones can contain more than 100 opportunities, we employ a logarithmic transformation for econometric reasons; to account for those with zero recorded opportunities, we add 0.1 to all values prior to logarithmic transformation.[3] From the dataset, we estimate 9.61 million latency arbitrage opportunities, 9.3 and 0.31 million of which are single-market and cross-market opportunities respectively.

We next compute the volume-weighted durations for all latency arbitrage opportunities identified in our data. We calculate the volume-weighted durations containing all types of latency arbitrage opportunities and divide the stock-minute-level data containing latency arbitrage opportunities for each stock into terciles as short, medium, and long. Then we employ dummy variables for different terciles ($ShortD_{i,t}$, $MiddleD_{i,t}$ and $LongD_{i,t}$) to divide our observations into groups. The idea of employing volume-weighted durations is that one observation may contain more than one latency arbitrage opportunity, and volume-weighted forms can guarantee that our divisions are not dramatically affected by small-volume opportunities, which finally provide proper average durations for each observation. The equation for calculating latency arbitrage opportunities durations is as follows.

$$Duration_{i,t} = \frac{\sum(Volume_{i,n,t} \times Duration_{i,n,t})}{\sum(Volume_{i,n,t})} \tag{5}$$

[3] The reported descriptive statistics do not include the added value.

In Equation (5), $Duration_{i,t}$ is the volume-weighted durations for divisions for dummies for stock i at time t. $Volume_{i,n,t}$ is the volume for nth latency arbitrage opportunity for stock i at time t, and $Duration_{i,n,t}$ is the duration for nth latency arbitrage opportunity for stock i at time t. Finally, we define $ShortD_{i,t}$ as the dummy for the shortest tercile, $MiddleD_{i,t}$ as the dummy for the middle tercile and $LongD_{i,t}$ as the dummy for the longest tercile. If $Duration_{i,t}$ falls into the shortest/medium/longest tercile, $ShortD_{i,t}$/$MiddleD_{i,t}$/$LongD_{i,t}$ is one, otherwise it is zero.

4.2.4. Frequent batch auctions

Consistent with Zhang and Ibikunle (2020), we measure FBA activity by computing the nominal and percentage values of transactions and currency volume for stock i at time t.[4] $FBATransactions_{i,t}$ is the number of FBA transactions for stock i at time t, and $\%FBATransactions_{i,t}$ is the percentage of FBA transactions in transactions from all exchanges for stock i at time t. $FBACurrencyVolume_{i,t}$ is the pound value of FBA volume for stock i at time t, and $\%FBACurrencyVolume_{i,t}$ is the pound value of FBA as a proportion of the pound value of volumes from all venues and mechanisms for stock i at time t. All FBA data are collected from Cboe, which is the most important venue for FTSE 100 stocks on FBA.

4.2.5. Other key variables

To control for potential non-latency-related information dynamics that could be driving the evolution of market quality characteristics in the presence of FBA, such as classic/non-latency-related information asymmetry or private information, our empirical framework incorporates adverse selection costs as a control variable. We estimate time-weighted adverse selection cost, $AdverseSelection_{i,t}$, for each stock-minute. This, in line with Foley and Putniņš (2016), is computed from per-transaction adverse selection, $AdverseSelection_{i,\tau}$:

$$AdverseSelection_{i,\tau} = q_{i,\tau} \times \frac{midpoint_{i,\tau+\Delta} - midpoint_{i,\tau}}{midpoint_{i,\tau}} \quad (6)$$

[4] We do not employ the stock volume as a proxy due to similar results to the currency volume.

where τ indexes trade at time τ, and $q_{i,\tau}$ is the buyer-seller indicator for the trade occurring at time τ; this is based on the Lee and Ready (1991) classification algorithm. Buyer- and seller-initiated transactions are allocated +1 and -1 values respectively. The $midpoint_{i,\tau}$ is the midpoint at time τ, and $midpoint_{i,\tau+\Delta}$ is the midpoint at time $\tau + \Delta$; to account for the high-frequency nature of the evolution of adverse selection in our data, Δ is 10 milliseconds. Time-weighted adverse selection costs, $AdverseSelection_{i,t}$, for minute t, is thereafter estimated from $AdverseSelection_{i,\tau}$.

The other relevant market and microstructure characteristics employed in this study as control variables include $Volume_{i,t}$, defined as the total pound volume for stock i at time t across all platforms and mechanisms. $RelativeSpread_{i,t}$, defined as the ratio of the difference between the prevailing best ask and bid prices to the midpoint, is an inverse proxy for liquidity, expressed as the time-weighted relative quoted spread for stock i at time t. $OrderImbalance_{i,t}$ is the proxy for order imbalance in stock i at time t and is based on the measure in Chordia et al. (2008). $Volatility_{i,t}$ is the proxy for volatility, defined as the 5-second-price variance for stock i at time t. $Price_{i,t}$ is the volume-weighted midpoint for stock i at time t. $Transactions_{i,t}$ is the number of transactions for stock i at time t.

Table 1 further defines all the variables.

INSERT TABLE 1 ABOUT HERE

4.3.Descriptive statistics

Table 2 presents the descriptive statistics for all the variables; in particular, the mean and standard deviation estimates are presented.

INSERT TABLE 2 ABOUT HERE

Drawing from 524 trading days' worth of trading activity, our data includes a total of 26,550,873 stock-minutes for the FTSE 100 stocks in our sample, which implies an average of 265,509 minutes of observations per stock. The time-weighted one-second relative spread is 0.074% for all stock minutes and the time-weighted high-frequency adverse selection cost is about 0.0005% per stock-minute. The average stock-minute pound volume traded excluding FBA is about £9,287 and the average number of transactions per stock-minute is about 11.3, underscoring the relative activeness of trading activity for the FTSE 100 stocks in our sample. FBA-linked trading activity represents only a small part of the total trading activity with FBA transactions and pound volume corresponding to only 7.33% and 4.72% of the total transactions and pound volume respectively. The lower pound volume share suggests that FBA-executed transactions' order sizes tend to be smaller than those executed via other mechanisms in aggregate. Furthermore, the low average number of FBA-executed transactions per stock-minute at about 0.896 shows that FBA is used sparingly in comparison to continuous trading. The latency arbitrage opportunities estimates suggest that opportunities observed in the case of our sample of stocks are largely triggered within exchanges rather than cross-platform. The estimates also show that one opportunity appears on average every three minutes, which is in line with Aquilina et al. (2020) who use a novel dataset (which we do not have access to). However, the fact that the cross-market latency arbitrage opportunities estimated in our sample correspond to only about 3% of all estimated opportunities in the market is at variance with Foucault et al. (2017) who employ data from the foreign exchange market. This variation could be explained by the rather more balanced trading nature of the foreign exchange market, while in our sample trading is dominated by the LSE, which is responsible for 82.95% and 86.37% of the respective transactions and pound volume recorded in our dataset. Therefore, trading occurring far more frequently on the LSE could be the single most important factor explaining the variation. A further, but potentially less crucial, explanation, is that, consistent with Ibikunle (2018), Cboe is faster at incorporating new/private information into the stock price, thereby offering snipers fewer latency arbitrage opportunities. The standard deviation of TOR_{it} is about three times its mean, suggesting a high degree of cross-sectional, and potential time series, variation. Therefore, the empirical framework described in Section 4.4 takes cross-sectional dependencies into consideration.

4.4. Empirical models

To test our first hypothesis regarding the effects of HFT on FBA, we estimate the following stock-minute panel and predictive regression model:

$$FBA_{i,t} = \gamma_i + \delta_t + \beta_1 HFTProxy_{i,t-1} + \beta_2 Control_{i,t} + \varepsilon_{i,t} \quad (7)$$

where $FBA_{i,t}$ corresponds to the natural logarithm of one of $FBATransactions_{i,t}$, $\%FBATransations_{i,t}$, $FBACurrencyVolume_{i,t}$, and $\%FBACurrencyVolume_{i,t}$ for stock i

at time t. $HFTProxy_{i,t-1}$ is one of $HFTVolume_{i,t-1}$ or $HFTTransactions_{i,t-1}$, for stock i at time $t-1$. $Control_{i,t}$ is a set of control variables for stock i at time t, which includes $AdverseSelection_{i,t}$, $RelativeSpread_{i,t}$, $OrderImbalance_{i,t}$, $Volatility_{i,t}$, and the natural logarithms of $Volume_{i,t}$, $Price_{i,t}$ and $Transactions_{i,t}$. All variables are as defined in Section 4.1, winsorized at 1% and 99%, and γ_i and δ_t are stock and time fixed effects respectively. Consistent with our hypothesis, and Menkveld and Zoican (2017), Baldauf and Mollner (2020) and Foucault et al. (2016), we would expect that β_1 will be either negative and statistically significant, or it will indicate a benign non-statistically significant relationship. This is due to the expectation that the greatest use of HFT is by endogenous liquidity suppliers and market-makers.

We next investigate whether our second hypothesis holds, i.e., whether an increase in market-making activity is predictively linked with a reduction in FBA volume. To this end, we estimate the following stock-minute panel and predictive regression model:

$$FBA_{i,t} = \gamma_i + \delta_t + \beta_1 TOR_{i,t-1} + \beta_2 Control_{i,t} + \varepsilon_{i,t} \quad (8)$$

where $FBA_{i,t}$ corresponds to the natural logarithm of one of $FBATransactions_{i,t}$, $\%FBATransations_{i,t}$, $FBACurrencyVolume_{i,t}$, and $\%FBACurrencyVolume_{i,t}$ for stock i at time t. $TOR_{i,t-1}$ is the transaction-to-order ratio for stock i at time $t-1$. $Control_{i,t}$ is a set of control variables for stock i at time t, which includes $AdverseSelection_{i,t}$, $RelativeSpread_{i,t}$, $OrderImbalance_{i,t}$, $Volatility_{i,t}$, and the natural logarithms of $Volume_{i,t}$, $Price_{i,t}$ and $Transactions_{i,t}$. All variables are as defined in Section 4.1, winsorized at 1% and 99%, and γ_i and δ_t are stock and time fixed effects respectively. Consistent with our hypothesis, and since $TOR_{i,t}$ is an inverse measure for the HFT activity of endogenous liquidity suppliers and market-makers, we would expect a significantly positive parameter for β_1 in this model.

In Equation (9), we address the premise of our third hypothesis, examining the relationship between latency arbitrage opportunities and FBA activity; we also address the potential interaction between the level of HFT activity in the market and latency arbitrage. The model is as follows:

$$FBA_{i,t} = \gamma_i + \delta_t + \beta_1 \log\left(LAO_{i,t-1}\right) + \beta_2 HFTD_{i,d} + \beta_3 \log\left(LAO_{i,t-1}\right) * HFTD_{i,d} +$$

$$\beta_4 Control_{i,t} + \varepsilon_{i,t} \tag{9}$$

where $FBA_{i,t}$ corresponds to the natural logarithm of one of $FBATransactions_{i,t}$, $\%FBATransations_{i,t}$, $FBACurrencyVolume_{i,t}$, and $\%FBACurrencyVolume_{i,t}$ for stock i at time t. $LAO_{i,t-1}$ is the number of latency arbitrage opportunities for stock i at time $t-1$; this variable includes both toxic and non-toxic cross-market and single-market latency arbitrage opportunities. $HFTD_{i,d}$ is a dummy variable corresponding to a period of higher-than-average HFT activity for stock i on day d. Two sets of dummy variables – $HFTVolumeD_{i,d}$ and $HFTTransactionsD_{i,d}$ – are employed in different versions of the model. When HFT activity ($HFTVolume_{i,d}$ and $HFTTrasactions_{i,d}$) for stock i on day d is larger by a minimum of one standard deviation for the surrounding 60 trading days (-30 days and +30 days), then $HFTD_{i,d}$ corresponds to one, and otherwise zero. $Control_{i,t}$ is a set of control variables for stock i at time t, which includes $AdverseSelection_{i,t}$, $RelativeSpread_{i,t}$, $OrderImbalance_{i,t}$, $Volatility_{i,t}$, and the natural logarithms of $Volume_{i,t}$, $Price_{i,t}$ and $Transactions_{i,t}$. All variables are as defined in Section 4.1, winsorized at 1% and 99%, and γ_i and δ_t are stock and time fixed effects respectively. Should our third hypothesis hold, we would expect β_1 to yield a positive and significant value; β_2 is expected to be negative given that high HFT activity is synonymous with the activities of liquidity suppliers and market-makers. β_3 should offer insights into the interactive effects of HFT and latency arbitrage on FBA. If competition follows the Menkveld and Zoican (2017) model, β_3 should be negative and statistically significant; however, it should have an absolute value smaller than β_1 because of the existence of slower traders who do not have HFT technologies.

Our next hypothesis focuses on the relationship between specific latency arbitrage opportunities and FBA volume. Endogenous liquidity suppliers may employ frequent batch auctions to avoid being sniped and, without sacrificing liquidity, to hit better prices, which may lead to them choosing to execute their orders via FBA for better prices. To test these effects, we estimate the following stock-minute panel predictive model:

$$FBA_{i,t} = \gamma_i + \delta_t + \beta_1 \log\left(SpecificOppo_{i,t-1}\right) + \beta_2 Control_{i,t} + \varepsilon_{i,t} \tag{10}$$

where $FBA_{i,t}$ corresponds to the natural logarithm of one of $FBATransactions_{i,t}$, $\%FBATransations_{i,t}$, $FBACurrencyVolume_{i,t}$, and $\%FBACurrencyVolume_{i,t}$ for stock i

at time t. y $SpecificOppo_{i,t-1}$ corresponds to a specific type of latency arbitrage opportunity, with one regression separately estimated for one opportunity type. $TCLAO_{i,t-1}$ proxies toxic cross-market latency arbitrage opportunities, $NCLAO_{i,t-1}$ proxies the non-toxic cross-market ones, $CLAO_{i,t-1}$ proxies all cross-market ones, and $SLAO_{i,t-1}$ proxies all single-market ones, for stock i at time $t-1$. $Control_{i,t}$ is a set of control variables for stock i at time t, which includes $AdverseSelection_{i,t}$, $RelativeSpread_{i,t}$, $OrderImbalance_{i,t}$, $Volatility_{i,t}$, and the natural logarithms of $Volume_{i,t}$, $Price_{i,t}$ and $Transactions_{i,t}$. All variables are as defined in Section 4.1, winsorized at 1% and 99%, and γ_i and δ_t are stock and time fixed effects respectively.

According to hypothesis 4, we expect different types of latency arbitrage opportunities to cause different effects on frequent batch auctions. Consistent with Budish et al. (2015) and Foucault et al. (2017), we expect β_1 to be positive and significant when employing $TCLAO_{i,t-1}$ and $SLAO_{i,t-1}$ in the regressions, while it should indicate a benign effect when employing $NCLAO_{i,t-1}$. Nevertheless, a positive and significant estimate for the latter could imply that liquidity suppliers overreact to the risk of being sniped, while a negative and significant estimate suggests that liquidity suppliers realize the profits of non-toxic cross-market opportunities. Hence, it may appear that liquidity suppliers are able to recognize non-toxic latency arbitrage opportunities and avail themselves of their advantages to earn profits.

Our final hypothesis relates to how the duration of latency arbitrage opportunities affects their impact on FBA activity. Shorter durations imply that snipers are more active and can thus make profits more rapidly when latency arbitrage opportunities arise, and this suggests that slower traders are more at risk than during longer duration latency arbitrage opportunities. We estimate the following equation to investigate this expectation:

$$FBA_{i,t} = \gamma_i + \delta_t + \beta_1 \log\left(ShortD_{i,t-1} \times LAO_{i,t-1}\right) + \beta_2 \log\left(MiddleD_{i,t-1} \times LAO_{i,t-1}\right) + \beta_3 \log\left(LongD_{i,t-1} \times LAO_{i,t-1}\right) + \beta_4 Control_{i,t} + \varepsilon_{i,t} \quad (11)$$

where $FBA_{i,t}$ corresponds to the natural logarithm of one of $FBATransactions_{i,t}$, $\%FBATransations_{i,t}$, $FBACurrencyVolume_{i,t}$, and $\%FBACurrencyVolume_{i,t}$ for stock i at time t. We employ three dummies to represent different tercile of durations of latency arbitrage opportunities. Terciles are divided based on volume-weighted durations of latency arbitrage opportunities for every stock-minute. The shortest, middle, and longest stock terciles correspond to $ShortD_{i,t-1}$, $MiddleD_{i,t-1}$, and $LongD_{i,t-1}$ respectively. $Control_{i,t}$ is a set of control variables for stock i at time t, which includes $AdverseSelection_{i,t}$, $RelativeSpread_{i,t}$, $OrderImbalance_{i,t}$, $Volatility_{i,t}$, and the natural logarithms of $Volume_{i,t}$, $Price_{i,t}$ and $Transactions_{i,t}$. All variables are as defined in Section 4.1, winsorized at 1% and 99%, and γ_i and δ_t are stock and time fixed effects respectively. Consistent with hypothesis 5, we expect significantly positive parameters for β_1, β_2 and β_3, given that all latency arbitrage opportunities, regardless of duration, will be harmful to slower traders, which should then encourage them to seek refuge in mechanisms like FBA. However, the most important point of this regression is the value of parameters. If the durations of latency arbitrage opportunities can indicate the relative activeness of the snipers, the parameter estimates should be in the following order: $\beta_1 > \beta_2 > \beta_3$. This suggests that slower traders are more cautious when they find HFT snipers to be more active and then they tend to employ more FBA. In the same vein, the parameters suggesting some inverse order (i.e., $\beta_1 < \beta_2 < \beta_3$) may be an indication of the evolution of FBA during latency arbitrage opportunities being related to the length of duration. However, in this scenario, longer durations trigger more FBA, which may suggest that slower traders tend to shift their orders away from continuous trading more eagerly when latency arbitrage opportunities persist. Indeed, slower traders will not be too cautious regarding how fast snipers are, but only note that snipers are faster than they are; hence, it is plausible that they just continuously shift their orders the longer a latency arbitrage opportunity lasts. Nevertheless, if we ultimately obtain estimates without any logical order, then it may be that durations are meaningless when examining the role of latency arbitrage opportunities in driving FBA volume.

5. Empirical Results

Our starting point in a test of hypothesis 1 is to investigate the overall effects of HFT on the evolution of FBA trading activity.

INSERT TABLE 3 ABOUT HERE

Table 3 reports the results for our first set of regressions; Panels A and B show the estimates for the modelling based on $HFTVolume_{i,t}$ and $HFTTransactions_{i,t}$ as respective proxies for HFT activity. In line with our expectations, all the β_1 coefficients, irrespective of the combination of FBA and HFT proxies, are negative, and seven of eight are statistically significant at conventional levels. This suggests that, in contrast to the implications of the modelling in Budish et al. (2015), HFT activity in continuous trading is inversely linked with FBA volume, i.e., *ceteris paribus* we would expect a reduced preference for trading via FBA when HFT activity is high. We find that a unit increase in $HFTVolume_{i,t-1}$ contributes to a decrease of about 10bps in FBA transactions and currency volume, and an increase of 1bp in $HFTTransactions_{i,t-1}$ contributes to a decrease of 1.02 and 1.08bps in FBA transactions and currency volume respectively. If increases in FBA volume are linked to the arrival of new participants, this increase should not trigger the statistically significant estimates observed because we would expect volume to increase across other mechanisms as well. The strength of the estimates and their statistical significance suggest that the observed relationship between HFT and FBA is not driven by the arrival of new participants, and this is likely the consequence of liquidity suppliers being in a position to deploy speed in updating their orders should they need to; this ability offers the confidence to increase their trading activity in the continuous market relative to other more opaque trading options, such as FBA, and supply more liquidity (see Rzayev et al., 2019).

The above results could be explained by the dynamics of the strategies deployed by the main types of HFTs in the market. According to Aquilina et al. (2020), HFT snipers have a relatively stable level of activity in the market, and considering this in tandem with Menkveld and Zoican (2017), our results suggest that the increase in HFT activities involves two stages. The first is that the HFT snipers who tend to capture profits from latency arbitrage and HFT market-makers/endogenous liquidity-suppliers employ HFT technologies to avoid being adversely selected and the provision of liquidity, and the second mainly involves HFT market-makers because the activities of HFT snipers are close to the limit. Based on the above conditions, a plausible explanation is that the number of snipers in the market is relatively stable, and while an increase in HFT activity might mean an increase in sniping activity, this level of activity is dwarfed by the activities of endogenous liquidity providers who need to avoid latency-induced adverse selection by updating their orders more frequently (see Menkveld and Zoican, 2017). The clear implication here is that the ability of market-making/liquidity-supplying HFTs to avoid adverse selection implies a reduction in their reliance on 'safe haven-type' trading avenues, such as FBA. Thus, our results support our first hypothesis that an increase in HFT activity is not linked to an increase in the use of FBA as a trading mechanism, and this is explained by the fact that liquidity-supplying HFTs are more active deployers of HFT. Their active deployment of HFT to avoid adverse selection also decreases their dependence on FBA as a trading option.

To further investigate the above arguments, in a test of our second hypothesis, we examine whether the increase in HFT activity that could be attributable to market-makers and endogenous liquidity-suppliers may be linked with a similar reduction in reliance on FBA. Hagströmer and Nordén (2013) argue that more HFT market-makers tend to trigger a higher order-to-transaction ratio in the market; this is due to the already argued need to update their orders to avoid adverse selection triggering more orders, but with little to no commensurate increase in the level of transactions. We exploit this argument to estimate the evolution of market-making HFT activity. In our setting, estimating models at the minute frequency, we acknowledge that we may end up with observations recording no transactions, which may lead to infinite values of order to transactions. Therefore, we employ an inverse measure, the transaction-to-order ratio ($TOR_{i,t}$), to estimate the level of HFT market-making activity; this is also employed by Comerton-Forde et al. (2019) to proxy high-frequency trading dynamics. In our case, higher $TOR_{i,t}$ implies a reduced incidence of HFT market-making activity, while, conversely, lower $TOR_{i,t}$ implies an increase in HFT market-making.

INSERT TABLE 4 ABOUT HERE

Table 4 reports the regression results based on the estimation of Equation (8). Consistent with our thesis, the results show a distinctly positive and statistically significant relationship between $TOR_{i,t}$ and FBA, thus illustrating that an increase in HFT market-making activity is linked with a decrease in FBA volume. It is instructive to note that the results obtained here indicate a stronger relationship between FBA and $TOR_{i,t}$ – an inverse proxy of market-making HFT – than was obtained in the estimation of Equation (7) showing the relationship between FBA and general HFT. Specifically, a 1% increase in $TOR_{i,t}$ is linked with ~1.08% and ~1.38% respective decreases in FBA transactions and currency volume, and about 6.3% in their percentage equivalents. Given that our estimations are at a minute frequency, these are arguably economically significant estimates. These estimates support the argument that HFT market-makers tend to employ HFT technologies to avoid the sniping activities of aggressive HFTs, and that this reduces their reliance on FBA as a safe haven-type trading mechanism. Admittedly, FBA will still be attractive to slower traders who do not have access to adverse selection-busting HFT technologies; however, the low level of FBA volume in our sample of European stocks that currently have the highest levels of global FBA volume (see also Zhang and Ibikunle, 2020) suggests that most market-makers and liquidity-suppliers now have competitive HFT capabilities (see also Rzayev et al., 2019). According to Baldauf and Mollner (2020), HFT market-makers generally maintain a presence in the market through continuous order posting; hence, when they face the risk of being sniped, they cancel and resubmit the orders to avoid adverse selection. The comparatively low level of FBA activity also indicates a preference for trading in the continuous market. Thus, when traders who can employ both HFT technology and FBA to protect themselves choose HFT technologies, they contribute to an offsetting effect, which reduces FBA activity. This is inferable from the strong and highly statistically significant estimates presented in Table 4. Therefore, the above results support our second hypothesis.

The results thus far show that general increases in HFT activity are not correlated with a phenomenon, such as latency arbitrage, that could induce an increased use of FBA. The implication here is that, consistent with Hagströmer and Nordén (2013) and Rzayev et al. (2019), the predominant users of HFT technology in the European context we examine are market-makers and endogenous liquidity-suppliers. This leads to the question: would the activities of non-market-making HFTs, such as snipers, have a different effect on FBA volume? To address this question, we estimate Equation (9).

INSERT TABLE 5 ABOUT HERE

Table 5 presents the results obtained from the estimation of Equation (9); Panel A presents the results of modelling where $HFTVolumeD_{i,d}$ is used as the HFT dummy, while Panel B presents the estimates for modelling done with $HFTTransactionsD_{i,d}$ as the HFT dummy. The results presented in the two panels are generally consistent; hence, we concentrate on discussing Panel A's estimates. The main variables of interest are the $LAO_{i,t-1}$ coefficients and their interactions. Consistent with our third hypothesis, the coefficient estimates for $LAO_{i,t-1}$ are positive and statistically significant at the 0.01 level irrespective of the FBA proxy they are related to. This is a strong indication that an increase in latency arbitrage opportunities in the market triggers the relocation of slower traders' orders to FBA. The estimates show that a 1% increase in $LAO_{i,t-1}$ is linked to 0.17% and 0.45% respective increases in FBA currency volume and number of transactions, as well as a general 8.3bps percentage increase in FBA activity. These estimates constitute a compelling set of evidence that FBA is an attractive shelter for slower traders who are at risk of being sniped. According to Budish et al. (2015), traders who are slower than HFT snipers should find FBA an attractive option, which is in line with our results suggesting that an increase in latency arbitrage opportunities triggers higher levels of FBA use.

Consistent with earlier results, the relationship between the HFT dummies and FBA remains negative and statistically significant at the 0.01 level. However, the observed effects are much stronger than those presented earlier in Table 3 because the estimation of Equation (9), with results reported in Table 5, captures HFT activity at the aggregate day level rather than at the minute level. We also note that, in comparison, the HFT effects are nevertheless weaker when compared to the documented FBA-LAO effects. What this implies is that HFT activity is not a reliable proxy for sniping activity or latency arbitrage opportunities and identifying snipers in a body of HFTs is challenging. This is further emphasized by our descriptive statistics showing that, on average, only one latency arbitrage opportunity appears every three minutes, which suggests that sniping activity constitutes a small fraction of daily HFT activity, and HFT market-makers and endogenous liquidity-suppliers are the main drivers of HFT activity – further underlining our earlier findings. The negative and statistically significant estimates reported for the interaction coefficients further support this view. Essentially, as further evidenced in Figure 1, an increase in sniping activity/latency arbitrage opportunities is accompanied by an increase in market-making/liquidity-supplying HFT activity designed to avoid adverse selection (see also Menkveld and Zoican, 2017), which in turn leads to a reduced reliance and an ameliorating effect on FBA activity. This is consistent with the view that HFT sniping activity is relatively stable and snipers perform similarly with different opportunities because of a high probability of successfully sniping slow traders (see also Aquilina et al., 2020; Baldauf and Mollner, 2020). Finally, it is important to note that the observed effects between LAO and FBA occur despite our having controlled for adverse selection costs in our model, which also has a positive and statistically significant (consistently at a 0.01 level) relationship with FBA. Therefore, our third hypothesis holds.

INSERT FIGURE 1 ABOUT HERE

Not all latency arbitrage opportunities are cut from the same cloth, which implies that their effects may differ; hence, we now further dissect latency arbitrage opportunities into different types and examine their interactions with FBA. The *raison d'être* of latency arbitrage is to take advantage of information asymmetry; thus, asymmetries arising in single-market and multi-market contexts can lead to the emergence of latency arbitrage opportunities. Budish et al. (2015) and Aquilina et al. (2020) focus on single-market latency arbitrage, while Foucault et al. (2017) examine cross-market latency arbitrage. In our case, based on a sample of stocks traded across a minimum of two exchanges, both types may appear. The London Stock Exchange, the listing exchange for the stocks in our sample, is the main market for FTSE 100 stocks, and it is a hybrid market dominated by a continuous trading downstairs market, with a less impactful upstairs broker-dealer market. Several other markets also provide platforms for trading FTSE 100 stocks, including Cboe, which contains both continuous trading and FBA trading avenues. This provides the condition for both types of information asymmetry and further implies that both cross-market and single-market opportunities can appear on FTSE 100 stocks. These opportunities can trigger different shocks in the market and the dynamics behind them can be different. For example, single-market opportunities may cause a sudden jump in price because of different reaction speeds to new information. Toxic cross-market latency arbitrage opportunities can increase the spread because they are related to information shock, whilst non-toxic ones are harmless to the market because they are linked to liquidity shocks.

INSERT TABLE 6 ABOUT HERE

Table 6 presents the results related to different types of latency arbitrage opportunities across four panels. Panels A, B, C and D present estimates for the respective results estimating the effects of single-market, cross-market, toxic cross-market, and non-toxic cross-market latency arbitrage opportunities on FBA. Consistent with our thesis, single-market, cross-market, and toxic cross-market latency arbitrage opportunities are all positively linked with FBA and all the coefficients are statistically significant at a 0.01 level of statistical significance. This is in line with all our preceding arguments and the preponderance of the literature. However, and unexpectedly, the non-toxic latency arbitrage opportunities are also positively related to FBA, with all the coefficients at a statistically significant 0.01 level as well. This later outcome contrasts with Foucault et al. (2017), who state that the non-toxic cross-market latency arbitrage opportunities are not harmful to slow traders and may even be beneficial to them, which implies that we should see a benign relationship, at a minimum, between these types of opportunities and FBA activity. Nevertheless, it appears from our results that traders are very cautious about the appearance of latency arbitrage opportunities, irrespective of whether they are toxic or not – or perhaps they are not as adept at deciphering which is which, especially given the speed advantage of snipers. Therefore, caution may well be the approach adopted by slow traders when it comes to dealing with latency arbitrage; this is even more so the case given the high probability of success enjoyed by snipers. These results imply a rejection of our fourth hypothesis, which claims that different types of latency arbitrage opportunities will affect FBA volume differently.

Interpreting the estimates as elasticities indicates that the observed effects are economically meaningful. A 1% increase in cross-market latency arbitrage opportunities is linked with an increase of ~0.06% and 0.18% in FBA currency volume and number of transactions respectively, while the respective increases are ~0.04 and 0.15 for a 1% increase in single-market latency arbitrage opportunities.

Finally, we address the question of what effect the duration of latency arbitrage opportunities has on FBA activity. The length of latency arbitrage opportunities varies, and it is decided by the closing orders for the opportunities. Although some market-makers and endogenous liquidity-suppliers have HFT technologies to compete with aggressive sniping HFTs, for slower traders, FBA, and other less transparent trading mechanisms, the only safe option may be to avoid these riskier periods. Furthermore, even if some traders have access to HFT technologies, employing FBA reduces their exposure to HFT snipers, which further dramatically reduces the possibility that they will be sniped (Budish et al., 2015). Our results above also suggest that detecting the level of HFT activities to judge FBA is not reliable due to the higher proportion of HFT market-makers in modern financial markets. Therefore, we examine the effects of duration of latency arbitrage opportunities on the evolution of FBA volume. Shorter latency arbitrage opportunities are, on average, suggestive of a high level of HFT sniping activity in the market, given that snipers will be closing out opportunities quicker – hence the short durations, and vice versa for longer duration opportunities. Therefore, we expect a variation in the effects of latency arbitrage opportunities along the duration curve, and, to examine this, we estimate Equation (11).

INSERT TABLE 7 ABOUT HERE

Results based on the estimation of Equation (11) are reported in Table 7. As expected, all interactive parameters are positive and statistically significant at the 0.01 level. Hence, the earlier finding that an increase in latency arbitrage opportunities is linked to increasing FBA volume still holds. However, a more interesting and clearer pattern emerges in the estimates presented in Table 7, with the results across all proxies of FBA showing that the effects of links between latency arbitrage opportunities are stronger for shorter duration opportunities, followed by mid-length opportunities, and the least strong effects are observed for the longer duration opportunities. Specifically, consistent with our fifth hypothesis, the observed order for the relevant coefficient estimates is $\beta_1 > \beta_2 > \beta_3$ for all the regressions reported in Table 7. Thus, as hypothesized, shorter durations of latency arbitrage opportunities suggest an increased state of activity by snipers and a worsening trading environment for slower traders. In such an environment, even trading with the use of HFT technologies can still constitute too much risk for slow traders, thus necessitating a migration to using FBA for order execution. The difference in the effects linked to duration is meaningful, with an average of ~20% in the reduction of parameters between the β_3 and β_1 estimates.

6. Conclusion

The preponderance of the evidence in the academic literature suggests that faster trading in markets enhances market quality characteristics, such as liquidity and price discovery. However, fast trading, and the deployment of HFT technologies in general, have been implicated as factors contributing to the impairment of market quality. Two of the most significant challenges are latency arbitrage and the potentially welfare-impairing technological arms race, which have both been attracting merited increased academic focus (see Aquilina et al., 2020; Budish et al., 2015; Foucault et al., 2017; Menkveld and Zoican, 2017). These issues have also drawn regulatory responses, often in the form of policies enabling the introduction of new trading mechanisms (see Khapko and Zoican, 2020; Zhang and Ibikunle, 2020). Cboe's launch of FBA is a consequence of these regulatory innovations and it offers opportunities to empirically examine existing theories regarding the interactions between FBA and latency arbitrage. Providing evidence on these interactions also has implications for how we might characterize the technological arms race. In this study, we exploit the recent growth of FBA as a trading mechanism in European markets to investigate the relationship between latency arbitrage and FBA.

We find clear evidence that trading via FBA has emerged as an effective approach for slower traders to avoid being adversely selected by HFT snipers. Firstly, general increases in HFT activity do not imply an increase in latency arbitrage activity, indeed HFT is not a reliable gauge of the exposure of slow traders to sniping activity. This is because, consistent with the literature (see, as an example, Hagströmer and Nordén, 2013), market-making and endogenous liquidity-supplying HFTs constitute a larger proportion of HFTs than snipers in European markets. Secondly, we find that, consistent with the arguments of Budish et al. (2015), a general increase in latency arbitrage opportunities is linked with a rise in FBA volume, which indicates a desire by slower traders to avoid being adversely selected by faster sniping HFTs. We also find that although non-toxic latency arbitrage is not harmful to slower traders, it nevertheless induces a flight to using FBA as a trading mechanism in an apparent bid to avoid being sniped. Indeed, irrespective of whether latency arbitrage opportunities are toxic or not, their effect on FBA is the same – they induce an increase in its use. This of course could also imply that slower traders who are at risk of being sniped are not sophisticated enough to differentiate toxic latency arbitrage opportunities from non-toxic ones. Finally, we find that the FBA volume-inducing effect of latency arbitrage opportunities is linked to how long the opportunities last. Shorter duration latency arbitrage opportunities appear to lead to a more cautious trading approach, which calls for a general increase in the use of FBA by slower traders. Specifically, shorter duration latency arbitrage opportunities seem to imply a higher level of sniping activity, thereby inducing a flight to the safety of FBA as a trading mechanism. We find that as the duration of latency arbitrage opportunities increases, their effect on FBA reduces along the duration curve.

Although the proportion of trading volume executed via FBA and periodic auctions more generally remains low globally, this study offers clear evidence of their potential as a mechanism for addressing the challenge of latency arbitrage that slower and less sophisticated traders face in financial markets. An equitable digital society should be predicated on fair market access; therefore, mechanisms like FBA/periodic auctions and speed bumps (see Baldauf and Mollner, 2020; Bellia et al., 2020) may become crucial in the regulators' attempts to further level the playing field in modern financial markets. As such, the insights this study provides demand further attention.

References

AMIHUD, Y., MENDELSON, H. & LAUTERBACH, B. 1997. Market microstructure and securities values: Evidence from the Tel Aviv Stock Exchange. *Journal of Financial Economics*, 45, 365-390.

AQUILINA, M., BUDISH, E. B. & O'NEILL, P. 2020. Quantifying the high-frequency trading “arms race”: A simple new methodology and estimates. *Chicago Booth Research Paper*.

AQUILINA, M., FOLEY, S., O’NEILL, P. & RUF, T. 2017. Dark pool reference price latency arbitrage. *May*, 10, 55.

BALDAUF, M. & MOLLNER, J. 2020. High-frequency trading and market performance. *The Journal of Finance*, 75, 1495-1526.

BARCLAY, M. J. & HENDERSHOTT, T. 2008. A comparison of trading and non-trading mechanisms for price discovery. *Journal of Empirical Finance*, 15, 839-849.

BARCLAY, M. J., HENDERSHOTT, T. & JONES, C. M. 2008. Order consolidation, price efficiency, and extreme liquidity shocks. *Journal of Financial and Quantitative Analysis*, 93-121.

BELLIA, M., PELIZZON, L., SUBRAHMANYAM, M. G., UNO, J. & YUFEROVA, D. 2020. Low-latency trading and price discovery without trading: Evidence from the Tokyo Stock Exchange in the pre-opening period and the opening batch auction. University of Venice "Ca' Foscari" Working Paper.

BERNALES, A. 2019. Make-take decisions under high-frequency trading competition. *Journal of Financial Markets*, 45, 1-18.

BIAIS, B., FOUCAULT, T. & MOINAS, S. 2015. Equilibrium fast trading. *Journal of Financial Economics*, 116, 292-313.

BONGAERTS, D., KONG, L. & VAN ACHTER, M. 2016. Trading speed competition: Can the arms race go too far? *Available at SSRN 2779904*.

BUDISH, E., CRAMTON, P. & SHIM, J. 2015. The high-frequency trading arms race: Frequent batch auctions as a market design response. *The Quarterly Journal of Economics*, 130, 1547.

Cboe. 2019. *Periodic Auctions Book* [Online]. Available: https://markets.cboe.com/europe/equities/trading/periodic_auctions_book/ [Accessed 26 October 2020].

Cboe. 2020. *European Equities Market Share by Market* [Online]. Available: http://markets.cboe.com/europe/equities/market_share/market/venue [Accessed 25 August 2020].

CHANG, R. P., RHEE, S. G., STONE, G. R. & TANG, N. 2008. How does the call market method affect price efficiency? Evidence from the Singapore Stock Market. *Journal of Banking and Finance*, 32, 2205-2219.

CHORDIA, T., ROLL, R. & SUBRAHMANYAM, A. 2008. Liquidity and market efficiency. *Journal of Financial Economics*, 87, 249-268.

COMERTON-FORDE, C., GRÉGOIRE, V. & ZHONG, Z. 2019. Inverted fee structures, tick size, and market quality. *Journal of Financial Economics*, 134, 141-164.

COMERTON-FORDE, C., LAU, S. T. & MCINISH, T. 2007. Opening and closing behavior following the introduction of call auctions in Singapore. *Pacific-Basin Finance Journal*, 15, 18-35.

CORDI, N., FOLEY, S. & PUTNIŅŠ, T. J. 2015. Is there an optimal closing mechanism? *Available at SSRN 2646361*.

DEWHURST, D. R., VAN OORT, C. M., RING IV, J. H., GRAY, T. J., DANFORTH, C. M. & TIVNAN, B. F. 2019. Scaling of inefficiencies in the US equity markets: Evidence from three market indices and more than 2900 securities. *ArXiv Preprint ArXiv: 1902.04691*.

EASLEY, D., LÓPEZ DE PRADO, M. M. & O'HARA, M. 2012. Flow toxicity and liquidity in a high-frequency world. *The Review of Financial Studies*, 25, 1457-1493.

EASLEY, D. & O'HARA, M. 1987. Price, trade size, and information in securities markets. *Journal of Financial Economics*, 19, 69-90.

FCA. 2018. *Periodic Auctions* [Online]. Available: https://www.fca.org.uk/publications/research/periodic-auctions [Accessed 25 August 2020].

FOLEY, S. & PUTNIŅŠ, T. J. 2016. Should we be afraid of the dark? Dark trading and market quality. *Journal of Financial Economics*, 122, 456-481.

FOUCAULT, T., HOMBERT, J. & ROŞU, I. 2016. News trading and speed. *The Journal of Finance*, 71, 335-382.

FOUCAULT, T., KOZHAN, R. & THAM, W. W. 2017. Toxic arbitrage. *The Review of Financial Studies*, 30, 1053-1094.

GLOSTEN, L. R. 1989. Insider trading, liquidity, and the role of the monopolist specialist. *Journal of Business*, 211-235.

GLOSTEN, L. R. & MILGROM, P. R. 1985. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14, 71-100.

HAGSTRÖMER, B. & NORDÉN, L. 2013. The diversity of high-frequency traders. *Journal of Financial Markets*, 16, 741-770.

HIRSCHEY, N. 2020. Do high-frequency traders anticipate buying and selling pressure? *Management Science*.

HOLLIFIELD, B., SANDÅS, P. & TODD, A. 2017. Latency arbitrage when markets become faster. *Riksbank Research Paper Series*.

IBIKUNLE, G. 2015. Opening and closing price efficiency: Do financial markets need the call auction? *Journal of International Financial Markets, Institutions and Money*, 34, 208-227.

IBIKUNLE, G. 2018. Trading places: Price leadership and the competition for order flow. *Journal of Empirical Finance*, 49, 178-200.

IBIKUNLE, G., AQUILINA, M., DIAZ-RAINEY, I. & SUN, Y. 2021. City goes dark: Dark trading and adverse selection in aggregate markets. *Journal of Empirical Finance*.

INDRIAWAN, I., ROBERTO, P. & SHKILKO, A. 2020. On the effects of continuous trading. *Available at SSRN 3707154*.

JOHANN, T., PUTNIŅŠ, T. J., SAGADE, S. & WESTHEIDE, C. 2019. Quasi-dark trading: The effects of banning dark pools in a world of many alternatives. *Available at SSRN 3365994*.

KHAPKO, M. & ZOICAN, M. 2020. Do speed bumps curb low-latency investment? Evidence from a laboratory market. *Journal of Financial Markets*, 100601.

KYLE, A. S. 1985. Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 1315-1335.

LEE, C. M. & READY, M. J. 1991. Inferring trade direction from intraday data. *The Journal of Finance*, 46, 733-746.

MADHAVAN, A. 1992. Trading mechanisms in securities markets. *The Journal of Finance (New York)*, 47, 607-641.

MALCENIECE, L., MALCENIEKS, K. & PUTNIŅŠ, T. J. 2019. High frequency trading and comovement in financial markets. *Journal of Financial Economics*, 134, 381-399.

MENKVELD, A. J., YUESHEN, B. Z. & ZHU, H. 2017. Shades of darkness: A pecking order of trading venues. *Journal of Financial Economics*, 124, 503-534.

MENKVELD, A. J. & ZOICAN, M. A. 2017. Need for speed? Exchange latency and liquidity. *The Review of Financial Studies*, 30, 1188-1228.

RZAYEV, K., IBIKUNLE, G. & STEFFEN, T. 2019. The market quality implications of speed in cross-platform trading: Evidence from Frankfurt-London microwave networks.

WAH, E. 2016. How prevalent and profitable are latency arbitrage opportunities on US stock exchanges? *Available at SSRN 2729109*.

WAH, E. & WELLMAN, M. P. 2016. Latency arbitrage in fragmented markets: A strategic agent-based analysis. *Algorithmic Finance*, 5, 69-93.

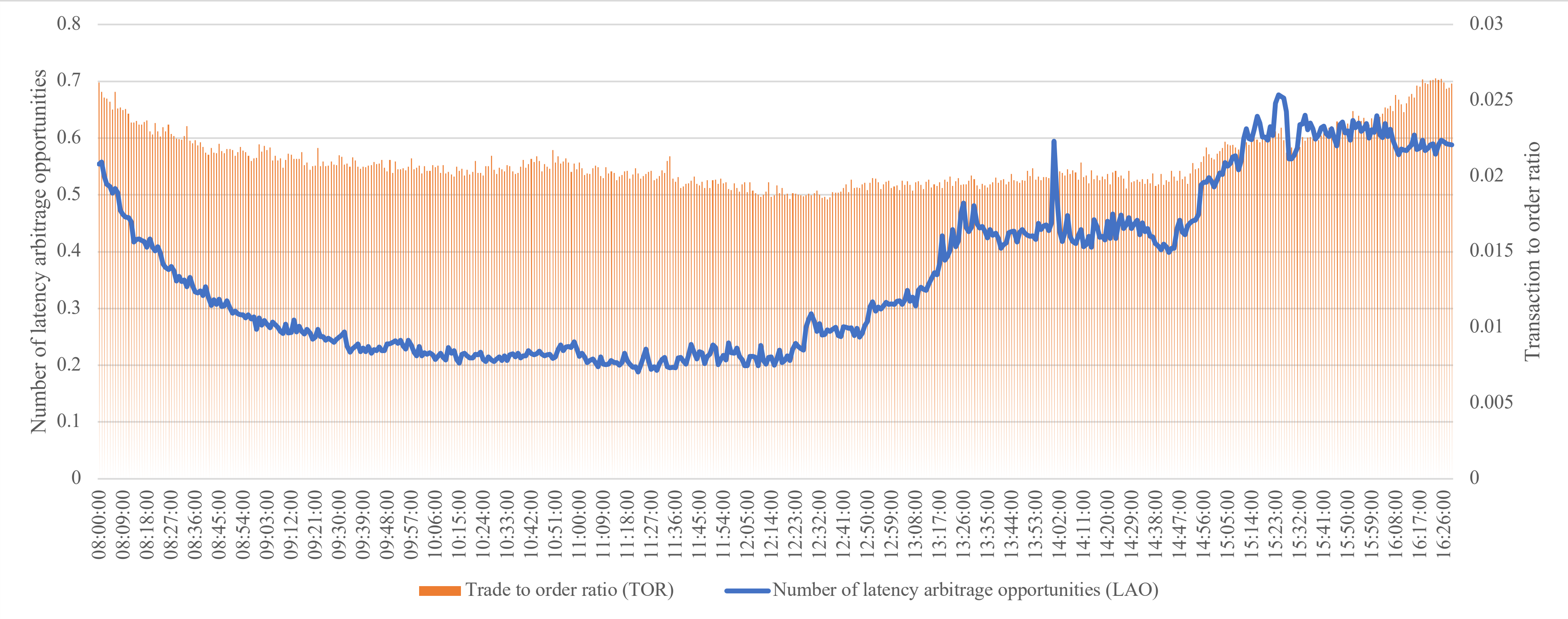
ZHANG, Z. & IBIKUNLE, G. 2020. Frequent batch auctions under liquidity constraints. *Available at SSRN 3752032*.

ZHU, H. 2014. Do dark pools harm price discovery? *The Review of Financial Studies*, 27, 747-789.

Figure 1. Latency arbitrage opportunities and high-frequency trading activity

This figure plots the stock-minute average of latency arbitrage opportunities ($LAO_{i,t}$) to transaction-to-order ratio ($TOR_{i,t}$, in Panel A) and high-frequency trading activity ($HFTTransactions_{i,t}$, as Panel B) proxies. Blue plots on the left vertical axes correspond to the stock-minute average of latency arbitrage opportunities, while orange bars on the right vertical axes represent the stock-minute average TOR_{it} and $HFTTransactions_{it}$ in panels A and B respectively. The sample consists of 100 FTSE 100 stocks trading in London's trading venues between 2nd January 2019 and 31st December 2020.

Panel A. Latency arbitrage opportunities and trade-to-order ratio



Panel B. Latency arbitrage opportunities and high-frequency trading activity

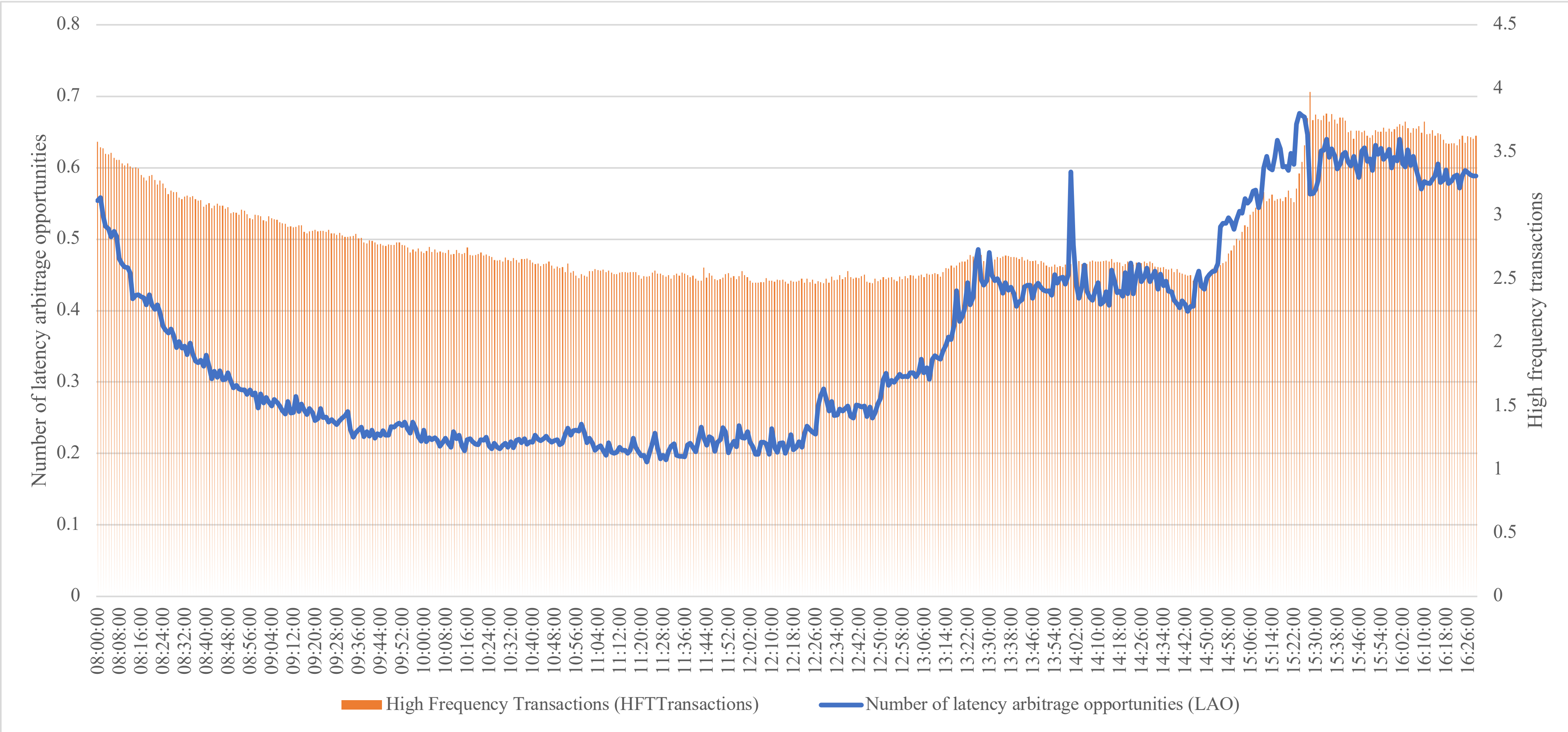


Table 1. Definitions

The table reports the variables' definitions as employed in this study.

$Variables$	$Unit$	$Definitions$
$FBATransactions_{i,t}$		Number of transactions of frequent batch auctions for stock i at time t, obtained from Cboe FBA/periodic auctions book.
$FBACurrencyVolume_{i,t}$	GBX	Currency volume of frequent batch auctions for stock i at time t, obtained from Cboe FBA/periodic auctions book.
$CLAO_{i,t}$		Cross-market latency arbitrage opportunities for stock i at time t, which occurs when bid prices for a stock on an exchange are

		at least 2bps higher than the ask prices available on a second exchange for the same stock at the same time.
$TCLAO_{i,t}$		Toxic cross-market latency arbitrage opportunities for stock i at time t, occurs when spreads following the emergence of a cross-market latency arbitrage opportunity.
$NCLAO_{i,t}$		Non-toxic cross-market latency arbitrage opportunities for stock i at time t, containing cross-market latency arbitrage opportunities, defined as when a liquid shock occurs with no corresponding widening of the spread observed thereafter.
$SLAO_{i,t}$		Single-market latency arbitrage opportunities for stock i at time t, occurs following a jump in the midpoint higher than the half spread of the midpoint prior to the jump.
$LAO_{i,t}$		All latency arbitrage opportunities for stock i at time t, as the sum of both $SLAO_{i,t}$ and $CLAO_{i,t}$.
$HFTTransactions_{i,t}$		A proxy for high-frequency trading activity in stock i at time t, defined as the ratio of messages to transactions for stock i at time t.
$HFTVolume_{i,t}$		A proxy for high-frequency trading activity in stock i at time t, defined as the ratio of the pound volume to the sum of messages for stock i at time t.
$TOR_{i,t}$		Transaction-to-order ratio for stock i at time t, defined as the ratio of the total volume of transactions to the total order volume at the best quotes for stock i at time t.
$RelativeSpread_{i,t}$	%	An inverse proxy for liquidity, defined as the ratio of the difference between the prevailing best ask and bid prices to the midpoint; expressed as the time-weighted relative quoted spread for stock i at time t.
$AdverseSelection_{i,t}$	%	A proxy for adverse selection cost, defined as $AdverseSelection_{i,\tau} = q_{i,\tau} \times \frac{midpoint_{i,\tau+\Delta} - midpoint_{i,\tau}}{midpoint_{i,\tau}}$, where τ indexes trade at time τ, $q_{i,\tau}$ is the buyer-seller indicator for the trade occurring at time τ. Buyer and seller-initiated transactions are allocated +1 and -1 values respectively. The $midpoint_{i,\tau}$ is the midpoint at time τ, and $midpoint_{i,\tau+\Delta}$ is the midpoint at time $\tau + \Delta$; to account for the high-frequency nature of the evolution of adverse selection in our data, Δ is 10 milliseconds. Time-weighted adverse selection costs, $AdverseSelection_{i,t}$, for minute t, is thereafter estimated from $AdverseSelection_{i,\tau}$.
$OrderImbalance_{i,t}$		Order imbalance for stock i at time t, defined as the difference between the number of buyer- and seller-initiated transactions divided by the sum of both sets of transactions in stock i at time t.
$Price_{i,t}$	GBX	The volume-weighted midpoint for stock i at time t.
$Volatility_{i,t}$		One-second midpoint variance for stock i at time t.
$Volume_{i,t}$	Pounds	Pounds volume for stock i at time t, excluding frequent batch auctions volume.
$Transactions_{i,t}$		Number of transactions for stock i at time t, excluding frequent batch auctions transactions.

Table 2. Descriptive statistics

The table reports the descriptive statistics of variables employed in this study. Means, standard deviations and number of observations are provided. $FBATransactions_{i,t}$ and $FBACurrencyVolume_{i,t}$ are the respective frequent batch auctions' number of transactions and currency volume for stock i at time t. $(T/N)CLAO_{i,t}$ and $SLAO_{i,t}$ are the respective numbers of (toxic/non-toxic) cross-market and single-market latency arbitrage opportunities for stock i at time t, and $LAO_{i,t}$ is the sum of $CLAO_{i,t}$ and $SLAO_{i,t}$. $HFTTransactions_{i,t}$ and $HFTVolume_{i,t}$ are high-frequency trading proxies for stock i at time t, while $TOR_{i,t}$ is the transaction-to-order ratio for stock i at time t, which proxies liquidity-supplying high-frequency trading activity. $RelativeSpread_{i,t}$ is the time-weighted one-second relative quoted spread for stock i at time t, and is an inverse proxy for liquidity. $AdverseSelection_{i,t}$ is the volume-weighted 10ms adverse selection cost proxy. $OrderImbalance_{i,t}$ proxies the imbalance between buyer- and seller-initiated transactions for stock i at time t. $Price_{i,t}$ is the volume-weighted midpoint for stock i at time t. $Volatility_{i,t}$ is the one-second midpoint variance for stock i at time t. $Volume_{i,t}$ is the pound volume, excluding frequent batch auctions, for stock i at time t, and $Transactions_{i,t}$ is the number of transactions for stock i at time t. The sample consists of 100 FTSE 100 stocks trading in London's trading venues between 2nd January 2019 and 31st December 2020.

$Variables$	$Mean$	$Standard\ Deviation$	$Number\ of\ Observations$
$FBATransactions_{i,t}$	0.896	2.223	26550873
$FBACurrencyVolume_{i,t}$	46115	1935846	26550873
$CLAO_{i,t}$	0.01	0.557	26550873
$TCLAO_{i,t}$	0.003	0.122	26550873
$NCLAO_{i,t}$	0.007	0.457	26550873
$SLAO_{i,t}$	0.351	1.626	26550873
$LAO_{i,t}$	0.362	1.759	26550873
$HFTTransactions_{i,t}$	2.784	2.986	26550873
$HFTVolume_{i,t}$	-17.236	661.307	26550873
$TOR_{i,t}$	0.021	0.061	26550873
$RelativeSpread_{i,t}$	0.074	0.135	26550873

$AdverseSelection_{i,t}$	0.00049	0.00108	26550873
$OrderImbalance_{i,t}$	1.17578	1.299858	26550873
$Price_{i,t}$	2004.381	2218.529	26550873
$Volatility_{i,t}$	0.23541	1.21302	26550873
$Volume_{i,t}$	9287.433	45029.62	26550873
$Transactions_{i,t}$	11.327	17.8	26550873

Table 3. Frequent batch auctions and high-frequency trading

This table reports the estimated coefficients for the following stock-minute model:

$$FBA_{i,t} = \gamma_t + \delta_i + \beta_1 HFTProxy_{i,t-1} + \beta_2 Control_{i,t} + \epsilon_{i,t}$$

where $FBA_{i,t}$ corresponds to one of the natural logarithm of frequent batch auctions proxies, i.e. $FBACurrencyVolume_{i,t}$ and $FBATransactions_{i,t}$, and one of the natural logarithm of percentage of frequent batch auctions proxies, i.e. $\%FBACurrencyVolume_{i,t}$ and $\%FBATransactions_{i,t}$ for stock i at time (minute) t. γ_i and δ_t are stock and time fixed effects respectively. $HFTProxy_{i,t-1}$ corresponds to one of HFT proxies ($HFTVolume_{i,t-1}$ and $HFTTransactions_{i,t-1}$) for stock i at time (minute) $t-1$. $Control_{i,t}$ contains a series of control variables for stock i at time t, including the natural logarithm of $Volume_{i,t}$, which is the pounds volume of transactions, excluding frequent batch auctions, in stock i at time t, the natural logarithm of $Price_{i,t}$, which is the volume-weighted midpoint for stock i at time t, the natural logarithm of $Transactions_{i,t}$, which is the number of transactions in stock i in time t, $OrderImbalance_{i,t}$, which proxies order imbalance for stock i at time t, and $Volatility_{i,t}$, the midpoint return volatility for stock i at time t. $Control_{i,t}$ also includes $RelativeSpread_{i,t}$, a time-weighted inverse proxy for liquidity for stock i at time t, and $AdverseSelection_{i,t}$, a time-weighted proxy for the adverse selection cost for stock i at time t. The t-statistics are presented in parentheses and derived from standard errors clustered by stock and time. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample consists of 100 FTSE 100 stocks trading in London's trading venues between 2nd January 2019 and 31st December 2020.

Panel A. Regressions with $HFTVolume_{i,t-1}$ as HFT proxy

Dependent Variable	log ($FBATranscations_{i,t}$)	log ($FBACurrencyVolume_{i,t}$)	log ($\%FBATranscations_{i,t}$)	log ($\%FBACurrencyVolume_{i,t}$)
$HFTVolume_{i,t-1}$	-9.960×10^{-7}** (-2.608)	-4.720×10^{-6}* (-2.539)	-1.950×10^{-6}* (-1.608)	-1.710×10^{-6} (-1.504)
$RelativeSpread_{i,t}$	3.985×10^{-2} (1.271)	2.683×10^{-1} (1.370)	3.985×10^{-2} (1.271)	2.177×10^{-1} (1.341)
$AdverseSelection_{i,t}$	9.050×10^{1}*** (7.285)	3.086×10^{2}*** (6.903)	1.300×10^{2}*** (6.276)	1.210×10^{2}*** (5.915)
log ($Volume_{i,t}$)	-1.059×10^{-1}*** (-22.643)	-4.503×10^{-2}*** (-26.778)	-1.764×10^{-1}*** (-31.037)	-2.213×10^{-1}*** (-33.770)
log ($Price_{i,t}$)	1.161×10^{-1}** (2.487)	7.563×10^{-1}*** (3.569)	4.857×10^{-1}*** (3.694)	4.716×10^{-1}*** (3.553)
log ($Transactions_{i,t}$)	3.593×10^{-1}*** (30.784)	1.615*** (37.290)	7.016×10^{-1}*** (48.542)	7.896×10^{-1}*** (48.851)

$Volatility_{i,t}$	-1.080×10^{-8} (-1.159)	-7.050×10^{-8} (1.204)	-5.950×10^{-8} (-1.227)	-5.990×10^{-8} (-1.231)
$OrderImbalance_{i,t}$	3.420×10^{-8} (0.824)	4.560×10^{-8} (0.236)	-4.330×10^{-9} (-0.041)	6.450×10^{-9} (0.052)
Observations	26,550,873	26,550,873	26,550,873	26,550,873
$\overline{R^2}$	0.1989	0.1762	0.1375	0.1343
Stock and time fixed effects	Yes	Yes	Yes	Yes

Panel B. Regressions with $HFTTransactions_{i,t-1}$ as HFT proxy

Dependent Variable	log ($FBATranscations_{i,t}$)	log ($FBACurrencyVolume_{i,t}$)	log ($\%FBATranscations_{i,t}$)	log ($\%FBACurrencyVolume_{i,t}$)
$HFTTransactions_{i,t-1}$	-8.755×10^{-3}*** (-8.893)	-3.656×10^{-2}*** (-8.696)	-1.443×10^{-2}*** (-6.317)	-1.431×10^{-2}*** (-6.228)
$RelativeSpread_{i,t}$	4.385×10^{-2} (1.265)	2.851×10^{-1} (1.357)	2.231×10^{-1} (1.332)	2.243×10^{-1} (1.335)
$AdverseSelection_{i,t}$	9.232×10^{1}*** (7.336)	3.162×10^{2}*** (6.969)	1.330×10^{2}*** (6.341)	1.240×10^{2}*** (5.984)
log ($Volume_{i,t}$)	-1.043×10^{-1}*** (-22.874)	-4.435×10^{-1}*** (-27.011)	-1.737×10^{-1}*** (-30.601)	-2.186×10^{-1}*** (-33.783)
log ($Price_{i,t}$)	1.131×10^{-1}** (2.430)	7.434×10^{-1}*** (3.524)	4.806×10^{-1}*** (3.659)	4.666×10^{-1}*** (3.517)
log ($Transactions_{i,t}$)	3.555×10^{-1}*** (31.146)	1.599*** (37.722)	6.954×10^{-1}*** (47.969)	7.834×10^{-1}*** (48.777)
$Volatility_{i,t}$	-1.210×10^{-8} (-1.173)	-7.600×10^{-8} (-1.208)	-6.170×10^{-8} (-1.228)	-6.200×10^{-8} (-1.231)
$OrderImbalance_{i,t}$	2.730×10^{-8} (0.670)	1.690×10^{-8} (0.089)	-1.570×10^{-8} (-0.151)	-4.760×10^{-9} (-0.038)
Observations	26,550,873	26,550,873	26,550,873	26,550,873

$\overline{R^2}$	0.1992	0.1764	0.1376	0.1344
Stock and time fixed effects	Yes	Yes	Yes	Yes

Table 4. Frequent batch auctions and liquidity-supplying high-frequency trading

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

$$FBA_{i,t} = \gamma_t + \delta_i + \beta_1 TOR_{i,t-1} + \beta_2 Control_{i,t} + \epsilon_{i,t}$$

where $FBA_{i,t}$ corresponds to one of the natural logarithm of frequent batch auctions proxies, i.e. $FBACurrencyVolume_{i,t}$ and $FBATransactions_{i,t}$, and one of the natural logarithm of percentage of frequent batch auctions proxies, i.e. $\%FBACurrencyVolume_{i,t}$ and $\%FBATransactions_{i,t}$ for stock i at time (minute) t. γ_i and δ_t are stock and time fixed effects respectively. $TOR_{i,t-1}$ corresponds to the transaction-to-order ratio for stock i and time (minute) $t-1$. $Control_{i,t}$ contains a series of control variables for stock i at time t, including the natural logarithm of $Volume_{i,t}$, which is the pounds volume of transactions, excluding frequent batch auctions, in stock i at time t, the natural logarithm of $Price_{i,t}$, which is the volume-weighted midpoint for stock i at time t, the natural logarithm of $Transactions_{i,t}$, which is the number of transactions in stock i at time t, $OrderImbalance_{i,t}$, which proxies order imbalance for stock i at time t, and $Volatility_{i,t}$, the midpoint return volatility for stock i at time t. $Control_{i,t}$ also includes $RelativeSpread_{i,t}$, a time-weighted inverse proxy for liquidity for stock i at time t, and $AdverseSelection_{i,t}$, a time-weighted proxy for the adverse selection cost for stock i at time t. The t-statistics are presented in parentheses and derived from standard errors clustered by stock and time. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample consists of 100 FTSE 100 stocks trading in London's trading venues between 2nd January 2019 and 31st December 2020.

Dependent Variable	log ($FBATranscations_{i,t}$)	log ($FBACurrencyVolume_{i,t}$)	log ($\%FBATranscations_{i,t}$)	log ($\%FBACurrencyVolume_{i,t}$)
$TOR_{i,t-1}$	3.200×10^{-2}*** (2.752)	1.428×10^{-1}*** (2.756)	8.127×10^{-1}*** (2.763)	8.070×10^{-1}*** (2.755)
$RelativeSpread_{i,t}$	3.856×10^{-2} (1.237)	2.555×10^{-1} (1.325)	2.087×10^{-2} (1.304)	2.106×10^{-1} (1.309)
$AdverseSelection_{i,t}$	9.033×10^{1}*** (7.234)	3.071×10^{2}*** (6.835)	1.292×10^{2}*** (6.193)	1.202×10^{2}*** (5.837)
log ($Volume_{i,t}$)	-1.060×10^{-1}*** (-22.755)	-4.511×10^{-1}*** (-26.998)	-1.768×10^{-1}*** (-31.278)	-2.216×10^{-1}*** (-33.907)
log ($Price_{i,t}$)	1.169×10^{-1}*** (2.845)	7.324×10^{-1}*** (3.879)	4.727×10^{-1}** (4.030)	4.614×10^{-1}*** (3.918)
log ($Transactions_{i,t}$)	3.588×10^{-1}*** (30.954)	1.613*** (37.579)	7.009×10^{-1}*** (48.794)	7.888×10^{-1}*** (49.231)
$Volatility_{i,t}$	-1.090×10^{-8} (-1.162)	-6.980×10^{-8} (-1.206)	-5.920×10^{-8} (-1.231)	-5.970×10^{-8} (-1.234)

$OrderImbalance_{i,t}$	3.680×10^{-8} (0.864)	5.100×10^{-8} (0.254)	-1.030×10^{-9} (-0.009)	1.030×10^{-8} (0.077)
Observations	26,550,873	26,550,873	26,550,873	26,550,873
$\overline{R^2}$	0.1991	0.1763	0.1377	0.1345
Stock and time fixed effects	Yes	Yes	Yes	Yes

Table 5. Frequent batch auctions and latency arbitrage opportunities

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

$$FBA_{i,t} = \gamma_t + \delta_i + \beta_1 \log\left(LAO_{i,t-1}\right) + \beta_2 HFTD_{i,d} + \beta_3 HFTD_{i,d} \times \log\left(LAO_{i,t-1}\right) + \beta_4 Control_{i,t} + \epsilon_{i,t}$$

where $FBA_{i,t}$ corresponds to one of the natural logarithm of frequent batch auctions proxies, i.e. $FBACurrencyVolume_{i,t}$ and $FBATransactions_{i,t}$, and one of the natural logarithm of percentage of frequent batch auctions proxies, i.e. $\%FBACurrencyVolume_{i,t}$ and $\%FBATransactions_{i,t}$ for stock i at time (minute) t. γ_i and δ_t are stock and time fixed effects respectively. $LAO_{i,t-1}$ corresponds to the number of latency arbitrage opportunities for stock i at time (minute) $t-1$. $HFTD_{i,d}$ is a dummy variable capturing unusually high levels of $HFTProxy_{i,d}$ for stock i on day d, it takes the value of one on day d when the daily HFT proxy $HFTProxy_{i,d}$ ($HFTVolume_{i,d}$ or $HFTTransactions_{i,d}$) is one standard deviation higher than the 60-day (-30 and +30 days) average, and zero otherwise. $Control_{i,t}$ contains a series of control variables for stock i at time t, including the natural logarithm of $Volume_{i,t}$, which is the pounds volume of transactions, excluding frequent batch auctions, in stock i at time t, the natural logarithm of $Price_{i,t}$, which is the volume-weighted midpoint for stock i at time t, the natural logarithm of $Transactions_{i,t}$, which is the number of transactions in stock i at time t, $OrderImbalance_{i,t}$, which proxies order imbalance for stock i at time t, and $Volatility_{i,t}$, the midpoint return volatility for stock i at time t. $Control_{i,t}$ also includes $RelativeSpread_{i,t}$, a time-weighted inverse proxy for liquidity for stock i at time t, and $AdverseSelection_{i,t}$, a time-weighted proxy for the adverse selection cost for stock i at time t. 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 100 FTSE 100 stocks trading in London's trading venues between 2nd January 2019 and 31st December 2020.

Panel A. Regressions with $HFTVolumeD_{i,d}$ as HFT dummy

Dependent Variable	log ($FBATranscations_{i,t}$)	log ($FBACurrencyVolume_{i,t}$)	log ($\%FBATranscations_{i,t}$)	log ($\%FBACurrencyVolume_{i,t}$)
log ($LAO_{i,t-1}$)	4.581×10^{-2}*** (13.138)	1.677×10^{-1}*** (12.919)	8.447×10^{-2}*** (11.260)	8.351×10^{-2}*** (11.021)
$HFTVolumeD_{i,d}$	-1.435×10^{-1}*** (-11.997)	-6.399×10^{-1}*** (-13.247)	-3.348×10^{-1}*** (-12.038)	-3.308×10^{-1}*** (-11.502)
$HFTVolumeD_{i,d}$ × log ($LAO_{i,t-1}$)	-2.374×10^{-2}*** (-5.268)	-9.013×10^{-2}*** (-5.057)	-4.062×10^{-2}*** (-4.092)	-4.009×10^{-2}*** (-3.882)
$RelativeSpread_{i,t}$	4.287×10^{-2} (1.258)	2.710×10^{-1} (1.328)	2.165×10^{-1} (1.305)	2.184×10^{-1} (1.310)
$AdverseSelection_{i,t}$	8.544×10^{1}*** (7.052)	2.902×10^{2}*** (6.624)	1.208×10^{2}*** (5.931)	1.119×10^{2}*** (5.567)

log ($Volume_{i,t}$)	-1.039×10^{-1}*** (-23.243)	-4.430×10^{-1}*** (-27.413)	-1.727×10^{-1}*** (-31.657)	-2.175×10^{-1}*** (-34.224)
log ($Price_{i,t}$)	1.291×10^{-1}*** (3.138)	7.722×10^{-1}*** (4.090)	4.916×10^{-1}*** (4.193)	4.800×10^{-1}*** (4.080)
log ($Transactions_{i,t}$)	3.525×10^{-1}*** (31.488)	1.590*** (38.000)	6.888×10^{-1}*** (49.966)	7.768×10^{-1}*** (49.775)
$Volatility_{i,t}$	-1.200×10^{-8} (-1.172)	-7.400×10^{-8} (-1.207)	-6.130×10^{-8} (-1.230)	-6.180×10^{-8} (-1.233)
$OrderImbalance_{i,t}$	2.850×10^{-8} (0.723)	1.490×10^{-8} (0.081)	-2.070×10^{-8} (-0.205)	-9.140×10^{-9} (-0.076)
Observations	26,550,873	26,550,873	26,550,873	26,550,873
$\overline{R^2}$	0.2002	0.1771	0.1382	0.1350
Stock and time fixed effects	Yes	Yes	Yes	Yes

Panel B. Regressions with $HFTTransactionsD_{i,d}$ as HFT dummy

Dependent Variable	log ($FBATranscations_{i,t}$)	log ($FBACurrencyVolume_{i,t}$)	log (%$FBATranscations_{i,t}$)	log (%$FBACurrencyVolume_{i,t}$)
log ($LAO_{i,t-1}$)	4.546×10^{-2}*** (14.003)	1.663×10^{-1}*** (13.677)	8.364×10^{-2}*** (11.742)	8.303×10^{-2}*** (11.523)
$HFTTransactionsD_{i,d}$	-1.217×10^{-1}*** (-13.546)	-5.412×10^{-1}*** (-15.756)	-2.846×10^{-1}*** (-13.912)	-2.891×10^{-1}*** (-14.078)
$HFTTransactionsD_{i,d}$ × log ($LAO_{i,t-1}$)	-1.851×10^{-2}*** (-5.306)	-6.879×10^{-2}*** (-5.109)	-2.945×10^{-2}*** (-3.612)	-3.101×10^{-2}*** (-3.835)
$RelativeSpread_{i,t}$	4.400×10^{-2} (1.270)	2.762×10^{-1} (1.336)	2.194×10^{-1} (1.310)	2.212×10^{-1} (1.315)
$AdverseSelection_{i,t}$	8.572×10^{1}*** (7.036)	2.916×10^{2}*** (6.603)	1.215×10^{2}*** (5.916)	1.127×10^{2}*** (5.559)

log ($Volume_{i,t}$)	-1.032×10^{-1}*** (-23.201)	-4.399×10^{-1}*** (-27.358)	-1.709×10^{-1}*** (-31.375)	-2.158×10^{-1}*** (-34.107)
log ($Price_{i,t}$)	1.330×10^{-1}*** (3.229)	7.905×10^{-1}*** (4.172)	5.016×10^{-1}*** (4.267)	4.900×10^{-1}*** (4.158)
log ($Transactions_{i,t}$)	3.511×10^{-1}*** (31.419)	1.583*** (37.922)	6.849×10^{-1}*** (49.503)	7.729×10^{-1}*** (49.476)
$Volatility_{i,t}$	-1.220×10^{-8} (-1.175)	-7.510×10^{-8} (-1.210)	-6.190×10^{-8} (-1.231)	-6.240×10^{-8} (-1.234)
$OrderImbalance_{i,t}$	2.870×10^{-8} (0.728)	1.570×10^{-8} (0.085)	-2.040×10^{-8} (-0.202)	-9.030×10^{-9} (-0.075)
Observations	26,550,873	26,550,873	26,550,873	26,550,873
$\overline{R^2}$	0.2000	0.1770	0.1381	0.1349
Stock and time fixed effects	Yes	Yes	Yes	Yes

Table 6. Frequent batch auctions and the varying effects of types of latency arbitrage opportunities

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

$$FBA_{i,t} = \gamma_t + \delta_i + \beta_1 \log(SpecificLAO_{i,t-1}) + \beta_2 Control_{i,t} + \epsilon_{i,t}$$

where $FBA_{i,t}$ corresponds to one of the natural logarithm of frequent batch auctions proxies, i.e. $FBACurrencyVolume_{i,t}$ and $FBATransactions_{i,t}$, and one of the natural logarithm of percentage of frequent batch auctions proxies, i.e. $\%FBACurrencyVolume_{i,t}$ and $\%FBATransactions_{i,t}$ for stock i at time (minute) t. γ_i and δ_t are stock and time fixed effects respectively. $SpecificLAO_{i,t-1}$ corresponds to the number of different types of latency arbitrage opportunities, i.e. single-market ($SLAO_{i,t-1}$), cross-market ($CLAO_{i,t-1}$), toxic cross-market ($TCLAO_{i,t-1}$), and non-toxic cross-market ($NCLAO_{i,t-1}$) latency arbitrage opportunities, for stock i at time (minute) $t-1$. $Control_{i,t}$ contains a series of control variables for stock i at time t, including the natural logarithm of $Volume_{i,t}$, which is the pounds volume of transactions, excluding frequent batch auctions, in stock i at time t, the natural logarithm of $Price_{i,t}$, which is the volume-weighted midpoint for stock i at time t, the natural logarithm of $Transactions_{i,t}$, which is the number of transactions in stock i at time t, $OrderImbalance_{i,t}$, which proxies order imbalance for stock i at time t, and $Volatility_{i,t}$, the midpoint return volatility for stock i at time t. $Control_{i,t}$ also includes $RelativeSpread_{i,t}$, a time-weighted inverse proxy for liquidity for stock i at time t, and $AdverseSelection_{i,t}$, a time-weighted proxy for the adverse selection cost for stock i at time t. The t-statistics are presented in parentheses and derived from standard errors clustered by stock and time. *, ** and *** correspond to statistical significance at 0.1, 0.05 and 0.01 levels respectively. The sample consists of 100 FTSE 100 stocks trading in London's trading venues between 2nd January 2019 and 31st December 2020.

Panel A. Single-market latency arbitrage

Dependent Variable	$\log(FBATranscations_{i,t})$	$\log(FBACurrencyVolume_{i,t})$	$\log(\%FBATranscations_{i,t})$	$\log(\%FBACurrencyVolume_{i,t})$
$\log(SLAO_{i,t-1})$	4.232×10^{-2}*** (12.895)	1.543×10^{-1}*** (12.632)	7.857×10^{-2}*** (10.982)	7.773×10^{-2}*** (10.765)
$RelativeSpread_{i,t}$	4.312×10^{-2} (1.270)	2.719×10^{-1} (-1.337)	2.169×10^{-1} (1.311)	2.188×10^{-1} (1.316)
$AdverseSelection_{i,t}$	8.442×10^{1}*** (6.990)	2.856×10^{2}*** (6.543)	1.183×10^{2}*** (5.840)	1.094×10^{2}*** (5.471)
$\log(Volume_{i,t})$	-1.042×10^{-1}*** (-23.169)	-4.443×10^{-1}*** (-27.310)	-1.733×10^{-1}*** (-31.644)	-2.182×10^{-1}*** (-34.152)
$\log(Price_{i,t})$	1.304×10^{-1}*** (3.156)	7.787×10^{-1}*** (4.094)	4.953×10^{-1}*** (4.203)	4.837×10^{-1}*** (4.093)

log ($Transactions_{i,t}$)	3.542×10^{-1}*** (31.367)	1.597*** (37.836)	6.928×10^{-1}*** (49.964)	7.808×10^{-1}*** (49.673)
$Volatility_{i,t}$	-1.200×10^{-8} (-1.174)	-7.390×10^{-8} (-1.209)	-6.120×10^{-8} (-1.231)	-6.170×10^{-8} (-1.234)
$OrderImbalance_{i,t}$	3.240×10^{-8} (0.822)	3.230×10^{-8} (0.176)	-1.150×10^{-8} (-0.115)	-2.840×10^{-11} (-0.000)
Observations	26,550,873	26,550,873	26,550,873	26,550,873
$\overline{R^2}$	0.1997	0.1766	0.1378	0.1346
Stock and time fixed effects	Yes	Yes	Yes	Yes

Panel B. Cross-market latency arbitrage

Dependent Variable	log ($FBATranscations_{i,t}$)	log ($FBACurrencyVolume_{i,t}$)	log (%$FBATranscations_{i,t}$)	log (%$FBACurrencyVolume_{i,t}$)
log ($CLAO_{i,t-1}$)	6.179×10^{-2}*** (7.393)	1.758×10^{-1}*** (6.794)	5.440×10^{-2}*** (3.878)	5.282×10^{-2}*** (3.708)
$RelativeSpread_{i,t}$	3.876×10^{-2} (1.235)	2.555×10^{-1} (1.322)	2.083×10^{-1} (1.301)	2.102×10^{-1} (1.306)
$AdverseSelection_{t,t}$	8.938×10^{1}*** (7.198)	3.045×10^{2}*** (6.795)	1.285×10^{2}*** (6.173)	1.196×10^{2}*** (5.818)
log ($Volume_{i,t}$)	-1.059×10^{-1}*** (-22.768)	-4.506×10^{-2}*** (-26.930)	-1.767×10^{-1}*** (-31.148)	-2.215×10^{-1}*** (-33.733)
log ($Price_{i,t}$)	1.137×10^{-1}*** (2.807)	7.173×10^{-1}*** (3.860)	4.639×10^{-1}*** (4.018)	4.526×10^{-1}*** (3.901)
log ($Transactions_{i,t}$)	3.590×10^{-1}*** (30.891)	1.615*** (37.411)	7.021×10^{-1}*** (48.649)	7.900×10^{-1}*** (48.878)
$Volatility_{i,t}$	-1.100×10^{-8} (-1.168)	-7.020×10^{-7} (-1.209)	-5.920×10^{-8} (-1.231)	-5.970×10^{-8} (-1.234)

$OrderImbalance_{i,t}$	3.210×10^{-8} (0.784)	3.210×10^{-8} (0.169)	-1.090×10^{-8} (-0.105)	6.010×10^{-10} (0.005)
Observations	26,550,873	26,550,873	26,550,873	26,550,873
$\overline{R^2}$	0.1990	0.1762	0.1376	0.1344
Stock and time fixed effects	Yes	Yes	Yes	Yes

Panel C. Toxic cross-market latency arbitrage

Dependent Variable	log ($FBATranscations_{i,t}$)	log ($FBACurrencyVolume_{i,t}$)	log (%$FBATranscations_{i,t}$)	log (%$FBACurrencyVolume_{i,t}$)
log ($TCLAO_{i,t-1}$)	6.339×10^{-2}*** (6.469)	1.658×10^{-1}*** (5.469)	4.331×10^{-2}** (2.601)	4.166×10^{-2}** (2.469)
$RelativeSpread_{i,t}$	3.851×10^{-2} (1.233)	2.547×10^{-1} (1.321)	2.080×10^{-1} (1.301)	2.099×10^{-1} (1.306)
$AdverseSelection_{i,t}$	8.984×10^{1}*** (7.212)	3.060×10^{2}*** (6.813)	1.290×10^{2}*** (6.187)	1.201×10^{2}*** (5.833)
log ($Volume_{i,t}$)	-1.060×10^{-1}*** (-22.722)	-4.509×10^{-1}*** (-26.901)	-1.768×10^{-1}*** (-31.139)	-2.216×10^{-1}*** (-33.716)
log ($Price_{i,t}$)	1.135×10^{-1}*** (2.804)	7.168×10^{-1}*** (3.859)	4.637×10^{-1}*** (4.017)	4.524×10^{-1}*** (3.900)
log ($Transactions_{i,t}$)	3.592×10^{-1}*** (30.844)	1.616*** (37.383)	7.023×10^{-1}*** (48.644)	7.902×10^{-1}*** (48.868)
$Volatility_{i,t}$	-1.090×10^{-8} (-1.165)	-6.990×10^{-8} (-1.208)	-5.920×10^{-8} (-1.231)	-5.960×10^{-8} (-1.234)
$OrderImbalance_{i,t}$	3.290×10^{-8} (0.806)	3.460×10^{-8} (0.182)	-1.000×10^{-8} (-0.097)	1.410×10^{-9} (0.011)
Observations	26,550,873	26,550,873	26,550,873	26,550,873
$\overline{R^2}$	0.1990	0.1762	0.1376	0.1343
Stock and time fixed	Yes	Yes	Yes	Yes

effects				

Panel D. Non-toxic cross-market latency arbitrage

Dependent Variable	log ($FBATranscations_{i,t}$)	log ($FBACurrencyVolume_{i,t}$)	log (%$FBATranscations_{i,t}$)	log (%$FBACurrencyVolume_{i,t}$)
log ($NCLAO_{i,t-1}$)	6.620×10^{-2}*** (7.017)	1.887×10^{-1}*** (6.387)	5.822×10^{-2}*** (3.667)	5.643×10^{-2}*** (3.498)
$RelativeSpread_{i,t}$	3.860×10^{-2} (1.234)	2.550×10^{-1} (1.322)	2.081×10^{-1} (1.301)	2.101×10^{-1} (1.306)
$AdverseSelection_{i,t}$	8.966×10^{1}*** (7.210)	3.053×10^{2}*** (6.807)	1.288×10^{2}*** (6.179)	1.198×10^{2}*** (5.825)
log ($Volume_{i,t}$)	-1.059×10^{-1}*** (-22.746)	-4.508×10^{-1}*** (-26.918)	-1.767×10^{-1}*** (-31.142)	-2.215×10^{-1}*** (-33.726)
log ($Price_{i,t}$)	1.135×10^{-1}*** (2.803)	7.168×10^{-1}*** (3.858)	4.637×10^{-2}*** (4.017)	4.524×10^{-1}*** (3.900)
log ($Transactions_{i,t}$)	3.591×10^{-1}*** (30.869)	1.615*** (37.399)	7.022×10^{-1}*** (48.643)	7.901×10^{-1}*** (48.872)
$Volatility_{i,t}$	-1.090×10^{-8} (-1.167)	-7.000×10^{-8} (-1.208)	-5.920×10^{-8} (-1.231)	-5.970×10^{-8} (-1.234)
$OrderImbalance_{i,t}$	3.230×10^{-8} (0.788)	3.270×10^{-8} (0.172)	-1.070×10^{-8} (-0.103)	7.840×10^{-10} (0.063)
Observations	26,550,873	26,550,873	26,550,873	26,550,873
$\overline{R^2}$	0.1990	0.1762	0.1376	0.1344
Stock and time fixed effects	Yes	Yes	Yes	Yes

Table 7. Frequent batch auctions and latency arbitrage opportunity durations

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

$$FBA_{i,t} = \gamma_t + \delta_i + \beta_1 log\left(shortD_{i,t-1} \times LAO_{i,t-1}\right) + \beta_2 log\left(middleD_{i,t-1} \times LAO_{i,t-1}\right) + \beta_3 log(longD_{i,t-1} \times LAO_{i,t-1}) + \beta_{14} Control_{i,t} + \epsilon_{i,t}$$

where $FBA_{i,t}$ corresponds to one of the natural logarithm of frequent batch auctions proxies, i.e. $FBACurrencyVolume_{i,t}$ and $FBATransactions_{i,t}$, and one of the natural logarithm of percentage of frequent batch auctions proxies, i.e. $\%FBACurrencyVolume_{i,t}$ and $\%FBATransactions_{i,t}$ for stock i at time (minute) t. γ_i and δ_t are stock and time fixed effects respectively. $LAO_{i,t-1}$ corresponds to the number of latency arbitrage opportunities for stock i and time (minute) $t-1$. Duration dummies are introduced based on the durations of latency arbitrage opportunities. $shortD_{i,t-1}$, $middleD_{i,t-1}$ and $longD_{i,t-1}$ are dummies corresponding to the shortest, middle and longest latency arbitrage opportunity duration terciles respectively. Duration terciles are obtained using volume-weighted durations of latency arbitrage opportunities. $Control_{i,t}$ contains a series of control variables for stock i at time t, including the natural logarithm of $Volume_{i,t}$, which is the pounds volume of transactions, excluding frequent batch auctions, in stock i at time t, the natural logarithm of $Price_{i,t}$, which is the volume-weighted midpoint for stock i at time t, the natural logarithm of $Transactions_{i,t}$, which is the number of transactions in stock i at time t, $OrderImbalance_{i,t}$, which proxies order imbalance for stock i at time t, and $Volatility_{i,t}$, the midpoint return volatility for stock i at time t. $Control_{i,t}$ also includes $RelativeSpread_{i,t}$, a time-weighted inverse proxy for liquidity for stock i at time t, and $AdverseSelection_{i,t}$, a time-weighted proxy for the adverse selection cost for stock i at time t. 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 100 FTSE 100 stocks trading in London's trading venues between 2nd January 2019 and 31st December 2020.

Dependent Variable	log ($FBATranscations_{i,t}$)	log ($FBACurrencyVolume_{i,t}$)	log ($\%FBATranscations_{i,t}$)	log ($\%FBACurrencyVolume_{i,t}$)
$shortD_{i,t-1}$ $\times$ log ($LAO_{i,t-1}$)	4.877×10^{-2}*** (14.534)	1.786×10^{-1}*** (14.812)	8.966×10^{-2}*** (12.623)	8.972×10^{-2}*** (12.609)
$middleD_{i,t-1}$ $\times$ log ($LAO_{i,t-1}$)	4.747×10^{-2}*** (12.432)	1.565×10^{-1}*** (11.828)	7.294×10^{-2}*** (9.396)	7.189×10^{-2}*** (9.083)
$longD_{i,t-1}$ $\times$ log ($LAO_{i,t-1}$)	3.813×10^{-2}*** (8.642)	1.322×10^{-1}*** (8.019)	6.370×10^{-2}*** (6.896)	6.245×10^{-2}*** (6.750)
$RelativeSpread_{i,t}$	4.220×10^{-2} (1.260)	2.677×10^{-1} (1.332)	2.144×10^{-2} (1.307)	2.163×10^{-1} (1.312)
$AdverseSelection_{i,t}$	8.523×10^{1}*** (6.989)	2.895×10^{2}*** (6.561)	1.208×10^{1}*** (5.885)	1.119×10^{2}*** (5.524)

log ($Volume_{i,t}$)	-1.047×10^{-1}*** (-23.086)	-4.464×10^{-1}*** (-27.220)	-1.745×10^{-1}*** (-31.512)	-2.194×10^{-1}*** (-34.044)
log ($Price_{i,t}$)	1.241×10^{-1}*** (3.024)	7.537×10^{-1}*** (3.998)	4.816×10^{-1}*** (4.121)	4.701×10^{-1}*** (4.009)
log ($Transactions_{i,t}$)	3.559×10^{-1}*** (31.260)	1.604*** (37.731)	6.965×10^{-1}*** (49.504)	7.845×10^{-1}*** (49.408)
$Volatility_{i,t}$	-1.180×10^{-8} (-1.175)	-7.310×10^{-8} (-1.210)	-6.070×10^{-8} (-1.232)	-6.120×10^{-8} (-1.235)
$OrderImbalance_{i,t}$	3.210×10^{-8} (0.809)	3.160×10^{-8} (0.171)	-1.170×10^{-8} (0.116)	-2.280×10^{-10} (-0.002)
Observations	26,550,873	26,550,873	26,550,873	26,550,873
$\overline{R^2}$	0.1995	0.1765	0.1377	0.1345
Stock and time fixed effects	Yes	Yes	Yes	Yes