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Quantifying the High-Frequency Trading "Arms Race": A Simple New Methodology and Estimates

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Abstract

We use stock exchange *message data* to quantify the negative aspect of high-frequency trading, known as "latency arbitrage." The key difference between message data and widely-familiar limit order book data is that message data contain *attempts* to trade or cancel that *fail*. This allows the researcher to observe both winners and losers in a race, whereas in limit order book data you cannot see the losers, so you cannot directly see the races. We find that latency-arbitrage races are very frequent (one per minute for FTSE 100 stocks), extremely fast (the modal race lasts 5-10 millionths of a second), and account for a large portion of overall trading volume (about 20%). Race participation is concentrated, with the top-3 firms accounting for over half of all race wins and losses. Our main estimates suggest that eliminating latency arbitrage would reduce the cost of trading by 17% and that the total sums at stake are on the order of $5 billion annually in global equity markets.

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"The market is rigged." – Michael Lewis, Flash Boys (Lewis, 2014)

"Widespread latency arbitrage is a myth." – Bill Harts, CEO of the Modern Markets Initiative, an HFT lobbyist (Michaels, 2016)

1 Introduction

Flash Boys, in which the seemingly arcane topic of high-frequency trading became a #1 best seller in the hands of Michael Lewis (2014), famously alleged that the U.S. stock market is "rigged for the benefit of insiders". According to the book, high-frequency trading firms (HFTs) use their speed advantage, combined with structural flaws in market plumbing created by exchanges for HFTs' benefit, to make large amounts of nearly risk-free profits at the expense of ordinary investors. HFT advocates, perhaps predictably, called the central thesis of the book a "myth" and often publicly disparaged the book as a "novel", i.e., as a work of fiction.[1] In the years since the book's publication in 2014 the academic literature on high-frequency trading has continued to be quite active,[2] and has not found empirical evidence consistent with the most extreme or alarmist readings of Flash Boys. But at the same time, the importance of speed in modern markets is undeniable. By some estimates, HFT firms account for over 50% of trading volume.[3] Significant sums are spent on straight-line microwave links between market centers (because information travels faster through air than glass), trans-oceanic fiber-optic cables (because previous communications links were not in a straight line), putting trading algorithms onto field programmable gate arrays (FPGAs, because hardware is faster than software), co-location rights and proprietary data feeds from exchanges (to get information faster from exchanges), real estate adjacent to and even on the rooftops of exchanges, and, perhaps most importantly, high-quality human capital.[4]

Budish, Cramton and Shim (2015, henceforth BCS) provide a conceptual framework for the role of HFT and the importance of speed in modern financial markets. In the BCS model, the fastest traders endogenously choose to engage in two functions. The first, liquidity provision, is useful. The second, "sniping" stale quotes, also known as "latency arbitrage," is harmful. BCS show that the root cause of latency arbitrage is the design of

[1] See Tabb (2014) and Narang (2014) for examples of prominent industry advocates calling Flash Boys a "novel" in print. The authors have heard the phrase "novel" used to refer to Flash Boys many other times in private conversations or at industry conferences.

[2] For surveys of the literature on HFT please see Jones (2013), Biais and Foucault (2014), O'Hara (2015), and Menkveld (2016). Papers that relate specifically to the benefits and costs of HFT include Hendershott, Jones and Menkveld (2011), Menkveld (2013), Brogaard, Hendershott and Riordan (2014), Hoffmann (2014), Biais, Foucault and Moinas (2015), Brogaard et al. (2015), Budish, Cramton and Shim (2015), Foucault, Kozhan and Tham (2016), Shkilko and Sokolov (2016), Du and Zhu (2017), Brogaard et al. (2018), Malinova, Park and Riordan (2018), Pagnotta and Philippon (2018), Weller (2018), Baldauf and Mollner (2019), Van Kervel and Menkveld (2019), and Breckenfelder (2019).

[3] See Meyer, Bullock and Rennison (2018) who attribute the 50% estimate to Tabb Group and provide a time series. The U.S. Securities and Exchange Commission (2010, pg. 45) writes "Estimates of HFT volume in the equity markets vary widely, though they typically are 50% of total volume or higher."

[4] Please see Laumonier (2014, 2019) and Laughlin, Aguirre and Grundfest (2014) regarding microwaves, CME Group, Inc. (2019) and Mulholland (2015) regarding the trans-atlantic Hibernia cable, Lockwood et al. (2012) for engineering details regarding the use of FPGAs for high-frequency trading, Investors' Exchange (2019) and Budish, Lee and Shim (2019) for details regarding co-location and proprietary data feeds, Baker and Gruley (2019) regarding the fight over real estate adjacent to the CME's Aurora data center, and Virtu Financial, Inc. (2019*b*) regarding the fight over access to the NYSE Mahwah data center's rooftop. Regarding human capital, Virtu's 2018 10-K filing reports average compensation costs of about $445,000 per employee (Virtu Financial, Inc., 2019*a*). Most other HFT firms are privately held but many firms report compensation for their European arms, for example Jump Trading International Limited (2018) implies compensation of $557,000 per employee. Additional such figures are reported in Clarke (2017).

modern financial exchanges, specifically the combination of (i) treating time as continuous (infinitely divisible) and (ii) processing requests to trade serially (one-at-a-time). These aspects of modern exchange design trace back to the era of human trading (e.g., trading pits, specialist markets), which also used versions of limit order books and price-time priority. But, to a computer, serial processing and time priority mean something much more literal than to a human. The consequence is that even *symmetric public information creates arbitrage rents*. We are all familiar with the idea that if you know something the rest of the market doesn't know, you can make money. BCS showed that even information seen and understood by many market participants essentially simultaneously—e.g., a change in the price of a highly-correlated asset or index, or of the same asset but on a different venue, etc.—creates arbitrage rents too. These rents lead to a never-ending arms race for speed, to be ever-so-slightly faster to react to new public information, and harm investors, because the rents are like a tax on market liquidity. BCS showed that the problem can be fixed with a subtle change to the underlying market design, specifically to discrete-time batch-process auctions; this preserves the useful function of algorithmic trading while eliminating latency arbitrage and the arms race.

Unfortunately, empirical evidence on the overall magnitude of the latency arbitrage problem has been scarce. BCS provide an estimate for one specific trade, S&P 500 futures-ETF arbitrage, and find that this specific trade is worth approximately $75 million per year. Aquilina et al. (2016) focus on stale reference prices in UK dark pools and estimate potential profits of approximately GBP4.2 million per year. The shortcoming of the approach taken in these studies is that it is unclear how to extrapolate from the profits in specific latency arbitrage trades that researchers know how to measure to an overall sense of the magnitudes at stake. Another notable study is Ding, Hanna and Hendershott (2014), who study the frequency and size of differences between prices for the same symbol based on exchanges' direct data feeds and the slower data feed in the U.S. known as the consolidated tape, which is sometimes used to price trades in off-exchange trading (i.e., dark pools). However, as the authors are careful to acknowledge, they do not observe which of these within-symbol price differences are actually exploitable in practice—not all are because of both noise in timestamps and physical limitations due to the speed at which information travels. Wah (2016) and Dewhurst et al. (2019) study the frequency and size of differences between prices for the same symbol across different U.S. equity exchanges. This is conceptually similar to and faces the same challenge as Ding, Hanna and Hendershott (2014), in that neither study observes which within-symbol price discrepancies are actually exploitable. For this reason, the magnitudes obtained in Wah (2016) and Dewhurst et al. (2019) are best understood as upper bounds on the within-symbol subset of latency arbitrage. Brogaard, Hendershott and Riordan (2014) and Baron et al. (2019) compute a large set of HFT firms' overall profits on specific exchanges (in NASDAQ data and Swedish data, respectively), and Baron et al. (2019) show that relatively faster HFTs earn significantly greater profits, but neither paper provides an estimate for what portion of these firms' trading profits arise due to latency arbitrage.

In the absence of comprehensive empirical evidence, it is hard to know how important a problem latency arbitrage is and hence what the benefits would be from addressing it. Indeed, if the total magnitudes of latency arbitrage are sufficiently small then the HFT lobby's "myth" claim, while perhaps a bit exaggerated, is reasonable. Conversely, if the magnitudes are sufficiently large then "rigged", while perhaps a bit conspiratorial, may be appropriate. Notably, while numerous regulators around the world have investigated HFT in some capacity (e.g., the FCA, ESMA, SEC, CFTC, US Treasury, NY AG), and in a few specific instances have been required to rule specifically on speed bump proposals designed to address latency arbitrage, there are still different perspectives on what are the positive and negative aspects of HFT, and what if any regulatory rules or interventions are appropriate.[5]

This paper uses a simple new kind of data and a simple new methodology to provide a comprehensive measure of latency arbitrage. The data are the "message data" from an exchange, as distinct from widely familiar limit order book datasets such as exchange direct feeds or consolidated datasets like TAQ (Trades and Quotes) or the SEC's MIDAS dataset. Limit order book data provide the complete play-by-play of one or multiple exchanges' limit order books—every new limit order that adds liquidity to the order book, every canceled order, every trade, etc.—often with ultra-precise timestamps. But what is missing are the messages that *do not affect the state of the order book, because they fail*.[6]

For example, if a market participant seeks to snipe a stale quote but fails—their immediate or cancel (IOC) order is unable to execute so it is instead just canceled—their message never affects the state of the limit order book. Or, if a market participant seeks to cancel their order, but fails—they are "too late to cancel"—then their message never affects the state of the limit order book. But in both cases, there is an electronic record of the participant's *attempt* to snipe, or *attempt* to cancel. And, in both cases, there is an electronic record of the exchange's response to the failed message, notifying the participant that they were too late.

Our method relies on the simple insight that these failure messages are a direct empirical signature of speed-sensitive trading. If multiple participants are engaged in a speed race to snipe or cancel stale quotes, then, essentially by definition, some will succeed and some will fail. The essence of a race is that there are winners and losers—but conventional limit order book data doesn't have any record of the losers. This is why it has been so hard to measure latency arbitrage. You can't actually see the race in the available data.

We obtained from the London Stock Exchange (by a request under Section 165 of the Financial Service and Markets Act) all message activity for all stocks in the FTSE 350 index for a 9 week period in Fall 2015.[7] The messages are time-stamped with accuracy to the microsecond (one-millionth of a second), and as we will describe in detail, the timestamps are applied at the right location of the exchange's computer system for measuring speed races (the "outer wall"). Using this data, we can directly measure the quantity of races, provide statistics on how long races take, how many participants there are, the diversity and concentration of winners/losers, etc. And, by comparing the price in the race to the prevailing market price a short time later, we can measure the economic stakes, i.e., how much was it worth to win.

Our main results are as follows:

- Races are frequent. The average FTSE 100 symbol has 537 latency-arbitrage races

[5] For regulatory investigations of HFT, please see Financial Conduct Authority (2018), Securities and Exchange Commission (2010), European Securities Market Authority (2014), Commodity Futures Trading Commission (2015), Joint Staff Report (2015), and New York Attorney General's Office (2014). Specific speed bump proposals include Cboe EDGA (2019), ICE Futures (2019), London Metals Exchange (2019), Chicago Stock Exchange (2016), and Investors' Exchange (2015).

[6] To our knowledge, ours is the first study to use exchange message data. All of the studies referenced above use limit order book data (either exchange direct feeds or consolidated datasets), in some cases with additional information such as participant identifiers.

[7] The FTSE 350 is an index of the 350 highest capitalization stocks in the UK. It consists of the FTSE 100, which are the 100 largest stocks, and roughly analogous to other countries' large-cap stock indices (e.g., the S&P 500 index), and the FTSE 250, which are the next 250 largest, and roughly analogous to other countries' small-cap stock indices (e.g., the Russell 2000 index).

per day. That is about one race per minute per symbol.

- Races are fast. In the modal race, the winner beats the first loser by just 5-10 microseconds, or 0.000005 to 0.000010 seconds. In fact, due to small amounts of randomness in the exchange's computer systems, about 4% of the time the winner's message actually arrives to the exchange slightly later than the first loser's message, but nevertheless gets processed first.
- A large proportion of daily trading volume is in races. For the FTSE 100 index, about 22% of daily trading volume is in latency-arbitrage races.
- Race participation is concentrated. The top 3 firms win about 55% of races, and also lose about 66% of races. For the top 6 firms, the figures are 82% and 87%.
- Races are worth small amounts per race. The average race is worth a bit more than half a tick, which on average comes to about 2GBP. Even at the 90th percentile of races, the races are worth just 3 ticks and about 7GBP.
- In aggregate, these small races add up to a meaningful proportion of price impact, an important concept in market microstructure. We augment the traditional bid-ask spread decomposition suggested by Glosten (1987), which is widely utilized in the microstructure literature (e.g., Glosten and Harris, 1988; Hasbrouck, 1991*a*,*b*; Hendershott, Jones and Menkveld, 2011), to separately incorporate price impact from latency-arbitrage races and non-race trading. Price impact from trading in races is about 31% of all price impact, and about 33% of the effective spread.
- In aggregate, these small races add up to meaningful harm to liquidity. We find that the "latency-arbitrage tax", defined as the ratio of daily race profits to daily trading volume, is 0.42 basis points if using total trading volume, and 0.53 basis points if using only trading volume that takes place outside of latency-arbitrage races. The average value-weighted effective spread paid in our data is just over 3 basis points. We show formally that the ratio of the non-race latency arbitrage tax to the effective spread is the implied reduction in the market's cost of liquidity if latency arbitrage were eliminated.[8] This implies that market designs that eliminate latency arbitrage would reduce investors' cost of liquidity by 17%.
- In aggregate, these small races add up to a meaningful total "size of the prize" in the arms race. The relationship between daily latency-arbitrage profits and daily trading volume is robust, with an R^2 of about 0.81, suggesting the latency-arbitrage tax on trading volume is roughly constant in our data.[9] Using this relationship, we find that the annual sums at stake in latency arbitrage races in the UK are about GBP 60 million. Extrapolating globally, we find that the annual sums at stake in latency-arbitrage races across global equity markets are about $5 billion per year.

[8] More precisely, the ratio we take is latency arbitrage profits in GBP divided by non-race effective spread paid in GBP, or, equivalently, the "latency arbitrage tax" on non-race trading in basis points, divided by the non-race average effective spread paid in basis points. Please see Section 5.5 for full details of this decomposition and the price impact decomposition.

[9] Daily volatility is also strongly related to daily latency-arbitrage profits, with an R^2 of about 0.66. Volume and volatility are highly correlated in our data, so adding volatility to the volume-only regression does not add much additional explanatory power. We present extrapolation results using both a volume-and-volatility model and a volume-only model, which is simpler; the results are very similar.

Discussion of Magnitudes Whether the numbers in our study seem big or small may depend on the vantage point from which they are viewed. As is often the case in regulatory settings, the detriment per transaction is quite small: the average race is for just half a tick, and a roughly 0.5 basis point tax on trading volume certainly does not sound alarming. But these small races and this seemingly small tax on trading add up to significant sums. A 17% reduction in the cost of liquidity is undeniably meaningful for large investors, and $5 billion per year is, as they say, real money—especially taking into account the fact that our results only include equities, and not other asset classes that trade on electronic limit order books such as futures, currencies, U.S. Treasuries, etc.

In this sense, our results are consistent with aspects of both the "myth" and "rigged" points of view. The latency arbitrage tax does seem small enough that ordinary households need not worry about it in the context of their retirement and savings decisions. Yet at the same time, flawed market design significantly increases the trading costs of large investors, and generates billions of dollars a year in profits for a small number of HFT firms and other parties in the speed race, who then have significant incentive to preserve the status quo.

Organization of the Paper The remainder of this paper is organized as follows. Section 2 describes the London Stock Exchange's systems architecture, to explain to the reader how our data are generated. Section 3 describes the message data in detail. Section 4 defines latency arbitrage and describes our methodology for detecting and measuring latency-arbitrage races. Section 5 presents the main results. Section 6 presents a number of sensitivity analyses. Section 7 extrapolates to an annual size of the prize for the UK and global equity markets. Section 8 concludes.

2 Inside a Modern Stock Exchange

The continuous limit order book is at heart a simple protocol.[10] We guess that most undergraduate computer science students could code one up after a semester or two of training. Yet, modern electronic exchanges are complex feats of engineering. The engineering challenge is not the market design per se, but rather to process large and time-varying quantities of messages with extremely low latency and essentially zero system downtime.

In this section we provide a stylized description of a modern electronic exchange. We do this both because it is a necessary input for understanding our data (described in detail in Section 3), and because we expect it will be useful per se to both academic researchers and

[10] We assume most readers are already familiar with the basics of a limit order book market but here is a quick primer for readers who need a refresher. The basic building block is a limit order, which consists of a symbol, price, quantity and direction (e.g., buy 100 shares of XYZ at 12.34). Market participants interact with the exchange by sending and canceling limit orders, and various permutations thereof (e.g., immediate-or-cancel orders, which are limit orders combined with the instruction to either fill the order immediately or to instead cancel it). Trade occurs whenever the exchange receives a new order to buy at a price greater than or equal to one or more outstanding orders to sell, or a new order to sell at a price less than or equal to one or more outstanding orders to buy. If this happens, the new order executes at the price of the outstanding order or orders, executing up to the new order's quantity, with the rest remaining outstanding. For example, if there are outstanding orders to sell 100 at 12.34 and another 200 at 12.35, a limit order to buy 600 at 12.35 would buy 100 at 12.34, buy another 200 at 12.35, and then the remaining 300 at 12.35 would "post" to the order book as a new outstanding order to buy. If there are multiple outstanding orders the new order could execute against, ties are broken based first on price (i.e., the highest offer to buy or lowest offer to sell) and then based on time (i.e., which outstanding order has been outstanding for the most time). Market participants may send new limit orders, or cancel or modify outstanding limit orders, at any moment in time. The exchange processes all of these requests, called "messages", continuously, one-at-a-time in order of receipt.

regulators who seek a better understanding of the detailed plumbing of modern financial markets.

Exchange operators do not typically disclose the full engineering details of their infrastructure, but some of them publicly disclose many of the relevant aspects. Our description in this section is based primarily on public documents published by the London Stock Exchange as well as discussions we had with the LSE in the process of conducting this study. We also have utilized public documents from other exchange families (e.g. Deutsche Börse, CME) and knowledge acquired through discussions with industry participants.[11]

2.1 A Stylized Description

2.1.1 The Matching Engine and Overall System Architecture

The core of a modern exchange (see Figure 2.1 for a schematic), and likely what most people think of as the exchange itself, is the *matching engine*. As the name suggests, this is where orders are matched and trades generated. A bit more fully, one should think of the matching engine as the part of the exchange architecture that executes the limit order book protocol. For each symbol, it processes messages serially in order of receipt, and, for each message, both economically processes the message and disseminates relevant information about the outcome of the message. For example, if the message is a new limit order, the matching engine will determine whether it can execute ("match") the order against one or more outstanding orders, or whether it should add the order to the book. It will then disseminate information back to the participant about whether their order posted, executed, or both; to any counterparties if the order executed; and to the public market data feeds about the updated state of the order book.

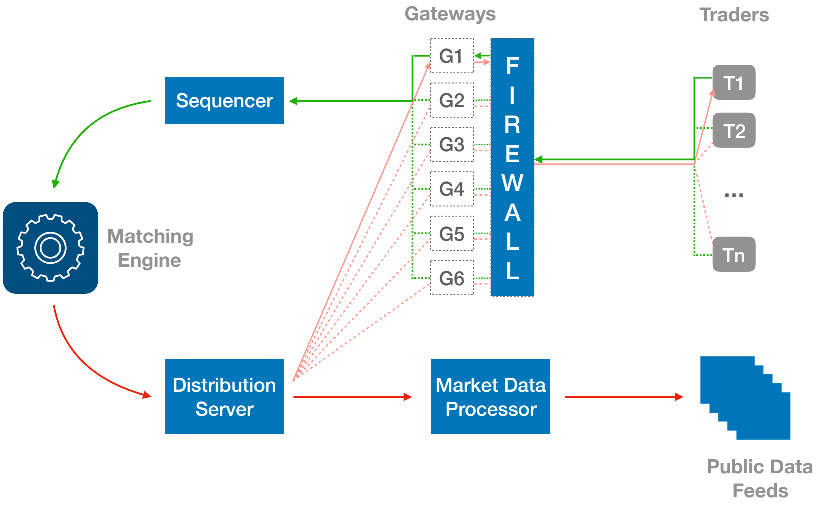
However, the matching engine is far from the only component of an exchange. Indeed, market participants do not even interact with the matching engine directly, in either direction. Rather, market participants interact with the exchange via what are known as *gateways*. Participants send messages to gateways, which in turn pass them on to a *sequencer*, which then passes the message to the matching engine for processing. The matching engine then transmits information back to a *distribution server*, which in turn passes private messages back to participants via the gateways, and public information to the market as a whole via the *market data processor*.

Before we describe each of these components, it is worth briefly emphasizing the overall rationale for this system architecture. The matching engine must, given the limit order book market design, process all messages that relate to a given symbol serially, in order of receipt. This serial processing is therefore a potential computational bottleneck. For a stark example, if a million messages arrived at precisely the same moment for the same symbol, the matching engine would have to process these million messages one-at-a-time.[12] Therefore, it is critical for latency to take as much of the work as possible "off of the shoulders" of the matching engine, and instead put it on to other components of the system.

[11] See London Stock Exchange Group (2015*a*,*b*,*c*,*d*,*e*), Deutsche Börse Group (2018) and NYSE Group (2018).

[12] Computational backlogs associated with such bursts of messages were thought to play a role in the U.S. Treasury Market Flash Crash of October 15, 2014. See Joint Staff Report (2015)

Figure 2.1: **Exchange Schematic**



Notes: Please see the text of Section 2.1 for supporting details for this figure.

2.1.2 Gateways

Gateways are the part of the exchange that participants directly interact with, in both directions. *Inbound*, participants send messages to the gateways using, in LSE’s case, one of either two languages, called *interfaces*. One interface is called FIX,[13] which can be used widely across lots of different exchanges but, because it is not customized to LSE’s system, is not optimized for speed. The other interface is called Native, because it is the “native” language of the LSE system; it is therefore faster.[14] Gateways receive messages from participants, verify their integrity, and then send them onwards. The verification includes things like checking that the message is of a valid length, all the required fields are populated and have valid parameters, etc., in addition to checking whether the message would violate the participant’s risk threshold at an exchange, trying to detect erroneous “fat finger” trades, etc. If a message is verified, it is then, roughly speaking, “translated” into the language of the matching engine, and passed on.

[13] FIX is an acronym for Financial Information eXchange Protocol. See https://www.fixtrading.org/what-is-fix/.

[14] Incoming messages are organized as a stream of information. For a FIX message, this stream is delineated using field tags, <tag>=<value>. As an example, a new FIX limit order to buy 234 shares of Vodafone stock (which has instrument ID 133215) for £4.56 per share, submitted by traderID 789, with ClientOrderID 9452, Account 616, and Clearer 3113, would look like this: 8=FIX50SP2|9=156|35=D|49=789|56=FGW|34=10012|11=9452|48=VOD|22=8|40=2|54=1|38=234 |1138=234 |44=4.56|581=1|528=P|60=20150817-12:01:01.100|10=999|. A native message in binary format is not delimited and is sent as a string of binary bytes. The binary format protocol stipulates the order, and the starting and ending bytes of each parameter. There are no delimiters, as the length of each byte is used to delineate fields. The following is a stylized example which details the parameters the byte represents in sequence, so we do not reproduce the ones and zeroes. We have also included field delimiters (“|”) to make it easier to interpret: 2|627|D|9452|789|616|3113|133215|0|0|2|0|20150817-13:01:01.100 |1|234|234|4.56|2|0|0|0|0|0|0|. The lack of delimiters makes the message shorter and quicker for the gateway to translate. Even the use of InstrumentID 133215 rather than VOD for Vodafone will be quicker for the exchange to read than converting the text. See London Stock Exchange Group (2015*c*,*d*)

Outbound, that is on the way back from the matching engine, gateways send messages back to participants informing them of the status of their order. For instance, that an outstanding order was executed, or a new order posted to the book, or a cancel request failed. Additionally, if on the way in the gateway failed to verify a message, then the gateway will send an outbound message notifying the participant of the failure.

Notice, from a systems design perspective, how the gateway takes work off of the matching engine, and that much of the gateway function can be parallelized.[15] Most importantly, the gateway offloads from the matching engine the work of verifying the integrity of messages, of doing risk-checks, and of translating the message from the participant interface language into a language optimized for the matching engine.

2.1.3 Sequencer

As emphasized above, it is valuable from a systems perspective to parallelize the gateway function, whereas the matching engine function intrinsically has to be serial (per symbol). The sequencer is essentially the bridge between the two. Its job is to receive input from all the gateways, and then, for each symbol, to pass on a single sequence of messages to the matching engine. From a systems perspective, this enables the matching engine to have to listen to only one input (per symbol) rather than many.

The details of the sequencer vary across exchanges. On the LSE, as well as many other exchanges including the New York Stock Exchange, the sequencer obtains messages from the gateways on a perpetual "round robin" basis, first obtaining a message from gateway 1 and then passing it to the matching engine, then obtaining a message from gateway 2, etc.[16] This means that it is possible that one message, say A, reaches its gateway before some other message, say B, reaches its gateway, yet B gets to the matching engine before A does. This will manifest in our data.

We note that the Chicago Mercantile Exchange's new architecture, adopted in 2015, is interestingly different in this design dimension. Instead of having a separate sequencer function, the sequencing is maintained within the gateway, and there is only one gateway per underlying instrument. This ensures that whichever message reaches the gateway first (A, in the above) is given to the matching engine first. This is at the cost of additional computational work for the gateway, but, crucially, this is work that is not put to the matching engine.[17]

2.1.4 Distribution Server

The matching engine, upon processing each order, sends the output of what happened to what is known as the distribution server. The distribution server's job is then to further process the output for sending on (i) private messages to participants affected by the outcome, via the gateway; and (ii) public updates to subscribers to market data feeds (the Market Data Feed Server in our diagram). The public market data feeds typically contain information about all trades as well as all updates to the state of the limit order book.

Crucially for our study, not all information that is conveyed back in private messages to participants makes it to publicly available market data feeds. In particular, "too late to cancel" messages and "expired" (failed) immediate-or-cancel messages are both sent on

[15] In practice, this parallelization is achieved by assigning different participants to different gateways.

[16] See NYSE Group (2018).

[17] For an overview of CME's architecture, called Market Segment Gateway, see CME Group, Inc. (2015)

to the relevant participants who either failed to cancel or failed to execute an immediate-or-cancel, but do not get sent on to public market data feeds because they do not affect the state of the order book. Similarly, such messages do not make it into academic data sets such as TAQ. Implicitly, these messages are viewed as “error messages”, relevant to the participant but not relevant to market observers.

3 Description of Data

As emphasized, the novel aspect of our data is that it includes all messages sent by participants to the exchange and by the exchange back to participants. Importantly, this includes messages that inform a participant that their request to trade or their request to cancel was not successful—such messages would not leave any empirical trace in traditional limit order book data. Also fundamental to our empirical procedure is the accuracy and location of the timestamps, which, as we will describe in detail below, are applied at the “outer wall” of the exchange’s network and therefore represent the exact time at which a market participant’s message reached the exchange. This timestamp location is ideal for measuring races, even more so than matching engine timestamps, as it represents the point at which messages are no longer under the control of market participants.[18]

We obtained these message data from the London Stock Exchange, following a request by the FCA to the LSE under Section 165 of the Financial Services and Markets Act. Our data cover the 44 trading days from Aug 17 – Oct 16 2015, for all stocks in the FTSE 350 index. We drop one day (Sept 7th) which had a small amount of corrupted data. This leaves us with 43 trading days and about 15,000 symbol-day pairs. In total, our data comprise roughly 2.2 billion messages, or about 150,000 messages per symbol-day.

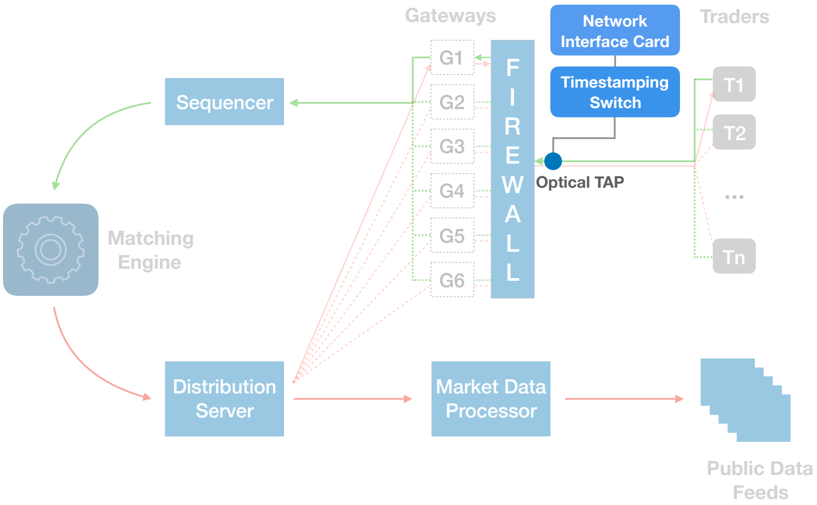
3.1 Where and How Messages are Recorded and Timestamped

As described in Section 2, participants send messages to the exchange, and receive messages from the exchange, via gateways. Between the participants’ own systems and the exchange’s system is a firewall, through which all messages pass, in both directions. Our data are recorded and timestamped on the external side of this firewall using an optical TAP (traffic analysis point); please refer to Figure 3.1. This is the ideal timestamping location for measuring race activity because it records the time at which the participant’s message reaches the “outer wall” of the exchange’s system. Participant speed investments affect the speed with which their messages reach this outer wall, but once a message reaches the outer wall it is out of the participant’s hands and in the exchange’s hands. Therefore, the outer wall is the right way to think about what is the “finish line” in a race.

Messages are timestamped to 100 nanosecond (0.1 microsecond) precision, at this point of capture, by a hardware clock. Importantly, all messages are timestamped by a single clock. Therefore, while the clock may drift slightly over the course of the trading day, the relative timestamps of different messages in a race can be compared with extreme accuracy.

[18] We emphasize though that our methodology could be replicated in other contexts using matching engine timestamps, so long as the research had the full set of messages including failed cancels and failed IOCs. We think of the full message activity as a “must have” for the method and the precise location of the timestamps as more of a “nice to have.”

Figure 3.1: **Exchange Schematic: Where the Message Data are Captured and Timestamped**



Notes: Please see the text of Sections 2.1 and 3.1 for supporting details for this figure.

3.2 Contents of Messages

Any action by a market participant generates at least two messages: one on the way into the exchange, and one or more on the way out of the exchange. For example, a new limit order that both trades against a resting order and posts the remainder to the book will have a single inbound message with the new order, an outbound message to the user whose order was passively executed, and an outbound message to the user who sent the new limit order reporting both the quantity/price traded and the quantity/price that remains and is posted to the book. In this section we describe the contents of such inbound and outbound messages in detail.

3.2.1 Inbound Messages

Each inbound message contains the following kinds of information:[19]

Identifiers. These fields contain the symbol and date the message is associated with; the UserID of the participant who submitted the message; and a participant-supplied ID for the message. Additionally, if the message is a cancel or modification of an existing order, then the message often contains the matching-engine-supplied OrderID for the existing order (though the user is free to use just the participant-supplied ID they used previously for the order they are canceling).

[19] There are some slight differences in how the information described below is organized in Native vs. FIX format messages (see Section 2 for more on Native vs. FIX). Since latency-sensitive participants essentially exclusively use Native format messages, our description focuses on Native and we do not note the small differences.

Timestamp. As described above, each message has a timestamp down to 100 nanosecond granularity. For both inbound messages and outbound messages, the timestamp is applied at the optical capture point on the external side of the exchange firewall.

Message Type Information. Each message indicates what type of message it is, economically: for instance, a new limit order, a cancel, a cancel-replace, or an immediate-or-cancel order. This information is conveyed in a set of fields: a MessageType, which indicates whether it is a new order or a cancel or modification of an existing order; an OrderType, if it is a new order, which is typically set to indicate that it is a limit order, but could also be a market order, stop order, stop limit order, pegged order, etc.; and a Time in Force parameter, which indicates whether, for instance, a limit order is outstanding for the full day or whether it is immediate-or-cancel or fill-or-kill.

Price/Quantity/Side Information. Last, if a message is a new order or a modification of an existing order, it will of course indicate the price, quantity, and direction (buy/sell).

3.2.2 Outbound Messages

Each outbound message contains the following kinds of information:

Identifiers. These fields typically contain all of the same information as the inbound message, with the addition, for new orders, of a matching-engine-supplied OrderID. That is, for new orders, on the way in they just have the participant-supplied ID, but on the way out they contain both the participant-supplied ID and the matching-engine-supplied ID.[20]

Timestamp. As described above, both inbound messages and outbound messages are timestamped with 100 nanosecond granularity at the optical capture point on the external side of the exchange firewall. Note that in principle, the sequence of timestamps at this external border of the exchange’s system can differ slightly from the actual sequence messages are executed in by the matching engine. We account for this issue in our method for maintaining the order book for a given symbol throughout the day, as described below in Section 3.4. Please note that neither the inbound nor outbound timestamps applied at this optical capture point are sent to market participants.

Message Outcome Information. Outbound messages contain information on the outcome of the message, as determined by the matching engine.[21] This outcome information is conveyed, primarily, in three fields. The first, ExecType, reports on what activity the matching engine just executed: a post to the book, a trade execution, a cancel, a cancel/replace, or an order expiration (in the event of a failed immediate-or-cancel order, for example). The second, OrderStatus, indicates the current status of the order: the main

[20] An exception is Cancel Reject messages, which do not contain either the symbol or the matching engine OrderID (the order no longer exists in the matching engine); we infer both the symbol and the OrderID from the participant-supplied ID.

[21] A small subset of messages have an outcome which is instead determined by the gateway, wherein the gateway rejects the message as having invalid parameters before it reaches the matching engine. This could be caused by a participant error, for instance.

status options are new, filled, partially filled, canceled, and expired. The last, MessageType, is where we see if a cancel message failed.[22]

Trade Execution Reports. In the event of a successful trade (conveyed in the ExecType field described above), the outbound message will contain the executed price, quantity, and side. Note that if an order matches with multiple counterparties or at multiple prices, there will be a separate outbound message for each such match.

Price/Quantity/Side Status Information. Any outbound message that relates to an order that has not yet been fully executed or canceled will also report the order's price, side, and remaining quantity.

Full details on all of these fields and additional ones can be found in the online data appendix.[23]

3.3 Event Classification

As described above, any action by any market participant is associated with one inbound message from that participant, one or more outbound messages back to that participant, and, if applicable, outbound messages to other participants whose orders were passively executed. An important piece of our code is to classify sets of such messages into what we call order book events—for instance, a "new order - executed in full" event, or a "resting order - passive execution" event.

In our code, we loop through each user and each order (using the information from both the participant-supplied IDs and the matching-engine supplied IDs) to classify each message according to what order book event it is a part of. We give a special designation to the first such message in each event—typically, the inbound message that initiates the event and utilize this message's timestamp for the purpose of race detection (described below). The only exception is if the first message in an event is a passive fill, in which case we use the outbound message timestamp to account for the fact that the inbound message associated with that fill could have reached the exchange a long time before the event. Table 3.1 gives the pattern of inbound and outbound message activity for the most important order book events.

3.4 Maintaining the Order Book

Observe that neither inbound nor outbound messages contain the state of the limit order book — i.e., the prices and quantities at the best bid and offer, and at other levels of the order book away from the best bid and offer. This is because conveying the state of the order book in each message, while convenient, would mean larger and hence slower messages. We thus have to build and maintain the state of the limit order book ourselves.[24]

[22] In this case, the MessageType field will indicate that the message is a cancel reject, whereas for most other messages the MessageType field just tells us that the message is an execution report (with an ExecType and an OrderStatus).

[23] Our codebase and a user guide will be made publicly available upon publication. Regulators and researchers interested in obtaining this codebase and user guide prior to publication should contact the authors.

[24] The familiar TAQ (trades-and-quotes) data contains information about the state of the order book. But, studies that have utilized direct-feed data from exchanges, such as Budish, Cramton and Shim (2015) and others, must build and maintain the order book themselves.

Table 3.1: **Classifying Inbound and Outbound Messages Into Events**

Event Name	**Inbound Message Type**	**Outbound Message Type**
New order posted to book	New Order (Limit)	New Order Accepted
New order aggressively executed in full	New Order (Limit) New Order (IOC)	Full Fill (Aggressive) Partial Fill (Aggressive) - multiple such orders that sum to the full quantity
New order aggressively executed in part	New Order (Limit)	Partial Fill (Aggressive) - one or more that sum to less than the full quantity
	New Order (IOC)	Order Expire - for IOCs, not Limits which will post the remainder
Order passively executed in part	-	Partial Fill (Passive)
Order passively executed in full	-	Full Fill (Passive)
Cancel accepted	Cancel	Cancel Accept
Failed cancel	Cancel	Cancel Reject
Failed IOC	New Order (IOC)	Order Expire

Notes: Please see the text of Section 3.3 for a description of Event Classification. Please see Section 3.2 for a description of the contents of inbound and outbound messages.

We maintain the state of the limit order book, for each symbol-date, on *outbound* messages. That is, whenever there is an outbound message reporting that any event occurred that updates the state of the limit order book—a new limit order is added to the book, a resting order is passively filled, a resting order is canceled, etc.—we update the state of the order book. We do this on outbound messages rather than on inbounds because outbound messages report what the matching engine actually did. In the instances where multiple inbound messages arrive very close together in time, it is possible that the matching engine executes messages in a different sequence from what we would have expected given their inbound message timestamps (as we will see below in Figure 5.1, this occurs in about 4-5% of races; see Section 2.1 above for the systems architecture reason for this). Hence, we use the actual outbound executions to update the book.

We include limit orders submitted before the market open if they are not labeled good for auction, i.e., if they are valid to rest on the book after the opening auction. During this period the order book may cross, i.e., there may be offers to buy that exceed offers to sell. Any orders that trade in the opening auction we remove accordingly from the book (and similarly orders that are canceled prior to the open).

A technical issue that affects how we maintain the order book is that our data is subject to a small amount of packet loss.[25] Packet loss only affects the data recorded by the optical capture point (used for an LSE internal reporting solution) and not the messages sent to market participants. The LSE states that the occurrence of packet loss is extremely low. Packet loss can cause our calculated state of the limit order book to be different from the actual state. We take two steps to address this issue.

First, we build checks into our code that builds the order book that corrects the state of the order book in the event that we observe a matching engine event that contradicts our current state of the order book. For example, if we think the state of the book is bid 10 – ask 11, and then observe a trade where the aggressor buys at 12 (but not 11), we update the book to eliminate the asks at 11 which we know must no longer be present in the book; either the passive fills associated with trades at 11 were lost or cancels of the orders at 11 were lost.[26]

[25] Packet loss is the term for when a computer network recording device records strictly less than 100.0% of all activity.

[26] We do two kinds of state corrections. One uses matching engine actions that contradict our understanding of

Second, we then produce audit statistics on both (i) the magnitude of the corrections, and (ii) the % of time that our order book state performs as expected. In a high-volume symbol (Vodafone) on a typical-volume day (09-23-2015), we are correct 99.95% of the time about whether a new limit order should trade against the book versus post to the book. On the highest-volume day of our sample (08-24-2015), which contained a mini-flash-crash and was noticeably an outlier on many measures relative to the other days, we are correct in this manner 99.82% of the time. Also reassuring, most of the time that we had to execute an order book correction, the correction concerned just a single level of the book, and involved a number of shares that was less than the mean depth at the top level of the book.

One other related note is that when we compute race statistics that rely on the order book, we always utilize the state of the order book as of the first message in the race. Thus, even if the burst of activity associated with races leads to a larger proportion of order book data issues, this should not affect our measures. Reassuringly, our measures of race profits based on depth in the order book at the start of the race are very similar to our measures of race profits based on the actual quantity traded and canceled in the race.

4 Defining and Measuring Latency Arbitrage Races

In this section we give the details for our method of measuring latency arbitrage activity using exchange message data. Section 4.1 provides a review of the relevant theory that motivates our approach. Section 4.2 proposes the empirical method utilizing exchange message data. Section 4.3 provides supporting analysis regarding some of the specific time parameters we utilize.

We note that the method detailed in Section 4.2 is meant to be generalizable—that is, researchers or regulators who obtain message data from other exchanges should be able to follow the method described in 4.2 as a reasonably direct blueprint for their own analysis—whereas the timing parameter analysis in 4.3 is specific to the London Stock Exchange circa the time of our data.

4.1 Theory of Latency Arbitrage

Budish, Cramton and Shim (2015) develop a model of trading on a continuous limit order book market that both (i) provides a formal theoretical definition of latency arbitrage, and (ii) articulates the economics of the high-frequency trading speed race. We base our empirical strategy on the main insights of that model. Therefore, it will be useful to provide a brief summary of the main features of the BCS model of continuous trading and what the model implies for the questions we are trying to answer in this study.

Readers familiar with the BCS model may skip to Section 4.2 without loss.

4.1.1 Setup of the Model

BCS study a market where a single security, denoted x, trades on a continuous limit order book market.[27] There is a public signal, denoted y, about the fundamental value of

the state of the book. The second uses a field in outbound messages called PriceDifferential which, for limit orders that post to the book, indicates whether they are at the best bid or offer or if not how many levels away they are.

[27] Readers unfamiliar with the continuous limit order book should consult footnote 10. Other terms for this market design are continuous-time limit order book, centralized limit order book and electronic limit order book. These

this security which can be observed by all market participants. This public signal can be interpreted as a metaphor for information that comes from correlated financial instruments (e.g., a change in the FTSE 100 index, or activity in the option market for a given stock or vice versa), information that comes from trade in the same security but on another venue (e.g., another exchange or a dark-pool), or public news announcements.

There are two types of agents in the model. First, *investors* who have an exogenous demand to buy or sell x. They exogenously arrive to market and behave essentially mechanically, either buying or selling at the prevailing best offer or best bid immediately upon their arrival. In BCS, it is assumed that investors have no private information, i.e., they can be interpreted as noise traders or liquidity traders. It is straightforward to enhance the model to have some investors be liquidity traders while other investors are informed traders of the sort modeled in Glosten and Milgrom (1985) and the large literature thereafter.[28]

Second, *trading firms* who have no intrinsic demand to either buy or sell x, but rather seek to buy x at prices lower than y and sell x at prices higher than y. BCS first analyze the case of an exogenous number of trading firms, each with exactly the same speed technology—that is, in the event y changes or there is some order book activity, all trading firms observe this information at exactly the same time. They then consider a model in which trading firms can endogenously choose to invest in speed technology, and those who invest are faster than those who do not.

Investors provide an incentive for trading firms to make markets, that is, to have orders resting on the book to buy at prices lower than y and sell at prices higher than y. If an investor arrives, the trading firm who provided liquidity to the investor—i.e., the trading firm whose resting bid or ask the investor traded against—earns a profit equal to the difference between their quoted price and the fundamental value y. In equilibrium, the bid and ask will be symmetric around the fundamental value, and therefore a trading firm who provides liquidity to an investor earns half the bid-ask spread.

4.1.2 Latency Arbitrage

If the public signal y jumps by more than half the bid-ask spread, there will be a race to "snipe" the resulting stale quotes. Specifically, if the jump in y is positive and exceeds the half-spread, the race will be to snipe the now-stale offers, and if the jump in y is negative and exceeds the half-spread, the race will be to snipe the now-stale bids. If the provider of the stale quotes is fast they will also be part of the race, seeking to cancel their stale quote before it is sniped. Indeed if there are multiple stale quotes, fast trading firms will seek to cancel all of their own stale quotes and snipe any others' stale quotes.

If a sniper wins the race, he earns arbitrage profits equal to the difference between the new value of y and the stale bid or offer (depending on the direction of the jump in y) at the direct expense of the quote provider (the trade is zero sum). If a canceler wins the race, he avoids the equivalent loss.

BCS's key conceptual insight is that even in the case where all trading firms have *exactly* the same technology, and *exactly* the same information, such public information creates arbitrage rents—because of the serial processing nature of the continuous limit order book. That is, even *symmetric public information* creates arbitrage rents in a continuous limit order book market. These rents then induce a never-ending speed race: if any firm is

all mean the same thing.

[28] For this extension, see Budish, Lee and Shim (2019), equation (3.1) and the surrounding text.

even a tiny bit faster than the others in the race, they win. Again, this is because of the continuous, serial processing of messages.

By *latency arbitrage*, then, BCS suggest we mean rents from symmetric public information, as opposed to the rents from asymmetric private information that are at the heart of classic models in market microstructure, such as Kyle (1985) and Glosten and Milgrom (1985). In the simple generalization of BCS's model referenced above, which also includes informed traders, both latency arbitrage from symmetric public information and traditional adverse selection arising from asymmetric information play a role in equilibrium. Both are costs of liquidity provision that in equilibrium affect the bid-ask spread and market depth.

We emphasize that while in a theoretical model it is possible to draw a sharp line between symmetric and asymmetric information, and hence between latency arbitrage and traditional adverse selection, in practice the dividing line is not always sharp. Our empirical method will attempt to account for this in two ways, as described below in Section 4.2.

4.1.3 Key Theoretical Results from BCS

We briefly list the key theoretical results from BCS that inform our study.

First, when there is a large-enough jump in a public signal, the activity should consist of fast trading firms attempting to snipe any stale quotes, and, if any of the stale quotes belong to fast trading firms, attempts to cancel the stale quotes. Stale quotes belonging to fast trading firms will get sniped with high probability — probability $(N-1)/N$, where N is the number of fast trading firms — and stale quotes belonging to non-fast market participants will get sniped with probability 100%.

Second, the "latency arbitrage prize" for a particular security includes both the profits in cases where a stale quote is sniped, and, in the case where a fast liquidity provider avoids a loss that a slow liquidity provider would not have avoided, the value of the avoided loss. The reason is that this loss avoidance profit is the way that a fast trader who provides liquidity is compensated for the opportunity cost of not instead being a sniper. We will return to this idea of loss avoidance in our spread decomposition exercise in Section 5.5.[29]

Third, the size of the latency arbitrage prize for a particular security depends on the probability of and size-distribution of jumps in y, and the bid-ask spread and market depth which themselves depend on the level of investor (noise trader) demand for the security. Hence, both the volume of trade and the volatility of the security are closely related to the size of the latency-arbitrage prize.

Fourth, for each security, the latency arbitrage prize ultimately comes out of the pockets of investors, via a higher-than-otherwise cost of liquidity as measured by either the bid-ask spread or market depth. The reason is that trading firms choose their equilibrium price

[29] Here are some important technical details of the model to support the logic described in the text and to clarify a subtle technical issue. In the equilibrium of the BCS model, all trading firms who engage in either liquidity provision and stale-quote sniping are fast. A fast liquidity provider will get sniped with probability $(N-1)/N$, and will "avoid the loss" with probability $1/N$. Each fast sniper wins the race with probability $1/N$. In equilibrium, fast trading firms are indifferent between liquidity provision and sniping – the economic intuition is that the liquidity provider is compensated both for the cost of getting sniped (with probability $(N-1)/N$) and the opportunity cost of not himself being a sniper (worth the $1/N$ probability that he would win if he switched places). Under some slightly different modeling conventions (as formalized in Budish, Lee and Shim (2019), there can also be an equilibrium in which liquidity is provided by a slow trading firm, and all N fast trading firms engage in sniping. Now, the slow trading firm gets sniped with probability 1 instead of $(N-1)/N$, and all fast trading firms still earn the same rent, the $1/N$ chance of winning the sniping prize, as in the other equilibrium. This equilibrium is economically equivalent to that in BCS in the sense that the total latency arbitrage prize is the same, the bid-ask spread and market depth are the same, and the total investment in speed is the same; however, it is different in the empirically relevant sense that some liquidity will be provided by slow trading firms, who get sniped with probability 100% rather than $(N-1)/N$. This case will prove useful to understand some of what we will see in the race data.

and quantity of liquidity endogenously, and this choice will factor in the “tax” of latency arbitrage, just like it factors in the cost of traditional adverse selection.

Finally, in the version of the model with endogenous investment in speed, the latency arbitrage prize is dissipated by such investments. These investments could take the form of communications links, hardware, specialized engineers, etc. In fact, in the model, there is an equivalence among (i) the latency arbitrage prize; (ii) socially wasteful investment in speed; and (iii) the cost to investors in the form of higher cost of liquidity.

4.2 Method for Measuring Latency Arbitrage Using Exchange Message Data

The theory described above suggests that the empirical signature of a BCS-style latency arbitrage race, as distinct from Glosten-Milgrom-style informed trading, is that:

1. Multiple market participants act on the same security, side, and price level or levels …
2. … at least some of whom are aggressing (i.e., sniping stale quotes), and potentially one or more of whom are cancelling (i.e., canceling stale quotes) …
3. … some succeed, some fail …
4. … all at the “same time.”

For each of these 4 characteristics, we describe our “baseline” definition and alternatives. We structure the analysis so that, for items #1-#3, our baseline is inclusive of all races and our alternatives filter down to more-conservative subsets of races.

In contrast, for item #4, our baseline definition of “at the same time” is more conservative than many of the alternatives we consider, and the baseline and alternative criteria do not have an exact subset relationship. We will discuss this in detail below.

Note that throughout, when we describe either actions or timestamps, we refer to the *inbound* messages and timestamps, enhanced with the event classification information described above in Section 3 using subsequent outbound messages. For example, if we refer to a failed IOC, we are referring to the inbound IOC message and its timestamp, having inferred from subsequent outbound messages that the IOC failed to execute.

4.2.1 Characteristic #1: *Multiple market participants act on the same security, side, and price level or levels*

Baseline. The “same security, side, and price level or levels” aspect is straightforward. Every limit order message (including IOC’s, etc.) includes the symbol, price, and side of the order. We interpret a limit or IOC order to buy at p as relevant to any race at price p or lower, and similarly a limit or IOC order to sell at p as relevant to any race at price p or higher. Cancel messages can be linked to the price and side information of the order that the message is attempting to cancel. We count a cancel order of a quote at price p as relevant to races at price p only.[30]

[30] For example, if we observed an IOC to buy at 20 and a cancel of an ask at 21 at the same time, we would not want to count that as a latency-arbitrage race at 20. Whereas, if we observed an IOC to buy at 21 and a cancel of an ask at 20 at the same time, we potentially would want to count that as a latency-arbitrage race at 20.

Our baseline definition of “multiple market participants” is 2+ unique UserIDs. Note that a particular trading firm might use different UserIDs for different trading desks. Our approach treats distinct trading desks within the same firm as potentially distinct competitors in a latency-sensitive trading opportunity.

Alternatives. For alternatives, we also consider

- Larger minimum requirements for the number of participants in the race, such as 3+
- Requiring that the FirmIDs are unique, not just UserIDs.

4.2.2 Characteristic #2: *at least some of whom are aggressing (i.e., HFTs sniping stale quotes), and potentially one or more of whom are canceling (i.e., HFTs canceling stale quotes)*

Baseline. For our baseline, we require that at least one of the multiple market participants is aggressing at p. Thus, a baseline race can consist of either 1+ aggressors and 1+ cancelers, or 2+ aggressors and 0 cancelers.

Defining a message as aggressing at p is straightforward. For a race at an ask of p, a limit order or IOC is aggressive if it is an order to buy at p or higher, and similarly for a race at a bid of p, a limit order of IOC is aggressive if it is an order to sell at p or lower.

Alternatives. For alternatives we also consider

- Requiring 2+ aggressors. (That is, excluding races with 1 aggressor and 1+ canceler).
- Requiring that there are 1+ aggressors and 1+ cancelers. (That is, excluding races with 2+ aggressors and 0 cancelers).
- Requiring that there are 2+ aggressors and 1+ cancelers.

4.2.3 Characteristic #3: *some succeed, some fail*

For our baseline, we require 1+ success and 1+ fail, defined as follows.

Baseline: Fails. A cancel attempt is a fail if the matching engine responds with a too-late-to-cancel error message. An immediate-or-cancel limit order is a fail if the matching engine responds with an “expired” message, indicating that the IOC order was canceled because it was unable to execute immediately. Note that an IOC order that trades any positive quantity will not count as a fail, even if the traded quantity is significantly less than the desired quantity.[31]

In our baseline, we count a limit order as a fail in a race at price p if it was priced aggressively with respect to p (i.e., is an order to buy at $\geq p$ or an order to sell at $\leq p$) but obtains zero quantity at p. That is, it either executes at a price strictly worse than p (e.g., it buys at $> p$), or it posts to the book at p or worse (e.g., instead of buying at p it becomes the new bid at p). While most sniping attempts in our data are IOCs, in a race it can make sense

[31] To be conservative, we do not allow for fill-or-kill orders to count as fails. FOK orders are rare (whereas IOCs are common) and do not make sense to use in a latency arbitrage race (whereas IOCs do make sense). For example, if there are 10,000 shares outstanding at a stale price, a sniper should attempt to take all 10,000, but should still want to take the rest even if some liquidity provider succeeds in cancelling some small order (say for 1,000 shares, leaving 9,000 remaining) before the sniper’s order is processed.

to use limit orders instead of IOCs for two reasons. First, by using a limit order instead of an IOC, the participant posts any quantity he does not execute to the book, which in principle may yield advantageous queue position in the post-race order book. Second, at the LSE, there was a small (0.01 GBP per message) fee advantage to using plain-vanilla limit orders instead of IOC orders.[32] This difference means that, technically, IOCs are often dominated by "synthetic IOCs" created by submitting a plain-vanilla limit order followed by a cancellation request.[33]

That said, limit orders that obtain zero quantity at p and instead post to the book may represent post-race liquidity provision reflecting the post-race value, as opposed to a failed attempt to snipe. For that reason, we also consider and will frequently emphasize the following alternative:

Alternatives: Fails.

- Not allowing non-IOC limit orders to count as fails. That is, only failed IOCs and failed cancel attempts count as fails.

Baseline: Successes. For our baseline, we consider an IOC or a limit order to be successful in a race at price p if it is priced aggressively with respect to p (i.e., is an order to buy at $\geq p$ or an order to sell at $\leq p$) and obtains positive quantity at a price p or better (i.e., it buys positive quantity at a price $\leq p$ or sells positive quantity at a price of $\geq p$). We consider a cancel to be successful in a race at price p if the order being canceled is at price p and the cancel receives a cancel-accept response.

We note that this requirement is inclusive in two senses. First, it counts an IOC or a limit order as successful even if it trades only part of its desired quantity. However, the fact that an IOC or limit order trades only part of its desired quantity, in conjunction with the requirement that some *other message fails*—i.e., some other participant tried to cancel and received a too-late-to-cancel message, or some other participant tried to aggress at p but executed zero quantity—will typically mean that the full quantity available at price level p was contested and there were genuine winners and losers of the race. The possible exception is a successful IOC or limit for a subset of the available liquidity at price p, in conjunction with a failed cancel for part of that same subset of the available liquidity at price p. This case should be rare and we will attempt to filter it out with an alternative below.

Second, it counts a cancel as a success even if it cancels just a small quantity relative to the full quantity available at price level p. However, if the only success is a cancel, then since we also require a fail and 1+ aggressor, this implies that the full quantity available at price level p was contested and there were genuine winners and losers of the race.

As alternatives, therefore, we also consider:

Alternative: Successes.

[32] At the time of our data, the LSE assessed an "Order management charge" of 0.01 GBP for non-persistent orders such as IOCs, whereas there was no order management charge for plain-vanilla limit orders. These order management charges are the same in the LSE's most recently posted fee schedule as of this writing (London Stock Exchange Group, 2015*f*).

[33] An exception is if the trader has triggered the "High usage surcharge" by having an order-to-trade ratio of at least 500:1; such traders must pay a fee of 0.05 GBP per message, so the synthetic IOC would be nearly twice as expensive as an IOC (London Stock Exchange Group, 2015*f*). However, our understanding is that triggering this surcharge is very rare.

- Requiring that 100% of depth at the race price is cleared in the race. This can be satisfied either by observing a failed IOC at the race price p, a limit order at the race price p that posts to the book at least in part, or by observing quantity traded plus quantity canceled of 100% of the displayed depth at the start of the race.
- Requiring that at least 50% of depth at the race price is cleared in the race.

4.2.4 Characteristic #4: *all at the "same time."*

Of the 4 characteristics, this last one is conceptually the hardest. In a theory model there can be a precise meaning of "at the same time", but in practice and in the data no two things happen at *exactly* the same time, if time is measured precisely enough. Indeed, even if a regulatory authority or exchange *intends* for market participants to receive a piece of information at exactly the same time, and even if the market participants have *exactly* the same technology and choose *exactly* the same response, there will be small measured differences in when they receive the information, and when they respond to the information, if time is measured finely enough.[34]

We propose two different approaches to this issue.

"At The Same Time" Method #1: Information Horizon. Our first approach, which we call the Information Horizon method, requires that the difference in time between the first and second participants in a race is small enough that we are essentially certain that the second participant is not reacting to the action of the first participant. Concretely, we measure the information horizon as:

$$\begin{aligned} Information\ Horizon = {} & Actual\ Observed\ Latency : M1\ Inbound \rightarrow M1\ Outbound \\ & + Minimum\ Observed\ Reaction\ Time : M1\ Outbound \rightarrow M2\ Inbound \end{aligned}$$

where: M1 refers to the first message in a race; M2 refers to the second message in the race; Actual Observed Latency M1 Inbound → M1 Outbound refers to the actual measured time between M1's inbound message's timestamp and its outbound message's timestamp, and Minimum Observed Reaction Time M1 Outbound → M2 Inbound refers to the minimum time it takes a state-of-the-art high-frequency trader to respond to a matching engine update, as measured from the outbound message's time stamp to the response's inbound message time stamp.

Given this formula, if M2's inbound message has a timestamp that follows M1's inbound message by strictly less than the information horizon, then the sender of M2 logically cannot be responding to information about the outcome of M1. Whereas, if M2's inbound message has a timestamp that follows M1 by more than the information horizon, it is logically possible that M2 is a response to M1. In this method, such a response would not be interpreted as the same time.

In our data we compute the Minimum Observed Reaction Time as 29 microseconds,[35]

[34] Try to blink your left eye and right eye at exactly the same time, measured to the nanosecond. You will fail! Computers are better at this sort of task than humans are, but even they are not perfect. See, e.g., MacKenzie (2019)

[35] This 29 microseconds reflects a combination of the minimum time it takes an HFT to react to a privately-received update from an outbound message, plus the difference in data speed between a private message sent to a particular market participant (M1 outbound) and data obtained from the LSE's proprietary data feed, which is different from our message data. In fact, our analysis suggests that the 29 microseconds is comprised of about 17 microseconds from the first component and about 12 microseconds from the second component, as we will

and the average Actual Observed Latency is about 200 microseconds. We provide details for these calculations in Section 4.3. We also decided, in consultation with FCA supervisors, to place an upper bound on the information horizon of 500 microseconds. That is, if the sum of the observed matching engine latency and the minimum observed reaction time exceeds 500 microseconds, we use 500 microseconds as the race horizon instead. The reason for this upper bound is that our assumption that M1 and M2 are responses to the same (or essentially same) information set becomes strained if the observed matching latency is sufficiently long, because even though M2 would not be able to see M1, they might see new data from other symbols or from other exchanges. We would expect all of these parameters to be potentially different for different exchanges or different periods in time.

“At The Same Time” Method #2: Sensitivity Analysis. Our second approach to defining what it means for multiple participants to act at the “same time” is more agnostic. For a range of choices of T, we define “same time” as no further apart than T. Clearly, if we choose T to be the finest amount of time observable in our data (100 nanoseconds) there will be essentially no races, whereas if we choose T to be too long the results will be meaningless. We will present these results for T ranging from 50 microseconds to 3 milliseconds. What T’s would be of interest we would expect to evolve over time as technology evolves.

4.2.5 A Note on Code Structure and Multi-Level Races

Depending on the size of the jump in value (i.e., y in the theory model), a latency-arbitrage race could occur on one level of the book or on multiple levels. We structure our code so that it identifies races that satisfy the four characteristics described above at one price level at a time. That is, if p and p' are separate price levels in a multi-level race, our code will detect two single-level races, one at p, starting at say time t, and one at p' starting at say time t'.

A related code structure issue to mention is that once we observe a race at a price level of p starting at time t, we do not look for other races at p until at least either the information horizon or T amount of time has passed. That is, we do not allow for “overlapping” races at a single price level.

4.3 Computing the Information Horizon

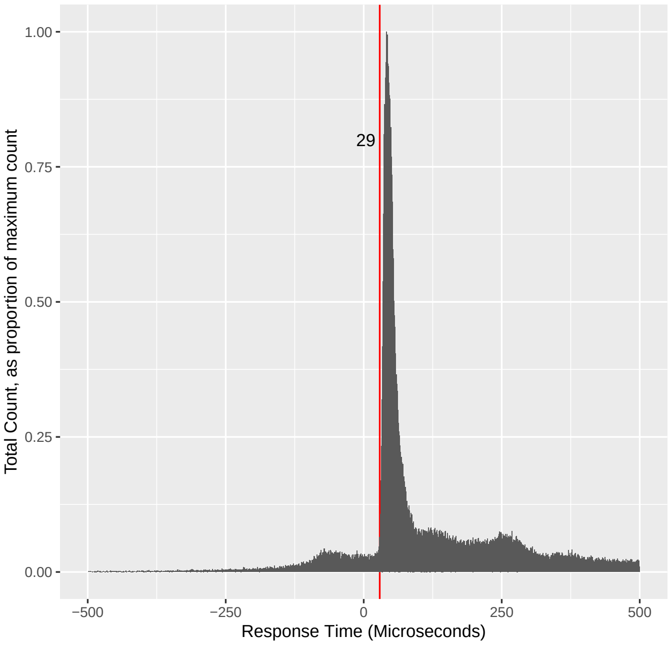
As described in Section 4.2.4, there are three elements of our Information Horizon calculation:

1. Actual Observed Latency: M1 Inbound → M1 Outbound
2. Minimum Observed Reaction Time: M1 Outbound → M2 Inbound
3. Upper bound on maximum possible information horizon

We can compute the Actual Observed Latency: M1 Inbound → M1 Outbound directly in our data, for each inbound message. This is obtained by taking the difference between the inbound message’s timestamp and its outbound message’s timestamp. The median response time is 157 microseconds, and there is considerable variation: the 5th percentile is 79 microseconds and the 95th percentile is 410 microseconds.

describe in Section 4.3.

Figure 4.1: **Distribution of Time between M1 Outbound New Limit Order → M2 Inbound Takes Liquidity**



Notes: Over all regular-hour messages from four high-volume symbols, BP, GLEN, HSBA, VOD, we obtain all cases where some outbound message confirms a new order added to the book and subsequently gets filled at least in part. We then obtain the first outbound message that is an execution against this new order, obtain the inbound message associated with this outbound execution message, and compute the difference in the message timestamp between the first order's (M1) outbound message and the second order's (M2) inbound message. Note that this difference can be negative if M2's inbound is sent by the participant before M1's outbound is sent by the outbound gateway. The distribution depicted is a microsecond-binned histogram truncated at -500 microseconds and +500 microseconds. As described in the text, we compute the start of the spike (29 microseconds) by computing the mean and standard deviation of the distribution in the period -100 microseconds to 0 microseconds, and then finding the first microsecond after 0 that is at least 5 standard deviations above this pre-0 mean.

To compute the Minimum Observed Reaction Time: M1 Outbound → M2 Inbound, we perform the following analyses. First, we look at instances of the specific sequence of events where M1 outbound is a new limit order that adds liquidity at some price level, and M2 inbound is a take from a different UserID at the same price level. In this sequence of events, M2 may be responding to the new liquidity at the price level by taking it. Clearly, sometimes this sequence of events will happen by chance, but sometimes this sequence of events will happen because M2 is responding to M1. Figure 4.1 reports the distribution of the difference in time between these two events.

As can be seen, this distribution spikes upwards a bit to the right of 0. We interpret the beginning of this spike as the minimum amount of time it takes the fastest market participants to respond to such an M1 with such an M2, as measured from the outbound time stamp to the inbound time stamp. Note that it need not be the case that the market participant is responding literally to the outbound message sent to the participant who sent M1; rather, the market participant is likely responding to their own receipt of information about the state of the order book from the LSE's proprietary data feed, sent through the message server as depicted earlier in Figure 2.1. Using the simple statistical criterion of looking for the start of the spike by asking what is the first microsecond at which the density is more than 5 standard deviations above the distribution in the 100 microseconds leading up to time 0, we determine that the spike starts at 29 microseconds.

We also examined the case where M1 is a partial fill, and M2 is a successful cancel. In this case, the participant might be responding to their own privately-received message—so we might expect this to be faster than what we saw above for the Add-Take sequence. Here (see Appendix Figure A.1), the spike starts at around 17 microseconds. An interpretation is that the 17 microseconds is the minimum response time to a privately-observed outbound message, and the additional 12 microseconds is the minimum difference in latency between a private message sent to a particular market participant and the LSE's broadly disseminated proprietary data feed.[36]

Last, the upper bound on the information horizon that we utilize, 500 microseconds, was determined in consultation with supervisors at the Financial Conduct Authority. This was based on the discussions they had with fast market participants on their reaction times, differences in the speeds of competing microwave connectivity providers, the variance in arrival times across long distances (such as Chicago to London), and the judgment of supervisory experts to establish an amount of time short enough for our assumption that M2 is not reacting to M1 to be reasonable. Given that in London many of the trading venues are located close to each other the time it takes for information to move from one exchange to the other is short. Hence even if M2 is not reacting to M1 on our exchange it is possible that participants are reacting to each other's actions on a different trading venue.

This 500 microsecond truncation of the information horizon binds in just under 4% of cases. In the remaining 96% of cases, the mean information horizon is 202 microseconds (st. dev 73 microseconds), with a minimum of 43 microseconds.

5 Main Results

This section presents all of our main results under the baseline specification as described in Section 4. In the following section (Section 6) we will explore various alternative specifications, sensitivity analyses, etc. Section 5.1 presents results on the frequency and duration of races. Section 5.2 presents results on the number of participants in races along with some statistics on participation patterns. Section 5.3 presents results on profits per race. Section 5.4 presents results on profits taken in aggregate, and what we call the "latency arbitrage tax". Section 5.5 presents two spread decompositions that explore what proportion of the bid-ask spread is the latency arbitrage component versus the traditional adverse selection component.

5.1 Frequency and Duration of Latency-Arbitrage Races

Races Per Day

The average FTSE 100 symbol in our sample has 537 latency-arbitrage races. Over an 8.5 hour trading day, this corresponds to a race roughly once per minute per symbol. There are fewer races for FTSE 250 symbols: the average FTSE 250 symbol has 70 races, or roughly one per 7 minutes. Also, while all FTSE 100 symbols have daily race activity (the minimum is 76 races per day), the bottom quartile of FTSE 250 symbols have zero or hardly any race activity. See Table 5.1, Panel A.

[36] A similar difference between the speed with which private messages are received versus book updates from proprietary data feeds was a source of controversy at the Chicago Mercantile Exchange and ultimately prompted a change to their matching engine and data dissemination architecture. See Patterson, Strasburg and Pleven (2013).

Across all symbols in our data, there are on average about 71,000 races per day, of which 54,000 are FTSE 100 and 17,000 are FTSE 250. This total number of races per day ranges from a min of 48,000 to a max of 144,000. See Table 5.1, Panel B.

Table 5.1: **Races Per Day**

Panel A: Number of races across symbols

Description	Mean	sd	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99
FTSE 100	537.24	473.26	132	184	240	352	619	1,134	2,067
FTSE 250	70.05	93.53	0	0	2	44	104	166	404
Full Sample	206.03	340.73	0	1	14	87	239	511	1,814

Panel B: Number of races across dates

Description	Mean	sd	Min	Pct10	Pct25	Median	Pct75	Pct90	Max
FTSE 100	54,261	15,660	35,174	40,490	44,036	51,361	60,632	70,588	117,370
FTSE 250	17,232	3,856	11,536	13,444	14,800	16,125	19,404	23,326	26,613
Full Sample	71,493	19,223	48,175	54,264	58,698	64,516	79,429	93,914	143,752

Notes: Please see Section 4.2 for a detailed description of the baseline race-detection criteria and Section 3 for details of the message data including how we classify inbound messages and how we maintain the order book. This table reports the distribution of the number of races detected at the symbol level (Panel A) and at the date level (Panel B). The symbol level averages across all dates for each symbol. The date level averages across all symbols for each date.

Race Durations

The average race duration in our data, as measured by the time from the first success message to the first fail message is 79 microseconds, or 0.000079 seconds. Table 5.2 and Figure 5.1 depict the distribution of race durations. The mode of the distribution is between 5-10 microseconds, and the median is 46 microseconds. There is then steady mass in the distribution up until about 150 microseconds, the 90th percentile is about 200 microseconds (which is about the mean information horizon), and there is a tail up to our truncation point of 500 microseconds.

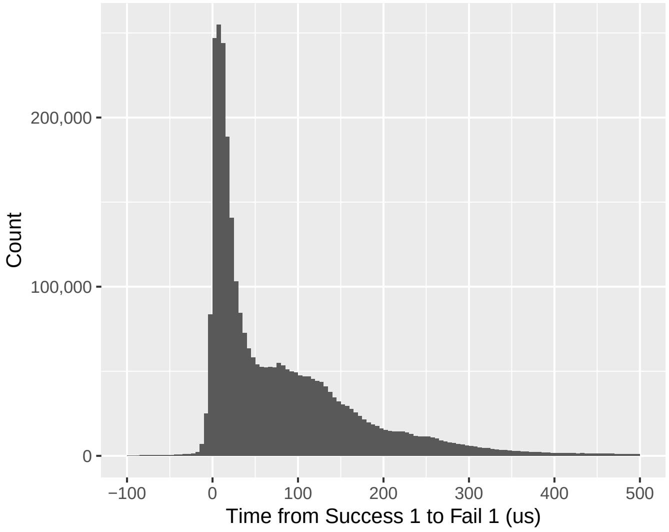
Table 5.2: **Race Duration**

Time from S1 to F1 (microseconds)

Description	Mean	sd	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99
FTSE 100	80.81	92.14	-9.00	3.70	12.60	48.50	123.70	207.50	402.80
FTSE 250	71.85	80.84	-4.40	4.30	12.80	37.10	111.70	185.60	338.00
Full Sample	78.65	89.63	-7.90	3.80	12.70	45.60	120.90	201.90	390.20

Notes: For each race in our race records dataset (see notes for Table 5.1) we compute the difference in message timestamps between the first inbound message in the race that is a success and the first inbound message in the race that is a fail (success and fail are defined in Section 4.2.3). Denote these messages S1 and F1, respectively. This table reports the distribution of F1's timestamp minus S1's timestamp in microseconds, that is, by how long did the first successful message in the race beat the first failed message.

Figure 5.1: **Duration of Races**



Notes: The figure plots the distribution of F1's timestamp minus S1's timestamp in microseconds, as defined in Table 5.2, for the full sample. The histogram has a bin size of 5 microseconds.

Sometimes the "Wrong" Message Wins

Interestingly, in Figure 5.1, there is a small amount of mass to the left of zero; that is, the first fail message arrives before the first success message. Recall from Section 3.1 that our timestamps are obtained at the outer wall of the exchange's system. It is therefore possible, if two race messages arrive to different gateways at nearly the same time, that they reach the matching engine in a different order from the order at which they reached the exchange's outer perimeter. Thus, the "wrong" message wins the race about 4% of the time in our data.

We do not think the fact that the wrong message wins is necessarily that economically interesting; it is akin to one shopper choosing a slightly faster queue than another shopper at the supermarket. Rather, we think of the result as reinforcing just how fast races are: they are so fast that randomness in exchange gateway processing is sometimes the difference between winning and losing.[37]

Significant Trading Volume in Races

For the average FTSE 100 symbol, latency arbitrage races take up 0.043 seconds per day, or about 0.0001% of the trading day. This is based on the 537 races per day reported in Table 5.1 and the 81 microsecond race duration reported in Table 5.2 (537 * 0.000081 = 0.043 seconds).

During this tiny slice of the trading day, an average of 21% of FTSE 100 trades take place corresponding to 22% of FTSE 100 daily trading volume (value-weighted). Please see Table 5.3.

For the average FTSE 250 symbol, latency arbitrage races take up about 0.00002% of the trading day, and during this slice of time 17% of trades take place constituting 17% of daily trading volume.

Table 5.3: **Volume and Trades in Races**

Panel A: Percentage of volume (value-weighted) in races across dates

Description	Mean	sd	Min	Pct10	Pct25	Median	Pct75	Pct90	Max
FTSE 100	22.15	1.90	17.84	20.09	21.15	22.02	23.11	24.85	26.08
FTSE 250	16.90	1.78	11.58	14.73	15.71	17.07	18.19	19.21	20.13
Full Sample	21.46	1.75	17.63	19.70	20.50	21.41	22.53	24.02	25.02

Panel B: Percentage of number of trades in races across dates

Description	Mean	sd	Min	Pct10	Pct25	Median	Pct75	Pct90	Max
FTSE 100	20.69	1.59	16.91	18.62	19.83	20.80	21.58	22.93	23.51
FTSE 250	16.96	1.50	13.29	15.24	16.01	17.01	18.07	18.91	19.31
Full Sample	19.70	1.42	16.07	18.04	18.94	19.65	20.68	21.73	22.22

Notes: For each symbol-date in our dataset, we obtain all outbound messages in regular-hours trading that are aggressive fills, i.e., that report a trade execution to a just-received new order that aggressed against a previously-received resting order. We then obtain the inbound message associated with each such outbound aggressive fill, and check whether the inbound is part of a race (see notes for Table 5.1). For Panel A, for each date, we then sum the quantity in GBP associated with all aggressive fills that are part of races, divided by the quantity in GBP associated with all aggressive fills, whether or not in race. We do this separately for the FTSE 100 (i.e., both the numerator and denominator sum across all symbols in the FTSE 100), the FTSE 250, and the full sample. For Panel B, for each date, we then sum the number of trades associated with all aggressive fills that are part of races, divided by the number of trades associated with all aggressive fills, whether or not in race.

[37] Please also see a recent essay of MacKenzie (2019) on various aspects of randomness in high-frequency trading races.

5.2 Race Participation

Number of Participants

Table 5.4, Panel A details the level of participation in races, as measured by the number of race-relevant messages, i.e., limit orders (including IOCs) at the race price or better, or cancels at the race price. Since the information horizon varies across races depending on the matching engine's processing lag, to keep the measure consistent across races we report the distribution for varying amounts of time T after the start of the race, ranging from 50 microseconds to 1 millisecond. Note that 50 microseconds is shorter than the information horizon for nearly all races and 1 millisecond is longer than the information horizon for all races (which is capped at 500 microseconds). Focusing on the 500 microseconds row, the average race has about 3.5 participants: the median has 3 participants, the 25th percentile has 2 participants, and there is a right tail with a 99th percentile of 9 participants and a max of 29. Comparing the 500 microseconds row to the 50 and 100 microseconds rows, we see that at shorter time horizons there are fewer participants; this is consistent with heterogeneity in speed. In the sensitivity analyses in Section 6, we will specifically consider using only races with at least a certain level of participation very quickly (e.g., 3 participants within the first 100 microseconds), and we will also consider less restrictive definitions of races that allow for participation over longer periods (up to a maximum of 3 milliseconds).

Table 5.4: **Number of Messages in Races**

Panel A: Number of race messages

Description	Mean	sd	Min	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99	Max
Messages within 50us	1.83	0.93	1	1	1	1	2	2	3	5	14
Messages within 100us	2.15	1.05	1	1	1	1	2	3	3	6	15
Messages within 200us	2.67	1.23	1	1	2	2	2	3	4	7	17
Messages within 500us	3.46	1.72	2	2	2	2	3	4	6	9	29
Messages within 1000us	3.90	2.19	2	2	2	2	3	5	7	12	41

Panel B: Number of take messages

Description	Mean	sd	Min	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99	Max
Takes within 50us	1.66	0.97	0	0	1	1	1	2	3	5	14
Takes within 100us	1.93	1.08	0	0	1	1	2	2	3	5	15
Takes within 200us	2.37	1.30	0	1	1	1	2	3	4	7	17
Takes within 500us	3.07	1.78	1	1	1	2	3	4	5	9	29
Takes within 1000us	3.45	2.19	1	1	1	2	3	4	6	11	40

Panel C: Number of cancel messages

Description	Mean	sd	Min	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99	Max
Cancels within 50us	0.17	0.41	0	0	0	0	0	0	1	1	8
Cancels within 100us	0.22	0.47	0	0	0	0	0	0	1	2	8
Cancels within 200us	0.30	0.56	0	0	0	0	0	1	1	2	12
Cancels within 500us	0.40	0.70	0	0	0	0	0	1	1	3	14
Cancels within 1000us	0.44	0.78	0	0	0	0	0	1	1	3	21

Notes: For each race in our race records dataset (see notes for Table 5.1) we obtain the timestamp of the first inbound message and the price and side of the race. We then use the message data to count the number of messages within the next T microseconds, for different values of T as depicted in the table, that are race relevant, defined as either new orders that are aggressive at the race price and side (i.e., if the race is to buy at p, then new orders to buy at ⩾ p, if the race is to sell at p, then new orders to sell at ⩽ p), or cancels at exactly the race price (i.e., if the race is to buy at p, cancels of offers to sell at p, and vice versa). Panel A depicts the distribution for all such messages, Panel B depicts the distribution for take messages, and Panel C depicts the distribution for cancel messages. Note that by definition the mean number of takes plus the mean number of cancels will equal the mean number of messages, for each duration.

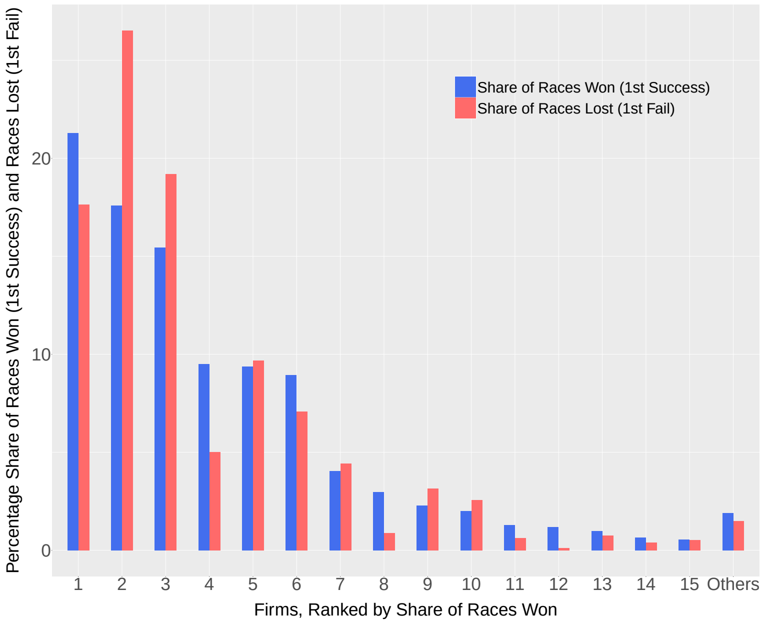
Panels B and C of Table 5.4 detail the number of takes and cancels in races, respectively. Focusing initially on the 500 microseconds row, we see that of the mean of 3.46 messages per race, about 3.07 are takes while just 0.40 are cancels. The median race has 0 cancels. These figures tell us that in most of the races we detect most of the activity is aggressive. This is consistent with a model in which the fastest traders primarily engage in sniping as opposed to liquidity provision, and substantial liquidity is provided by participants who are not the very fastest participants in the market.

Of these 3.07 take attempts, the large majority, 2.81, are immediate-or-cancel orders (IOCs) that are marketable at the race price, with the remainder, 0.25, being ordinary limit orders that are marketable at the race price. Please see Appendix Table A.4 for this and additional participation data. In Section 6 we will consider a sensitivity analysis that does not allow ordinary limit orders to count as losers of a race, since they may reflect an intention to provide liquidity at the new price rather than sniping liquidity at the old price. (Ordinary limit orders that execute at the race price will still count as winners of course, and indeed there can be a tiny economic advantage to sniping with an ordinary limit order relative to an IOC, as discussed in Section 4.2.3).

Pattern of Winners and Losers

Figure 5.2 displays data on the pattern of winners and losers across races, focusing on races for symbols in the FTSE 100. The figure is sorted by firm based on the proportion of races in which they are the first successful message (S1). As can be seen, the top 3 firms are each either S1 or F1 (i.e., the first fail message) in over one-third of races, with firm 1 winning 21% of races while losing another 18% of races, firm 2 winning 18% of races while losing 27%, and firm 3 winning 15% of races while losing 19%. The next 3 firms then each win about another 9% of races each, and then there are another 4 firms that win between 2-4% of races each.

Figure 5.2: **Percentage of 1st Successful and Failed Messages by Firm**



Notes: For each race in our race records dataset (see notes for Table 5.1), we obtain the FirmID of the participant who sends the first success message and the first fail message (i.e., S1 and F1, respectively, in Table 5.2). We then compute, over all races for FTSE 100 symbols, for each FirmID that appears, the portion of races in which that FirmID is the first success message, and the portion of races in which that FirmID is the first fail message. The table sorts FirmIDs based on the proportion of races won. The "Others" bar sums all FirmIDs outside of the top 15.

It is notable that there is clear concentration of winners, with the top 3 firms winning 54% of races, and the top 6 firms winning 82% of races. Yet, these same firms who win a lot of races also lose a lot of races. The top 3 winning firms lose 63% of races, and the top 6 lose 85%. These patterns are consistent with the model in two important ways. First, as the model suggests, fast trading firms "sometimes win, sometimes lose," and indeed in any particular race who wins may be a bit random. Second, as the model suggests, firms not at the cutting edge of speed should essentially never be competitive in a latency-arbitrage race. Put differently, these facts are consistent with the idea that there is an arms race for speed, and that, at least in UK equity markets circa 2015, there are a relatively small number of firms competitive in this race.[38]

[38] Around this time, a US high-frequency trading CEO described to one of the authors of this study that, in the US, there were 7 firms in what he called the "lead lap" of the speed race.

Expected Number of Races By Chance

We can use the arrival rate of messages that could potentially be part of a race to compute the number of races we would expect to observe by chance if messages arrived randomly. We say that a message is potentially-race-relevant if the message is either a marketable limit order (including marketable IOCs) or is a cancel of a message at the best bid or offer. For each symbol-date, we compute the total number of such potentially-race-relevant messages per day to get an average arrival rate; to fix ideas, the average arrival rate for FTSE 100 symbols is a bit over 1 potentially-race-relevant message per second. We then use these arrival rates to compute the number of times per day we would expect to observe N such messages within T time on the same side of the order book. For the mean FTSE 100 symbol-date, the number of times per day we should expect to see $N = 2$ such messages on the same side of the order book within $T = 500\,\mathrm{microseconds}$, the upper bound of the information horizon, is just 3.6, in contrast with 537 races in our data. Increasing T to 1 millisecond increases the number to about 7. For the FTSE 250, the number of times per day we should expect to see $N = 2$ such messages within $T = 500$ microseconds is just 0.04, in contrast with 70 races in our data. The number of times we would expect to see $N = 3$ or more such messages arrive by chance is essentially zero. Even for the maximum symbol-date in our data set, at $T = 1\ \mathrm{millisecond}$, the number of such instances per day would be 0.4. For the mean FTSE 100 symbol-date, the figure is 0.003 and for the mean FTSE 250 symbol-date, the figure is 0.000. (For full details, please see Appendix Table A.5).

Keep in mind as well that all of these figures are *upper bounds* on the number of N-participant races that would occur by chance, because occurrences of messages on the same side of the order book at the same time only constitute a race if our other race criteria are satisfied (in particular, at least one message must fail).

The bottom line is that the number of races we would observe by chance is de minimis.

5.3 Race Profits

Profits Per-Race

Table 5.5 presents statistics on per-race profits. As in BCS, we compute profits as the signed difference between the price in the race and the midpoint in the near future, which has the interpretation of the mark-to-market value for the asset in the race.[39] Our main results use the midpoint 10 seconds out, and we will report figures for horizons ranging from 1 millisecond to 100 seconds shortly.

The average FTSE 100 race is worth about half a tick per share (0.48 ticks), or about 1.20 basis points. This comes to about 2 GBP per race, measured either using all of the displayed depth at the start of the race (1.95 GBP) or all of the quantity traded or canceled during the race (1.84 GBP). For the FTSE 250, the figures are 0.77 ticks, 3.09 basis points, and GBP 1.55 per race based on displayed depth, and GBP 1.48 per race based on quantity traded or canceled. For the full sample, the figures are 0.55 ticks, 1.66 basis points, GBP 1.85, and GBP 1.76.

[39] Note that while successful snipers must "cross the spread" in the trade that snipes a stale quote, they need not cross the spread in unwinding this position. This is both because trading firms that engage in sniping often also engage in liquidity provision (though this seems not to predominantly be the case in this setting, per our results in Table 5.4), and because sniping opportunities are equally likely to be buys versus sells. Also note that it is appropriate to ignore trading fees in computing the size of the latency arbitrage prize, as long as exchanges' marginal costs of processing trades are zero, because trading fees assessed on latency-arbitrage trades simply extract some of the sniping prize (and they are quite small in any case, as shown in Budish, Lee and Shim (2019)).

There is of course significant variation in profitability across races. This reflects both that some races are more profitable ex ante than others, i.e., reflect larger jumps in public information, and that over a 10 second horizon other information can materialize, either positively or negatively, that affects realized race profits ex post. Across our full sample, a 90th percentile race is worth 3.00 ticks and 7.98 basis points; a 99th percentile race is worth 10 ticks and 27.02 basis points.

Table 5.5: **Detail on Race Profits (Per-Share and Per-Race) Marked to Market at 10s**

Panel A: FTSE 100

Description	Mean	sd	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99
Per-share profits (ticks)	0.48	4.17	-7.00	-1.50	-0.50	0.00	1.00	2.50	10.00
Per-share profits (GBX)	0.16	1.61	-2.50	-0.50	-0.05	0.00	0.25	1.00	3.50
Per-share profits (basis points)	1.20	7.75	-13.95	-4.02	-1.18	0.00	3.42	6.31	20.32
Per-race profits displayed depth (GBP)	1.95	17.87	-22.99	-3.29	-0.42	0.00	2.37	7.99	45.50
Per-race profits qty trade/cancel (GBP)	1.84	17.07	-20.74	-3.06	-0.40	0.00	2.23	7.46	41.92

Panel B: FTSE 250

Description	Mean	sd	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99
Per-share profits (ticks)	0.77	2.99	-4.50	-1.00	-0.50	0.50	1.50	3.00	11.00
Per-share profits (GBX)	0.20	0.99	-1.50	-0.25	-0.05	0.05	0.25	0.75	3.50
Per-share profits (basis points)	3.09	11.07	-18.12	-5.14	-1.70	1.37	6.12	13.28	38.78
Per-race profits displayed depth (GBP)	1.55	9.63	-9.13	-1.52	-0.20	0.09	1.67	5.25	27.68
Per-race profits qty trade/cancel (GBP)	1.48	9.34	-8.48	-1.40	-0.19	0.09	1.55	4.94	26.40

Panel C: Full Sample

Description	Mean	sd	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99
Per-share profits (ticks)	0.55	3.92	-6.50	-1.50	-0.50	0.50	1.00	3.00	10.00
Per-share profits (GBX)	0.17	1.48	-2.00	-0.50	-0.05	0.01	0.25	1.00	3.50
Per-share profits (basis points)	1.66	8.71	-15.00	-4.26	-1.29	0.50	3.89	7.98	27.02
Per-race profits displayed depth (GBP)	1.85	16.27	-20.00	-2.76	-0.34	0.00	2.15	7.27	41.50
Per-race profits qty trade/cancel (GBP)	1.76	15.57	-18.13	-2.56	-0.32	0.00	2.02	6.78	38.44

Notes: For each race in our race records dataset (see notes for Table 5.1) we obtain the race price and side, the quantity in the book at that price and side as of the last outbound message before the initial race message, and the quantity traded and canceled in the race. Per-share profits in ticks, pence (GBX), and basis points are computed by comparing the race price to the midpoint price 10 seconds after the first race message (i.e., as of the last outbound message before 10 seconds after the timestamp of the first race message). Per-race profits are computed by multiplying per-share profits in GBX, times 1/100 to convert to GBP, times either the quantity displayed or the quantity traded and canceled. Panel A shows the distribution for all races for FTSE 100 symbols, Panel B for FTSE 250 symbols, and Panel C for the full sample.

Table 5.6 presents statistics on average per-race profits for different mark-to-market time horizons. As can be seen, average per-race profits increase with the time horizon, eventually flattening out at around 10 seconds for the FTSE 100 and at around 60 seconds for the FTSE 250. Our finding that it takes non-zero time for race profits to materialize, and that with this time comes noise as well, is consistent with both discussions with practitioners as well as empirical evidence in Conrad and Wahal (2019) on what they term the “term structure of liquidity.”

Table 5.6: **Average Race Profits (Per-Share and Per-Race) for Different Mark to Market Horizons**

Panel A: FTSE 100

Description	1ms	10ms	100ms	1s	10s	30s	60s	100s
Mean per-share profits (ticks)	0.08	0.24	0.31	0.39	0.48	0.49	0.50	0.51
Mean per-share profits (GBX)	0.05	0.09	0.11	0.14	0.16	0.16	0.16	0.16
Mean per-share profits (basis points)	0.31	0.68	0.83	1.01	1.20	1.23	1.24	1.25
Mean per-race profits displayed depth (GBP)	0.40	1.14	1.42	1.72	1.95	1.89	1.86	1.82
Mean per-race profits qty trade/cancel (GBP)	0.43	1.10	1.35	1.62	1.84	1.78	1.74	1.70

Panel B: FTSE 250

Description	1ms	10ms	100ms	1s	10s	30s	60s	100s
Mean per-share profits (ticks)	-0.10	0.12	0.24	0.43	0.77	0.94	1.04	1.06
Mean per-share profits (GBX)	-0.01	0.05	0.08	0.12	0.20	0.24	0.26	0.26
Mean per-share profits (basis points)	-0.26	0.64	1.09	1.78	3.09	3.74	4.14	4.24
Mean per-race profits displayed depth (GBP)	-0.09	0.41	0.65	0.97	1.55	1.79	1.92	1.93
Mean per-race profits qty trade/cancel (GBP)	-0.06	0.41	0.64	0.93	1.48	1.71	1.84	1.85

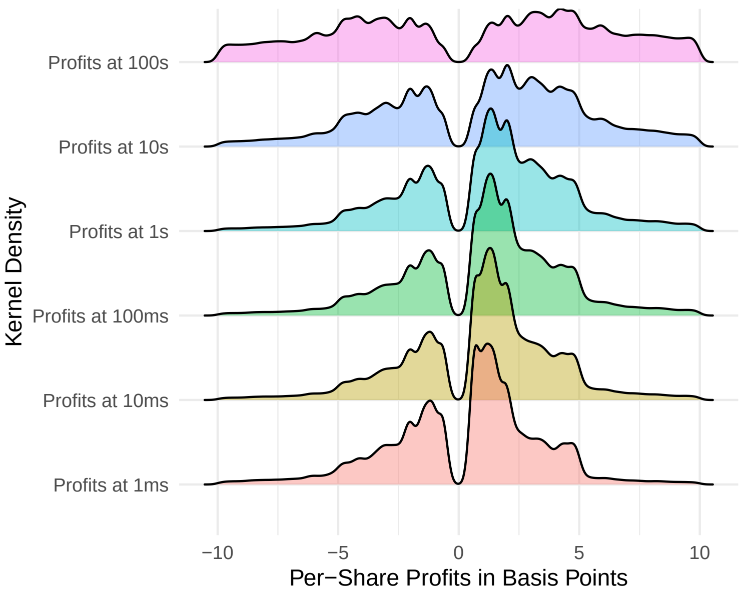
Panel C: Full Sample

Description	1ms	10ms	100ms	1s	10s	30s	60s	100s
Mean per-share profits (ticks)	0.03	0.21	0.29	0.40	0.55	0.59	0.63	0.64
Mean per-share profits (GBX)	0.03	0.08	0.10	0.13	0.17	0.18	0.18	0.18
Mean per-share profits (basis points)	0.18	0.67	0.89	1.20	1.66	1.83	1.94	1.97
Mean per-race profits displayed depth (GBP)	0.28	0.96	1.24	1.54	1.85	1.86	1.88	1.84
Mean per-race profits qty trade/cancel (GBP)	0.31	0.94	1.18	1.45	1.76	1.76	1.77	1.74

Notes: For each race in our race records dataset (see notes for Table 5.1), and for each race profits measure described in Table 5.5, we re-compute the profits measure for different mark to market horizons, ranging from 1 millisecond to 100 seconds. That is, for each measure, we compute race profits by comparing the price and side in the race to the midpoint price T later, for T ranging from 1 millisecond to 100 seconds (Table 5.5 used T = 10 seconds). We then report the mean at each horizon.

Figure 5.3, which complements Table 5.6, presents the distribution of per-race profits for different mark-to-market time horizons. Focus first on 1ms. At this relatively short time horizon, many races are worth either a small positive or a small negative amount per share. The small negative amounts likely reflect the fact that at the moment of a first success in a race, the mark-to-market profits of the winner are often still negative. For example, if the market is at bid 10 – ask 12, so the midpoint is 11, and there is positive public news triggering a race to buy at 12, then a successful sniper buys at 12 while the midpoint is still 11 (or, if the market becomes bid 10 – ask 13, the midpoint becomes 11.5)—for a small mark-to-market loss. Of course, the sniper does this with the expectation that prices will soon move in their favor. Even by 1 millisecond, many races are profitable on a mark-to-market basis. As the figure progresses from 1ms, to 10ms, and all the way to 100 seconds, you can see visually that more and more mass comes out of the center of the distribution. On average, this mass moves to the right (as shown in Table 5.6), though of course there is meaningful noise as well, especially at longer horizons such as 100 seconds.

Figure 5.3: **Race Profits Distributions at Different Mark-to-Market Time Horizons**



Notes: For each race in our race records dataset (see notes for Table 5.1) we obtain per-share profits in basis points at different mark to market horizons ranging from 1 millisecond to 100 seconds. Please see Table 5.5 for description of per-share profits in basis points and Table 5.6 for description of varying the mark to market horizon. The figure plots the kernel density of the distribution of per-share profits in basis points at different horizons; to make the distribution readable, at each horizon, we drop all races with profits of exactly zero basis points.

5.4 Aggregate Profits and the “Latency Arbitrage Tax”

Table 5.7 presents statistics on the total daily race profits in our sample. Panel A reports statistics at the symbol level, and Panel B reports statistics aggregated across all symbols in the FTSE 100, FTSE 250, and full sample. Note that all of these numbers are daily race profits in our data from the London Stock Exchange; we will extrapolate from these numbers to the full UK market, and to other markets, later in Section 7.

Table 5.7: **Daily Profits in GBP**

Panel A: Daily Profits by Symbol

Description	Mean	sd	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99
FTSE 100	1,046.9	729.6	199.7	340.5	526.6	909.3	1,410.5	1,967.2	3,431.8
FTSE 250	108.3	134.1	-0.7	0.5	7.6	67.1	160.8	257.2	606.3
Full Sample	381.5	590.7	-0.6	1.5	26.7	135.1	466.2	1,184.5	2,273.8

Panel B: Daily Profits by Date

Description	Mean	sd	Min	Pct10	Pct25	Median	Pct75	Pct90	Max
FTSE 100	105,734	32,852	62,980	78,777	87,038	93,074	117,979	153,712	223,187
FTSE 250	26,643	8,592	14,667	19,501	21,376	23,100	30,392	40,100	49,066
Full Sample	132,378	40,266	82,391	99,363	108,706	116,636	147,814	183,227	272,253

Notes: For each race in our race records dataset (see notes for Table 5.1) we take per-race profits in GBP based on displayed depth with prices marked to market at 10 seconds (see notes for Table 5.5). We then compute daily profits for each symbol-date, by summing all races for that symbol on that date. In Panel A, for each symbol, we compute its average daily race profits, and report the distribution across symbols. In Panel B, for each date, we compute total daily race profits summed across all symbols, and report the distribution across dates. For each Panel, we perform the analysis separately for FTSE 100, FTSE 250, and full sample.

Referring to Panel A, we see that the average symbol in the FTSE 100 has daily race profits of GBP 1,047, and the 99th percentile symbol has daily race profits of GBP 3,432. For the FTSE 250 the average and 99th percentile are GBP 108 and GBP 606, respectively.

Referring to Panel B, we see that the average day in in our data set has race profits of GBP 105,734 for the FTSE 100, GBP 26,643 for the FTSE 250, and GBP 132,378 for the full sample.

These aggregate profits numbers are difficult to interpret in isolation. A more interpretable measure is obtained by dividing race profits by daily trading volume, with both measures in GBP. We refer to this ratio as the “Latency Arbitrage Tax,” since, following the theory, the prize in latency arbitrage races is like a tax on overall market liquidity. We consider two versions of this measure, the first based on all trading volume, and the second based on all non-race trading volume. The version based on all trading volume is both simpler to describe and more appropriate for out-of-sample extrapolation. However, the version based on all non-race trading volume more closely corresponds to the theory, which shows that latency arbitrage imposes a tax on non-race trading (both noise trading and non-race informed trading).

For the average symbol in the FTSE 100, the latency arbitrage tax is 0.49 basis points based on the all-volume measure, and 0.68 basis points based on the non-race-volume measure. (Please see Table 5.8). For the average FTSE 250 symbol, the latency arbitrage tax is 0.56 based on the all-volume measure and 0.69 basis points based on the non-race-volume measure. Higher-volume symbols tend to have lower latency arbitrage taxes, so the overall value-weighted average daily latency arbitrage tax, for all symbols in the FTSE 350, is 0.42 basis points using the all-volume measure and 0.53 basis points using the non-race-volume measure.

An interpretation of the first figure is that for every GBP 1 billion that is transacted in the market overall, latency arbitrage adds GBP 42,000 to trading costs. An interpretation of the second figure is that for every GBP 1 billion that is transacted by participants not in latency-arbitrage races, latency arbitrage adds GBP 53,000 to trading costs.

Table 5.8: **Latency Arbitrage Tax**

Panel A: Distribution Across Symbols

Sub-Panel (i): Measure 1, Latency Arbitrage Tax based on All Trading Volume (basis points)

Description	Mean	sd	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99
FTSE 100	0.492	0.235	0.163	0.236	0.292	0.454	0.627	0.827	1.035
FTSE 250	0.562	0.393	-0.022	0.022	0.267	0.565	0.817	1.043	1.540
Full Sample	0.542	0.356	-0.014	0.054	0.283	0.519	0.774	0.960	1.508

Sub-Panel (ii): Measure 2, Latency Arbitrage Tax based on Non-Race Trading Volume (basis points)

Description	Mean	sd	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99
FTSE 100	0.675	0.362	0.200	0.303	0.387	0.587	0.870	1.180	1.595
FTSE 250	0.692	0.504	-0.028	0.024	0.287	0.678	1.029	1.304	2.042
Full Sample	0.687	0.466	-0.020	0.057	0.345	0.651	0.995	1.275	2.032

Panel B: Distribution Across Dates

Sub-Panel (i): Measure 1, Latency Arbitrage Tax based on All Trading Volume (basis points)

Description	Mean	sd	Min	Pct10	Pct25	Median	Pct75	Pct90	Max
FTSE 100	0.383	0.053	0.286	0.329	0.345	0.381	0.415	0.456	0.516
FTSE 250	0.663	0.099	0.495	0.552	0.591	0.653	0.725	0.790	0.912
Full Sample	0.419	0.053	0.313	0.360	0.382	0.416	0.450	0.495	0.537

Sub-Panel (ii): Measure 2, Latency Arbitrage Tax based on Non-Race Trading Volume (basis points)

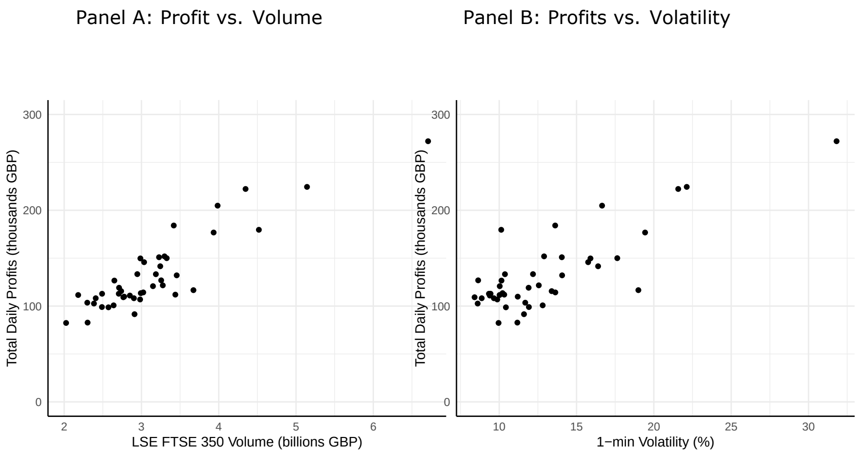
Description	Mean	sd	Min	Pct10	Pct25	Median	Pct75	Pct90	Max
FTSE 100	0.493	0.075	0.351	0.418	0.443	0.487	0.533	0.603	0.656
FTSE 250	0.800	0.133	0.577	0.653	0.712	0.788	0.899	0.969	1.136
Full Sample	0.534	0.076	0.384	0.454	0.481	0.531	0.581	0.652	0.680

Notes: Panel A. For each symbol, we compute total race profits in GBP, summed over all dates in our sample, using per-race profits in GBP based on displayed depth with prices marked to market at 10 seconds (see notes for Table 5.5). We then compute total regular-hours trading volume in GBP, and total non-race regular-hours trading volume in GBP (see notes for Table 5.3). Panel A(i) reports the distribution across symbols of race profits divided by all trading volume. Panel A(ii) reports the distribution across symbols of race profits divided by non-race trading volume. Panel B is the same except at the date level (with race profits, all volume and non-race volume each summed across all symbols) instead of at the symbol level. All analyses are conducted separately for FTSE 100, FTSE 250, and full sample.

Relationship between Profits, Volume and Volatility

Figure 5.4 presents scatterplots of latency arbitrage profits against trading volume (Panel A) and 1-minute realized volatility (Panel B). Each dot represents one day of our data. As can be seen, latency arbitrage profits are highly correlated to both volume and volatility. The R^2 of the relationship between profits and volume is 0.811 and the R^2 of the relationship between profits and 1-minute volatility is 0.661. These relationships are consistent with the theory in BCS, which suggests that the size of the latency arbitrage prize should be related to both volume and volatility.

Figure 5.4: **Latency Arbitrage Profits Correlation with Volume and Volatility**

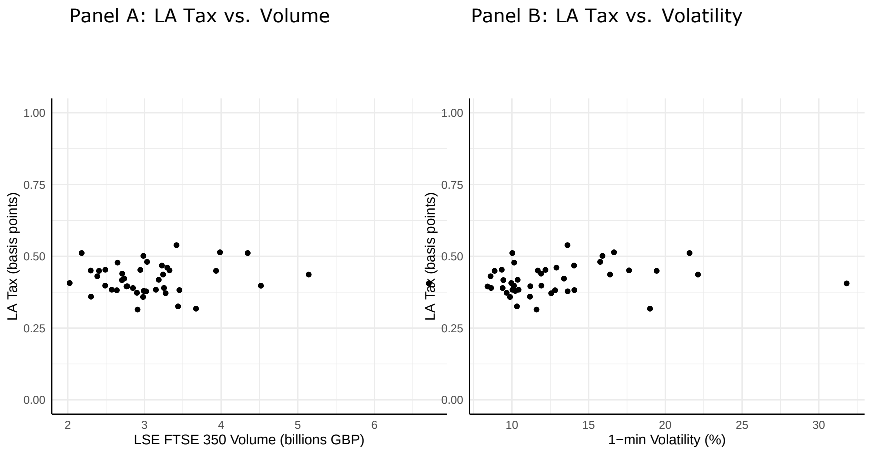

Panel A: Profit vs. Volume

Panel B: Profits vs. Volatility

Notes: Panel A presents a scatterplot of daily race profits for the full sample, computed as in Table 5.7 (Panel B), against daily regular-hours trading volume (see notes for Table 5.3). Panel B presents a scatterplot of daily race profits for the full sample, against daily realized 1-minute volatility for the FTSE 350 index, computed using Thomson Reuters Tick History (TRTH) data.

Figure 5.5 presents scatterplots of the latency arbitrage tax (Measure 1, all volume) against these same measures: trading volume (Panel A) and 1-minute realized volatility (Panel B). The figures show that once we divide latency arbitrage profits by daily trading volume, to obtain the latency arbitrage tax in basis points, the result is realtively flat across the days in our sample. We will report further details on these relationships in Section 7, where they will be used for the purpose of out-of-sample extrapolation.

Figure 5.5: **Latency Arbitrage Tax Correlation with Volume and Volatility**


Panel A: LA Tax vs. Volume

Panel B: LA Tax vs. Volatility

Notes: Panel A presents a scatterplot of the daily latency arbitrage tax, defined as daily race profits for the full sample divided by daily regular-hours trading volume, against regular-hours trading volume. Panel B presents a scatterplot of the daily latency arbitrage tax against daily realized 1-minute volatility for the FTSE 350 index. Please see the notes for Figure 5.4 which is closely related.

5.5 Latency Arbitrage's Share of the Cost of Liquidity

In this sub-section we quantify latency arbitrage as a proportion of the overall cost of liquidity. We present two distinct approaches.

Approach #1: Traditional Spread Decomposition An influential decomposition of the bid-ask spread (e.g., Glosten, 1987; Stoll, 1989; Hendershott, Jones and Menkveld, 2011) is:

$$\mathit{EffectiveSpread} = \mathit{PriceImpact} + \mathit{RealizedSpread} \tag{5.1}$$

where *EffectiveSpread* is defined as the value-weighted difference between the transaction price and the midpoint at the time of the transaction, *PriceImpact* is defined as the value-weighted change between the midpoint at the time of the transaction and the midpoint at some time in the near future (e.g., 30 seconds), and *RealizedSpread* is the remainder. *EffectiveSpread* is typically interpreted as the revenue to liquidity providers from capturing the bid-ask spread, *PriceImpact* as the cost of adverse selection, and *RealizedSpread* as revenues net of adverse selection.

The theory of latency arbitrage as presented in Section 4.1 suggests two refinements to (5.1). First, we can decompose the price impact component of the spread into two components: one that reflects latency arbitrage and one that reflects traditional private information. Specifically, for each symbol-day, we sum the value-weighted price impacts for all trades that are part of a latency arbitrage race, and we sum the value-weighted price impacts for all trades that are not part of a latency arbitrage race. Second, the theory shows that the equilibrium bid-ask spread also reflects the value of "losses avoided" by fast liquidity providers who successfully cancel in a latency arbitrage race. The intuition is that fast liquidity providers must earn a rent in equilibrium for being fast that is equal to the rent earned by fast traders who try to snipe; i.e., they earn the "opportunity cost of not sniping."

Formally, we start with equation (3.1) of Budish, Lee and Shim (2019), which gives the equilibrium bid-ask spread in the continuous limit order book (CLOB) market as

$$\lambda_{invest}\frac{s^{CLOB}}{2} = (\lambda_{public} + \lambda_{private}) \cdot L(\frac{s^{CLOB}}{2}), \tag{5.2}$$

with the notation defined as follows. λ_{invest}, λ_{public} and $\lambda_{private}$ are, respectively, the Poisson arrival rates of investors who trade and thus pay the half-spread to a liquidity provider, publicly observed jumps in the fundamental value which cause a sniping race, and privately observed jumps in the fundamental value which lead to Glosten and Milgrom (1985) adverse selection. s^{CLOB} denotes the equilibrium bid-ask spread. $L(\frac{s^{CLOB}}{2})$ denotes the expected loss to a liquidity provider, at this spread, if there is a jump in the fundamental value and they get sniped or adversely selected. It can be shown that this equation (5.2) implies the spread decomposition:

$$\mathit{EffectiveSpread} = \mathit{PriceImpact}_{Race} + \mathit{PriceImpact}_{NonRace} + \mathit{LossAvoidance} + \mathit{RealizedSpread} \tag{5.3}$$

with terms defined as follows. $\mathit{EffectiveSpread}$ is defined in the standard way, as the value-weighted absolute difference between the price paid in trades and the midpoint at the time of the trade (i.e., the value-weighted half-spread). $\mathit{PriceImpact}_{Race}$ and $\mathit{PriceImpact}_{NonRace}$ are, respectively, the value-weighted change between the midpoint at the time of the trade and the midpoint at some time in the near future (we will use 10 seconds), for trades in latency-arbitrage races and trades not in latency-arbitrage races. That is we take the usual definition of $PriceImpact$ and decompose it into two components, for trades in and not in races, respectively, so that $PriceImpact = PriceImpact_{Race} + PriceImpact_{NonRace}$. Last, $LossAvoidance$ is defined as the value-weighted change between the race price and the midpoint in the near future for successful cancels in latency arbitrage races. Note that $LossAvoidance$ is calculated as race price to midpoint, whereas $PriceImpact_{Race}$ is calculated as midpoint to midpoint. This difference reflects the fact that $LossAvoidance$ measures trades that a fast liquidity provider *avoided*, so no liquidity taker paid the effective spread; in contrast, in races won by an aggressor, the aggressor pays the effective spread and the liqudity provider’s losses are price impact less this effective spread they collected.[40]

Table 5.9 gives details for decomposition (5.3) at the symbol level. For the average symbol in the FTSE 100, averaged over the days of our data set, the effective spread is 3.27 basis points, of which price impact is 3.62 basis points, loss avoidance is 0.01 basis points, and realized spread is -0.36 basis points. That price impact slightly exceeds the effective spread, so that realized spread is slightly negative, is relatively common in modern markets, as noted in O’Hara (2015), and documented in Battalio, Corwin and Jennings (2016); Malinova, Park and Riordan (2018); Baron et al. (2019).[41] That loss avoidance is small is consistent with our finding earlier that most race activity is aggressive. Effective spread is similar in races and outside of races (3.18 and 3.29 basis points, respectively).

[40] Here are the formal details supporting this decomposition. For notational simplicity, assume that the jump distribution J is the same for public and private information and that all jumps are at least the equilibrium half-spread, so that all jumps generate attempts to trade. This assumption can be relaxed without affecting the economic conclusion, but at considerable notational burden because one has to keep track of jump distributions conditioning on the jump exceeding the half-spread. Under this assumption, $L(\frac{s^{CLOB}}{2}) \equiv E(J) - \frac{s^{CLOB}}{2}$ is the expected cost to a liquidity provider of getting sniped or adversely selected. In the notation of Budish, Lee and Shim (2019), the *EffectiveSpread* is $[\lambda_{invest} + (\frac{N-1}{N}\lambda_{public} + \lambda_{private})] \cdot \frac{s^{CLOB}}{2}$: trade occurs whenever an investor arrives (at rate λ_{invest}), whenever an informed trader arrives ($\lambda_{private}$), and whenever there is public news (λ_{public}) and the race is won by a sniper ($\frac{N-1}{N}$, where N is the number of fast traders). Next, $PriceImpact_{Race}$ is equal to the $\lambda_{public}\frac{N-1}{N}$ probability that a sniper wins a race, times the size of the jump, which will be the change in the midpoint: this can be written as $\lambda_{public}\frac{N-1}{N}E(J) = \lambda_{public}\frac{N-1}{N}(\frac{s^{CLOB}}{2} + L(\frac{s^{CLOB}}{2}))$. $PriceImpact_{NonRace}$ is, by similar logic, $\lambda_{private}(\frac{s^{CLOB}}{2} + L(\frac{s^{CLOB}}{2}))$. Last, $LossAvoidance$ is $\lambda_{public}\frac{1}{N}L(\frac{s^{CLOB}}{2})$. Thus, if we take (5.2) and add $(\frac{N-1}{N}\lambda_{public} + \lambda_{private}) \cdot \frac{s^{CLOB}}{2}$ to both sides of the equation, we obtain (5.3).

[41] A common style of explanation for this empirical fact is that many limit order providers are institutional investors trading in a particular direction and hoping to avoid crossing the spread; such investors prefer a slightly negative realized spread to paying the half-spread as an aggressor. Also notable is that in our data realized spreads are slightly positive if price impact is measured at a shorter duration, such as 100ms or 1s rather than 10s (please see Appendix Tables A.8 and A.9). This is consistent with Conrad and Wahal (2019), who find that realized spreads decrease as the time interval decreases.

Table 5.9: **Spread Decomposition**

Panel A: FTSE 100 by Symbol

Description	Mean	sd	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99
Effective spread paid (basis points)	3.27	1.22	1.22	1.75	2.28	3.18	4.13	4.91	5.79
Effective spread paid - in races (basis points)	3.18	1.22	0.99	1.70	2.21	3.17	4.05	4.89	5.98
Effective spread paid - not in races (basis points)	3.29	1.22	1.25	1.78	2.30	3.17	4.15	4.96	5.71
Price impact (basis points)	3.62	1.36	1.40	1.92	2.52	3.56	4.52	5.55	6.99
Price impact in races (basis points)	1.24	0.63	0.44	0.50	0.76	1.13	1.66	2.14	2.74
Price impact not in races (basis points)	2.38	0.81	0.95	1.36	1.76	2.43	2.86	3.42	4.27
Loss avoidance (basis points)	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.03
Realized spread (basis points)	-0.36	0.32	-1.07	-0.76	-0.55	-0.35	-0.17	0.01	0.39
PI in races / PI total (%)	33.16	6.09	19.99	24.88	29.53	32.13	37.23	41.72	44.72
PI in races / Effective spread (%)	36.90	7.18	19.79	27.73	33.06	36.59	41.97	46.44	51.67

Panel B: FTSE 250 by Symbol

Description	Mean	sd	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99
Effective spread paid (basis points)	8.06	3.81	2.65	4.63	5.59	7.14	9.84	13.10	19.11
Effective spread paid - in races (basis points)	6.74	3.03	2.42	4.32	4.97	6.08	7.63	9.96	15.62
Effective spread paid - not in races (basis points)	8.22	3.87	2.72	4.70	5.72	7.31	9.94	13.34	19.55
Price impact (basis points)	8.09	3.54	2.64	4.96	5.71	7.10	9.40	12.95	19.91
Price impact in races (basis points)	1.59	0.76	0.19	0.59	1.12	1.56	2.00	2.42	4.06
Price impact not in races (basis points)	6.50	3.43	2.01	3.56	4.13	5.50	7.80	11.02	18.64
Loss avoidance (basis points)	0.01	0.02	-0.02	0.00	0.00	0.01	0.01	0.02	0.07
Realized spread (basis points)	-0.04	1.14	-2.30	-1.02	-0.53	-0.14	0.34	0.96	2.67
PI in races / PI total (%)	21.60	9.50	1.79	6.00	14.89	22.98	28.19	32.16	39.60
PI in races / Effective spread (%)	22.50	10.92	1.58	5.62	14.84	23.57	30.44	34.79	47.67

Panel C: Full Sample by Date

Description	Mean	sd	Min	Pct10	Pct25	Median	Pct75	Pct90	Max
Effective spread paid (basis points)	3.17	0.27	2.74	2.92	3.06	3.12	3.22	3.38	4.52
Effective spread paid - in races (basis points)	2.99	0.13	2.64	2.84	2.90	2.99	3.06	3.16	3.28
Effective spread paid - not in races (basis points)	3.22	0.32	2.77	2.95	3.09	3.17	3.29	3.44	4.90
Price impact (basis points)	3.38	0.19	2.96	3.19	3.23	3.38	3.52	3.61	3.80
Price impact in races (basis points)	1.03	0.11	0.79	0.92	0.96	1.03	1.10	1.18	1.23
Price impact not in races (basis points)	2.35	0.16	2.03	2.20	2.24	2.30	2.43	2.62	2.69
Loss avoidance (basis points)	0.01	0.00	-0.01	0.00	0.00	0.01	0.01	0.01	0.01
Realized spread (basis points)	-0.22	0.23	-0.62	-0.38	-0.31	-0.26	-0.15	-0.09	1.08
PI in races / PI total (%)	30.58	2.64	22.91	27.88	29.88	30.81	31.93	33.39	35.81
PI in races / Effective spread (%)	32.82	3.73	17.38	29.92	31.60	33.66	34.70	36.54	39.52

Notes: Please see the text of Section 5.5 for definitions of Effective Spread (ES), Price Impact (PI), Loss Avoidance, and Realized Spread (RS). Please note that ES in races and ES not in races are each value-weighted averages over trades, whereas PI in races and PI not in races is a decomposition of PI into these two components. Therefore, ES in races and ES not in races *average* (value-weighted) to overall ES, whereas PI in races and PI not in races *sum* to overall PI. Panel A reports the distribution of these statistics by symbol, for all symbols in the FTSE 100. Panel B reports the distribution for all symbols in the FTSE 250. We only include symbols that have at least 100 races summed over all dates; this drops about one-quarter of FTSE 250 symbols and does not drop any FTSE 100 symbols. Panel C reports the distribution of these statistics by date for the full sample.

Of this 3.62 basis points of price impact, about one-third (33.2%) occurs in races, with the remaining two-thirds in non-race trading volume. Since price impact is an object of per se interest to market microstructure researchers, the finding that a substantial percentage of price impact occurs in latency arbitrage races is potentially of interest for the literature.

For symbols in the FTSE 250,[42] effective spreads are higher, at 8.06 basis points, realized spreads are a bit less negative at -0.04 basis points, and loss avoidance remains small (0.01

[42] This table conditions on the symbol having at least 100 races in the sample period, or a bit more than 2 per day, to ensure that the comparisons between races and non-races is meaningful. This drops a bit over a quarter of FTSE 250 symbols. The dropped symbols have noticeably wider effective spreads than the FTSE 250 symbols with non-trivial race activity.

basis points). Effective spreads are noticeably a bit narrower in races versus not in races, at 6.74 basis points in races versus 8.22 basis points outside of races. Of the 8.09 basis points of price impact, about 22% is in races with the remainder outside of races.

Approach #2: Implied Reduction of the Bid-Ask Spread if Latency Arbitrage Were Eliminated Our second approach asks what would be the proportional reduction in the market cost of liquidity if there were no latency arbitrage. Formally, we seek to empirically measure:

$$\frac{\frac{s^{CLOB}}{2}-\frac{s^{FBA}}{2}}{\frac{s^{CLOB}}{2}} \tag{5.4}$$

where s^{CLOB} is the bid-ask spread under the continuous limit order book and s^{FBA} is the bid-ask spread under frequent batch auctions, which eliminate latency arbitrage. To turn (5.4) into something empirically measurable, we take the following steps. First, we multiply the numerator and denominator of (5.4) by $(\lambda_{invest}+\lambda_{private})$. Second, we use (5.2) to solve out for $\lambda_{invest}\frac{s^{CLOB}}{2}$ in the numerator. Third, we use equation (5.1) of Budish, Lee and Shim (2019),

$$\lambda_{invest}\frac{s^{FBA}}{2}=\lambda_{private}\cdot L(\frac{s^{FBA}}{2}) \tag{5.5}$$

to solve out for $\lambda_{invest}\frac{s^{FBA}}{2}$ in the numerator of (5.4). Observe that the difference between the equilibrium bid-ask spread characterization for frequent batch auctions, (5.5), and the equilibrium bid-ask spread for continuous trading, (5.2), is the $\lambda_{public}L(\cdot)$ term, i.e., the rate at which public information arrives times the expected profits in a latency arbitrage race conditional on public information.

Last, assume for notational simplicity (as discussed in footnote 40) that all jumps are of size at least $\frac{s^{CLOB}}{2}$, so that $L(\frac{s^{CLOB}}{2})=E(J-\frac{s^{CLOB}}{2})$ without the need for conditioning on whether the jumps are larger than the half-spread. Using these manipulations and some algebra yields that (5.4) is equivalent to:

$$\frac{\frac{s^{CLOB}}{2}-\frac{s^{FBA}}{2}}{\frac{s^{CLOB}}{2}}=\frac{\lambda_{public}L(\frac{s^{CLOB}}{2})}{(\lambda_{invest}+\lambda_{private})\frac{s^{CLOB}}{2}} \tag{5.6}$$

Both the numerator and denominator of (5.6) are measurable. The numerator is simply latency arbitrage profits (including both races where an aggressor wins and races where a cancel wins). The denominator is the non-race portion of the effective spread; that is, it is all of the bid-ask spread revenue collected by liquidity providers outside of latency arbitrage races. These objects can be measured either in GBP terms, or, by dividing both numerator and denominator by non-race trading volume, in basis points terms. Thus, we have the relationship:

$$\begin{aligned}\text{Proportional Reduction in Liquidity Cost} &= \frac{\text{Race Profits (GBP)}}{\text{Non-Race Effective Spread (GBP)}} \\ &= \frac{\text{Latency Arbitrage Tax (Non-Race Volume)}}{\text{Non-Race Effective Spread (bps)}}\end{aligned} \tag{5.7}$$

Table 5.10 presents our computation of (5.7). For the average symbol in the FTSE 100, eliminating latency arbitrage would reduce the cost of liquidity by 20.0%. For the FTSE 250, the figure is 11.9%. Even though race profits are higher as a proportion of trading volume for the FTSE 250 (per Table 5.8), bid-ask spreads are several times wider for FTSE

250 symbols than for FTSE 100 symbols, so eliminating latency arbitrage would reduce the overall cost of liquidity by less for the FTSE 250 than for the FTSE 100.

For the market as a whole, value-weighted and averaging over all dates in our sample, eliminating latency arbitrage would reduce the cost of liquidity by 16.7%.

Table 5.10: **Percentage Reduction in Liquidity Cost, if Latency Arbitrage Eliminated**

Panel A: Symbol level

Description	Mean	sd	Pct01	Pct10	Pct25	Median	Pct75	Pct90	Pct99
FTSE 100	19.95	5.29	8.87	13.30	16.79	19.69	23.58	26.50	32.54
FTSE 250	11.93	6.31	0.58	3.12	8.05	11.91	15.33	18.58	31.31
Full Sample	14.77	7.09	0.70	5.55	10.03	14.55	19.41	24.10	32.22

Panel B: Date level

Description	Mean	sd	Min	Pct10	Pct25	Median	Pct75	Pct90	Max
FTSE 100	19.06	3.29	7.49	16.53	17.53	18.97	21.48	22.25	25.40
FTSE 250	11.39	1.66	8.27	9.43	10.22	11.17	12.45	13.36	16.18
Full Sample	16.73	2.57	7.88	14.57	15.19	16.82	18.66	19.17	21.58

Notes: For each symbol, we implement equation 5.7 by dividing total race profits in GBP, across all dates, and dividing by total non-race Effective Spread paid in GBP, across all dates. Race profits in GBP are as described in Table 5.7 and Effective Spread paid in GBP is as described in Table 5.9. Analogously, for each date, we implement equation 5.7 by dividing total race profits in GBP, across all symbols, and dividing by total non-race Effective Spread paid in GBP, across all symbols. We do both exercises separately for FTSE 100, FTSE 250, and full sample. As in Table 5.9, the symbol-level measures drop symbols with fewer than 100 races summed across all dates in our sample.

6 Sensitivity Analysis

In this section we present sensitivity analyses for the main results presented in Section 5.

Section 6.1 explores sensitivity to the race horizon, i.e., to the definition of what counts as "at the same time." Section 6.2 explores sensitivity to the number of race participants, e.g., requiring 3+ participants at the same time rather than 2+. Section 6.3 explores sensitivity to requiring cancel attempts in the race, i.e., to not counting races that contain only aggressive orders, and also explores stricter requirements on the number of aggressive orders. Section 6.4 explores varying the definition of what counts as a success and a fail. Together, then, Sections 6.1-6.4 explore sensitivity to the four components of our race definition: multiple participants, at the same time, at least some of whom are aggressive, and at least some of whom succeed and some of whom fail. In Section 6.5 we combine the insights from all of the sensitivity analyses to discuss lower and upper bounds on our measures of race profits and the harm to liquidity provision.

6.1 Sensitivity to Race Horizon

As a reminder, our baseline method requires that messages satisfying the baseline race requirements (i.e., 2+ messages from distinct users, 1+ aggressing, 1+ success, and 1+ fail) arrive within the "information horizon" of the first message of the race or 500 microseconds, whichever is smaller. The information horizon, which is the window of time such that we can be essentially certain that inbound messages in the race are not responding to earlier messages' outbound reports (see Section 4.3) has a mean of just over 200 microseconds in our data. The 500 microsecond truncation binds 4% of the time.

Table 6.1 presents sensitivity analysis for changes to the race horizon. The first column of the table re-presents our main results from Section 5 for this baseline specification, to facilitate comparison. The next set of columns presents these same results using fixed race horizons of varying lengths, from 50 microseconds to 3 milliseconds. That is, instead of allowing the race window to vary with the observed lag in information processing by the LSE's matching engine, we just fix a time window, and consider a wide range of such windows. The 50 microsecond window roughly corresponds to the minimum observed information horizon (which is 43 microseconds), the 200 microsecond window roughly corresponds to the mean observed information horizon, and 500 microseconds corresponds to the upper bound on the information horizon we determined in consultation with FCA supervisory experts. The horizons beyond that are included to capture races among firms of varying technological sophistication that could still be considered racing one another. For instance, the threshold should be wide enough to include a firm that is not utilizing the fastest connections to exchanges in the United States or elsewhere, but is using the next-fastest.[43] We consulted with HFT industry contacts and FCA supervisors to agree on an appropriate horizon. Following these discussions, we determined 3 milliseconds would capture most of these additional potential races, though for races originating from signals far from London (e.g., Chicago) differences in speed between cutting-edge HFTs and relatively sophisticated firms could easily exceed that number. The last set of columns runs a sensitivity analysis specifically on the choice of the truncation parameter for our information horizon method.

Focus first on the number of races per day per symbol in the FTSE 100, the first row of the table. In the baseline there are 537 races per symbol per day. In the 50 microsecond column, this number is reduced to 297. As the race horizon increases, so does the number of races detected. The growth is especially steep up to 500 microseconds, reaching 793 races per symbol per day, and then tapers off, with 870 races at a horizon of 1 millisecond and 946 races at a horizon of 3 milliseconds. Varying the truncation parameter for the information horizon method does not yield much additional insight beyond what we have already learned from the baseline and the fixed horizon columns. Using a 100 microsecond truncation parameter yields results that are very similar to the 100 microsecond fixed race horizon, which makes sense since this truncation parameter will bind most of the time. Using a 1 millisecond truncation parameter yields results that are similar to the baseline with the 500 microsecond truncation parameter, which again makes sense because neither truncation parameter will bind very much.

Turn next to the measures of per-race profits. Interestingly, per-race profits, whether measured per-share (ticks, pence (GBX), basis points) or in GBP per-race (either displayed depth or quantity actually traded/canceled), are relatively similar across these different specifications. This tells us that the additional races being picked up by the longer race horizons are, on average, of similar profitability to the races being picked up at shorter race horizons. This will not be the case for some of the subsequent sensitivities.

As a result, the latency arbitrage tax measures are all increasing with the race horizon. At a 50 microsecond race horizon, the FTSE 350 latency arbitrage tax, using the all-volume measure (Measure 1), is 0.20 basis points, versus 0.42 basis points in our baseline specification. At the 3 millisecond race horizon, the latency arbitrage tax is 0.81 basis points, or 4 times higher, roughly proportional to the increase in the number of races. The effect on the second measure of the latency arbitrage tax, based on non-race trading volume, is even

[43] Other sources of speed differential include using code and hardware that is not optimized for speed, not being co-located, and not using microwave connections where possible to do so.

Table 6.1: **Sensitivity Analysis: Different Race Horizons**

		Fixed Race Horizon of Duration T							**Info Horizon, Max T**	
Measure	**Baseline**	50μs	100μs	200μs	500μs	1ms	2ms	3ms	100μs	1ms
Frequency and Duration of Races										
Races per day										
FTSE 100 - per symbol	537.24	296.66	388.58	521.53	793.01	869.73	921.08	946.48	387.96	542.99
FTSE 250 - per symbol	70.05	41.37	52.78	69.22	112.99	127.04	134.06	138.37	52.71	70.28
Mean race duration (microseconds)	78.65	16.12	30.80	72.18	194.20	304.96	450.87	572.12	30.61	84.85
% of races with wrong winner	4.30	8.18	6.41	4.21	1.98	1.67	1.43	1.32	6.42	4.24
% of volume in races										
FTSE 100	22.15	9.99	13.65	19.71	37.43	43.53	47.11	48.61	13.64	22.65
FTSE 250	16.90	8.36	11.20	15.99	33.34	38.37	41.23	42.63	11.20	17.07
Full Sample	21.46	9.77	13.32	19.21	36.88	42.84	46.33	47.82	13.32	21.92
Mean number of messages within 500 μs	3.46	3.51	3.51	3.51	3.39	3.01	2.83	2.76	3.51	3.44
Per-Race Profits										
Per-share profits										
ticks	0.55	0.54	0.53	0.51	0.53	0.55	0.56	0.57	0.53	0.56
GBX	0.17	0.16	0.16	0.16	0.16	0.16	0.17	0.16	0.16	0.17
basis points	1.66	1.68	1.63	1.57	1.61	1.64	1.65	1.65	1.63	1.67
Per-race profits GBP										
displayed depth	1.85	1.58	1.59	1.60	1.84	1.94	1.97	1.97	1.60	1.90
qty trade/cancel	1.76	1.38	1.44	1.51	1.84	1.95	2.00	2.00	1.44	1.81
Aggregate Profits and LA Tax										
Daily Profits										
FTSE 100 - per symbol	1,047	490	647	872	1,520	1,769	1,909	1,965	647	1,089
FTSE 250 - per symbol	108	57	73	96	184	211	226	231	73	110
Full Sample - aggregate	132,378	63,573	83,233	111,722	198,700	230,586	248,291	255,408	83,181	137,173
Latency Arbitrage Tax, All Volume (bps)										
FTSE 100	0.38	0.18	0.24	0.32	0.56	0.65	0.70	0.72	0.24	0.40
FTSE 250	0.66	0.35	0.45	0.59	1.13	1.30	1.39	1.42	0.45	0.68
Full Sample	0.42	0.20	0.26	0.35	0.63	0.73	0.78	0.81	0.26	0.43
Latency Arbitrage Tax, Non-Race Volume (bps)										
FTSE 100	0.49	0.20	0.27	0.40	0.89	1.15	1.32	1.40	0.27	0.52
FTSE 250	0.80	0.38	0.50	0.71	1.70	2.12	2.37	2.49	0.50	0.82
Full Sample	0.53	0.22	0.30	0.44	1.00	1.28	1.47	1.55	0.30	0.56
Spread Decomposition										
Price impact in races / All price impact %	30.58	12.84	17.89	25.69	49.79	58.71	64.34	66.82	17.88	31.76
Price impact in races / Effective spread %	32.82	13.77	19.19	27.57	53.42	62.99	69.03	71.69	19.19	34.08
Loss avoidance / Effective spread %	0.19	0.07	0.13	0.26	0.53	0.94	1.31	1.48	0.13	0.20
Implied Reduction in Cost of Liquidity										
% Reduction in liquidity cost										
FTSE 100 - by symbol	19.95	7.98	10.97	15.91	35.73	46.95	55.24	59.20	10.97	21.00
FTSE 250 - by symbol	11.93	6.17	7.96	10.79	24.36	28.46	31.70	32.90	7.95	12.17
Full Sample - by date	16.73	6.96	9.49	13.62	30.38	39.20	45.62	48.75	9.49	17.49

Notes: For descriptions of the sensitivity scenarios please see the text of Section 6.1. Descriptions of each of the items in this table can be found in the following table notes in Section 5. Races per day: Table 5.1. Mean race duration and % of races with wrong winner: Table 5.2. % of Volume in Races: Table 5.3. Mean number of messages: Table 5.4. Per-race profits: Table 5.5. Aggregate profits: Table 5.7. Latency Arbitrage Tax: Table 5.8. Spread decomposition: Table 5.9. Implied Reduction in Cost of Liquidity: Table 5.10.

larger, because as the numerator (race profits) is increasing, the denominator (non-race volume) is also shrinking. This figure increases from 0.22 basis points at 50 microseconds, to 0.53 basis points in our baseline specification, all the way up to 1.55 basis points at 3 milliseconds. For FTSE 250 stocks, the latency arbitrage tax is as high as 2.49 basis points at 3 milliseconds.

Last we discuss the implied reduction in the cost of liquidity. In our baseline, eliminating latency arbitrage would reduce the cost of liquidity by 20.0% for the average FTSE 100 symbol and by 16.7% for the market overall. Using a 50 microsecond race horizon lowers these figures to 8.0% and 7.0%, respectively. Using a 3 millisecond race horizon increases these figures all the way to 59.2% and 48.8%, respectively. Again, this large change relative to the baseline is driven by both the increase in the numerator (race profits) and decrease in the denominator (non-race effective spread paid).

6.2 Sensitivity to Number of Race Participants

Our baseline method requires that there are at least 2 race participants within the information horizon. Table 6.2 presents sensitivity analysis for requiring 3+ participants; the appendix presents the same table for 5+ participants. In both cases, the other race criteria are held the same, specifically we require 1+ aggressors, 1+ successes, 1+ fails. Given the large effect that the race's time horizon had on the number of races and race profits, we include this sensitivity for multiple race horizons, including the baseline information horizon method and fixed race horizons from 50 microseconds to 3 milliseconds.

Focus first on the 3+ race participants within information horizon column; this column is exactly the same as the baseline but replacing 2+ race participants with 3+. Requiring 3+ race participants reduces the number of races by about 60%; for example, for the FTSE 100 the number of races per symbol per day declines from 537 to 229. However, these races are significantly more profitable, on a per-share basis and particularly on a GBP per-race basis. The net effect is that total race profits are reduced by about 30%. This roughly 30% reduction can be seen in the aggregate race profits measures, the latency arbitrage tax measures, and the liquidity cost reduction measures.

Increasing the race horizon increases the number of races detected, just as in the baseline case with 2+ participants. At a 50 microsecond race horizon there are 87 3+ participant races per day for the average FTSE 100 symbol, up to 482 races per symbol per day at a 500 microsecond race horizon, and up to 686 races at a 3 millisecond race horizon. With this increase in the number of races detected comes a commensurate increase in the various race profits measures and harm-to-liquidity measures.

We note that the 3+ race participants within 500 microseconds sensitivity is on most measures relatively similar to the baseline case of 2+ race participants within the information horizon. The number of races is a bit smaller but they are more profitable on average, with the net effect that the overall profits measures and liquidity-harm measures are about 20-30% higher than in the baseline. The 3+ race participants within 1 millisecond sensitivity yields a latency arbitrage tax (all-volume) of 0.65, versus 0.42 in baseline, and yields an implied harm to the cost of liquidity of 30.7%, versus 16.7% in baseline. In this sense, our baseline specification is meaningfully more conservative than the requirement of 3+ within 1 millisecond.

In the appendix we report a similar table for 5+ participants (Table A.10). There are very few (38) races per FTSE 100 symbol per day within the information horizon, versus

Table 6.2: **Sensitivity Analysis: Different Number of Race Participants**

			3+ Race Participants Within						
Measure	**Baseline**	InfoHor	50μs	100μs	200μs	500μs	1ms	2ms	3ms
Frequency and Duration of Races									
Races per day									
FTSE 100 - per symbol	537.24	228.98	86.73	134.38	236.14	482.47	585.98	655.57	685.98
FTSE 250 - per symbol	70.05	30.68	13.40	19.92	32.98	67.54	82.20	90.01	93.47
Mean race duration (microseconds)	78.65	77.56	14.26	28.54	75.54	194.56	305.95	449.76	553.83
% of races with wrong winner	4.30	5.08	10.66	7.88	4.59	2.01	1.71	1.44	1.33
% of volume in races									
FTSE 100	22.15	12.75	3.84	6.32	11.57	27.97	35.53	39.99	41.83
FTSE 250	16.90	9.33	3.38	5.24	9.35	23.68	29.59	32.95	34.39
Full Sample	21.46	12.30	3.78	6.17	11.28	27.40	34.74	39.06	40.85
Mean number of messages within 500 μs	3.46	4.68	4.83	4.82	4.62	4.21	3.58	3.28	3.17
Per-Race Profits									
Per-share profits									
ticks	0.55	0.71	0.73	0.71	0.64	0.61	0.63	0.64	0.65
GBX	0.17	0.23	0.23	0.22	0.20	0.19	0.19	0.19	0.19
basis points	1.66	2.24	2.36	2.29	2.03	1.90	1.91	1.92	1.92
Per-race profits GBP									
displayed depth	1.85	2.98	2.55	2.60	2.43	2.52	2.57	2.58	2.58
qty trade/cancel	1.76	2.87	2.29	2.40	2.33	2.55	2.62	2.65	2.64
Aggregate Profits and LA Tax									
Daily Profits									
FTSE 100 - per symbol	1,047	736	238	375	612	1,273	1,583	1,770	1,848
FTSE 250 - per symbol	108	70	27	41	65	147	181	200	208
Full Sample - aggregate	132,378	91,506	30,701	47,980	77,738	164,760	204,272	228,064	237,757
Latency Arbitrage Tax, All Volume (bps)									
FTSE 100	0.38	0.27	0.09	0.14	0.23	0.47	0.58	0.65	0.68
FTSE 250	0.66	0.43	0.17	0.25	0.40	0.90	1.11	1.23	1.28
Full Sample	0.42	0.29	0.10	0.15	0.25	0.52	0.65	0.72	0.75
Latency Arbitrage Tax, Non-Race Volume (bps)									
FTSE 100	0.49	0.35	0.10	0.16	0.28	0.75	1.03	1.23	1.32
FTSE 250	0.80	0.51	0.18	0.28	0.48	1.36	1.81	2.11	2.24
Full Sample	0.53	0.37	0.11	0.18	0.31	0.83	1.14	1.35	1.45
Spread Decomposition									
Price impact in races / All price impact %	30.58	19.13	5.64	9.34	16.39	38.37	48.96	55.92	58.99
Price impact in races / Effective spread %	32.82	20.54	6.05	10.03	17.61	41.17	52.54	60.01	63.31
Loss avoidance / Effective spread %	0.19	0.18	0.07	0.13	0.27	0.63	1.09	1.50	1.65
Implied Reduction in Cost of Liquidity									
% Reduction in liquidity cost									
FTSE 100 - by symbol	19.95	12.46	3.69	5.94	10.23	26.26	36.90	45.30	49.49
FTSE 250 - by symbol	11.93	7.67	3.03	4.50	7.09	19.05	24.47	28.10	28.85
Full Sample - by date	16.73	10.43	3.19	5.13	8.79	22.18	30.65	37.13	40.29

Notes: For descriptions of the sensitivity scenarios please see the text of Section 6.2. Descriptions of each of the items in this table can be found in the following table notes in Section 5. Races per day: Table 5.1. Mean race duration and % of races with wrong winner: Table 5.2. % of Volume in Races: Table 5.3. Mean number of messages: Table 5.4. Per-race profits: Table 5.5. Aggregate profits: Table 5.7. Latency Arbitrage Tax: Table 5.8. Spread decomposition: Table 5.9. Implied Reduction in Cost of Liquidity: Table 5.10.

537 in the baseline and 229 with 3+. That said, these few races are quite profitable: they are about twice as profitable per share and more than three times as profitable in GBP per race as in the baseline. Increasing the race horizon to 500 microseconds yields 122 races per FTSE 100 symbol per day, and to 1 millisecond yields 202 races per day, again with races that are signficantly more profitable per race than in the baseline. As a consequence, the sensitivity for 5+ participants within 500 microseconds yields overall profits that are about 60% of the baseline, and the sensitivity for 5+ participants within 1 millisecond yields overall profits and harm to liquidity that are just about the same as in the baseline.

The appendix also includes a sensitivity for requiring 2+ unique firms as opposed to our baseline requirement of 2+ unique participants (Table A.11). As mentioned earlier, some firms use different UserIDs for different trading desks. This sensitivity reduces the number of races and various profits measures by about 10%.

6.3 Sensitivity to Requiring Cancels or Multiple Takes

Our baseline method requires that of the 2+ messages in a race, at least 1 is aggressive. Thus, a race could have 1+ aggressive messages and 1+ cancel messages, or it could have 2+ aggressive messages and 0 cancel messages. Table 6.3 presents sensitivity analysis for these requirements. In the first set of columns after the baseline, we require 1+ cancel message and 1+ aggressive message, i.e., exclude races with 0 cancels (and hence 2+ aggressive messages). In the second set of columns, we require 2+ aggressive messages, i.e., exclude races with exactly 1 aggressive message (and hence 1+ cancel messages).

Focus first on the 1+ cancel within information horizon column. Requiring a cancel attempt within the race horizon window reduces the number of races significantly, from 537 to 173 per day for the average symbol in the FTSE 100. These races are also less profitable on average. This reduction in profitability is driven by races with exactly 1 aggressive message. If we require 2+ aggressive messages alongside a cancel (see Appendix Table A.12), profits per race are higher than in the baseline, especially in GBP per race where profits are nearly double.

Looking across the different race horizons does not change this picture much. The number of races goes up with the race horizon, as before, but the number of races and overall profitability are meaningfully smaller than without the 1+ cancel requirement, at all horizons.

These results are consistent with our findings in Section 5, specifically Table 5.4 which showed that the number of cancel messages in races is small, and Table 5.9 which found that Loss Avoidance plays only a small role in our spread decomposition. Races that include cancel attempts correspond to only about 20-30% of total latency arbitrage profits and harm to liquidity.

Now focus on the columns that require at least 2 aggressive messages; that is, a race must have 2+ takes, along with 1+ success and 1+fail, within the race horizon. Relative to the baseline, this excludes races with exactly 1 take and with 1+ cancels, which as we just discussed are relatively unprofitable. The number of races with 2+ takes within the information horizon is 424 for FTSE 100 symbols, versus 537 under the baseline scenario, a reduction of about 20%. These races are more profitable on average than the baseline races, so the net effect on profits and the harm-to-liquidity measures is smaller, roughly 10-15%. This magnitude of reduction relative to the baseline requirements persists across the other time horizons.

Table 6.3: **Sensitivity Analysis: Requiring Cancels or Multiple Takes**

		1+ Cancel Within					2+ Takes Within				
Measure	**Baseline**	InfoHor	50μs	500μs	1ms	3ms	InfoHor	50μs	500μs	1ms	3ms
Frequency and Duration of Races											
Races per day											
FTSE 100 - per symbol	537.24	172.70	71.55	242.59	303.68	380.88	423.86	241.67	695.44	774.40	851.41
FTSE 250 - per symbol	70.05	14.40	6.76	23.42	31.10	40.89	60.91	36.30	103.85	117.33	127.31
Mean race duration (microseconds)	78.65	92.77	19.05	206.89	373.48	768.59	74.52	15.42	194.72	300.04	547.27
% of races with wrong winner	4.30	3.15	7.42	2.01	1.50	0.99	4.63	8.34	1.89	1.62	1.30
% of volume in races											
FTSE 100	22.15	8.49	2.31	12.71	17.30	22.75	17.40	8.39	33.90	40.55	46.15
FTSE 250	16.90	3.31	1.08	6.17	9.21	13.02	15.20	7.65	32.02	37.04	41.19
Full Sample	21.46	7.82	2.15	11.87	16.26	21.49	17.11	8.28	33.64	40.08	45.49
Mean number of messages within 500 μs	3.46	3.36	3.26	3.65	3.09	2.73	3.66	3.65	3.50	3.11	2.85
Per-Race Profits											
Per-share profits											
ticks	0.55	0.37	0.24	0.37	0.39	0.40	0.62	0.62	0.57	0.59	0.62
GBX	0.17	0.11	0.07	0.11	0.12	0.12	0.19	0.19	0.17	0.18	0.18
basis points	1.66	0.99	0.70	1.03	1.11	1.14	1.92	1.93	1.75	1.79	1.82
Per-race profits GBP											
displayed depth	1.85	1.92	1.18	1.92	2.14	2.24	2.03	1.74	1.96	2.08	2.19
qty trade/cancel	1.76	1.82	0.95	1.83	2.07	2.19	1.92	1.54	1.97	2.11	2.24
Aggregate Profits and LA Tax											
Daily Profits											
FTSE 100 - per symbol	1,047	361	92	505	705	917	907	441	1,418	1,690	1,968
FTSE 250 - per symbol	108	15	5	28	44	64	104	55	181	209	233
Full Sample - aggregate	132,378	40,205	10,502	57,933	81,993	108,273	117,054	57,996	187,719	222,151	256,194
Latency Arbitrage Tax, All Volume (bps)											
FTSE 100	0.38	0.13	0.03	0.19	0.26	0.34	0.33	0.16	0.52	0.62	0.72
FTSE 250	0.66	0.10	0.03	0.18	0.27	0.39	0.63	0.34	1.11	1.28	1.43
Full Sample	0.42	0.13	0.03	0.19	0.26	0.35	0.37	0.18	0.59	0.70	0.81
Latency Arbitrage Tax, Non-Race Volume (bps)											
FTSE 100	0.49	0.17	0.04	0.30	0.46	0.66	0.43	0.18	0.83	1.10	1.40
FTSE 250	0.80	0.11	0.03	0.27	0.45	0.69	0.76	0.37	1.67	2.10	2.52
Full Sample	0.53	0.16	0.04	0.30	0.46	0.66	0.47	0.20	0.94	1.23	1.56
Spread Decomposition											
Price impact in races / All price impact %	30.58	11.86	2.79	16.95	23.55	31.72	24.14	11.02	44.66	53.98	63.58
Price impact in races / Effective spread %	32.82	12.73	2.99	18.20	25.28	34.05	25.91	11.83	47.92	57.92	68.22
Loss avoidance / Effective spread %	0.19	0.19	0.07	0.53	0.94	1.48	0.16	0.06	0.59	1.09	1.76
Implied Reduction in Cost of Liquidity											
% Reduction in liquidity cost											
FTSE 100 - by symbol	19.95	5.41	1.23	8.17	12.44	17.83	16.24	7.17	31.12	41.37	54.89
FTSE 250 - by symbol	11.93	1.57	0.57	2.85	4.43	6.60	11.32	5.94	24.11	27.57	32.13
Full Sample - by date	16.73	4.49	1.09	6.80	10.21	14.63	13.80	6.23	26.82	35.18	45.82

Notes: For descriptions of the sensitivity scenarios please see the text of Section 6.3. Descriptions of each of the items in this table can be found in the following table notes in Section 5. Races per day: Table 5.1. Mean race duration and % of races with wrong winner: Table 5.2. % of Volume in Races: Table 5.3. Mean number of messages: Table 5.4. Per-race profits: Table 5.5. Aggregate profits: Table 5.7. Latency Arbitrage Tax: Table 5.8. Spread decomposition: Table 5.9. Implied Reduction in Cost of Liquidity: Table 5.10.

Thus, while excluding races with 0 cancels has a large effect on the number and profitability of races, excluding races with exactly 1 take and 1+ cancels does not have that large an effect. This overall pattern is consistent with a model in which many of the fastest traders primarily engage in sniping as opposed to liquidity provision, and significant liquidity is provided by market participants not at the cutting edge of speed.

6.4 Sensitivity to Varying the Definitions of Success and Fail

Our baseline method defined success and fail as follows. A take attempt succeeds if it executes at least in part, and otherwise fails. A cancel attempt succeeds if at least some of the order's quantity is successfully canceled, and otherwise fails. As discussed in Section 4.2.3, while the definition of success might sound quite loose — e.g., if there are 10,000 shares in the book, an attempt to take 10,000 shares that "succeeds" in taking just 100 shares is counted as a success — it has some real bite in conjunction with the requirement that a race has a fail, because someone else likely got or canceled the other 9,900 shares, for there then to be yet another participant who then fails to get anything or cancel anything. The exception is if there is a successful take attempt for a small amount (e.g., the order is for just 100 shares) followed by a cancel attempt for a small amount (e.g., 100 shares) where, by coincidence, the cancel fails because it was that user's 100 shares that just got taken. Thus, to deal with this possibility, our first sensitivity imposes that 100% of the depth at the race level is cleared, either through takes or cancels. As can be seen this reduces the number of races by about 13% (from 537 to 467), and reduces our measures of aggregate profits, latency arbitrage tax, and harm to liquidity by about 20%, depending on the measure. For completeness, we also include a sensitivity that requires that 50% of the depth at the race level is cleared.

For our definition of fail, the concern we mentioned in Section 4.2.3 is that we count limit orders that post to the book as a fail. A worry, especially at longer race horizons, is that we are picking up as "latency arbitrage races" cases where the "fail" is in fact simply a participant posting new liquidity at a new price, using a plain vanilla limit order, at a price that happened to be the price of the last successful trade. As a sensitivity, therefore, we only allow failed IOCs and failed cancels to count as fails.[44] That is, we do not allow ordinary limit orders to count as fails, even though some participants may in fact use them in latency arbitrage races, because of the fee advantage described earlier.

In the baseline, the strict fail criterion only reduces the number of races detected by about 8% (from 537 to 494), and race profits by about 5%. At longer horizons, as expected, the strict fails criterion reduces the number of races detected, and overall race profits, by larger amounts—for instance, at 3ms, the reduction in the number of races is about 15% (from 946 to 800) and the reduction in total profits is about 10% (from 255,000 per day to 232,000 per day). This makes sense because at longer horizons we should be more concerned about mistaking limit orders that post to the book as failed race attempts. For this reason, when we consider what the sensitivity analyses suggest about upper bounds on race profits in the next section, when we use longer race horizons we will always do so in conjunction with the strict fail requirement.

[44] Note as well that this sensitivity has the interpretation of only allowing as fails the "error messages"—failed IOCs and failed cancel attempts—that are unique to our message data relative to ordinary limit-order book data.

Table 6.4: **Sensitivity Analysis: Definitions of Success and Fail**

		Strict Success			**Strict Fail**			
Measure	Baseline	100%	$\geq$ 50%	InfoHor	50μs	500μs	1ms	3ms
Frequency and Duration of Races								
Races per day								
FTSE 100 - per symbol	537.24	466.72	504.52	494.26	266.32	719.71	768.02	799.91
FTSE 250 - per symbol	70.05	62.22	66.38	65.95	38.08	105.09	115.94	123.01
Mean race duration (microseconds)	78.65	69.87	75.16	81.74	15.87	195.83	294.52	509.37
% of races with wrong winner	4.30	4.47	4.27	4.50	8.79	2.07	1.79	1.47
% of volume in races								
FTSE 100	22.15	18.82	21.49	20.64	8.83	35.33	40.54	44.27
FTSE 250	16.90	15.07	16.52	16.26	7.87	32.16	36.79	40.17
Full Sample	21.46	18.32	20.84	20.06	8.70	34.89	40.03	43.72
Mean number of messages within 500 μs	3.46	3.45	3.48	3.51	3.54	3.48	3.15	2.94
Per-Race Profits								
Per-share profits								
ticks	0.55	0.55	0.55	0.54	0.52	0.52	0.54	0.55
GBX	0.17	0.17	0.17	0.17	0.16	0.16	0.16	0.16
basis points	1.66	1.68	1.66	1.64	1.64	1.59	1.64	1.64
Per-race profits GBP								
displayed depth	1.85	1.66	1.81	1.89	1.57	1.91	2.04	2.09
qty trade/cancel	1.76	1.74	1.82	1.78	1.38	1.92	2.07	2.16
Aggregate Profits and LA Tax								
Daily Profits								
FTSE 100 - per symbol	1,047	800	953	985	437	1,437	1,650	1,783
FTSE 250 - per symbol	108	93	103	103	53	174	200	213
Full Sample - aggregate	132,378	103,745	121,493	124,904	57,048	187,989	215,794	232,457
Latency Arbitrage Tax, All Volume (bps)								
FTSE 100	0.38	0.30	0.35	0.36	0.16	0.53	0.61	0.65
FTSE 250	0.66	0.57	0.63	0.63	0.32	1.07	1.23	1.31
Full Sample	0.42	0.33	0.39	0.40	0.18	0.60	0.68	0.74
Latency Arbitrage Tax, Non-Race Volume (bps)								
FTSE 100	0.49	0.38	0.45	0.46	0.18	0.82	1.02	1.18
FTSE 250	0.80	0.69	0.76	0.76	0.35	1.59	1.95	2.20
Full Sample	0.53	0.42	0.49	0.50	0.20	0.92	1.14	1.31
Spread Decomposition								
Price impact in races / All price impact %	30.58	26.10	29.78	28.92	11.70	47.38	55.27	61.61
Price impact in races / Effective spread %	32.82	28.02	31.97	31.04	12.56	50.84	59.31	66.11
Loss avoidance / Effective spread %	0.19	0.14	0.17	0.18	0.06	0.62	1.07	1.51
Implied Reduction in Cost of Liquidity								
% Reduction in liquidity cost								
FTSE 100 - by symbol	19.95	14.37	17.95	18.66	7.24	33.19	42.45	50.59
FTSE 250 - by symbol	11.93	10.12	11.28	11.42	5.64	23.12	27.56	29.90
Full Sample - by date	16.73	12.74	15.33	15.63	6.25	28.12	35.37	41.64

Notes: For descriptions of the sensitivity scenarios please see the text of Section 6.4. Descriptions of each of the items in this table can be found in the following table notes in Section 5. Races per day: Table 5.1. Mean race duration and % of races with wrong winner: Table 5.2. % of Volume in Races: Table 5.3. Mean number of messages: Table 5.4. Per-race profits: Table 5.5. Aggregate profits: Table 5.7. Latency Arbitrage Tax: Table 5.8. Spread decomposition: Table 5.9. Implied Reduction in Cost of Liquidity: Table 5.10.

6.5 Discussion of Sensitivity Analyses

Based on what we have learned from the various sensitivity analyses, Table 6.5 highlights several specific scenarios that we feel give a sense of the overall range of estimates for race profits and the effect on liquidity.

As Low scenarios, since we learned that race profits are especially sensitive to the choice of race horizon (Table 6.1) and to stricter requirements on the level of participation (Table 6.2), we highlight: 2+ within 50 microseconds, 2+ within 100 microseconds, 3+ within 100 microseconds, and 3+ within the information horizon.

As High scenarios, we highlight: 2+ within 1 millisecond, 2+ with 3 milliseconds, 3+ within 1 millisecond, and 3+ within 3 milliseconds. For each of these scenarios we also add the strict fails requirement, given the importance of this requirement at longer time horizons (as discussed around Table 6.4).

Over this set of scenarios, the latency arbitrage tax ranges from 0.15 to 0.74 basis points on the all-volume measure, and from 0.18 to 1.31 basis points on the non-race volume measure. The overall percentage harm to liquidity ranges from 5.1% to 41.6%.

We acknowledge that this exercise is somewhat subjective. At the lower end, we know conceptually that if we reduce the race horizon sufficiently and/or increase the participation requirements sufficiently we can find a lower bound that is essentially zero (e.g., 5+ within 50 microseconds yields very low numbers, see Appendix Table A.10). Similarly, at the high end, one could be more inclusive than seems reasonable (e.g., not imposing the strict fails requirement, or looking at horizons even longer than 3 milliseconds). Still, we think this exercise provides a useful sense for the range of magnitudes we find using our method. This range will inform our analysis in Section 7.

Table 6.5: **Sensitivity Analysis: Selected Low and High Scenarios**

		Low Scenarios				**High Scenarios**			
Measure	**Baseline**	2+, 50μs	2+, 100μs	3+, 100μs	3+, IH	2+, 1ms	3+, 1ms	2+, 3ms	3+, 3ms
Frequency and Duration of Races									
Races per day									
FTSE 100 - per symbol	537.24	296.66	388.58	134.38	228.98	768.02	544.87	799.91	609.01
% of volume in races									
Full Sample	21.46	9.77	13.32	6.17	12.30	40.03	33.20	43.72	38.14
Per-Race Profits									
Per-share profits									
ticks	0.55	0.54	0.53	0.71	0.71	0.54	0.62	0.55	0.64
GBX	0.17	0.16	0.16	0.22	0.23	0.16	0.19	0.16	0.19
basis points	1.66	1.68	1.63	2.29	2.24	1.64	1.92	1.64	1.92
Per-race profits GBP									
displayed depth	1.85	1.58	1.59	2.60	2.98	2.04	2.63	2.09	2.67
qty trade/cancel	1.76	1.38	1.44	2.40	2.87	2.07	2.69	2.16	2.76
Aggregate Profits and LA Tax									
Daily Profits									
Full Sample - aggregate	132,378	63,573	83,233	47,980	91,506	215,794	195,552	232,457	221,526
Latency Arbitrage Tax, All Volume (bps)									
Full Sample	0.42	0.20	0.26	0.15	0.29	0.68	0.62	0.74	0.70
Latency Arbitrage Tax, Non-Race Volume (bps)									
Full Sample	0.53	0.22	0.30	0.18	0.37	1.14	1.04	1.31	1.25
Spread Decomposition									
Price impact in races / All price impact %	30.58	12.84	17.89	9.34	19.13	55.27	47.01	61.61	55.54
Price impact in races / Effective spread %	32.82	13.77	19.19	10.03	20.54	59.31	50.45	66.11	59.61
Implied Reduction in Cost of Liquidity									
% Reduction in liquidity cost									
FTSE 100 - by symbol	19.95	7.98	10.97	5.94	12.46	42.45	34.63	50.59	44.21
FTSE 250 - by symbol	11.93	6.17	7.96	4.50	7.67	27.56	23.95	29.90	28.12
Full Sample - by date	16.73	6.96	9.49	5.13	10.43	35.37	28.83	41.64	36.20

Notes: For descriptions of the sensitivity scenarios please see the text of Section 6.5. Descriptions of each of the items in this table can be found in the following table notes in Section 5. Races per day: Table 5.1. % of Volume in Races: Table 5.3. Mean number of messages: Table 5.4. Per-race profits: Table 5.5. Aggregate profits: Table 5.7. Latency Arbitrage Tax: Table 5.8. Spread decomposition: Table 5.9. Implied Reduction in Cost of Liquidity: Table 5.10.

Table 7.1: **Extrapolation Models**

	Dependent variable:					
	Latency Arbitrage Profits (GBP)					
	(1)	(2)	(3)	(4)	(5)	(6)
Volume (10,000 GBP)	0.4319***	0.4213***			0.3405***	0.3354***
	(0.0326)	(0.0082)			(0.0544)	(0.0415)
Volatility (1 min) * Average Volume			0.0228***	0.0313***	0.0065**	0.0066**
			(0.0025)	(0.0009)	(0.0032)	(0.0031)
Constant	−3,562		39,226***		−1,532	
	(10,611)		(11,032)		(10,263)	
Observations	43	43	43	43	43	43
R^2	0.811	0.810	0.661	0.567	0.829	0.829

*p<0.1; **p<0.05; ***p<0.01

Notes: The dependent variable in all regressions is daily race profits in GBP, for the full sample, as described in Table 5.7. Volume is daily regular-hours LSE trading volume in GBP, as first described in Table 5.3, in units of 10,000 GBP so that the coefficient is interpretable as a latency-arbitrage tax in basis points. Volatility is realized 1-minute volatility for the FTSE 350 index in percentage points, using TRTH data, as described in Figure 5.4. Volatility in percentage points is multiplied by average daily volume in 10,000 GBP so that the coefficient has the interpretation of the effect of a 1 percentage point change in volatility on the latency arbitrage tax in basis points. Regressions are ordinary least squares. R^2 in the regressions without constant terms is computed according to the formula $1 - \text{Var}(\hat{e})/\text{Var}(y)$. P-values are computed using the student-t distribution.

7 Total Sums at Stake

7.1 Extrapolation Models

Figure 5.4 in Section 5.4 showed visually that daily latency arbitrage profits are highly correlated to market volume and volatility, as expected given the theory. Table 7.1 presents these same relationships in regression form.

Columns (1-2) regress daily in-sample latency arbitrage profits on daily LSE regular-hours trading volume in GBP (10,000s). The coefficient of 0.421 in (2) is directly interpretable as the all-volume latency arbitrage tax in basis points. Including a constant term changes the coefficient only slightly, to 0.432. This single variable has an R^2 of 0.81.

Columns (3-4) regress daily in-sample latency arbitrage profits on daily realized 1-minute volatility.[45] To make the results interpretable in units of latency arbitrage tax, realized volatility in percentage points is multiplied by the sample-average of daily trading volume.[46] Here, including the constant term does provide a meaningfully better fit, which can also be seen visually in the scatterplot in Figure 5.4, Panel B. The coefficient of 0.023 in (3) means that every additional percentage point of realized volatility adds 0.023 basis points to that day's latency arbitrage tax. This variable has lower explanatory power than volume, but still high, with an R^2 of 0.661.

Columns (5-6) present results for a two-variable model in which daily latency arbitrage profits are regressed on both trading volume and realized volatility. Again, to make the results interpretable, realized volatility is multiplied by average daily trading volume.[47]

[45] In the appendix we report regression results for 5-minute volatility and for a measure of volatility emphasized in BCS called distance traveled. 5-minute volatility has lower explanatory power than 1-minute volatility. Distance traveled actually has greater explanatory power than 1-minute volatility, but we emphasize the latter because it is more easily measurable across markets and over time, and more widely utilized in practice and in the literature.

[46] That is, we regress $\text{LatencyArbProfits}_t = \alpha + \beta(\sigma_t \cdot \text{AvgDailyVolume})$ where σ_t is in percentage points and AvgDailyVolume is in GBP 10,000s.

[47] That is, we regress $\text{LatencyArbProfits}_t = \alpha + \beta\text{Volume}_t + \gamma(\sigma_t \cdot \text{AvgDailyVolume})$. We also considered the specification $\text{LATax}_t = \alpha + \beta \cdot \frac{\text{Volume}_t - \text{AvgDailyVolume}}{\text{AvgDailyVolume}} + \gamma\sigma_t$, that is, the latency arbitrage tax in basis points is the LHS variable. In this specification, the coefficient on volatility is roughly the same as in Column 6, at 0.0061, and the coefficient on volume is -0.0008 and statistically insignificant. These coefficients imply that on a day where trading volume is 10 percentage points higher than the average, holding volatility fixed, the latency arbitrage tax is -0.008 basis points lower than average.

Both variables are significant, and the two-variable model has higher explanatory power than the single-variable model, but the difference is modest, with an R^2 of 0.83 versus 0.81. The reason for this is that volume and volatility are highly correlated to each other, with an in-sample correlation of 0.82 in our data. The coefficients can be interpreted as follows. On a day with average 1-minute volatility (about 13% in our sample), the latency-arbitrage tax is $0.3354 + 13 * 0.0066 = 0.42$ basis points, the overall sample average. On a particularly high realized volatility day, say 25%, the latency arbitrage tax would be 0.50 basis points. On a relatively calm day, say 10% realized volatility, the latency arbitrage tax would be 0.40 basis points.

Before we turn to out-of-sample extrapolation, we emphasize that the standard errors on these coefficients are much smaller than the variation in the latency-arbitrage tax we found in Section 6 when we considered different specifications for race detection. Therefore, we will emphasize two kinds of out-of-sample results: (i) results based on the volume and volatility model presented in Column (6); and (ii) results based on the volume-only model in column (2), which is economically equivalent to a constant latency arbitrage tax model, using both the baseline latency arbitrage tax and the range of latency arbitrage taxes across the various sensitivity analyses discussed in Section 6.5.

7.2 Out-of-Sample Extrapolation: UK Equity Markets

Table 7.2: **Annual Latency Arbitrage Profits in UK Equity Markets (GBP Millions)**

	(1)	(2)	(3)	(4)
	Volume-	Volume-	Low	High
Year	Volatility	Only	Scenario	Scenario
2014	52.0	56.7	20.5	99.1
2015	58.9	61.6	22.3	107.7
2016	63.3	63.8	23.0	111.4
2017	51.0	57.5	20.8	100.4
2018	55.8	60.6	21.9	105.9

Note: We compute UK regular-hours trading volume by dividing LSE's monthly reported regular-hours trading volume by LSE's monthly reported regular-hours market share. We compute UK 1-minute realized volatility using TRTH data for the FTSE 350 index, computing the realized volatility on each day and then computing the root mean square. Model (1) uses the coefficients from Regression (6) in Table 7.1. Model (2) uses the coefficient from Regression (2) in Table 7.1. Model (3) and Model (4) use the min and max latency-arbitrage taxes found in Table 6.5, of 0.15 bps and 0.74bps, respectively.

Table 7.2 presents our estimates of the annual sums at stake in latency arbitrage races in the UK for the five year period 2014-2018. In Column (1) we present the estimate based on the volume and volatility regression model, i.e., column (6) of Table 7.2. For volume data we use LSE reports of their daily trading volume and monthly regular-hours market share to estimate total daily regular-hours trading volume.[48] For volatility data, we compute daily one-minute realized volatility of the FTSE 350 index using Thomson Reuters data. In Column (2) we present the estimate based on the volume-only model, i.e., based on the latency-arbitrage tax of 0.42 basis points. In Columns (3)-(4) we present the range of estimates implied by the sensitivity analyses discussed in Section 6.5; these are based on latency-arbitrage taxes of 0.15 basis points in the lowest of the Low scenarios and 0.74 basis points in the highest of the High scenarios.

[48] Bloomberg data for the UK markets are also available but include auction volume, which we seek to exclude since the opening and closing auctions are not subject to latency arbitrage.

The volume-and-volatility model implies annual latency arbitrage profits in UK equity markets ranging between GBP 51.0 Million to GBP 63.3 Million per year. The volume-only model yields slightly higher estimates. At the low end of our sensitivity analyses the annual profits are about GBP 20 million and at the high end the annual profits are about GBP 100 million.

7.3 Out-of-Sample Extrapolation: Global Equity Markets

Table 7.3 presents estimates of the annual sums at stake in latency arbitrage races in global equity markets. We use volume data from the World Federation of Exchanges (2018). The advantage of WFE data is that it covers nearly all exchange groups around the world, but a caveat is that there may be some inconsistencies in how exchange groups report their data to the WFE. We compute volatility based on the one-minute realized volatility of regional equity market indices using Thomson Reuters data. As in Table 7.2 above, Column (1) presents estimates based on the volume and volatility regression model, Column (2) presents estimates based on the volume-only model, and Columns (3)-(4) present the range implied by the sensitivity analyses. Please note that this exercise uses data from UK latency arbitrage races to extrapolate to other countries, to get a sense of the overall global magnitudes. We hope that others in the future will use message data from other countries to produce better numbers.

Table 7.3: **Annual Latency Arbitrage Profits in Global Equity Markets (USD Millions) in 2018**

	(1)	(2)	(3)	(4)
	Volume-	Volume-	Low	High
Exchange Group	Volatility	Only	Scenario	Scenario
NYSE Group	1,006	1,023	370	1,787
BATS Global Markets - U.S.	895	910	329	1,590
Nasdaq - U.S.	847	862	311	1,505
Shenzhen Stock Exchange	327	336	122	588
Japan Exchange Group	281	286	103	500
Shanghai Stock Exchange	260	268	97	468
Korea Exchange	118	120	43	209
London Stock Exchange Group∗∗	109	119	43	207
BATS Chi-X Europe	110	119	43	207
Hong Kong Exchanges and Clearing	102	104	38	182
Euronext	89	96	35	168
Deutsche Börse Group	78	85	31	148
TMX Group	56	61	22	107
National Stock Exchange of India	47	49	18	86
SIX Swiss Exchange	40	43	16	76
Global Total (WFE Data Universe)	4,674	4,799	1,734	8,383

**London Stock Exchange Group includes London Stock Exchange as well as Borsa Italiana

Note: Trading volume is from the World Federation of Exchanges (2018). We sum the volume of listed symbols and exchange traded funds traded on electronic order books (“EOB Value of Share Trading” and “ETFs EOB Turnover”). Please note that there may be inconsistencies across exchanges in how they report data to WFE. The data is comprehensive and helps give a sense of the overall global magnitudes but for any particular exchange better volume data may be available. Volatility is computed using TRTH data for the following indices. NYSE, BATS and Nasdaq: S&P 500. Shenzhen and Shanghai: Shanghai composite. Japan: Nikkei225. Korea: KOSPI. LSE Group: FTSE 350. BATS Chi-X, Euronext, Deutsche Börse, Swiss: EuroStoxx600. Hong Kong: Hang Seng. India: SENSEX. Canada TMX Group: TSX Composite. The row denoted Global Total (WFE Data Universe) includes all exchange groups in the WFE data. All estimates reported in the table are computed analogously to Table 7.2 with the exception of the global total in Column (1): since we do not have volatility indices for all exchange around the world, we compute this as (Sum of Volume-and-Volatility Model Profits for Top 15 Exchanges) / (Sum of Volume-Only Model Profits for Top 15 Exchanges) * (Global Total Profits Based on Volume-Only Model).

Our main estimate of a latency arbitrage tax of 0.42 basis points implies annual latency arbitrage profits of $4.8 billion for global equity markets. The volume-and-volatility model yields a slightly lower estimate since volatility was lower in 2018 than in our sample period. At the low end of our sensitivity analyses the annual latency arbitrage profits for global equity markets are about $1.7 billion, and at the high end the annual profits are about $8.3 billion.

8 Conclusion

We conclude by summarizing the paper's contributions to the academic literature and discussing our hopes for future work.

The paper's first contribution is methodological: utilizing exchange message data to measure latency arbitrage. The central insight of the method is simple: an important part of the activity that theory implies should occur in a latency-arbitrage race will not actually manifest in traditional limit order book data—the *losers* of the race. To see the full picture of a latency-arbitrage race requires seeing the full message traffic to and from the exchange, including the exchange error messages sent to losers of the race (specifically, failed IOCs and failed cancels). Armed with this simple insight and the correct data, it was conceptually straightforward, albeit human-time and computer-time intensive, to develop and implement the empirical method described in Section 4.[49]

The paper's second—and we think main—contribution is the set of empirical facts we document about latency arbitrage in Section 5. We show that races are very frequent and very fast, with an average of 537 races per day for FTSE 100 stocks, lasting an average of just 81 microseconds, and with a mode of just 5-10 microseconds, or less than 1/10000th of the time it takes to blink your eye. Over 20% of trading volume takes place in races. Most races are for very small amounts of money, averaging just over half a tick and just under GBP 2. But, because of the large volume, these small amounts add up. The "latency arbitrage tax," defined as latency arbitrage profits divided by trading volume, is 0.42 basis points based on all trading volume, and 0.53 basis points based on all non-race volume. This amounts to about GBP 60 million annually in the UK. Extrapolating from our UK data, our estimates imply that latency arbitrage is worth about $5 billion annually in global equity markets.

A third contribution, narrower and more technical in nature but we hope useful to the microstructure literature, is the development of two new approaches to quantifying latency arbitrage as a proportion of the overall cost of liquidity. These new methods, used in conjunction with the results described above, show that latency arbitrage accounts for about 31% of all price impact, and that eliminating latency arbitrage would reduce the cost of liquidity for investors by 17%.

One natural direction for future research is to utilize this paper's method for detecting latency-arbitrage races to then try to better understand their sources. One could imagine, for instance, trying to quantify what proportion of latency arbitrage races involve public signals from the same symbol traded on a different venue, what proportion involve a change

[49] The final run of our code, including all sensitivity analyses, required about 24 days of computer time on a 128-core AWS server. From receipt of data to first completed draft, the paper required about 3 years of work. The main reason the project has been time intensive, despite its conceptual simplicity, is that message data had never been used before for research (neither academic research nor, we think, industry research) and it took a lot of false starts to understand. We expect that future research using message data will be a lot more efficient than our study.

in a correlated market index, what proportion involve signals from different asset classes or geographies, etc.

Our main hope for future research, however, is simply that other researchers and regulatory authorities replicate our analysis for markets beyond UK equities. Of particular interest would be markets like US equities that are more fragmented than the UK; and assets such as ETFs, futures and currencies that have lots of mechanical arbitrage relationships with other highly-correlated assets. The "hard" part of such a study is obtaining the message data. Once one has the message data, applying the method we have developed in this paper is relatively straightforward.[50] To our knowledge, most regulators do not currently capture message data from exchanges, and exchanges seem to preserve message data somewhat inconsistently. We hope this will change. The limit order book is viewed as the official record of what happened, but we argue that the message data, and especially the "error messages" that indicate that a particular participant has failed in their request, are key to understanding speed-sensitive trading.

[50] To this end, our codebase and a user guide will be made publicly available upon publication of this paper. Regulators and researchers interested in obtaining this codebase and user guide prior to publication should contact the authors.

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