The Microgeography of Financial Market Communications: Modelling The Effect of High Frequency Latency-Arbitrage Strategies on Bid-Ask Spreads

Anna E.W.

29th March 2020

Abstract

Are latency-arbitrage trading strategies harmful to markets? Following Boehmer, Fong and Wu (2018), I conduct an investigation into the effect of latency-arbitrage algorithmic trading strategies (LAS), which exploit geographically fragmented markets, on effective bid-offer spreads in the SPDR S&P 500 trust exchange-traded fund (SPY ETF) market for the year 2019. A two stage least squares approach is employed to establish a causal relationship between an exogenous increase in LAS strategies and effective bid-ask spreads, via changes to the market data transmissions network that connects trading venues to trading firms in Secaucus, Mahwah and Carteret, in the United States. I find that an increase in LAS is induced by a latency reducing upgrade to the network, and that this increased participation improves effective bid-ask spreads. The results are in line with Boehmer et al and much of the academic literature and are robust to higher frequency sampling and longer samples.

Keywords: Market microstructure, latency arbitrage, high frequency data, effective bid-ask spreads

Contents

Acknowledgements

List of Figures

List of Tables

1. Introduction

Trading strategies that are bound by, yet aim to exploit the fact that markets are separated by physical space, represent up to 80 percent of volumes in the major modern equity markets. In this paper, I employ a simple structural equation approach to draw conclusions about whether the participation of LAS harms or improves market quality; namely effective bid-ask spreads as a measure of the informational content of prices as well as being reflective of transaction costs.

I obtain access to Level 1 (Best Bid and Best Offer) order book data and reconstruct Hendershott, Jones and Menkveld (2011) proxy for LAS participation from order-message traffic data. To establish the causal relationship between LAS participation and bid-offer spread width whilst solving the issue of endogeneity, I follow Boehemer, Fong and Wu (2018) and employ a two-stage least squares with instrumental variable (IV) model, in which the date of an announcement of an latency reducing upgrade to the market data transmissions network infrastructure, that connects LAS with trading venues, is instrumented. This approach enables me to make a novel observation about how when private firms engaging in LAS make changes to the communications infrastructure of financial markets, market dynamics undergo changes.

I use high frequency intraday data, timestamped to the nanosecond at 5 minute and 1 minute intervals in the SPY ETF (NYSEARCA:SPY) market for the full year 2019 (1st January 2019 - 31st December 2019). This market was chosen as it exhibits high LAS participation (Gaughlin et al, 2012) and is otherwise important due to the fact that it is designed to track the movement of the S&P 500 index. The SPY ETF is the largest fund in the world; it is considered a barometer of the US economy. Other researchers, similar to Bohemer et al, employ the introduction of co-location services (services allowing the placement of trading firm servers next to trading venues) to establish causal relationships and to measure the impact of co-location offerings, however, this is the first paper that asks questions about the effect of changes in the private market data transmission infrastructure that connects trading venues, on market quality measures. This approach raises several new and interesting questions for competition and policy that are consequently different to those raised in other papers.

This paper is structured as follows; the remainder of this section provides some background on how LAS are an artefact of geographically fragmented markets. I connect the wider debate around emergent LAS phenomena to my research question and explain why this question is important. Important clarifications and definitions are also introduced. In Section 2 I compare the wider public debate to a review of the academic literature. Section 3 describes the sample and its source. Section 4 introduces the dependent, independent and control variables and details their construction. Section 6 describes the methodology employed for this study. Section 7 presents and discusses the results. I conclude with a traditional trading venues (of which there are some that list instruments whose prices co-vary with instruments traded on traditional exchanges e.g. the Chicago Mercantile Exchange's Globex trading platform in Aurora, Illinois, USA lists futures which are correlated with equities traded 800 miles away in New York), has given rise to a category of investor that maxmises against this market design by exploiting opportunities fractionally faster than other, slower traders in the market. I refer to these here as LAS, elsewhere in the literature they are sometimes referred to as High Frequency Traders and Low Latency Traders. These traders are computers, their reaction times are in nanoseconds, and they send orders to trade through a private network of fibre optic cables and microwave towers, planned meticulously to route orders over physical space in the quickest way possible - in a perfectly straight line; a physical resource over which they must compete. Their 'round trip time', defined as the time taken for a LAS to receive information, act on it, and receive confirmation that the action has been taken, is in the millisecond domain. The aim is to transmit information at the theoretical lowest latency; the speed of light in a vacuum at 299,792.458 km/s, denoted $\boldsymbol{c}$. There are differences in how light propagates through different media. When using a cable medium, transmission is, in LAS terms, slow. The speed of light in optical fibre is approximately $\frac{2}{3}$ the speed of light in a vacuum at $0.66\boldsymbol{c}$, with a large variance for different cable materials and constructs. Earth's atmosphere provides far less resistance to travelling light, such that I may round up the negligible additional latency to $1\boldsymbol{c}$. Taking the distance between the exchanges in Aurora, Illinois (where the S&P 500 E-mini future trades) and New York (where SPY ETF trades, whose price lags the E-mini price in Chicago (Gaughlin et al, 2012)) to be 1,200 kilometers, point to point transmission takes 6 milliseconds using optimcal fibre, yet just ***4 milliseconds*** beamed through the air at $1\boldsymbol{c}$. At such extreme low latencies, all speed advantages matter for a LAS to realise an arbitrage opportunity before the competition[1]. These speeds hover stubbornly a fraction above the theoretical universal speed limit, impeded only by the 'pipe-length', that is, factors of proximity of the LAS agent to the trading venue. These factors include server location, software and hardware components of infrastructure, network design, connectivity and features of the natural geography. These factors, when optimised, compress space-time and enable informed agents with the shortest 'pipe-lengths' to exploit the delay in price updates across trading venues. Therefore, the LAS is a direct consequence of geographically fragmented markets.

Previous research finds LAS to be a significant feature of modern markets (Brogaard, Hendershott and Riordan, 2015), it is therefore important to determine whether these changes harm or improve 'market quality'; characteristics of markets that allow for successful trading and enable markets to function smoothly, which I typically measure in terms of liquidity, information content of prices, transaction costs, volatility and price resilience. The issue of informational advantage specifically has attracted significant interest in the financial market professional and public domain. The wide appeal is warranted given the importance of smoothly functioning security markets for overall economic stability and growth (later, to conduct the empirical analysis, I use data from the New York Stock Exchange to observe risk allocation and investment activity in the wider economy). Furthermore, LAS are associated with a group of emergent phenomena; so-called ‘Flash Crashes’, ‘spoofing’, ‘quote stuffing’, ’speed arms-races’ and ‘run-games’, the latter two being a direct results of LAS speed superiority giving them an informational advantage over high-latency human traders (see Menkveld (2016) for an overview of the research on these LAS phenomena). These have gained significant public and academic attention over the last decade, during which time LAS have matured as an industry. What Michael Lewis’ bestselling book ‘Flash Boys: A Wall Street Revolt’ (Lewis, 2014), styled as an investigation into LAS (where human traders supposedly ‘revolt’ against unsporting LAS traders who seem to know what orders human traders are about to send to the market, race them to the exchange, and move the price against them) lacked in rigour and non-partiality (Manoj, 2014), it made up for in its appeal to suspicious high-latency human traders and the wider public who, despite LAS having existed in some form for more than one-hundred years[2], were introduced to them as ominous and unfair. Lewis pop-business book had an impact somewhat disproportionate to its highly anecdotal approach, and led to congressional hearings, a separate FBI, New York State attorney general and U.S attorney general investigation and even the construction of a new trading venue; IEX, which has paid for several academic investigations into the ill effects of LAS. These papers appear in the bibliography, but are not included in the literature review as they did not meet my eligibility criteria, failing namely to meet the standard of impartiality. I also had serious concerns about the logic of their claim[3], in the face of so much high quality empirical work of the opposite opinion, that adding a ‘speed bump’[4] for LAS orders improves price discovery. Lastly, publicly available data[5] was starkly at odds with claims made by IEX regarding improved spreads and high execution rates. To clarify the dimensions of market quality which I investigate; the effective bid-ask spread, the following definitions are important.

Quoted Bid-Ask Definition

DEFINITION: *The difference between the quoted selling and buying price for an immediate transaction, that is, the highest price a buyer is willing to pay and the lowest price that a seller is willing to accept for immediate liquidity.*

In the literature, the various bid-ask spread measures are an accepted gauge of liquidity, explicit transaction costs ex brokerage fees, liquidity costs and the informational content of prices. The two prices quoted for a single security arise from the activity of a type of trader referred to as the ‘market-maker’. Traditionally this individual or entity is a brokerage who supplies liquidity to the market; that is they quote one price at which they are willing to sell the security (the ask), and one price at which they are willing to buy the security (the

[2] Today foreign exchange traders refer to the exchange rate between the US Dollar and the British Pound Sterling as ‘cable’, the origin of this term is the laying of the first trans-Atlantic cable in 1866. The first GBP/USD rate was published on 10 August 1866.

[3] Firstly, delaying orders within the exchange has no effect on the speed race prior to this from trading firm’s servers to the exchange and secondly, randomly applying a delay to orders disrupts the natural flow

bid). They 'make the market' by providing a flow of buying and selling quotes, reflective of supply and demand information to which they are privy as middle-men, to facilitate trades. Purchasing low from one trader and selling higher to another, the market-maker generates an income by 'earning the spread'. To protect his earnings in the presence of uncertainty as to the informedness of his counterparty, the market-maker may widen the quoted spread. This typically happens when a large order is received and the market maker suspects that his counterparty is an informed trader. Typically, highly liquid markets that do not suffer from frequent large information asymmetries exhibit narrower spreads. As such, there is a fee component and an informational component to the bid-ask spread. Whilst it is not within the scope of this study to quantitatively disentangle these components, in reporting LAS effect on bid-ask spread width I can make some inferences on how the cost of transacting and the level of information contained in bid-ask spreads changes relatively after an increase in the presence of LAS after the construction of a new low-latency transmissions network. This will be discussed after results are reported.

In this paper, I used the *Effective Spread* as a measure of transaction costs and asymmetrical information costs. The *Quoted Bid-Ask Spread* defined above, has been shown to overestimate transaction costs and the informational content of prices. Quoted bid-ask spreads might overestimate these measures because;

- The market-maker may execute trades at a price within the spread, the mid for example. Especially true for large market orders who have negotiating leverage.
- Large orders tend to be executed incrementally throughout the trading session to avoid price impact, in the order book this appears as a small trade when really, like an iceberg, it only represents a small fraction of the total order size. If the entire size of a limit order is hidden, and the price limit falls within the spread, increments of the total order will be executed within the quoted spread.

Odders-White (2000) and Ellis et al. (2000) report evidence for this when they find that the trade classification algorithm used by NYSE to label buy and sell trades, systematically misclassifies trades at the mid-point 15% and 22% of the time respectively, because buyers are being filled *below* the mid-point (closer to the seller's price than to the buyer's price). The *Effective Spread* is widely used in the literature to avoid such overestimation.

Effective Bid-Ask Spread Definition

DEFINITION: *The difference between the execution price and the mid-quote in the market in the instant immediately before. The mid-quote is the mid-point between the quoted buying and selling price.*

a trader and in providing this service demands a premium - the 'effective spread'- relative to the underlying value of the security. The mid-quote approximates the underlying value of the security. According to the literature (Glosten and Harris (1988); Huang (1997); Madhavan et al., (1997) Olbryś (2018)) the Effective Spread has two main components;

- Costs associated with inventory and order processing
- A cost associated with asymmetric information

Therefore, this study asks if LAS participation has a measurable effect on the above.

2. Literature Review

The academic literature also finds itself concerned with the question; are LAS good, or are they bad? (Hasbrouck and Saar, 2010; Broggard, Hendershott and Riordan, 2011; Hendershott, Jones and Menkveld, 2011; Riodan and Storkenmaier, 2012; Carrion, 2013; Ersan and Ekinci, 2016; Boehmer, Fong and Wu, 2018). There is a growing body of literature concerning the effect of LAS on bid-ask spreads. Yet between the academic literature, regulatory findings, media reports and professional and public opinion there is a great deal of conflict. This may have arisen due to conflicting interests, differences in methodology, sampling variation or flawed modelling. As such, it is not overwhelmingly clear to many where the debate stands, and more importantly, which results and statements can be confidently relied upon.

In this section I identifying the academic literature which investigates if effective bid-ask spreads are improved by low-latency strategies. The academic literature is overwhelmingly positive about the LAS effect on effective bid-ask spreads. The structure of the literature review is as follows; Firstly, I provide an introduction to the academic literature. Next, a comprehensive list of systematic literature reviews and a comment on possible gaps in the literature. I follow this with an overview of recent sentiment toward LAS among the public and in the media. Next, an intuitive example is provided to help us think about what me might reasonably expect from the literature and from our own empirical efforts. Then, I give an overview of the statistics that describe how bid-ask spreads have changed over time. Next, I present the classical agent based models and what they suggest about how LAS might impact effective bid-ask spreads. I follow this with the first theoretical models of LAS participation, then the LAS empirical literature, and lastly the theoretical studies that claim that LAS is harmful of effective bid-ask spreads.

Over the last decade, the existing academic research has contributed significantly towards clarifying the issue of whether LAS are harmful to markets, in a wider environment of concern, anger and suspicion. The only inconsistency in the literature appear to be between pricing and therefore ability to model microstructure noise when handling tick data, as well as inconsistent assumptions across theoretical models in the level of informedness of their traders (Menkveld (2016)). It should also be noted that empirical studies are restricted in that when working with intraday and tick data, very large amounts of data are needed to investigate relatively short time periods (for example, Gaughlin et al (2011) find themselves using 20 terabytes of data to measure latency relating to two securities over two years). For a basket of instruments, this quantity multiplies, and if multiple trading venues are studied, the data become exponentially larger than end of day price data. This could reasonably cause results from empirical and theoretical models to diverge, if empirical models use one time frames that do not capture the full effects of the introduction of LAS over time.

Several independent and comprehensive systematic reviews of the literature on high-frequency trading and market quality have been undertaken (Biais and Woolley (2011); Gomber, Arndt, Lutat, amd Uhle (2011); Chordia, Goyal, Lehmann and Saar (2013); Easley, Lopez de Prado and O'Hara (2013); Kirilenko and Lo (2013); Biais and Foucault (2014); Goldstein, Kumar and Graves (2014); O'Hara 2015, Menkveld, (2016)). However, there has been little investigation into private low-latency transmission infrastructure and no comment on how its design might impact market quality. This fact perhaps suggests a gap in the understanding of LAS. A spatial analysis of such networks, and the documented emergence of monopolistic behaviour among large LAS firms is not within the scope of this study, however, the experimental design enables me to make a modest inference that the construction of a new lowest-latency transmission route attracts LAS which in turn improves effective bid-ask spreads.

Public Sentiment and LAS

The conversations I had with colleagues when I worked in the high-latency voice brokerage sector about LAS were typically of a concerned tone. They were suspicious and distrusting and the paranoia followed a somewhat 'humans vs robots' narrative; I had personally experienced the chaos of the Facebook NASDAQ IPO and the Knight Capital 'glitch'[6], both in large part consequences of markets with high LAS participation (Narang (2013)). Outside of work, when I mentioned my occupation, LAS was often one of the first things people would ask me about, although I knew almost nothing about them. Opinions are strong, when it comes to LAS. It is helpful, therefore, in a way removed from the heat of public opinion on the topic, to use some intuition about how markets function, and maybe incorporate some of the stylised facts of classical agent-based models to ask ourselves what I can reasonably expect from empirical research, and later from my own empirical effort.

Here is an intuitive example. On an average trading day, a market-making brokerage desk receives several orders to buy and sell. They turn this information into bid and ask quotes that they then disseminate to the market. Throughout the day, traders are drip fed quotes ple I can easily see that, whilst the market probably still exists somewhere in that security, the market-maker has no price information to disseminate. He cannot update his quotes to truly reflect the underlying value of the security. Under this uncertainty he increases the bid-ask spread to protect himself should he face problems either finding immediate liquidity or accepting a trade from an informed trader. I might reasonably expect then from the literature that when trading with very high frequency, price information is likewise with very high frequency disseminated to the market. Under certainty that this is the case, the market-maker quotes a narrow spread. Leaving the trading desk example behind, in modern automated markets LAS play the role of market-maker (SEC, 2016), supplying the liquidity that exchanges once were obligated to. I might reasonably expect then that in the presence of LAS participation, information is disseminated quickly and efficiently, and spreads narrow.

Firstly, let us look at the wider market trend in the size of effective bid-ask spreads. Angel, Harris and Spatt (2015) show that NYSE/NASDAQ effective[7] spreads in the period from 2001 to 2011 declined dramatically from 20 basis points in 2001 when LAS emerged to 7 basis points in 2011 when their participation was at its peak. Datasets that explicitly identify LAS activity show that it is LAS participation that causes spreads to tighten.

Next I turn to the classical agent-based models and microstructure models within the academic literature (which existed for many decades before millisecond trading was realised) to provide further insight.

Glosten and Milgrom (1984), model effective bid-ask spreads as an adverse selection problem by framing them as an informational phenomenon that exist even when the market-makers fixed and variable costs are zero (Copeland and Galai (1983) had recently formalised this). They show that the initial arrival of orders from informed traders causes spreads to widen. However, as informed traders continue to send orders to the market-maker, more information is revealed through prices at which trades are executed. Following this, effective bid-ask spreads tighten. I might expect therefore in my own study that, if I were to look at the point in time immediately after the network was switched on, spreads might widen just as informed LAS appear, but then as time passes they narrow again, overtaking their previous level because post LAS participation there is greater information dissemination. Glosten and Putnins (2015) restate that informed traders cause an initial widening in the bid-ask spread which then narrows when with a higher frequency of informed traders information is reflected faster in prices. They then show that if this information is available for long enough to be processed by other traders, the welfare gain of narrower spreads later will outweigh the welfare loss of initial wider spreads. In the presence of a constant flow of informed orders, the welfare loss arising from an uninformed trader refusing to trade with an informed trader is a decreasing function. Similarly, Kyle (1985) modeled how informed traders help auctions recover from uninformative shocks. His simulations found that market resilience goes to infinity as the trading frequency of informed traders in a market approaches infinity.

new information.

Cvitanic and Kirilenko (2010) are the first to employ a theoretical approach, modelling an order book with human traders, and then introducing a high-frequency trader. They do not report any results on the effect on effective bid-ask spreads, but their main result is that when high frequency trading is introduced, average transaction prices change and the predictability of prices is improved. The latter result might reasonably suggest an ability of LAS to influence spreads. Some theoretical models suggest the harmful effects of LAS on effective bid-ask spreads. Bernales (2014) uses a dynamic general equilibrium model of low-latency trading and finds that traders with only a speed advantage reduce global welfare, and when less-skilled traders are the majority, harm liquidity. Generally however, theoretical models that show negative results are rare.

Ding, Hanna and Hendershott (2014) find benefits of some trader's access to private low-latency data transmission when some traders are still using 'public' consolidated feeds. The National Best Bid and Offer (NBBO) for highly liquid stocks, reported via 'public' data feeds, are often not the fastest NBBO's that traders can obtain. LAS avoid this latency cost by paying exchanges directly, which enables them to calculate a proprietary NBBO faster than sending a request via the public channel. They find that several times a day, the publicly reported NBBO and the NBBO calculated with private data from the exchange are dislocated, allowing informed traders to realise arbitrage opportunities. As such, the faster proprietary feeds generate informed trades which lead to information rich prices. The other literature then suggests that in the presence of a flow of these informed trades, spreads narrow and welfare loss is a decreasing function of informed trades. Hasbrouck and Saar (2010) find that increased LAS participation narrows effective bod-ask spreads. Hasbrouck (2015) finds that LAS help the bid-ask spread to recover when widened by the shock of a large market order. Brogaard and Garriott (2015) also find a narrowing in effective bid-ask spreads, which is especially pronounced when LAS are first into the market. However, when LAS act on news announcements, Budish, Cramton and Shim (2015) show that they behave like human market-makers, anticipating adverse selection and subsequently widening the effective bid-ask spread and imposing higher costs on slower traders. Such 'speed duels' (Han, Khapko and Kyle, 2014; Li, 2015, Menkveld and Zoican, 2016; Brogaard, Hendershott and Riordan, 2016) result in mixed, yet non-trivial effects on the effective bid-ask spread.

Causal Effects of LAS on Effective Bid-Ask Spreads

There is a literature that exploits exogenous shocks to markets to establish causal relationships between LAS and measures of market quality. Hendershott, Jones and Menkveld (2011) use an approach similar to that of this paper; they use the introduction of auto-quoting on the NYSE as an exogenous event to demonstrate a causal a decline in effective bid-ask spreads from LAS activity, which they attribute to lower adverse selection costs. Ma-

Wu (2018), who use the introduction of co-location services (when LAS firms place their servers directly next to the exchange to reduce latency) in 42 countries and find, in line with the wider empirical literature, that an increase of one standard deviation in LAS activity narrows effective bid-ask spreads by 0.7 standard deviations.

In summary, there is a dramatic gap between public, media, professional and academic perception of LAS on market quality. However, the empirical academic literature points to LAS having a causal relationship with narrowing effective bid-ask spreads, with very few theoretical studies suggest the opposite. Much of the heat of the wider debate on whether LAS are good or bad appears to be generated by non-LAS human traders and exchanges whose interest lies in attracting non-LAS traders who are suspicious of LAS.[8]

3. Data Sample

Firstly, I provide an overview of the data and their source. Secondly, the 2SLS model is presented; it is a special case of instrumental variable model, employed to establish a causal relationship between an exogenous increase in LAS participation and effective bid-ask spreads, along with a discussion of the choice of the date of an announcement of an upgrade in the market data transmission network as an instrument. Thirdly, I present the LAS and effective bid-ask spread proxies; LAS and S (the Effective Spread Estimator) respectively, and detail their construction. Fourthly, an explanation of the control variables and their construction is presented. Lastly, the preferred model and descriptive statistics are discussed.

Thomson Reuters Tick History (TRTH), accessed via subscription to the Refinitive Datascope product, was used to obtain intraday Level 1 Quote data from NASDAQ. Quote data was for the SPDR S&P 500 trust exchange-traded fund market (SPY ETF) which tracks the movement of the S&P 500. Its value is $\frac{1}{10}$ the cash value of the S&P 500 index. At the time of writing, its average daily volume was 112 million units. A highly liquid market, it attracts significant LAS participation. Data for the SPY ETF were obtained using the Reuters Instrument Code RIC:SPY, which is a ticker-like code that identifies instruments. TRTH provides quote and trade data at nanosecond granularity at 20 levels of price depth. Understandably, for the very liquid markets, such data requests can be extremely large and cumbersome to work with and store. To provide context; I extracted a year's worth of SPY data in ten minute intervals, considered relatively low granularity, which returned over 2 million data points. This illustrates how the researcher is very limited according to the time and resources they have when handling high frequency data sets. Because I are interested in the novel question of what role the trading communications infrastructure that connects trading venues plays in market quality, SPY quote data were chosen for the fact that there is a known price movement in the SPY at NASDAQ after price changes in the

Quote data was obtained in nanosecond granularity and aggregated over 5 and 1 minute intervals for fine grained sampling for the full year 2019. Fields in the data include labels that identify bid and ask quotes and high and low quotes for the intervals. In line with the literature, the sample was restricted to trading hours only; I therefore identify and remove all hours before and after the close (trading hours for NASDAQ are 09:30-16:00 ET), weekends and all 2019 US holidays (and hours affected either side). In total, this produced 18,719 observations for the 5 minute interval sample, and 93,959 observations in the 1 minute sample. All prices are in USD, with the tick size (minimum trading increment) of a penny (0.01 USD). Our main analysis is of a sample of Level 1 quote data for the SPY ETF for the entire year 2019 at 5 minute intervals. Data are winsorised at 0.5% and 0.95%, that is I replace some of the extreme values with a smaller data value to make the sample mean more robust to outliers, in order that results be comparable with Boehmer, Fong and Wu (2018). Prior to doing this I conduct a visual inspection and Resistant Normality Checks (Hamilton) to identify mild and severe potential outliers and the possibility of processes not present in the main body of the data that might be of concern. Subsequently, I conduct a robustness check on an unlimited sample. My reasoning for this is described by Tukey (1960) who explains that over-zealous de-tailing of observations leads to the data, by definition, failing to be a true sample. A critical implication given the fundamental assumption of regression analysis that the data are from a random sample. Furthermore, such financial data are characteristically fat-tailed, with large price movements that contain valuable information more common than what a Gaussian distribution implies. Therefore, I should be careful not to lose information by forcing the data and arrive at inferences that are too small. Boehmer et al. do not provide reasoning for their decision to transform the data in this way. In our checks for outliers I see no observations that do not make economic sense, or that are likely the results of error. Furthermore, though habits vary within econometrics, winsorising data is a highly contentious practice as a prelude to modelling. Consequently, I take a more cautious approach, presenting statistics for both winsorised and unlimited datasets, and so attempt to find a model that best fits the entire dataset. I conduct further robustness tests on a dataset at 1 minute intervals for the year 2019, again using both unlimited and winsirosed samples. Our final robustness test is of a winsorised and an unlimited 18 month 5 minute interval sample. The original sample was expanded by 3 months at each end, so the new sample spans from 1st October 2018 to 1st March 2020.

On inspection prior to modelling, the data were found to be characteristically non-normal and for the higher frequency 1 minute interval sample, and the 18 month 5 minute interval sample heteroskedastic (White Test and Pagan-Hall test for heteroskedasticity using IV levels, I reject the null hypothesis that the disturbance is homoskedastic at 1%, but fail to reject at the 5% level) upon initial visual inspection, and this was confirmed with a Shapiro-Wilk W test. Non-identical classical and robust standard errors contain important information and suggested room for specification improvement (Leamer, 2010). Boehmer et al. unfortunately report no classical standard errors for such a comparison. When no that doing away with classical standard errors is effectively ignoring the stochastic component of the model, and causes results to be highly dependent upon the model (King, 2015). Consequently, it would be optimistic to hope that everything reported did not suffer from some sort of bias. The best-case scenario involves estimators being inefficient, though there is a considerable chance that estimators are also biased. I also lose the chance of obtaining confidence intervals and counterfactuals. The wider the deviation between the two types of error, the more evidence of missecification. Estimation might be improved for tests and models that make the assumption of normality if non-normal variables undergo a Box-Cox Transformation for heteroskedascity. In doing this, I found that the residuals benefited very little from this procedure, and I decided that, whilst both practices have legitimacy, a very modest divergence in classical and robust standard errors was preferable to forcing the data to fit the chosen model. Furthermore, I wanted to make my results readily comparable with others. Hence, I select a 2 Stage Least Squares model, which is robust to the non-normality of the data structure, and I report both classical and robust standard errors. Throughout this paper, the chosen model passes all statistical diagnostic tests, unless otherwise specified.

4. Variables and Construction

Explanatory Variable: LAS Proxy

Algorithmic trading strategies are heterogeneous, with only a subset of algorithmic trading being low-latency strategies. Within the set low-latency strategies, there exists a further diversity of strategies. There is a literature that attempts to identify types of strategy, or to isolate and observe individual strategies and understand their behaviour. This paper is concerned with the detection of all strategies that perform latency arbitrage, through the observation of order book dynamics characteristic of such strategies. I aim to understand the relationship between LAS participation and market quality, namely the informational content of prices as a measure of market quality, proxied here by effective bid-ask spreads.

Several proxies for algorithmic trading exist in the literature as a result of the anonymity of financial markets. A few privileged researchers have had access to datasets where LAS firms are explicitly identified, the most frequently cited being that of Baron et al (2017), in which the researchers work with NASDAQ to explicitly identify 26 LAS traders in their dataset. Given the economically large sample size and the accuracy of the identification, valuable generalisations can be made from their results with some confidence. Because of this, Carrion (2010) uses the same dataset to measure LAS profitability. Broggard, Hendershott and Riordan (2011) use a dataset with explicit identifiers of LAS firms to further differentiate between their individual characteristics across different market conditions, enabling them to shed further light on profitability. Hasbrouck and Saar (2010) identify low-latency participation by identifying runs of linked orders of the same magnitude and in very close succession ($<$100ms); submissions, executions and cancellations, the extent of which they as LAS activity; as a consequence, some noise is introduced into the models. Furthermore, some LAS might be more strategic; submitting orders of varying sizes. Detection of these orders seems impossible.

In a similar way, our dataset does not contain explicit identifiers of LAS firms and hence our indirect strategy will inevitably capture non-LAS activity. In the absence of a dataset that explicitly identifies LAS firms (as in Baron et al. (2012)) in the spirit of Boehmer, Fong and Wu (2018), I replicate Hendershott, Jones and Menkveld's (2011) construction of a proxy for 'Algorithmic Trading' which captures rapid order submissions that are characteristic of LAS (Hendershott, Jones and Menkveld (2011)).

$$LAS_t = \frac{-Volume_t/100\,USD}{Message\ Traffic_t} \tag{1}$$

Where *Message Traffic* is the accumulation of all bids and offers to the order book over the interval. *Message Traffic* is normalised by USD traded volume to account for a possible increase in overall trading volumes in the period. The normalised measure is therefore intended to capture the change in LAS only. Higher values of LAS indicate higher levels of LAS activity. Boehmer, Fong and Wu (2018) note that whether using Order Book data (with n levels of price depth) or using Level 1 Quote data, as do we, results are comparable. It should be noted that our dataset does not contain explicit cancellations and amendments, as TRTH does not provide this information at the intraday level. It is therefore not clear if our measure captures the full extent of rapid order submissions. Furthermore, missing from all the aforementioned studies and datasets is the subset of orders that ***fail*** to enter the order book. For example; an LAS might submit an order but on receiving information on changing market conditions, send a cancellation request to the exchange. Given the inherent round trip time in the infrastructure, this request might be unsuccessful if the order is executed before it is cancelled. No publicly available dataset shows such failed attempts. During our research, the Financial Conduct Authority published a paper (Aquilina, Budish and O'Neill, (2020)) in which they use their position as regulator to demand such information from the London Stock Exchange, enabling them to study LAS races' and observe the 'losers' in the dataset. Clearly, the nature of such data is highly sensitive and other researchers will have to make do without.

Dependent Variable: Corwin-Schultz Effective Bid-Ask Spread Estimator

In order to establish a causal relationship between LAS participation and market quality, I construct a measure of market quality; namely the effective bid-ask spread. According to theory, narrow effective bid-ask spreads are reflective of a liquid market, where liquidity

Corwin and Schultz (2012) demonstrate that it is possible to use interval high (which are nearly always buy trades) and interval low (which are nearly always sell trades) to estimate effective bid-ask spreads. Applying these two assumptions for convenience is not problematic, and they demonstrate that their results are robust to the relaxation of these assumptions. Deriving an effective spread estimator is possible for the fact that within the high-low price ratio there is information about the price variance component and the bid-ask spread component. Because the variance component is proportional to return in the high-low ratio but the bid-ask spread component is not, I can create a bid-ask spread estimator that is a function of the high-low ratio.

The following assumptions must be made in the construction of the bid-ask estimator;

ASSUMPTION 1: *The instrument trades continuously during trading hours.*

ASSUMPTION 2: *Its value does not change when the market is closed.*

ASSUMPTION 3: *The high (low) is the buyer (seller) initiated price, and her price includes the addition (discount) of half of the spread.*

ASSUMPTION 4: *For the duration of the estimation period there is a constant spread of S% which causes buy (sell) trades to be printed higher (lower) than their true value.*

ASSUMPTION 5: *The true or actual value of the stock price follows a diffusion process, specifically it is assumed that it follows a geometric Brownian motion; a continuous time-stochastic process in which the log of the variable follows a Brownian motion.*

The intuition behind the estimator is based on the fact that the high-low price ratio reflects some range of the price (related to its fundamental value and some transitory fluctuation) and the bid-ask spread. Corwin and Schultz (2012) show that because the bid-ask spread component does not grow proportionately with the time period, I can use a simultaneous equations approach to solve for both components. The author's simulations show a 0.9 correlation between the estimator and NYSE Trade and Quote data effective spreads, hence I can be confident that it is an appropriate proxy for effective bid-ask spreads.

The estimator S_t is given as;

$$S_t = \frac{(2^{\alpha} - 1)}{1 + e^{\alpha}} \tag{2}$$

Where in equation (3) the first quantity is the adjustment for a single interval, and the second quantity the adjustment for a 2 interval period, calculated using below variables;

$$\beta = E\left\{\sum_{j=0}^{1}\left[ln\frac{H^O_{t+j}}{L^O_{t+j}}\right]^2\right\} \tag{4}$$

$$\gamma = E\left\{\sum_{j=0}^{1}\left[ln\frac{H^O_{t,t+1}}{L^O_{t,t+1}}\right]^2\right\} \tag{5}$$

Where H^O_t and L^O_t denote the observed high and low prices in the interval, respectively. In this way I arrive at an estimator for the bid-ask component of the high-low ratio.

Control Variables

Following Boehmer, Fong and Wu (2018) I construct a vector of control variables, such that inferences are robust to other factors affecting effective bid-ask spreads. There is a clear *a priori* intuition behind their controls and my testing shows them to be significant. I include the lagged dependent variable S_{-1} to capture the dynamic effect of the variation in the bid-ask spread, lagged volatility Vol_{-1} and the inverse price $InvP$; another proxy for liquidity costs as a consequence of its relationship with the minimum tick size (larger tick-size reflect higher transaction costs (Harris, 1996) because smaller tick-size lowers the cost of price improvement as it costs less to achieve price priority with smaller minimum price movement). All controls have been shown to have some relationship to the liquidity costs dimension of market quality (Hasbrouck and Saar (2010), Brogaard, Hendershott and Riordan (2011), Riodan and Storkenmaier (2012), Carrion (2013)). A Cumby-Huizinga test run on the model without lagged volatility revealed that the data exhibit autocorrelation, confirming the need for a lagged volatility proxy. This is an artefact of the phenomenon of volatility clustering (Mandelbrot, 1963) and hence accurately models our data (as opposed to pointing to some other process that suggests misspecification). There are several constructed measures of volatility in the literature to be considered. In the spirit of Parkinson (1980), I use the first logarithmic difference between the high and the low prices in the interval. Unlike Boehmer, Fong and Wu (2018)., who study a basket of equities, I analyse a single security that tracks the main US equity index. Therefore I omit share turnover and the log value of market capitalisation as stock specific controls.

The 'true' model is approximated in this study with a simple 2SLS model. Switching conin a misspecified model, therefore, is by no means a sure way of improving the model and reasonably might worsen an omitted variable bias problem that the research is not aware of.

Omitted Variables

Including many variables reduces the explanatory power of a model, however, their exclusion might seriously flaw inferences (King et al. (1994)). Including a greater number of controls and combinations of controls enables us to relax the assumption that I are certain that I have the 'true' model. Though I do not include them here due to time and computational constraints, Martell and Wolf (1987) suggest that other possible determinants of the bid-ask spread useful for robustness testing include;

- Changes in expected physical position. Wang et al (2008) attribute this to changes in the information set available to traders.
- Informational shocks, such as news events.
- Other fees, such as exchange fees which may vary over time.
- The risk free rate, proxied by US Treasury bills.

An Instrument for LAS Participation

In modelling the effect of LAS participation on bid-ask spreads, researchers face a joint endogeneity problem. For my research, this becomes an opportunity to also investigate the role of market infrastructure as I search for an instrument to solve the feedback loop within the model. Because random shocks affecting LAS participation might also affect effective bid-ask spreads, I treat LAS participation as endogenous. Both the Durbin test and Wu-Hausman test were found to be highly significant, and so I reject the null hypothesis of exogeneity and LAS is endogenous. I construct an instrumental variable that relates to a change in the market data transmission network and is causally related to LAS participation by construction, but does not affect effective bid-ask spreads, which I believe to have a negative correlation with LAS participation. Hence, our instrument satisfies the exclusion restrictions (Wooldridge (2010)) and gives our model the ability to identify a causal relationship.

The measure LAS is used to compare levels of participation before and after the upgrade announcement of a new network, where higher levels of the LAS mean value indicate higher levels of participation. A two-sample t-test with null hypothesis of equal means where the period before the announcement ($\overline{X_{before}}$ = -2113.27) and the period after the announcement ($\overline{X_{after}}$= -2015.74) are considered two independent populations had a p value of < 0.001, upgrading of network on 7th May 2019, and 1 thereafter. On this date, wireless network provider MacKay Brothers Communications Limited[9], who are the market leader in extreme low-latency microwave networks for financial market clients, announced they had connected the major US equity exchanges in Mahwah, Carteret and Secaucus, the New Jersey Equity Triangle, a route previously controlled by private trading firms, with the lowest latency. The reduction in latency effectively pulls geographically separated markets closer together for LAS, creating new arbitrage opportunities and possibly widening information asymmetry between LAS and their high latency counterparts. Therefore, it can be expected the announcement coincides with an increase in LAS activity for the security in the sample.

I ensure that the instrument meets all conditions, that is; relevance; that on adding it to the model the mode is not under or over identified; and that the instrument be statistically significantly correlated with the endogenous variable being instrumented. On meeting these conditions, the instrument is considered strong. I report Cragg and Donald (1993) minimum eigenvalue statistics (F statistic) for the main study and robustness checks, which exceeds all Stock-Yogo weak ID critical test values (Stock and Yogo (2005)) at bias tolerance levels of 5%, I can reject the null hypothesis that the instrument is weak, or that the estimator's Nagar (1959) bias is large when compared relatively to a 'worst-case' benchmark for 2SLS and LIML models. The non-homoskedastic robust Kleibergen-Paap F statistic exceeds the lower boundary of 10 required for inference as suggested by Stock, Wright, and Yogo (2002). I are therefore confident that I have found an appropriate instrument for our analysis.

Model Specification and Robustness

Following Boehmer, Fong and Wu (2018) I adopt a 2-Stage Least Squares model, a special case of Instrumental Variable estimation first proposed by Thiel (1953) (but also independently by Bausman (1957), in which the first stage involves estimating the reduced form parameters by regressing endogenous variables, which are regressed on exogenous variables in a system of simultaneous equations. The estimated values from this first stage are then used in the second stage as instruments to estimate the parameters using OLS regression for the endogenous variables. Several robustness tests and exercises for the 2SLS specification were implemented throughout this study to assess the appropriateness of the chosen 2SLS model. The primary reason for taking the 2SLS approach is a) it enables us to make inferences about the relationship the private market data transmissions network has with the market quality dimensions of effective bid-ask spreads because by design it is robust to wrong-way causality, b) it is appealing because of the plausibility of its application and c) the relative simplicity of the model used here enables rigorous testing of assumptions so that I are not left trying to theoretically defend what I cannot verify. I test for the selected instrument being weak. Stock and Yogo's (2005) second characterisation is that a Wald test at the 5% level has an actual rejection rate not exceeding 10% (c.v 16.38), 15% (c.v 8.96), 20% (c.v 6.66), or 25% (c.v 5.53). For robustness, I test alternative specificications cal estimates, and the Wald test-statistic exceeds all critical values for the main study and sample expansion robustness checks, hence there is no bias toward the OLS specification. An Augmented Dickey-Fuller (Dickey and Fuller, 1979) test (with Schwarz Criterion for lag determination) was used in the main study, and for the unlimited and expanded samples shows a stationary process and therefore does not demand that differencing is required. A final remark on my preference for the 2SLS model; the econometric literature (Cragg (1968)) describes the 2SLS model as more robust to misspecification than ML models. In 2SLS, each equation is estimated independent of coefficients in previous equations, which gives rise to the attractive property that mispecification in one part of the model is isolated. This contrasts to Full-Information Maximum Liklihood models whose iterative nature may spread bias from one part of the system to others. Generally, Maximum Likelihood models have similar performance to 2SLS when the model is correctly specified (Bollen (2007)), hence I have confidence that using the 2SLS model in the spirit of Boehmer et al. remains appropriate.

Lastly, I considered a Regression Discontinuity design to ensure that the model is robust against error in the instrumented announcement date, which can also be thought of as an implementation date on which LAS firms utilise the change in the communications network, which will likely be heterogeneous across firms. I decided that if such errors are random and are captured by the error term in the model, then the consistency of the IV estimator should not be impacted. I depart from the fixed-effects modelling approach of Boehmer, Fong and Wu (2018) because I only observe a single security rather than a basket of heterogenous stocks with time-invariant individual characteristics

In the main study, the model passes all standard diagnostic tests of correct specification, as well as very similar classical and robust standard errors, suggesting the appropriateness of the model and variables chosen with one exception. The control variable inverse price caused a significant multicollinearity issue (collinear with our variable of interest) and was subsequently removed from the model to restore reliability to the coefficients and remove noise. Furthermore, I could not think of any urgent theoretical reason for the control to remain in the model after such a result. The p value for inverse price was <0.000, however, given the large sample sizes this is not informative. The means of the variables LAS, Vol_{-1} and S_{-1} were -0.173, -1.576 and 0.0006908 respectively, and the standard deviations were 0.224, 0.624 and 0.00006205.

5. Methodology

I use a 2SLS approach. In the first stage, I create a new variable by regressing LAS on the network upgrade instrument;

Where X is a vector control variables that include the lagged dependent variable (I expect the current bid-ask spread to be influenced by the past bid-ask spreads (Keele, L. and Kelly N. J. (2005))), and lagged Parkinson (1980) proxy for volatility, in line with Boehmener, Fong and Wu (2018) which they do to ensure predetermination. The second stage involves the regression of the effective bid-ask estimator on $LAS*$ which is the predicted value generated by the first stage;

$$S_t = \alpha_t + \beta LAS*_t + \beta X_t + \epsilon_i \tag{7}$$

Given the fact that a regression calculates a distribution of values of the relationship between two variables, one of the most important statistics returned is the standard deviation of the distribution of the coefficients. They are crucial in that they determine how accurate the estimation is. An earlier inspection of the data structure suggested using standard errors robust to conditional heteroskedasticity, or White-Huber robust variance estimation (White, 1980), to ensure the precision of the estimators. Heteroskedasticity makes some estimators inefficient but not biased, and others biased. I therefore use robust standard errors in the model. I avoid the application of HAC standard errors which whilst convenient, may fail to capture important predictive information and are not to be treated as a panacea for mispecified models. Ultimately, heteroskedasticity rarely results in very significant changes in inference, and in large samples such as ours where I do not know the structure of the heteroskedasticity, I may safely use robust standard errors.

6. Results and Discussion

Firstly, the results of the main study on the sample of winsorised observations at 5 minute intervals for the effect of LAS participation on bid-ask spreads are presented (for direct comparison to Boehmer, Fing and Wu (2018)). For robustness I then present results obtained using an unlimited version of the sample, and also of the 1 minute interval sample with the data winsorised and unlimited. I also present results for robustness of an expanded sample of 18 months of 5 minute interval data. All results are standardised for ease of interpretation.

In the first stage, I regress our measure of LAS participation on the instrumented date of the communications network update and find that this event produces a statistically significant increase in LAS participation in all samples. The choice of instrument is strong for LAS participation, with an Kleinberg-Paap rk Walk F-statistic exceeding cut off of 10 for the main study and all robustness checks, inferring the existence of a causal effect. The Stock and Yogo Weak IV test for 2SLS regression exceeds 10% maximum acceptable bias towards OLS (critical value 16.38) and is satisfied. Heteroskedasticity-robust Wald statistics shows joint significance for the model in the main study and across all robustness checks.

Main Study

I find that the upgrade in the network significantly contributes to LAS participation, with a coefficient on the MW instrument of 0.223 and t score= 23.2. My main finding is that LAS has explanatory power for, and tightens effective bid-ask spreads significantly. These results are similar to Boehmer, Fong and Wu (2018). I report that a one standard deviation increase in the LAS measure tightens spreads by 0.78 standard deviations in the winsorised sample and 0.75 standard deviations in the unlimited sample (Boehmer, Fong and Wu (2018) report spreads tightening by 0.7 standard deviations). Given the effective bid-ask spread measure is a proxy for market quality, namely the informational content of prices and transaction costs, it appears that increased LAS participation lowers liquidity costs and increases the informational content of prices. I should be careful however not to suggest that LAS has this effect across market orders of all sizes, and across all markets. Further study on large, mid sized and small stocks perhaps using an instrumental variable size dummy approach might be required.

Robustness Testing on Unlimited and Expanded Samples

Model uncertainty as the result of simplifying assumptions, omitted explanatory variables and their interactions, and unknown boundary conditions is widespread in econometric practice. In a robust model, the coefficients of core estimators are the same under two different specifications. If the coefficients are also plausible, then I can infer a valid specification. More commonly this is is done by adding or removing regressors but often fails to be informative of structural validity (Lu and White, 2014). The results of my main study are in line with Boehmer, Fong and Wu (2018), whom I attempt to replicate, but to test whether this fact reflects correctly modelled data, or chance (I mentioned earlier that Boehmer, Fong and Wu (2018) do not report classical standard errors and therefore immediately harm experimental transparency), I must probe the model internally. I test the plausibility of the chosen specification against other datasets of non-winsorised (unlimited) data, higher frequency sampling (1 minute intervals over the year 2019) and longer time frames (5 minute intervals over 18 months). In the robustness testing, the same relationship is found to exist, with increased LAS participation tightening effective bid-ask spreads. In the 5 minute interval 18 month sample, effective bid-ask spreads tightened by 0.84 and 0.72 standard deviations for every 1 standard deviation increase in LAS participation in the unlimited and winsorised samples respectively. In the winsorised 1 minute interval full year 2019 sample, the instrument MW was statistically significant at the 99% level with a t-score of 7.49. In the unlimited sample MW was significant only at the 5% level. The coefficient on LAS was -1.57 and -2.59 in the winsorised and unlimited samples respectively, much larger than the magnitude of the 5 minute interval results. The coefficients are not comparable to Boehmer, Fong and Wu (2018) as I sample at a higher frequency than they do in their study.

a possible artefact of 'microstructure noise'. Whilst it can be expected that any bid-ask spread time series is inherently autocorrelated, in high frequency sampling, the problem is very pronounced because I are not modelling the correlation between the data points sufficiently i.e. the model is mispecified. To apply HAC errors to patch the problem would be negligent, as calculated HAC errors were nearly five times as large as their classical standard error counterparts (for example, for $LAS*$ the classical standard error was 0.811 but the HAC error was 3.71). This divergence is a clear indication of mispecification. To leave the autocorrelation in the model would have the implication of underestimating the standard errors, and overestimating the t-scores, especially in large samples. I must model the underlying process, that is however beyond the scope of this study.[10]

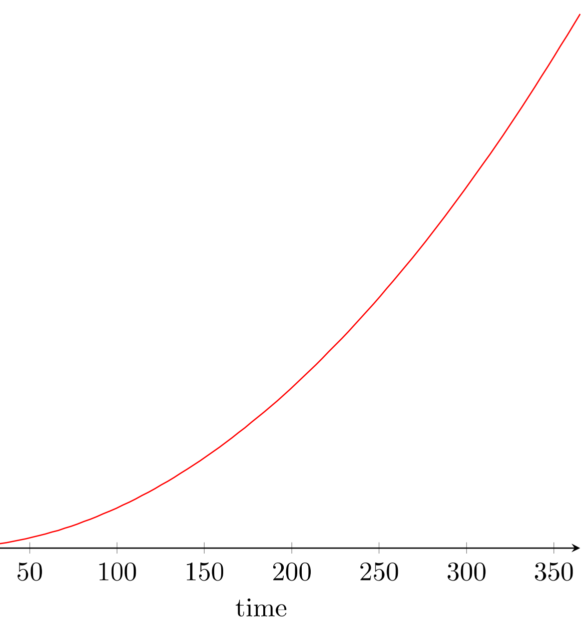
In summary, my results are similar to that of Boehmer, Fong and Wu (2018), and my robustness testing finds that the model is robust to longer sampling time frames, but not to higher frequency sampling, where I pick up significant 'noise' that I am unable to model. Figure 1 presents the results from the second stage regression of LAS on effective bid-ask spreads on all samples. Heteroskedasticity-robust Wald statistics in place of t-statistics are reported. Classical and robust standard errors are both reported for comparison. As shown, the two types of error are very similar, suggesting that the model is correctly specified.

Conclusion and Empirical Implications

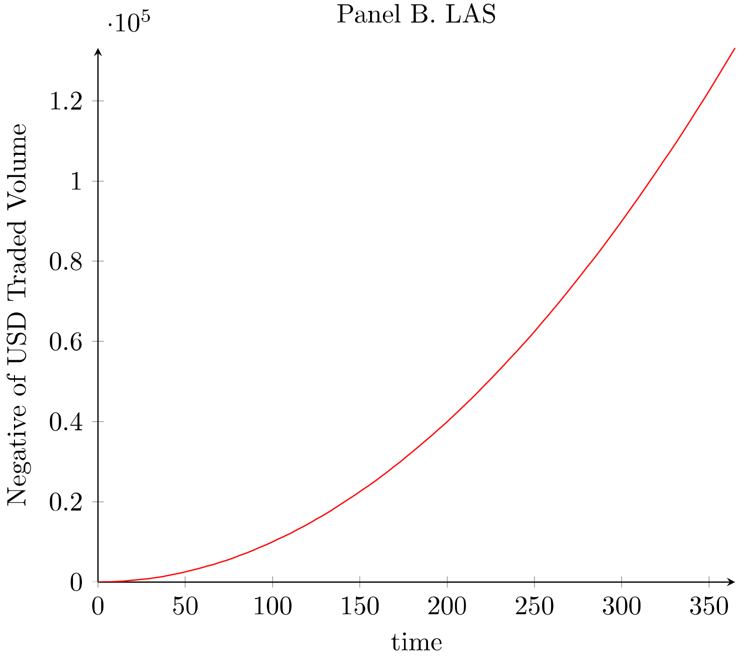
I use the exogenous shock of the announcement of a new low-latency market data transmission network to model the causal effect of LAS participation on effective bid-ask spreads, and in doing so am able to describe how private changes in the physical microstructure impact the two components of the effective spread; transaction costs and the informational content of prices. I show that an increase in LAS participation improves spreads in the SPY ETF market However, I must exercise extreme caution in interpreting the results; I should be careful not to suggest that LAS has this effect across market orders of all sizes, and across all markets. Furthermore, the results suggest that higher LAS participation causes *either one or both* of these components to change; that is, increased LAS participation might reduce the effective bid-ask spread by reducing transaction fees, *or* it might reduce the effective bid-ask spread by reducing adverse selection costs, *or* it might impact *both* dimensions simultaneously, perhaps unequally. Furthermore, I cannot say that one of the two components does not increase even as the effective bid-ask spread narrows overall. Plainly put, it is not within the scope of this study to argue exactly how increased LAS participation affects changes within the effective bid-ask spread.

I may make a more modest inference however, that increased LAS participation has a non-trivial effect on an important indicator of market quality associated with transaction costs and informative prices with an important caveat being that it might not always decrease and Harris (1988) estimate the components of the effective bid-ask spread using NYSE common stock transaction prices. This suggests that an interesting direction for future research might be the modelling of the informational content component of effective bid-ask spreads, and how it is causally affected by the building of private market data transmission routes. If the effect is non-trivial in either direction, then I have important policy implications for any result. If, on one hand, increased LAS participation followed the building of a private network and effective bid-ask spreads became more informative, then I might conclude that private investment results in positive externalities and should be encouraged by the regulator. If on the other hand effective bid-ask spreads were less informative, I might suspect that information asymmetry was becoming increasingly unbalanced with further private investment. Given the high level of investment needed to build and maintain such networks, there might need to be a regulatory intervention if a lack of economic competition emerges. This may be feasible in future if network providers and LAS firms (who undoubtedly are of the opinion that they improve market quality) are willing to provide what is usually closely guarded data on the development and usage of their networks.

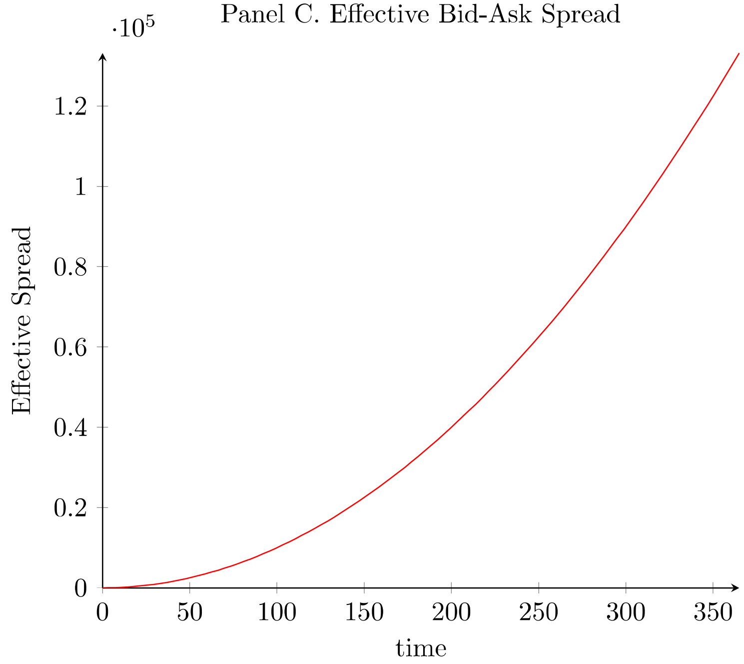
Panel A. Message Traffic



Panel B. LAS



Panel C. Effective Bid-Ask Spread



A, B and C are dummy graphs. Due to the Covid-19 pandemic and related IT issues and my datasets being large, I could not generate the above graphs with real data. I have included these to

Panel A shows Message Traffic, LAS participation and Effective Spreads over time.

ive Bid-Ask Spreads	5 minute, 1 year, unlimited		5 minute, 1 year, winsorised		1 minute, 1 year, unlimited		1 minute, 1 year, winsorised		5 minute, 18 months, unlimited		5 minute, 18 months, winsorised	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
		24.7***		15***		18***		-6.38***		-71.3***		-89.6***
LAS*	-0.749	(0.296)	-0.781	(0.413)	-2.592	(0.811)	-1.568	(0.246)	-0.84	(0.069)	-0.723	(0.052)
		22.9***		14***		13.3***		-6.57***		-73.3***		-85.6***
		(0.276)		(0.217)		(0.835)		(0.239)		(0.068)		(0.058)
ontrols												
		3*		7.4***		27.2***		-4.32**		383.2***		16.5***
S_{-1}	-0.176	(0.037)	-0.237	(0.237)	-0.115	(0.0503)	-0.108	(0.025)	-0.07	(0.018)	-0.059	(0.018)
		6.3***		2.8*		25.7***		-4.25**		24***		28.9***
		(0.04)		(0.045)		(0.0472)		(0.025)		(0.027)		(0.028)
		151.8***		68.9***		125.8***		17.54***		11.2***		401.1***
Vol_{-1}	0.612	(0.60)	0.725	(0.061)	0.664	(0.088)	0.662	(0.378)	0.58	(0.017)	0.591	(0.017)
		154.8***		166.9***		129.5***		17.15***		314***		308.1***
		(0.58)		(0.062)		(0.083)		(0.386)		(0.022)		(0.023)
	Coeff	0.223	Coeff	0.223	Coeff	0.223	Coeff	0.223	Coeff	0.223	Coeff	0.223
MW	t-stat	23.2	t-stat	23.2	t-stat	23.2	t-stat	23.2	t-stat	23.2	t-stat	23.2
	Kleinberg-Paap	18.9949	Kleinberg-Paap	29.7062	Kleinberg-Paap	15.251	Kleinberg-Paap	56.122	Kleinberg-Paap	343.725	Kleinberg-Paap	471.031

orts the results of the 2SLS regression. LAS was regressed on an effective bid-ask spread proxy, with an exogenous shock of a new market data transmission network being announced as an instrument for LAS. standardised. Both classical and robust standard errors are reported, with the first bracketed term being the classical standard error, and the second being the robust standard error.*, **, *** indicate significance nd 1% level respectively. Kleinberg-Paap rk Walk F statistics are for instrument strength and all exceed the Stock-Wright-Yogo cut off of 10 indicating a strong instrument. For each sample used MW is also a ent.

References

SEC chair to Congress: 'The markets are not rigged' kernel description. https://www.reuters.com/article/us-sec-highspeed-trading/sec-chair-to-congress-the-markets-are-not-rigged-idUSBREA3S0OO20140429. Accessed: 2020-03-29.

Kalemli-Ozcan Selin Sayek Alfaro, Chanda. Fdi and economic growth: the role of local financial markets. *Journal of International Economics*, 10 2004.

H Rubin Anderson TW. Estimation of the parameters of a single equation in a complete system of stochastic equations. *The Annals of Mathematical Statistics*, 20(01):pp.46–63., 6 1949.

James Angel, Lawrence E. Harris, and Chester S. Spatt. Equity trading in the 21st century: An update. *Quarterly Journal of Finance (QJF)*, 05(01):pp. 1–39, 2015.

Budish Aquilina and O'Neill. Quantifying the high-frequency trading "arms race": A simple new methodology and estimates. *FCA Occasional Paper in Financial Regulation*, 2020.

Matthew Baron, Jonathan Brogaard, Björn Hagströmer, and Andrei A. Kirilenko. Risk and return in high-frequency trading. *Journal of Financial and Quantitative Analysis (JFQA)*, 2017.

M. E. Schaffer Baum C.F and S. Stillman. *Enhanced routines for instrumental variables/generalized method of moments estimation and testing, Volume 7 Number 4.* Stata Journal, 2007.

Alejandro Bernales. *Algorithmic and High Frequency Trading in Dynamic Limit Order Markets.* 2014.

Hendershott Brogaard and Riordan. Price discovery without trading: Evidence from limit orders. *Journal of Finance*, 74:pp. 1621–1658., 2015.

Rama Cont. Empirical properties of asset returns: stylized facts and statistical issues. *Quantitative Finance*, 01:pp. 223–236., 2001.

Rama Cont. The limit-price mechanism. 07 2001.

A. Corwin and Schultz. Quantifying the high-frequency trading "arms race": A simple new methodology and estimates. *The Journal of Finance*, 2012.

J. C. Cragg and S. Donald. Testing identifiability and specification in instrumental variable models. *Econometric Theory*, 9(02):pp. 222–240., 1993.

Robert E. Cumby and John Huizinga. Testing the autocorrelation structure of disturbances in ordinary least squares and instrumental variables regressions. *Econometrica*, 01 1992.

Jaksa Cvitanic and Andrei Kirilenko. High frequency traders and asset prices. *SSRN Electronic Journal*, 03 2010.

Hanna Ding and Hendershott. *How Slow Is the NBBO? A Comparison with Direct Exchange Feeds.* 2014.

Christopher Dougherty. *Introduction to Econometrics FOURTH EDITION.* Oxford University Press, 2011.

Alex Frino, Vito Mollica, and Robert Webb. The impact of co-location of securities exchanges' and traders' computer servers on market liquidity. *Journal of Futures Markets*, 34, 01 2014.

L. e Rand Tālis J. Putniņš Glosten. Welfare costs of informed trade. *Columbia Business School Research Paper*, pages pp. 16–58, 2016.

Edwin Hu. Intentional access delays, market quality, and price discovery: Evidence from iex becoming an exchange. *Available at SSRN 3195001*, 06 2018.

Edwin Hu. Intentional access delays, market quality, and price discovery: Evidence from iex becoming an exchange. *Available at SSRN* $https://papers.ssrn.com/sol3/papers.cfm?abstract_id = 3195001, 2018.$

Keele and J. Kelly. Dynamic models for dynamic theories: The ins and outs of lagged dependent variables. *Political Analysis*, 14:pp.186–205., 11 2006.

Patrick J. Curran Pamela M. Paxton Feinian Chen Kenneth A. Bollen, James B. Kirby. Latent variable models under misspecification: Two-stage least squares (2sls) and maximum likelihood (ml) estimators. *Sociological Methods Research available at https://journals.sagepub.com/home/smr*, 36:pp. 48–86., 08 2007.

G. King and M. Roberts. How robust standard errors expose methodological problems they do not fix, and what to do about it. *Political Analysis*, 2015.

Michael Lewis. *Flash Boys : a Wall Street Revolt.* New York :Simon Schuster, 2014.

X. Lu and H. White. Robustness checks and robustness tests in applied economics. *Journal of Econometrics*, 178:pp. 194–206., 2014.

Katya Malinova, Andreas Park, and Ryan Riordan. Do retail traders suffer from high frequency traders? *Available at SSRN 2183806*, 01 2012.

B. Mandelbrot. The variation of certain speculative prices. *The Journal of Business*, 36(04):pp. 394–419, 1963.

T.F. Martell and A.S. Wolf. Determinants of trading volume in futures markets. *The Journal of Futures Markets*, 07(03):pp. 233–244., 1987.

R. Narang. *Inside the Black Box: A Simple Guide to Quantitative and High Frequency Trading.* JOhn Wiley and Sons, 2014.

J. Olbryś. Components of the effective spread: Evidence from the warsaw stock exchange.

Miller R. and Shorter G. High frequency trading: Overview of recent developments. *Congressional Research Service Report*, 04 2016.

Baldev. Raj. Henri theil's biography and his contributions to economics and econometrics: An overview. *Journal of Business Economic Statistics*, pages pp. 3–16., 1992.

SEC. Fast answers-market maker. *U.S. Securities and Exchange Commission*, 2016.

M. Stock J.; H Wright; Yogo. A survey of weak instruments and weak identification. *Journal of Business Economic Statistics*, 20(04):pp. 518–529., 6 2002.

Copeland T. and Galai C. Information effects on the bid-ask spread. *Journal of Finance*, 38:pp. 1457–1469, 1983.

Hendershott T., Jones C., and Menkveld J. Does algorithmic trading improve liquidity. 2011.

H. White. Estimating the components of the bid/ask spread. *Econometrica*, 48(04):pp. 817–838., 05 1980.

H. White. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48(04):pp. 817–838., 05 1980.

Jeffrey M. Wooldridge. Econometric analysis of cross section and panel data. 2010.

Ekkehart Boehmer Kingsley Fong Juan (Julie) Wut. Algorithmic trading and market quality: International evidence. *AFA 2013 San Diego Meetings Paper*, 2018.