Fast and furious: the market quality implications of speed in cross-border trading

KHALADDIN RZAYEV*
Systemic Risk Centre, London School of Economics and Political Science, United Kingdom

GBENGA IBIKUNLE
University of Edinburgh, United Kingdom
European Capital Markets Cooperative Research Centre, Pescara, Italy

TOM STEFFEN
Osmosis Investment Management, London, United Kingdom

Abstract Using a measure of transmission latency between exchanges in Frankfurt and London and exploiting speed-inducing technological upgrades, we investigate the impact of international transmission latency on liquidity and volatility. We find that a decrease in transmission latency increases liquidity and volatility. In line with existing theoretical models, we show that the amplification of liquidity and volatility is associated with variations in adverse selection risk and aggressive trading. We then investigate the net economic effect of high speed and find that the liquidity-enhancing benefit of increased trading speed in financial markets outweighs its volatility-inducing effect.

JEL Classification: G10; G14

Keywords: transmission latency; microwave connection; high-frequency trading; liquidity; volatility.

---

*Corresponding author's contact information: Systemic Risk Centre, London School of Economics and Political Science, Houghton Street, London WC2A 2AE, United Kingdom; e-mail: k.rzayev@lse.ac.uk; phone: +442034862603.
We thank Alexandre Laumonier and Stéphane Tyc for their comments on microwave connections between the UK and Germany. Khaladdin gratefully acknowledges the support of the Trans-Atlantic Platform by the Economic and Social Research Council (ESRC) [grant number ES/R004021/1].

"The rise of high-frequency traders has opened up a debate among investors, brokers and exchanges. Critics have long claimed that speed-driven traders unfairly hurt traditional investors… Supporters argue that faster traders are now a vital element of modern markets…"

Financial Times, 15th May 2019

1. Introduction

The speed of trading and, ultimately, of price adjustment, is an important factor in the price discovery process. That factor, today, holds a significance that transcends market quality implications. It is the driving force behind a recent upsurge of latency arbitrage in modern financial markets, as markets become increasingly dominated by ultra-high-frequency algorithmic traders. However, speed (differentials) may also be good for markets.[1] The evidence of this has thus far been inconsistent. Some studies find that speed is good for liquidity and price discovery (see as examples, Hendershott et al. 2011; Brogaard et al. 2014; Hoffmann 2014), while others suggest a positive relationship between speed and adverse selection cost (see as examples, Hendershott and Moulton 2011; Biais et al. 2015; Foucault et al. 2016; Foucault et al. 2017), thus implying a negative effect on market quality and liquidity in particular. Jovanovic and Menkveld (2016) show that better informed high-frequency traders (HFTs) can reduce welfare, and Kirilenko et al. (2017) argue that although HFTs did not trigger the flash crash, they nevertheless exacerbated it by demanding immediacy.

While the existing literature focuses on traders' execution speed in their examination of the role of speed on market quality, we focus on a new variable capturing the combination of microwave/fiber optic connection latency, traders' information execution time, and exchange latency. We call this variable of interest *Transmission Latency (TL)*. The distinction we make here is important since speed between different exchanges is not only dependent on the heterogeneous technological capacity of traders, but also depends on the connection latency

[1] In this manuscript, we use speed and speed differentials interchangeably. This is because, as argued by Menkveld and Zoican (2017), any improvements in (exchange) speed will directly impact only some fraction of traders, HFTs, while these improvements can be used by all traders.

between financial markets and exchange latencies of different financial markets. This implies that *TL* holds economic significance for market quality beyond what the factors linked to trader execution speed hold. Furthermore, modern financial markets are characterized by high fragmentation. This underscores how critically inter-venue speeds must be incorporated into any examination of market quality implications of speed. The economic insights this consideration could generate are likely substantial (see also Menkveld and Zoican 2017). In addition, recent arguments by regulators and investors suggest that while higher information transmission speed attained by HFTs improves liquidity (and by extension, market quality), it nevertheless contributes to higher volatility and market risk, and hence impairs market quality.[2] Motivated by these contrasting arguments and the incomplete picture drawn by the existing literature, we investigate the effects of speed on the quality of financial markets by applying the measure of latency, *TL*. Therefore, the focus of our study is closely related to the works of Shkilko and Sokolov (2016), Menkveld and Zoican (2017), and Baron et al. (2019).

Shkilko and Sokolov (2016) examine liquidity when severe speed differentials exist among traders. Our study differs from the setup in Shkilko and Sokolov (2016) for two reasons: 1) the former study investigates the impact of speed on market quality within a national setting, and most importantly, because 2) the competitive environment for HFTs has evolved substantially over recent years. Specifically, Shkilko and Sokolov (2016) focus on the 2011-2012 period, during which microwave networks were only accessible to a small group of sophisticated trading firms such that only a few HFT firms were competing across borders. By contrast, we use more recent data, which allows us to study transnational high-frequency trading during a period that captures the effects of microwave technology when it has lost much of its exclusivity. Microwave connectivity is nowadays available for an affordable nominal fee,

---

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

leading to many HFT firms trading in linked venues. Thus, our empirical study focuses on investigating the role of speed in in an environment where many HFTs participate in cross-border trading, complementing Shkilko and Sokolov (2016). An important motivation for studying in the market quality effects of speed in this environment is offered by Bernales (2019), who shows that the relationship between market quality and trading at high speed depends on the participation rate of HFTs in the market. Specifically, Bernales (2019) builds a dynamic equilibrium model to investigate the impact of speed in financial markets and finds that liquidity deteriorates (improves) when few (many) HFTs compete in financial markets. This may explain Shkilko and Sokolov's (2016) finding regarding the positive relationship between speed and adverse selection/trading cost, and makes it necessary for us to examine the impact of speed in a market where the use of speed-enabling technology is the norm.

Similar to our approach, Baron et al. (2019) construct measures of latency from transaction-level data, and examine performance and competition among HFTs. There are two important differences between this current study and Baron et al.'s (2019). Firstly, Baron et al. (2019) do not estimate transmission latency *between* trading venues, which is particularly important in today's highly fragmented markets. Specifically, Baron et al. (2019) estimate what they call *Decision Latency*, which is the difference between timestamps from a passive trade to a subsequent aggressive trade by the same firm, in the same security and at the same exchange. Secondly, and more importantly, their study analyzes the impact of latency on HFTs' trading performance, not liquidity and volatility, in financial markets.

Menkveld and Zoican (2017) model the HFT arms race by adding the impact of *exchange speed* to Budish et al.'s (2015) model, and find a nontrivial relationship between exchange speed and liquidity (see also Brogaard et al. 2015). It is important to note that in Menkveld and Zoican's (2017) model, exchange latency does not include the trader's execution latency, and thus is assumed to be the same for all traders. The main difference between our study and Menkveld and Zoican's (2017) is that while Menkveld and Zoican (2017) focus on the role of exchange latency in financial markets, our main variable of interest, *TL*, captures the *combined* effect of trader execution latency, exchange latency, and connection latency between exchanges.

Our empirical approach involves first estimating the *TL* between the home exchange in Frankfurt (Xetra Stock Exchange – XSE) and a satellite exchange in London (Cboe Stock Exchange – Cboe), where XSE-listed stocks are cross-listed, and then examining its effect on liquidity and volatility of cross listed stocks in the satellite market. We thereafter investigate the channels, as informed by various theoretical models, through which our latency measure impacts market quality metrics.

We find that 49% (80%) of price-changing trades on Cboe occur within 3 (5) milliseconds (ms) of similar and proportional price-changing trade on XSE. This means that the existing microwave and fiber optic connections affect price responses on Cboe within 3-5ms of price changes on XSE. These estimates are consistent with the anecdotal evidence provided by industry practitioners active in both markets, since the latency (3-5ms) includes the traders' execution latencies, exchange latencies in Cboe and XSE, and connection latency between XSE and Cboe. For example, Perseus, one of the microwave connection providers between London and Frankfurt, states that a round trip latency via microwave and fiber optics between London and Frankfurt is 4.6ms and 8.4ms, respectively (see Footnote 2). The significance of these estimates is that analysis shows that higher *TL* leads to lower liquidity and volatility (i.e. speed enhances liquidity and increases volatility). The results are robust to alternative proxies for liquidity and volatility and more importantly, the magnitudes of these effects are economically meaningful. In order to address potential endogeneity concerns, we present causal evidence from a quasi-experimental setting, studying the impact of two technological upgrades by XSE on liquidity and volatility in Cboe. We compare the liquidity and volatility of stocks that are impacted by these updates with those that are not and show that, consistent with the previous results, increases in speed lead to enhanced liquidity and higher volatility.

The positive effect of speed on liquidity is linked to fast traders using their speed advantage to avoid adverse selection risk, and thereby decreasing price impact and increasing liquidity. Another channel through which speed impacts market quality metrics, often suggested to be negative, is explained by the prediction of Roşu (2019) suggesting that speed increases the aggressiveness of traders and this aggressiveness then leads to higher price volatility (see also Collin-Dufresne and Fos 2016). Thus, it appears that while speed enhances market quality by enhancing liquidity, it impairs it by intensifying market volatility. This implies a trade-off between the benefits of speeds (liquidity improvements) and its unwanted effects (increased volatility). We therefore examine the net economic implication of latency on market quality, with liquidity and volatility as market quality characteristics. The analysis shows that while high speed connections can harm market quality by increasing volatility, the liquidity improvement effect dominates the volatility inducement effect. This implies that the net effect of increasing speed is the enhancement of market quality.

This study offers significant insights on the effects of speed and market quality and therefore makes important contributions to the academic literature, practice and policy. Firstly, to our knowledge, this study is the first to empirically estimate *TL* between the two biggest European financial centers, Frankfurt and London, and by so doing corroborates the information provided on connection speed by the microwave and fiber optic connection providers (such as McKay Brothers). This exercise is particularly important in Europe, where financial markets have become increasingly fragmented across dominant national exchanges and a dominant London-based pan-European trading venue, Cboe. Secondly, we provide causal evidence on the direct impact of speed on market quality variables thus far understudied, such as volatility. Thirdly, we complement the existing empirical literature that examines the relationship between speed and market quality by analyzing the combined role of traders' execution latency, exchange latency, and connection latency (microwave or fiber connections) between exchanges on liquidity and volatility of transnational financial markets. Our practical approach measures the impact of speed on market quality in a fragmented trading environment – the reality of trading in modern financial markets. Finally, and critically, using a framework that controls for the undesirable (increased volatility) and desirable (enhanced liquidity) effects of speed, we show that that the liquidity-enhancing effect of speed in trading outweighs its volatility-inducing effect.

2. Theory and hypotheses

2.1 Latency and liquidity

While the theoretical literature proposes several channels that could explain the relationship between speed and liquidity, the evidence regarding the impact of speed on liquidity has hitherto been inconsistent. This inconsistency is a result of HFTs' mixed behavior. On the one hand, high-frequency market makers may exploit higher speeds in updating their quotes faster and, hence, face a substantially reduced level of adverse selection risk – labelled the "adverse selection avoidance" channel (see as an example, Jovanovic and Menkveld 2016). On the other hand, speculative high-frequency traders can use higher speed to pick off limit orders of market makers, and thus, increase adverse selection risk – called the "picking-off" channel (see as an example, Biais et al. 2015). Specifically, Biais et al. (2015) show that while high speed market connections increase investors' gains from trade, they also generate higher adverse selection risk. Furthermore, the study argues that fast traders generally do not consider these contrasting externalities and therefore, their investment on speed may be socially unbeneficial. Congruently, Foucault et al. (2017) also find that HFT raises adverse selection cost for slow traders and is linked to deterioration of liquidity. In contrast, Jovanovic and Menkveld (2016) document that speed can help fast market makers to avoid being adversely selected and may therefore increase their liquidity supply (see also Roşu 2019).

Generally, the results of empirical studies on the role HFTs play in liquidity generation are not clear cut. Chakrabarty et al. (2015) show that the speed advantage of fast traders increases trading cost and adverse selection. Consistent with Chakrabarty et al. (2015), Brogaard et al. (2017) find that HFTs raise adverse selection risk for slow traders and reduce liquidity. Shkilko and Sokolov (2016), already discussed, find that higher speed is associated with higher adverse selection and trading costs. Contrastingly, Hendershott et al. (2011), exploiting the introduction of Autoquote on the NYSE as an exogenous shock, find that speed is associated with liquidity improvement. This is consistent with Brogaard et al. (2015) who show that fast market makers use increased trading speed to avoid adverse selection risk and thus provide more liquidity to financial markets.

Bernales (2019) argues that the structure of HFT competition may be the main determinant of the mixed adverse-selection-avoidance/picking-off behavior. By building a dynamic equilibrium model, Bernales (2019) contends that the relationship between speed and liquidity depends on the number of HFT firms competing in financial markets. Specifically, liquidity improves (reduces) when there are many (few) HFTs. This is because when there are many HFTs in financial markets, they compete by using limit orders and rely on speed to avoid being adversely selected while deploying market making strategies (see Menkveld 2013). However, when only a few HFTs compete they often prefer to "pick-off" the limit orders of slow traders by using market orders and by doing so, they increase price impact and impair liquidity. Participants' choice of trading strategy as induced by the composition of market participants therefore either improves liquidity by reducing price impact (see Boehmer et al. 2018b) or impairs liquidity by increasing price impact.

This current study focuses on the 2017-2018 period, a period characterized by a widespread deployment of microwave networks. This implies that during our sample period, many HFT firms participate in quasi-competitive cross-border trading. Hence, we expect to find a positive (negative) relationship between speed and liquidity (price impact). To this end, we test the following hypothesis:

Hypothesis I. Speed improves liquidity by reducing price impact.

2.2 Latency and volatility

The speed-volatility relationship has been investigated by several empirical studies, with conflicting results. On the one hand, Hasbrouck and Saar (2013) and Brogaard et al. (2014) find that speed lowers short-term volatility. On the other hand, Zhang (2010) and Boehmer et al. (2018a) detect a positive relationship between volatility and high-frequency trading.

Roşu (2019) proposes a theoretical model to explain (and reconcile) the relationship between speed and volatility. The model shows that, consistent with Menkveld (2013) and Hagströmer and Nordén (2013), HFTs largely employ market making strategies and therefore price impact decreases and market liquidity improves as a result of increased speed in financial markets (see also Jovanovic and Menkveld 2016). However, facing a lower price impact and improved liquidity, encourages increased (aggressive) trading activity and this consequently increases stock price volatility [see Collin-Dufresne and Fos 2016 for further discussion about the relationship between aggressiveness and volatility].

In line with Roşu (2019), we hypothesize that, in our competitive setting, market making strategies are employed, and that this first improves liquidity and thereafter increases aggressiveness and volatility. Specifically, we test the following hypothesis with respect to speed and volatility:

Hypothesis II. Speed increases stock price volatility by intensifying aggressiveness in trading.

3. Institutional and technical backgrounds

3.1 Transmission latency between financial markets

In today's trading environment, information transmission speeds between trading venues play an important role in facilitating price discovery in an increasingly fragmented market. A decade ago, the most common way to transmit information from Frankfurt to London was via a fiber optic cable; at this time fiber optics offered information transmission latencies of about 4.2ms.[3] Although fiber optic technology offers fast transmission, it is not the fastest. This is simply because with fiber optic technology, "information" (photons) travels through cables and it is difficult to place cables in a straight line between trading venues. For example, Shkilko and Sokolov (2016) argue that until 2010 the fiber optic cabling between Chicago and New York exceeded the straight line distance between the two cities by about 200 miles. In contrast to fiber optic technology, with microwave technology, "information" (microwaves) travels through air. Hence, microwave networks offer information transmission speeds that are between 30 and 50% faster than with fiber optic technology. For example, microwaves shave about 1.9ms off the information transmission latency between Frankfurt and London when compared to fiber optics, a reduction from 4.2ms to 2.3ms.[4] It is therefore not surprising that the past decade has seen an emergence of the operation of microwave networks between major financial trading locations, such as London and Frankfurt.[5] Some of these networks are operated by specialist network providers (e.g., McKay Brothers), while others are operated directly by HFTs (e.g., Jump Trading).

INSERT FIGURE 1 ABOUT HERE

---

[3] https://www.reuters.com/article/us-highfrequency-microwave/lasers-microwave-deployed-in-high-speed-trading-arms-race-idUSBRE9400L920130501
[4] https://www.quincy-data.com/product-page/#latencies
[5] https://www.bloomberg.com/news/articles/2014-07-15/wall-street-grabs-nato-towers-in-traders-speed-of-light-quest

Figure 1 shows the microwave networks between the UK and Germany, and their respective providers (see Laumonier 2016). Given the notable speed advantage of microwave networks, HFTs are ready to pay significant amounts of money to obtain several microseconds of speed advantage over their competitors.[6]

In this study, we estimate the information transmission latency between XSE and Cboe by using transaction-level data. Our *TL* estimate is therefore composed of the following elements: (i) the connection latency between XSE and Cboe, (ii) the exchange latencies for XSE and Cboe, and (iii) the traders' execution latencies. Explicitly, the connection latency is the time it takes for information to travel via microwave/fiber optic connections between XSE and Cboe. The exchange latencies consist of the time it takes for the exchanges to process incoming and outgoing instructions. According to Menkveld and Zoican (2017), the exchange latency is the sum of gateway-processing latency and gateway-to-matching-engine latency. Gateway-processing latency equals the time spent inside the gateway application, and gateway-to-matching-engine latency is the time between an order's departure from the gateway and when the matcher begins processing the order. Finally, the transaction-level data from Thomson Reuters Tick History (TRTH) that we employ provides exact exchange timestamps for *executed* transactions. It thus also takes into account the time needed to execute transactions, which includes the traders' execution latencies, i.e. their signal processing and reaction times.

3.2 Technological upgrades on XSE

In order to address potential endogeneity concerns, we study the impact of two technological upgrades implemented by XSE on liquidity and volatility at Cboe. These

[6] https://www.businessinsider.com/locals-angry-at-flash-boy-traders-want-to-build-a-tower-taller-than-the-shard-2017-1?r=US&IR=T

technological upgrades are (1) the "New T7 Trading Technology" upgrade first offered on July 3, 2017, and (2) the "Introduction of PS gateways" upgrade first offered on April 9, 2018.[7] The Deutsche Börse T7 Trading Technology system reduces order processing time significantly and should be captured by our *TL* measure. The PS (Partition Specific) gateways upgrade for all cash market instruments operates in parallel to the existing HF gateways. Usually, latency jitters on parallel inbound paths encourage multiplicity to reduce latency. However, this leads to greater system load and choking at busy times, and thus less predictable latencies may arise. The PS gateways upgrade introduces a single low-latency point of entry, which addresses this issue and consequently reduces exchange latency at XSE. This reduction should also be captured by *TL*. Since the two technological upgrades are introduced to reduce exchange latency at XSE, they could be employed as exogenous shocks in our quasi-natural experiment to examine the relationship between transmission latency and market quality characteristics.

4. Data and latency estimation

Our data source is the TRTH v2 (Datascope). The most important feature of the Datascope-sourced datasets that makes them highly suitable for our analysis is that they provide exact *exchange timestamps* – which are synchronized with UTC during the sample period – in milliseconds for exchange-traded transactions and order flow. The main dataset employed in this study consists of ultra-high-frequency tick-by-tick data for the most active 100 German stocks that trade both on XSE in Frankfurt (home market) and on Cboe in London (satellite market). The dataset includes transaction-level data for trading days between March 2017 and August 2018. We select this period for two reasons. Firstly, Datascope does not provide exchange timestamps for European markets before June 2015. Secondly, as noted, to address

[7] The details of the upgrades can be found at https://www.xetra.com/dbcm-en/newsroom/press-releases/New-T7-trading-technology-goes-live-on-Xetra-144756 and https://www.xetra.com/resource/blob/228942/0bbe6323aa5436a88648d298d9b41512/data/143_17e.pdf

potential endogeneity concerns, we employ a quasi-natural experiment approach using the two technological upgrades described above. The upgrade dates are July 3, 2017 and April 9, 2018. We then select a data coverage period spanning four months before and after the upgrades for our difference-in-difference (DiD) framework. The Datascope data contain standard transaction-level variables such as date, time (both TRTH and exchange timestamps), price, volume, bid price, ask price, bid volume, and ask volume.

From the raw data we determine the prevailing best bid and ask quotes for each transaction, enabling us to see the status of the order book at the time of each transaction. We divide the sample of 100 stocks into quartiles using their level of trading activity; trading activity is measured by euro trading volume.

4.1 Trading summary statistics

Table 1 reports trading activity statistics for XSE and Cboe.

INSERT TABLE 1 ABOUT HERE

Panels A and B of Table 1 present market activity statistics for XSE and Cboe respectively, and Panel C presents the difference in full-sample trading activity between the two stock exchanges along with p-values obtained using different statistical approaches (two-sample t-tests and Wilcoxon-Mann-Whitney tests). The p-values are reported for the null that there is no difference in trading activity between XSE and Cboe. Going by the number of transactions and nominal and euro-denominated trading volume, XSE appears to be more active than Cboe for the selected sample of stocks. This is expected since XSE is the home market for our selected sample of German stocks.

4.2 Price discovery

Our latency (*TL*) estimation method assumes that information is transmitted from Frankfurt to London; an assumption supported by prior research (see Grammig et al. 2005). Indeed, it is implausible to assume that the preponderance of firm-specific information about German companies originates from outside of Germany. The expectation that information for German stocks largely flows from Germany is also supported by the superior volume of transactions recorded for XSE compared to Cboe (see Table 1). Nevertheless, it is important to ascertain that XSE holds price leadership relative to Cboe for our sample of stocks, especially since the European markets have become increasingly fragmented over the past decade. This fragmentation has in some cases upended the natural expectation that superior trading activity confers higher levels of price discovery. For example, Ibikunle (2018) investigates price leadership for a sample of London Stock Exchange (LSE)-listed stocks cross-listed on Cboe, and finds that although LSE holds superior trading activity for the stocks, Cboe leads price discovery in those stocks for much of the trading day.

INSERT TABLE 2 ABOUT HERE

Table 2 presents the results of the price leadership analysis between XSE and Cboe. For robustness, we employ three measures of price discovery computed using price data sampled at the one-second frequency. The first and second measures are the information share metric (IS) developed by Hasbrouck (1995), and the component share metric (CS) developed by Gonzalo and Granger (1995).[8] These methods are based on the vector error correction model (VECM), and usually provide similar results if the VECM residuals are not correlated. However, as suggested by Yan and Zivot (2010), both metrics suffer from bias if noise levels differ across trading venues. Therefore, we also employ the information leadership share metric

[8] We would like to acknowledge that the computation of the information follows the SAS codes that can be obtained from Joel Hasbrouck's website: http://pages.stern.nyu.edu/~jhasbrou/EMM%20Book/SAS%20Programs%20and%20Data/Description.html

(ILS) prescribed by Putniņš (2013), which corrects for the differential treatment of noise by the IS and CS measures and provides a cleaner measure of information leadership. The results are consistent with earlier studies, in that price discovery occurs mainly on XSE for German stocks; IS, CS and ILS estimates are 0.69, 0.64 and 0.61 respectively for the full sample of stocks. This result implies that the majority of information is incorporated on XSE first. Therefore, our assumption regarding the information transmission direction appears valid and while Cboe may occasionally generate signals for cross-listed German stocks, the information content of these signals will be less useful for traders as it will be accompanied by a higher proportion of noise in comparison with the XSE signal. Table 2 further reports that the information share of XSE is typically highest for the most active stocks. This result is consistent with the empirical findings of Brogaard et al. (2014), and suggests that HFTs are more active in the most active stocks.

4.3 Latency measurement

In general, latency can be considered as the delay between a signal and a response (see Baron et al. 2019). Following Laughlin et al. (2014), we define the signal as a price-changing trade in the home market, and the response as a near-coincident same direction price-changing trade in the satellite market.[9] Laughlin et al. (2014) validly employ this method for futures-ETF pairs in the US financial markets, and we apply it to measure latency in the case of the 100 most active cross-listed German stocks between XSE and Cboe. According to the law of one price, the price of the cross-listed stocks should be the same regardless of location.

[9] While order-level data can also be used in estimating latency (see Laughlin et al. 2014), transaction-level data sufficiently captures this. This is because Shkilko and Sokolov (2016) show that the abnormality in trade executions (96.10%) is about 3.5 times higher than the abnormality in quote changes (27.46%) following a signal (information) generation from the lead (home market in our setting) market/venue. This implies that following the generation of a signal, we are able to fully observe the linked activity in transaction-level data and thus, employing this level of data is sufficient for the purposes of our study. Furthermore, we employ the most active stocks and hence, we have enough transactions to estimate latency in an unbiased manner.

Specifically, the difference between cross-listed security prices in different exchanges should simultaneously be eliminated in a no-arbitrage scenario and if markets are informationally efficient.[10]

The latency measurement approach involves first identifying the exact exchange timestamp for each price-changing trade on XSE. We then look for a near-coincident same direction price-changing trade on Cboe. In order to identify the near-coincident trade in Cboe we examine trades occurring within 10ms of each price-changing trade on XSE. We select the 10ms interval since the average information transmission latencies between Frankfurt and London are 2.3ms and 4.2ms for microwave and fiber optic connections, respectively.[11]

INSERT TABLE 3 ABOUT HERE

Panel A in Table 3 reports the number of responses on Cboe to the signals on XSE for various latencies. We exclude the responses that fall in the 2ms interval. This is because the 2ms interval is less than the theoretical limit of 2ms it should take light to travel in a vacuum between the two locations. The number of responses in this interval account for only 2% of all responses, hence the exclusion should not have any material impact on our analysis. Laughlin et al. (2014) argue that the responses at less than the speed-of-light can be considered as a proof of the predictive capacity of HFTs. We do not examine this argument since it is outside of the scope of this study.

There are two important findings in Panel A. First, it shows that 48.61% (80.74%) of all responses (after excluding the [0 – 2ms] interval) fall within the 3ms (5ms) bin. These latencies are consistent with those provided by the microwave network and fiber optic connection providers, and corroborate the view that our latency measure indeed captures the

---

[10] One may argue that no-arbitrage limits and liquidity and trading cost can prevent market participants perfectly arbitraging price differences away. However, this argument cannot cause any serious concerns in our framework for two reasons. Firstly, we are using well-traded stocks in a major economy and secondly, on average, overwhelmingly, we would expect to see changes replicated across both platforms.

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

transmission latency between the two trading venues. For example, McKay Brothers recently announced that their average microwave latency between the XSE (FR2) and Cboe (LD4) data centers is 2.3ms (see Footnote 4). Furthermore, it is generally acknowledged that the average latency via fiber optic connections is about 4.2ms (see Footnote 2). These announced latencies, 2.3ms and 4.2ms, are only transmission latencies between exchanges and do not take into account the exchange latencies and the traders' order execution latencies. Therefore, we expect the actual trading latencies to be closer to our estimated transmission latencies. Panel A's estimates suggest that traders are more likely to employ the faster microwave technology than fiber optic options for connecting Frankfurt and London. Secondly, on average, the most active stocks have quicker response times, with 50.39% (81.98%) of all responses falling in the 3ms (5ms) bin. This is unsurprising given that existing studies suggest that HFTs trade more in the most active stocks (see Brogaard et al. 2014). Panel B in Table 3 presents the mean and standard deviation of latencies for the full sample and each quartile. The average latency for the full sample is 4.39ms and, consistent with Panel A in Table 3, the most active stocks have the lowest transaction latency.

The empirical relevance of our latency estimation is underscored by the literature (see Laughlin et al. 2014), but we also directly test its precision by examining the latency evolution around the technology upgrade events. A downward adjustment of the latencies on the event dates would provide support to the accuracy of our estimation. Figure 2 illustrates the impact of the "New T7 Trading Technology" upgrade on our estimated latency variable, *TL*. The figure shows a sharp decrease in latency on the day of the upgrade, with the average latency falling by 0.105ms to 4.297ms – a reduction of 2.4%. In addition, Panel C in Table 3 tests the statistical significance of the difference between the latencies 21 trading days before and after the implementation of the upgrade. The estimates show that the average latency reduction is statistically significant.[12]

INSERT FIGURE 2 ABOUT HERE

The fact that our estimated latency variable decreases following the implemented upgrade provides suggestive evidence that our latency measure is empirically relevant and correctly captures the delay between a signal and a response.

5. Empirical findings and discussion

5.1 Latency and Liquidity

Our first hypothesis suggests that speed increases liquidity by reducing price impact, we test this by estimating the following regression models:

$$Spread_{i,t} = \alpha_i + \beta_t + \gamma latency_{i,t} + \sum_{k=1}^{5} \delta_k C_{k,i,t} + \varepsilon_{i,t} \qquad (1)$$

$$PRIMP_{i,t} = \alpha_i + \beta_t + \gamma latency_{i,t} + \sum_{k=1}^{6} \delta_k C_{k,i,t} + \varepsilon_{i,t} \qquad (2)$$

where $Spread_{i,t}$ corresponds to one of quoted $(Qspread_{i,t})$ or effective $(Espread_{i,t})$ spreads for stock *i* and transaction *t*, $PRIMP_{i,t}$ is the price impact for stock *i* and transaction *t*, α_i and β_t are stock and time fixed effects, $latency_{i,t}$ is the transmission latency between Frankfurt and London for stock *i* and transaction *t*. $Qspread_{i,t}$ is computed as the difference between ask and bid prices for stock *i* corresponding to transaction *t*, $Espread_{i,t}$ is measured as twice the absolute value of the difference between the transaction price and the midpoint of the prevailing bid-ask spread for stock *i* and transaction *t*, $PRIMP_{i,t}$ is computed as $2q_t(mid_{t+1} - mid_t)$, where q_t is the direction of the trade,[13] and mid_t and mid_{t+1} are the prevailing midquotes for transactions *t* and *t+1* respectively. $C_{k,i,t}$ is a set of *k* control variables which

[12] Although not explicitly reported, the picture is comparable for the second technological upgrade. The "Introduction of PS gateways" leads to a significant latency reduction of 1.6%. The results are available on request.

[13] We employ the Lee and Ready (1991) algorithm to classify trades as sell and buy trades.

includes the standard deviation of stock returns *($Stddev_{i,t}$)* for stock *i* and transaction *t* as a proxy for volatility, the inverse of price *($InvPri_{i,t}$)* for stock i and transaction t, the natural logarithm of trading volume *($lnTV_{i,t}$)* for stock *i* and transaction *t*, market depth *($Depth_{i,t}$)* for stock i and transaction $t,$ momentum *($Momentum_{i,t}$)* for stock i and transaction t and $Espread_{i,t}$ (in the price impact model) for stock i and transaction *t*. All our variables are transactions-based (i.e. *t* represents trade time rather than clock time) because our measure of latency is transactions-based.[14]

$Stddev_{i,t}$ is calculated as the standard deviation of returns for contemporaneous and previous transactions (transactions at time *t* and t-1) for stock *i*, $InvPri_{i,t}$ is the inverse of the transaction price for stock *i* and transaction *t*, $lnTV_{i,t}$ is the natural logarithm of trading volume for stock *i* and transaction t, $Depth_{i,t}$ is the sum of prevailing bid and ask sizes for stock *i* corresponding to transaction *t,* and $Momentum_{i,t}$ is the first lag of the stock return for stock *i* and transaction *t* (momentum for transaction *t* is the stock return corresponding to transaction t-1).

INSERT TABLE 4 ABOUT HERE

Panels A and B in Table 4 report the mean and standard deviation estimates for all variables, and the correlation between the variables employed in the fixed effects model, respectively. As evident in Panel A, $Qspread_{i,t}$, $Espread_{i,t}$, $PRIMP_{i,t}$ and $Stddev_{i,t}$ are lower for the most active stocks. The narrower spreads and price impact on the most active stocks suggest that higher trading volume encourages traders to provide liquidity, i.e. HFTs are more active in the most active stocks (see Brogaard et al. 2014). Furthermore, the smaller absolute value of price changes ($AbsCha_{i,t}$) and $Stddev_{i,t}$ on the most active stocks are

[14] For robustness, we follow Baron et al. (2019) approach, and estimate our model for clock times (daily frequency) too. Specifically, we form the daily distribution of response times and then define *TL* as the 0.1% quantile of this distribution. The clock time results are identical to the trade time-based results and are available on request.

consistent with Kyle (1985) model, in that informed traders participate more in the most active stocks, and this reduces price volatility [see Wang 1993 for the relationship between informed trading and volatility]. The low correlation coefficient estimates between the variables (except for the $Qspread_{i,t}$ and $Espread_{i,t}$, which is to be expected) suggest that we do not face multicollinearity issues in the regression models. It is important to note that all variables, except $latency_{i,t}$, are computed for Cboe. This is because, as discussed in Section 4.2, information is propagated from Frankfurt to London, hence the effects of latency can only be captured for the satellite market.[15]

Equation (1) allows us to capture the relationship between speed and liquidity while with Equation (2) we investigate the potential channel explaining this relationship as argued in Section 2.1. Specifically, we argue that speed allows market making fast traders to avoid price impact and that this leads to them providing more liquidity. We estimate both Equations (1) and (2) for the full sample of stocks and stock trading activity quartiles. We estimate the equation for stock quartiles because Menkveld and Zoican (2017) show that the relationship between exchange latency and financial markets may depend on the liquidity of stocks.

INSERT TABLES 5 AND 6 ABOUT HERE

The results obtained from the estimation of Equation (1) and (2) are presented in Tables 5 and 6 respectively. Standard errors are robust to heteroscedasticity and autocorrelation. The coefficient estimates reported in Table 5 show that there is a positive relationship between information transmission latency and both $Qspread_{i,t}$ and $Espread_{i,t}$. The results hold for all the stock quartiles as well as for the overall sample.[16] This implies that the increases (decreases)

---

[15] Although we show that traders are less likely to use Cboe signals as information because of its noisy content (see Section 4.2), for robustness, we estimate all our regression models by computing variables for XSE and changing transmission direction to the Cboe-XSE route and find no significant relation. It again shows that the effects of latency can only be captured for Cboe.

[16] The results presented in Panels A and B of Table 5 are generally consistent, but there is a notable point of departure. While Panel A's estimates show that the effect of latency on spreads is larger in magnitude for the most active stocks compared to the least active stocks, Panel B's estimates show otherwise. This inconsistency may be

in transmission latency (speed) are associated with deteriorations in liquidity. Specifically, the $Qspread_{i,t}$ and $Espread_{i,t}$ widen by 10 and 7bps respectively for each one-unit increase (decrease) in latency (speed). Both estimates are statistically significant at the 0.01 level. The magnitude of the association is also economically meaningful. For example, a 1ms decrease in latency is expected to reduce $Qspread_{i,t}$ ($Espread_{i,t}$) by about 10/454 = 2.2% (7/427 = 1.6%). It simply implies that using microwave over fibre optic cables (the difference between these two transmission methods is about 1.9ms) for trading information transmission can potentially reduce $Qspread_{i,t}$ ($Espread_{i,t}$) by 4.2% (3%). This is a substantial change in economic terms, especially, considering the staggering number of such trades that could be placed over the course of one day. The $\overline{R^2}$s for the full sample for the $Qspread_{i,t}$ and $Espread_{i,t}$ regressions are 42% and 41% respectively, which is high for estimations at transaction (sub-minute) frequency.

The estimated latency coefficient in Table 6 is positive and statistically significant at the 0.05 level. The results suggest that $PRIMP_{i,t}$ increases (decreases) by 10bps per ms increase in latency (speed). The magnitude of the effect is also economically meaningful; a 1ms increase in latency (speed) is expected to increase (decrease) $PRIMP_{i,t}$ by 4% (10/254). The $\overline{R^2}$ for the full sample is 14%.

The results reported in Tables 5 and 6 are consistent with the predictions of Hoffmann (2014) and Jovanovic and Menkveld (2016), and the findings of the empirical studies of Hendershott et al. (2011) and Menkveld (2013). Hypothesis I is therefore upheld. Our study complements the existing literature, an example is that of Shkilko and Sokolov (2016) who

---

linked to differences in intuition behind the computation of $Qspread_{i,t}$ and $Espread_{i,t}$. $Qspread_{i,t}$ is considered the better estimate of trading cost if trades are executed at the quoted prices, while the $Espread_{i,t}$ is a better measure of trading cost when trades are executed inside the quoted spread (see Petersen and Fialkowski 1994). Petersen and Fialkowski (1994) further show that the inaccuracy of the $Qspread_{i,t}$ when trades are executed inside the spread is notably stronger for the very active stocks. Thus, we urge that the evidence presented in Panel A, suggesting that the relationship between liquidity and speed is mainly driven by the most active stocks be interpreted with caution.

find that liquidity (adverse selection) improves (reduces) when exogenous weather-related shocks disrupt microwave connection, i.e. increase (reduce) latency (speed). The inconsistency between the results and those of Shkilko and Sokolov (2016) may be driven by the structure of the competition among HFTs. Specifically, in Shkilko and Sokolov (2016), microwave networks are strictly exclusive and thus, only a few HFTs participate in cross-border trading, whereas in our setting, microwave networks use is more widespread, with many HFTs trading between transnationally linked venues. As shown by Bernales (2019), HFTs decrease (increase) liquidity when there are few (many) fast traders in markets. Therefore, in contrast to Shkilko and Sokolov (2016), we expect to find a positive relationship between speed and liquidity and our findings are consistent with this expectation.

5.2 Latency and volatility

Next, we test our second hypothesis which suggests that speed increases volatility by raising aggressiveness in financial markets. To test this, we estimate the following regression models:

$$Volatility_{i,t} = \alpha_i + \beta_t + \gamma latency_{i,t} + \sum_{k=1}^{5} \delta_k C_{k,i,t} + \varepsilon_{i,t} \quad (3)$$

$$Aggressiveness_{i,t} = \alpha_i + \beta_t + \gamma latency_{i,t} + \sum_{k=1}^{6} \delta_k C_{k,i,t} + \varepsilon_{i,t} \quad (4)$$

where $Volatility_{i,t}$ corresponds to either the absolute value of price changes ($AbsCha_{i,t}$) or the standard deviation of stock returns ($Stddev_{i,t}$) (see Karpoff 1987). $AbsCha_{i,t}$ is computed as the absolute value of transaction price differences between transaction *t* and *t-1*. $Aggressiveness_{i,t}$ is a binary dependent variable for stock *i* and transaction *t*, and equals 1 for an aggressive trade and 0 otherwise. In order to classify trades according to their aggressiveness, we employ the modified version of the approach proposed by Barber et al. (2009) and Kelley and Tetlock (2013). We start by determining the direction of each transaction in the spirit of Lee and Ready (1991). Then, we compare the transaction price with the prevailing best bid (ask) price for sell (buy) transactions. If the transaction price is below (above) or equal to the prevailing best bid (ask) price, we classify this sell (buy) transaction as an aggressive trade. $C_{k,i,t}$ is a set of k control variables, which includes $Espread_{i,t}$, $InvPri_{i,t}$, $lnTV_{i,t}$, $Depth_{i,t}$, and $Momentum_{i,t}$ and $Stddev_{i,t}$ (in Equation (4)). All these variables are as previously defined.

INSERT TABLE 7 AND 8 ABOUT HERE

Equation (3) is employed to analyze the impact of speed on volatility, whereas with Equation (4) we seek to explain how speed impacts volatility, the model specification is based on the arguments presented in Section 2.2. Specifically, we argue that speed-induced improvements in liquidity leads to an increase in aggressive trading. We present the results for the full sample and quartile estimations of Equations (3) and (4) in Table 7 and 8 respectively. Panels A and B of Table 7 show the results for the two stock price volatility proxies. Standard errors are robust to heteroscedasticity and autocorrelation. The estimates suggest a negative (positive) relationship between latency (speed) and volatility for both proxies. Specifically, the $AbsCha_{i,t}$ and the $Stddev_{i,t}$ decrease by 0.7 and 0.2bps respectively per unit increase (decrease) in latency (speed). $AbsCha_{i,t}$ and $Stddev_{i,t}$ are statistically significant at the 0.01 and 0.05 levels respectively. Economically what this means is that a decrease in latency from 4.2ms (fibre optic cable) to 2.3ms (microwave connection) is expected to increase $Stddev_{i,t}$ by 1.9 * 0.2/13 = 2.9%. The estimates imply that an increase (decrease) in the speed (latency) of order transmission increases volatility in stock prices. This may not necessarily be a negative effect on market quality if increased speed simply means that new information arrives at the market more often (see Section 6 for more detailed discussion). If this is the case, we would expect to see more rapid changes in prices as investors revise their beliefs about the value of their holdings (see Madhavan et al. 1997). It is important to note that for the $AbsCha_{i,t}$, the negative (positive) relation between latency (speed) and volatility holds for all quartiles (except

Quartile 3) and the overall sample; however, the results for the $Stddev_{i,t}$ suggest that this negative relation is mainly driven by the most active stocks, which indicates cross-sectional differences in the impact of latency on volatility. $\overline{R^2}$s for the full sample results are 42% and 18% respectively, again indicating that our model has a high explanatory power when the frequency of the estimation is considered.

Table 8 reports the estimation results for the logit model. The results are qualitatively similar for the overall sample and quartiles. We also report marginal effects in parentheses, which show an increase in the probability of aggressive trades if the explanatory variable increases by one standard deviation, conditional on all other explanatory variables being at their unconditional means. Our results show that the $latency_{i,t}$ coefficient is negative and statistically significant at 0.01 level, which implies that indeed increases (reduction) in latency (speed) decrease the probability of aggressive trading. Based on the marginal effects, traders are 0.3% less (more) likely to trade aggressively subsequent to increasing latency (speed). Overall, we conclude that improvements in the speed of order execution ultimately drive increased trading aggressiveness and hence, increase volatility. This finding is consistent with the Roşu (2019) aggressiveness theory and Hypothesis 2 is therefore upheld. The *McFadden* R^2 for the full sample is 27%, a substantial explanatory level for an estimation based on an intraday estimation frequency.

5.3 Difference-in-difference estimation of the relationship between speed and market liquidity and volatility

In order to address potential endogeneity, specifically that an unobserved variable correlated with information latency might be driving liquidity/volatility or that there exists some reverse causality between market quality variables (i.e. liquidity and volatility in our set-up), we use a quasi-experimental setting studying two technological upgrades that improved latency on XSE. Specifically, we attempt to causally link the observed changes in liquidity and volatility to latency by employing a DiD framework.

On July 3, 2017 and April 9, 2018, XSE implemented upgrades to increase the exchange's speed (see Section 3.2 for details on the two upgrades). We compare the changes in the liquidity and volatility of stocks affected by the technological upgrades with those that are unaffected by estimating the following regression model:

$$DP_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_d + \gamma_2 Treatment_i + \gamma_3 Event_d \times Treatment_i + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d} \quad (5)$$

where i denotes stocks and d denotes days. α_i and β_d are stock and time (day) fixed effects. The dependent variable $DP_{i,d}$ corresponds to one of the liquidity and volatility proxies: quoted ($Qspread_{i,d}$) and effective ($Espread_{i,d}$) spreads for liquidity, and absolute value of price changes ($AbsCha_{i,d}$) and standard deviation of stock returns ($Stddev_{i,d}$) for volatility. $Qspread_{i,d}$ is the average of the differences between the ask and bid prices corresponding to each transaction, $Espread_{i,d}$ is a daily average, each intraday value is computed as twice the absolute value of the difference between a transaction's price and the prevailing bid-ask spread, $AbsCha_{i,d}$ measures the absolute difference between the last prices for stock i for days d and d-1, and $Stddev_{i,d}$ is the standard deviation of intraday hourly midquote returns. Consistent with previous models, all variables are computed for Cboe.

$Event_d$ is a dummy taking the value 0 for the pre-upgrade period and 1 for the post-upgrade period. We employ a 4-month horizon to assess the impact; d comprises [-120; +120] days. It is important to note that our results are robust to different horizons: 1-, 2-, or 3-month periods before and after the upgrade. $Treatment_i$ is a dummy taking the value 1 for stocks that are affected by the upgrade and 0 for stocks that are not. Specifically, our treatment group is the 100 stocks that are cross-listed on both XSE and Cboe. Hence, any XSE exchange latency upgrade will impact the *TL* of these stocks. Our control group comprises of 100 stocks that are only listed on Cboe and not on XSE; thus, upgrades should not have any impact on them. In this framework, our treatment and control groups belong to different countries. However, this should not have a material impact on our results for at least two reasons. Firstly, the results are based on variations at frequencies less than one second; at these frequencies, microstructure effects are unlikely to be driven by regulatory regimes in the case of stocks trading in quite similar market structures. Secondly, all of the stocks in both groups are domiciled and traded within the jurisdiction of the European Securities Market Authority (ESMA), and are therefore covered by largely similar regulatory regimes. The approach of including stocks from different countries within the same DiD framework is consistent with the literature (see as an example, Malceniece et al. 2019). Furthermore, in order to ensure that we compare like-for-like as much as possible, we employ the approach developed by Boulton and Braga-Alves (2010) to match each of the treatment stocks to a corresponding control stock; the matching variable is trading activity. While we compare like-for-like as much as possible, the DiD modelling approach relies on the parallel trend assumption and the violation of this assumption may bias our estimates. Therefore, it is useful to ensure that this assumption holds. A visual inspection of the outcome variables for the treatment and control groups during pre-treatment is a useful guide as to whether the assumption holds. This is because the assumption requires that the dependent variables (in our case, these are $Espread_{i,d}$ and $Qspread_{i,d}$ for the liquidity model and $Stddev_{i,d}$ and $AbsCha_{i,d}$ for the volatility model) for treatment and control groups have parallel trends in the absence of an event.

INSERT FIGURE 3 ABOUT HERE

Panels A and B of Figure 3 clearly show that the two outcome variables employed in the models, $Espread_{i,d}$ and $Stddev_{i,d}$, have similar trends during the pre-treatment period.[17]

[17] We observe a similar trend for both $Qspread_{i,d}$ and $AbsCha_{i,d}$ as well, for parsimony the results are not presented, but are available upon request.

This implies that our treatment and control groups can be used in the DiD framework and our modelling approach satisfies the parallel trend assumption requirement.

$C_{k,i,d}$ is a set of k control variables, which includes $Momentum_{i,d}$, $InvPri_{i,d}$, $Stddev_{i,d}$ (in the liquidity equations), $Espread_{i,d}$ (in the volatility equations), $lnTV_{i,d}$, $TimeT_{i,d}$, $Depth_{i,d}$, $Transactions_{i,d}$, and $Macro_{i,d}$. $Momentum_{i,d}$ is the first lag of daily return ($Momentum_{i,d}$ is the return of stock i on day *d-1*), $InvPri_{i,d}$ is the inverse of last transaction price, $lnTV_{i,d}$ is the natural logarithm of trading volume, $TimeT_{i,d}$ is a trend variable starting at 0 at the beginning of the sample period and increasing by one every trading day d, $Depth_{i,d}$ is computed as the sum of ask and bid sizes, $Transactions_{i,d}$ is the number of transactions and $Macro_{i,d}$ is a dummy taking the value 1 for days with macroeconomic announcements, and 0 otherwise. $Stddev_{i,d}$ and $Espread_{i,d}$ are as previously defined. γ_1 captures any common effects that might have impacted all stocks following the upgrade, γ_2 captures any pre-existing differences between the treatment and control groups. γ_3, the key coefficient, captures the interaction of $Event_d$ and $Treatment_i$ and thus estimates any incremental effect of the upgrades on the treatment group. The model is estimated with firm and time fixed effects, and standard errors are robust to heteroscedasticity and autocorrelation. Similar to the main fixed effects models, we estimate the model for the full sample and stock quartiles. The DiD model is also estimated under various specifications, with and without the control variables.[18]

INSERT TABLE 9 ABOUT HERE

Table 9 reports the estimation results for when $DP_{i,d}$ in Equation (5) corresponds to either the $Qspread_{i,d}$ and $Espread_{i,d}$.

[18] We find that there is no material difference in the coefficients of interest between the two specifications. For parsimony, we present the results with control variables only.

The interaction coefficients (γ_3) suggest that the technological upgrades are linked with decreases of about 4.5bps and 10bps in $Qspread_{i,d}$ and $Espread_{i,d}$ respectively for the treated group of stocks, when compared to the control group. Both estimates are statistically significant at the 0.01 level. In order to put the economic significance of this result into some perspective, recall that the average latency reduction from the two upgrades, based on our analysis (see Panel C in Table 3 and Footnote 12), is about 2% or 0.08ms (2% * 4.39). Thus, a 2% (0.08ms) reduction in latency is estimated to decrease $Qspread_{i,d}$ ($Espread_{i,d}$) by 4.5/454 = 1% (10/427 = 2.3%). This implies that, following the upgrade, liquidity increases, and the trading costs decrease more for our treatment group relative to the control group, and it further shows that the latency improvements are, over and above other controlled effects, driving stock market liquidity. Importantly, the fact that stocks that were expected to benefit from the technological upgrades see a significant improvement in liquidity allows us to establish a causal relationship between speed and liquidity, while ruling out endogeneity concerns. Therefore, the results are consistent with the earlier fixed effect models. The findings of the DiD frameworks are also consistent with the predictions of Hoffmann (2014) and Jovanovic and Menkveld (2016), and with the empirical findings of Menkveld (2013) and Hendershott et al. (2011), and suggest that speed is generally used by high-frequency market makers as a means of reducing adverse selection risk, thus leading to their provision of a higher level of liquidity. Similar to the earlier estimated fixed effects model for liquidity, while the positive relationship between speed improvements and $Qspread_{i,d}$ is driven by the most active stocks, the positive relationship between speed improvements and $Espread_{i,d}$ is driven by the least active stocks (see Footnote 16). The estimated coefficients of the control variables are generally consistent with the literature. The $\overline{R^2}$ for the $Qspread_{i,d}$ and $Espread_{i,d}$ models are 36% and 30%, respectively. These are substantial explanatory levels for daily frequency estimations.

INSERT TABLE 10 ABOUT HERE

Table 10 reports the estimation results for the volatility measures, i.e. the $AbsCha_{i,d}$ and the $Stddev_{i,d}$ for stock i on day d. The interaction coefficients (γ_3) suggest that the technological upgrades are linked with increases in volatility. $AbsCha_{i,d}$ and $Stddev_{i,d}$ (volatility proxies) increase by 25.50 and 2.8 bps respectively for the treatment group of stocks in comparison to the control group; the changes are statistically significant at 0.01 ($Stddev_{i,d}$) and 0.05 ($AbsCha_{i,d}$) levels. These results imply that a 2% (0.08ms) reduction in latency increases $Stddev_{i,d}$ ($AbsCha_{i,d}$) by about 2.8/312 = 0.89% (25.5/3125 = 0.81%).[19] The economic significance of these estimates is put into some perspective when we recall that the difference between the latencies of microwave and fibre optic cable is about 23 times higher than this reduction (1.9/0.08). Again, the results are a confirmation of the causal link between speed and volatility. Generally, the findings presented in Table 10 further support our earlier results and are consistent with the empirical findings of Shkilko and Sokolov (2016) and Boehmer et al. (2018a). As already noted, the positive relationship between speed and volatility is related to increased aggressiveness in financial markets (see Roşu 2019). The $\overline{R^2}$ for the $AbsCha_{i,d}$ and $Stddev_{i,d}$ models are 26% and 30%, respectively.

6. Economic implications: the trade-off between higher (lower liquidity/volatility) and lower (higher liquidity/volatility) latency

In Section 5, we find that, as argued by various regulators and investors,[20] lower (transmission) latency between financial markets leads to better liquidity and higher volatility. In the market microstructure literature, liquidity and volatility are considered to be two important market quality metrics (see as examples, Hendershott et al. 2011; Malceniece et al. 2019). Specifically, higher liquidity is perceived as good whereas higher volatility might be

[19] The means of daily $Stddev_{i,d}$ and $AbsCha_{i,d}$ are 312 and 3125 bps, respectively.

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

perceived as less beneficial. Thus, our main empirical finding, i.e. lower latency improves liquidity and increases volatility, is unable to show whether speed is beneficial or harmful for financial markets overall; more explicitly, our analysis does not allow us to show the (net) economic implication of latency. Nevertheless, our analysis suggests that there is a trade-off, or at least an inflection point at which the liquidity enhancing benefits of speed are offset by its volatility increasing effects. Therefore, in this section, we examine the relative impact of liquidity, volatility, and latency on expected return by interacting liquidity/volatility with latency. This approach allows us to attempt an estimation of the economic implication of latency, and to investigate the trade-off between higher (lower liquidity/volatility) and lower latency (higher liquidity/volatility). Specifically, we investigate the impacts of volatility and liquidity on expected return during regular trading periods and higher/lower speed periods, and then compare them.

We employ expected return as a key speed-impacting variable for two reasons. Firstly, to an investor, expected return serves as an indicator of profits relative to risk; hence it holds significant economic implications. Secondly, making a valid comparison between high and low latency in this study requires that we employ a variable impacted by both liquidity and volatility. More explicitly, the net economic impact of speed does not only depend on how speed impacts liquidity and volatility, but also on how liquidity and volatility affect capital formation and asset allocation – proxied by expected return in our setting. The literature shows that, indeed, expected return is a direct measure satisfying this criterion. For example, Holmström and Tirole (2001) and Acharya and Pedersen (2005) propose asset pricing models in which expected return is positively correlated with liquidity risk, and Pástor and Stambaugh (2003) empirically test this relationship and find that indeed, expected stock returns are positively related to fluctuations in aggregate liquidity. Poterba and Summers (1986) explain the theoretical (positive) relationship between expected return and volatility, and French et al.

(1987) empirically show the positive relationship between expected return and volatility (see also Pindyck 1984).

In addition to the well-established literature about the relationship between liquidity/volatility and expected return, Malceniece et al. (2019) and Brogaard et al. (2014) show the potential relationship between latency and the cost of capital/market efficiency, i.e. the efficiency of capital allocation. The overwhelming view in the literature is therefore that expected return is impacted by volatility, liquidity, and latency. Developing a framework estimating the marginal impacts of latency-interacted liquidity and volatility proxies is thus a valid approach. Our framework includes the following specification:

$$ER_{i,t} = \alpha_i + \beta_t + \beta_1 Stddev_{i,t} + \beta_2 Espread_{i,t} + \beta_3 latency_{i,t} + \beta_4 Stddev_{i,t} * D_{latency,i,t} + \beta_5 Espread_{i,t} * D_{latency,i,t} + \sum_{k=1}^{4} \delta_k C_{k,i,t} + \varepsilon_{i,t} \quad (6)$$

where $ER_{i,t}$ is the expected return for stock *i* at interval *t* and computed as the mean of returns for the previous 60 transaction intervals.[21] α_i and β_t are stock and time fixed effects, and $latency_{i,t}$ is the *TL* between XSE and Cboe. Our dependent variable, $ER_{i,t}$, is a high frequency approximation of expected return and thus, is suspected of being a noise proxy. Specifically, at such high frequencies, $ER_{i,t}$ may be influenced by microstructure noise. In order to ensure that our results are not susceptible to this possible noise effect, we first follow Cartea and Karyampas (2011) and de-noise our high frequency returns series by using Kalman filtering [see Durbin and Koopman 2012 for more details about Kalman filtering]. Second, we employ $C_{k,i,t}$ control variables to further control for the impact of microstructure noise on our results. $C_{k,i,t}$ includes $Depth_{i,t}$, $InvPri_{i,t}$ and $lnTV_{i,t}$ and $D_{i,t}^{sell}$. $D_{i,t}^{sell}$ is a dummy equaling 1 if a transaction is a sell and included to control for order imbalance.[22] All other variables are as previously defined.

[21] For robustness, we compute expected return as the mean of returns for the previous 30, 90 and 120 intervals. Our results are qualitatively similar to the results reported in Table 11.
[22] We use Lee and Ready (1991) algorithm to classify transactions as buys and sells.

In Equation (6), the most important variables are the interacted variables, $Stddev_{i,t} * D_{latency,i,t}$ and $Espread_{i,t} * D_{latency,i,t}$. $Stddev_{i,t}$ and $Espread_{i,t}$ are as previously defined and $D_{latency,i,t}$ is a dummy capturing different connection methods. Specifically, we estimate three variants of Equation (6). In the first specification, $D_{latency,i,t}$ equals 1 during intervals of microwave connection, i.e. when $latency_{i,t} \leq 4ms$. In the second specification, $D_{latency,i,t}$ equals 1 when information is transmitted via either microwave or fiber optic connections, i.e. when $latency_{i,t} \leq 6ms$. In the third specification, $D_{latency,i,t}$ equals 1 when information is transmitted by predominantly using non-microwave connections (for example, only fiber optic), i.e. when $latency_{i,t} \geq 4ms$. [23]

As noted, we aim to examine the relative impact of liquidity and volatility on $ER_{i,t}$, and therefore, we standardize all variables to compare the size of coefficients on a comparable scale.[24]

INSERT TABLE 11 ABOUT HERE

Table 11 reports the estimation results for Equation (6). Panel A and C capture respective microwave and non-microwave connection periods, whereas Panel B captures the joint periods of microwave and fiber optic connections. First, we discuss the coefficient estimations for two important explanatory variables, i.e. proxies for volatility ($Stddev_{i,t}$) and liquidity ($Espread_{i,t}$). The results reported in all panels show that both $Stddev_{i,t}$ and $Espread_{i,t}$ are individually positively and significantly related with $ER_{i,t}$. Specifically, in Panel A, a one standard deviation increase in $Stddev_{i,t}$ and $Espread_{i,t}$ raises $ER_{i,t}$ by 0.00350

[23] The thresholds are defined by using the numbers provided by various connection providers. It is widely known that fibre optic latency is about 4.2ms which implies that fiber optic cannot transmit information with less than 4 ms latency. Furthermore, as the approximate fibre optic latency is 4.2ms, we assume that the latency between two venues may not exceed 6ms (see https://www.reuters.com/article/us-highfrequency-microwave/lasers-microwave-deployed-in-high-speed-trading-arms-race-idUSBRE9400L920130501).

[24] For robustness, we compute standardize coefficients based on un-standardized variables within the regression model as well. The results obtained are qualitatively similar with the ones we present in the paper.

(12.5%) and 0.00323 (11.5%) standard deviations respectively.[25] This result is economically significant and consistent with predictions of the theoretical models developed by Acharya and Pedersen (2005) and Poterba and Summers (1986). The estimates show that volatility and liquidity risks are indeed priced, and therefore higher volatility and lower liquidity leads to higher $ER_{i,t}$ [see French et al. 1987; Pástor and Stambaugh 2003 for empirical consistency]. The positive $Stddev_{i,t}$ and $ER_{i,t}$ relation further confirms the reliability of our volatility variable, $Stddev_{i,t}$, as a proxy for market/price risk. As noted in Section 5.2, the positive relationship between speed and volatility may not necessarily be a negative effect if increased volatility implies that new information arrives in the market. Explicitly, in our setting, volatility may be the proxy for efficient price discovery rather than market/price risk. The positive $Stddev_{i,t}$ and $ER_{i,t}$ relation confirms that $Stddev_{i,t}$ is a proxy for market risk rather than for price discovery. Otherwise, we would expect to see negative relation between volatility and $ER_{i,t}$, as higher price discovery implies more efficient markets and therefore, high frequency investors would require lower compensation in that case.

Notwithstanding, the main focus for this estimation are the interaction variables' coefficients. These coefficients indicate several important findings. Firstly, we observe that, in Panels A and B, $Espread_{i,t} * D_{latency,i,t}$ is negatively related with $ER_{i,t}$. The implication of these findings is that, while on average illiquidity leads to higher $ER_{i,t}$ (see the coefficient estimates of $Espread_{i,t}$ in Panel A (0.00323), B (0.00490) and C (0.00274)), consistent with our main findings, increased speed (when information is transmitted by using either microwave or both microwave and fiber optic connections) has an ameliorating effect on illiquidity, leading to reduced compensation since the risk presented by illiquidity reduces. However, in Panel C, $Espread_{i,t} * D_{latency,i,t}$ is positively related with $ER_{i,t}$, implying that when

[25] The percentage figure is computed by multiplying the coefficient estimate with standard deviation of $ER_{i,t}$ (0.000717) and then, dividing it by the mean of $ER_{i,t}$ (0.00002).

information is transmitted via non-microwave connections (we expect to observe high latency for these periods), then fast traders require higher return as higher latency is expected to lead to lower liquidity (see Table 5), i.e. higher illiquidity risk. Secondly, in Panels A and B, $Stddev_{i,t} * D_{latency,i,t}$ is positively related to $ER_{i,t}$ and the magnitudes of $Stddev_{i,t} * D_{latency,i,t}$ (0.00366 and 0.00502) are 4.5% and 10.6% higher than the magnitudes of $Stddev_{i,t}$ (0.00350 and 0.00454) implying that, in line with our main findings, increased speed (when information is transmitted via either microwave or both microwave and fiber optic connections) is linked to increased volatility and a demand for higher compensation since the risk presented by volatility increases. However, in Panel C, $Stddev_{i,t} * D_{latency,i,t}$ is negatively related to $ER_{i,t}$ indicating that higher latency leads to lower volatility (see Table 7) and therefore, traders require less compensation for risks presented by volatility during high latency periods (when non-microwave connections are used). The practical implication of these two findings is that the *TL* metric we proposed – the combination of traders' execution latency, exchange latency, and connection latency – is one of the most important determinants of the relationship between volatility/liquidity and expected return. Therefore, it plays a vital role in today's financial markets and the economy. This insight is consistent with recent empirical findings in the literature, for example, the literature on the potential relationship between HFT and the cost of capital (see as an example, Malceniece et al. 2019), and the economic importance of market fragmentation in the efficiency of modern financial markets (see as an example, O'Hara and Ye 2011).

Thirdly, comparing the magnitudes of the coefficients of $Stddev_{i,t} * D_{latency,i,t}$ and $Espread_{i,t} * D_{latency,i,t}$ provides an indication of the net economic impact of speed and various information transmission technologies. Panel A presents the results on the estimation of the impact of speed linked to microwave technology. The results suggest that while using microwave technology to transmit information is linked to increases in $ER_{i,t}$ by 0.00366

(13.1%) standard deviations through its volatility inducing channel, it reduces $ER_{i,t}$ by 0.00398 (14.3%) standard deviations through its liquidity improvement channel; thus, the net impact of using microwave technology is a reduction of $ER_{i,t}$ by 0.00033 (1.2%) standard deviations. The estimates presented in Panel B shows that using both microwave and fiber optic connections is linked to net increases of 0.00008 (0.3%) standard deviations in $ER_{i,t}$, i.e. 0.00008 = 0.00502 – 0.00494. Finally, Panel C's estimates show net increases of 0.00174 (6.20%) standard deviations in $ER_{i,t}$ when non-microwave connections are used for information transmission, i.e. 0.00174 = 0.00358 – 0.00184. The extent of the difference in the net effects on $ER_{i,t}$ by microwave and non-microwave connections is economically meaningful. These results suggest that microwave connection is a better information propagation method because it is linked to a higher net economic benefit. Using both microwave and fiber optic connections does not have any (economically) significant net economic impact and relying only on non-microwave connections results in net economic losses. The practical implication of these is that investors may view the risk of trading in slow markets as being as high as the risk of trading in markets where price volatility is driven by increased speed, perhaps even seeing the former risk as being higher than the latter. Thus, the net effect of low latency is the enhancement of market quality. While latency influences the effects of both liquidity and volatility on expected return, the effect is more defining and stronger for liquidity. It is important to note that the domination of the liquidity channel is prevalent for the most active stocks only (see Quartiles 3 and 4 in Panel A) suggesting cross-sectional differences in the net impact of speed in financial markets. This result may be explained by the concentration of HFTs in the most active stocks.

Our findings are consistent with that of Aït-Sahalia and Saglam (2013), who show that the speed advantage of HFTs improves the welfare of all traders, i.e. both HFTs and low frequency traders, in financial markets, and hence the benefits of high speed outstrips its risks.

The $\overline{R^2}$ for the full sample is 42%, which shows that our model explains a substantial part of the variation in $ER_{i,t}$ at the intraday level. For comparison, return predictability models typically explain single percentage digits (see Chordia et al. 2008; Rzayev and Ibikunle 2019).

7. Conclusion

In this study, we examine the role of latency on market quality by focusing on liquidity and volatility proxies; our findings are four-fold.

By estimating latency between Frankfurt and London from transaction-level data, we provide empirical evidence that prices in London respond to price changes in Frankfurt within 3-5ms. This result is consistent with the latencies claimed by the providers of microwave and fiber optic connections between London and Frankfurt, and thus demonstrates the empirical relevance of our information transmission latency estimation method.

Secondly, we report that decreases in the information transmission latency between the home and satellite markets increases liquidity and volatility in the satellite market; the results are robust to alternative liquidity and volatility proxies and more importantly, economically meaningful. In order to address potential endogeneity concerns we employ a difference-in-difference framework and test the role of technological upgrades in the home market on the liquidity and volatility in the satellite market, by examining cross-listed stocks. We find that, indeed, liquidity and price volatility in the satellite market increases significantly more for stocks directly impacted by the technological innovations in the home market. This allows us to establish a causal relationship between speed on the one hand and liquidity and volatility on the other, thus ruling out endogeneity concerns.

Thirdly, we examine the potential channels through which latency impacts liquidity and volatility. We provide empirical evidence consistent with the predictions of theoretical market microstructure models, suggesting that fast traders use increased speed to avoid being adversely selected. This ability to avoid adverse selection risk leads to a reduction in price impact, which in turn increases liquidity. Faced with lower price impact and higher liquidity, traders engage even more readily, leading to increased aggressive trading and higher price volatility.

The positive effect of speed on market quality through the enhancement of liquidity and its adverse effect on market quality through its increasing of volatility implies a trade-off between speed's positive and negative effects. Therefore, we investigate the relative impact of liquidity, volatility, and latency on expected return; the latter is driven by the other three. We show that latency is an important determinant for the relationship between volatility/liquidity and expected return, and more importantly, we find that while high speed, enabled by microwave technology, impact market quality via liquidity and volatility, the liquidity improvement effect dominates the heightened volatility effect. This implies that the net effect of low latency is the enhancement of market quality. We further demonstrate that microwave connections have a higher net economic benefit than other information transmission methods in use in today's financial markets.

References

Acharya, V.V., Pedersen, L.H., 2005. Asset pricing with liquidity risk. Journal of Financial Economics 77, 2, 375-410

Aït-Sahalia, Y., Saglam, M., 2013. High frequency traders: Taking advantage of speed. National Bureau of Economic Research

Barber, B.M., Lee, Y., Liu, Y., Odean, T., 2009. Just How Much Do Individual Investors Lose by Trading? The Review of Financial Studies 22, 2, 609-632

Baron, M., Brogaard, J., Hagströmer, B., Kirilenko, A., 2019. Risk and return in high-frequency trading. Journal of Financial and Quantitative Analysis 54, 3, 993-1024

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

Biais, B., Foucault, T., Moinas, S., 2015. Equilibrium fast trading. Journal of Financial Economics 116, 2, 292-313

Boehmer, E., Fong, K.Y., Wu, J., 2018a. Algorithmic trading and market quality: International evidence. In: AFA 2013 San Diego Meetings Paper

Boehmer, E., Li, D., Saar, G., 2018b. The competitive landscape of high-frequency trading firms. The Review of Financial Studies 31, 6, 2227-2276

Boulton, T.J., Braga-Alves, M.V., 2010. The skinny on the 2008 naked short-sale restrictions. Journal of Financial Markets 13, 4, 397-421

Brogaard, J., Hagströmer, B., Nordén, L., Riordan, R., 2015. Trading fast and slow: Colocation and liquidity. The Review of Financial Studies 28, 12, 3407-3443

Brogaard, J., Hendershott, T., Riordan, R., 2014. High-frequency trading and price discovery. The Review of Financial Studies 27, 8, 2267-2306

Brogaard, J., Hendershott, T., Riordan, R., 2017. High frequency trading and the 2008 short-sale ban. Journal of Financial Economics 124, 1, 22-42

Budish, E., Cramton, P., Shim, J., 2015. The high-frequency trading arms race: Frequent batch auctions as a market design response. The Quarterly Journal of Economics 130, 4, 1547-1621

Cartea, Á., Karyampas, D., 2011. Volatility and covariation of financial assets: A high-frequency analysis. Journal of Banking & Finance 35, 12, 3319-3334

Chakrabarty, B., Jain, P.K., Shkilko, A., Sokolov, K., 2015. Speed of market access and market quality: Evidence from the SEC naked access ban.

Chordia, T., Roll, R., Subrahmanyam, A., 2008. Liquidity and market efficiency. Journal of Financial Economics 87, 2, 249-268

Collin-Dufresne, P., Fos, V., 2016. Insider trading, stochastic liquidity, and equilibrium prices. Econometrica 84, 4, 1441-1475

Durbin, J., Koopman, S.J., 2012. Time series analysis by state space methods. Oxford university press.

Foucault, T., Hombert, J., Roşu, I., 2016. News trading and speed. The Journal of Finance 71, 1, 335-382

Foucault, T., Kozhan, R., Tham, W.W., 2017. Toxic arbitrage. The Review of Financial Studies 30, 4, 1053-1094

French, K.R., Schwert, G.W., Stambaugh, R.F., 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 1, 3-29

Gonzalo, J., Granger, C., 1995. Estimation of common long-memory components in cointegrated systems. Journal of Business & Economic Statistics 13, 1, 27-35

Grammig, J., Melvin, M., Schlag, C., 2005. Internationally cross-listed stock prices during overlapping trading hours: price discovery and exchange rate effects. Journal of Empirical Finance 12, 1, 139-164

Hagströmer, B., Nordén, L., 2013. The diversity of high-frequency traders. Journal of Financial Markets 16, 4, 741-770

Hasbrouck, J., 1995. One security, many markets: Determining the contributions to price discovery. The Journal of Finance 50, 4, 1175-1199

Hasbrouck, J., Saar, G., 2013. Low-latency trading. Journal of Financial Markets 16, 4, 646-679

Hendershott, T., Jones, C.M., Menkveld, A.J., 2011. Does algorithmic trading improve liquidity? The Journal of Finance 66, 1, 1-33

Hendershott, T., Moulton, P.C., 2011. Automation, speed, and stock market quality: The NYSE's hybrid. Journal of Financial Markets 14, 4, 568-604

Hoffmann, P., 2014. A dynamic limit order market with fast and slow traders. Journal of Financial Economics 113, 1, 156-169

Holmström, B., Tirole, J., 2001. LAPM: A liquidity-based asset pricing model. The Journal of Finance 56, 5, 1837-1867

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

Jovanovic, B., Menkveld, A.J., 2016. Middlemen in limit order markets.

Karpoff, J.M., 1987. The relation between price changes and trading volume: A survey. Journal of Financial and Quantitative Analysis 22, 1, 109-126

Kelley, E.K., Tetlock, P.C., 2013. How Wise Are Crowds? Insights from Retail Orders and Stock Returns. The Journal of Finance 68, 3, 1229-1265

Kirilenko, A., Kyle, A.S., Samadi, M., Tuzun, T., 2017. The Flash Crash: High-frequency Trading in an Electronic Market. The Journal of Finance 72, 3, 967-998

Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica 53, 6, 1315-1335

Laughlin, G., Aguirre, A., Grundfest, J., 2014. Information transmission between financial markets in Chicago and New York. Financial Review 49, 2, 283-312

Laumonier, A., 2016. HFT in the banana land. Blog SiM (Ed.)

Lee, C.M., Ready, M.J., 1991. Inferring trade direction from intraday data. The Journal of Finance 46, 2, 733-746

Madhavan, A., Richardson, M., Roomans, M., 1997. Why do security prices change? A transaction-level analysis of NYSE stocks. The Review of Financial Studies 10, 4, 1035-1064

Malceniece, L., Malcenieks, K., Putniņš, T.J., 2019. High frequency trading and comovement in financial markets. Journal of Financial Economics 134, 2, 381-399

Menkveld, A.J., 2013. High frequency trading and the new market makers. Journal of Financial Markets 16, 4, 712-740

Menkveld, A.J., Zoican, M.A., 2017. Need for speed? Exchange latency and liquidity. The Review of Financial Studies 30, 4, 1188-1228

O'Hara, M., Ye, M., 2011. Is market fragmentation harming market quality? Journal of Financial Economics 100, 3, 459-474

Pástor, Ľ., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 3, 642-685

Petersen, M.A., Fialkowski, D., 1994. Posted versus effective spreads: Good prices or bad quotes? Journal of Financial Economics 35, 3, 269-292

Pindyck, R.S., 1984. Risk, Inflation, and the Stock Market. The American Economic Review 74, 3, 335-351

Poterba, J.M., Summers, L.H., 1986. The Persistence of Volatility and Stock Market Fluctuations. The American Economic Review 76, 5, 1142-1151

Putniņš, T.J., 2013. What do price discovery metrics really measure? Journal of Empirical Finance 23, 68-83

Roşu, I., 2019. Fast and slow informed trading. Journal of Financial Markets 43, 1-30

Rzayev, K., Ibikunle, G., 2019. A state-space modeling of the information content of trading volume. Journal of Financial Markets 46,

Shkilko, A., Sokolov, K., 2016. Every cloud has a silver lining: Fast trading, microwave connectivity and trading costs.

Wang, J., 1993. A model of intertemporal asset prices under asymmetric information. The Review of Economic Studies 60, 2, 249-282

Yan, B., Zivot, E., 2010. A structural analysis of price discovery measures. Journal of Financial Markets 13, 1, 1-19

Zhang, F., 2010. High-frequency trading, stock volatility, and price discovery.

Figure 1. A map of microwave networks connecting the British Isles to continental Europe

Microwave networks between the UK and continental Europe as mapped out by Laumonier (2016). The providers of the microwave networks are also indicated.

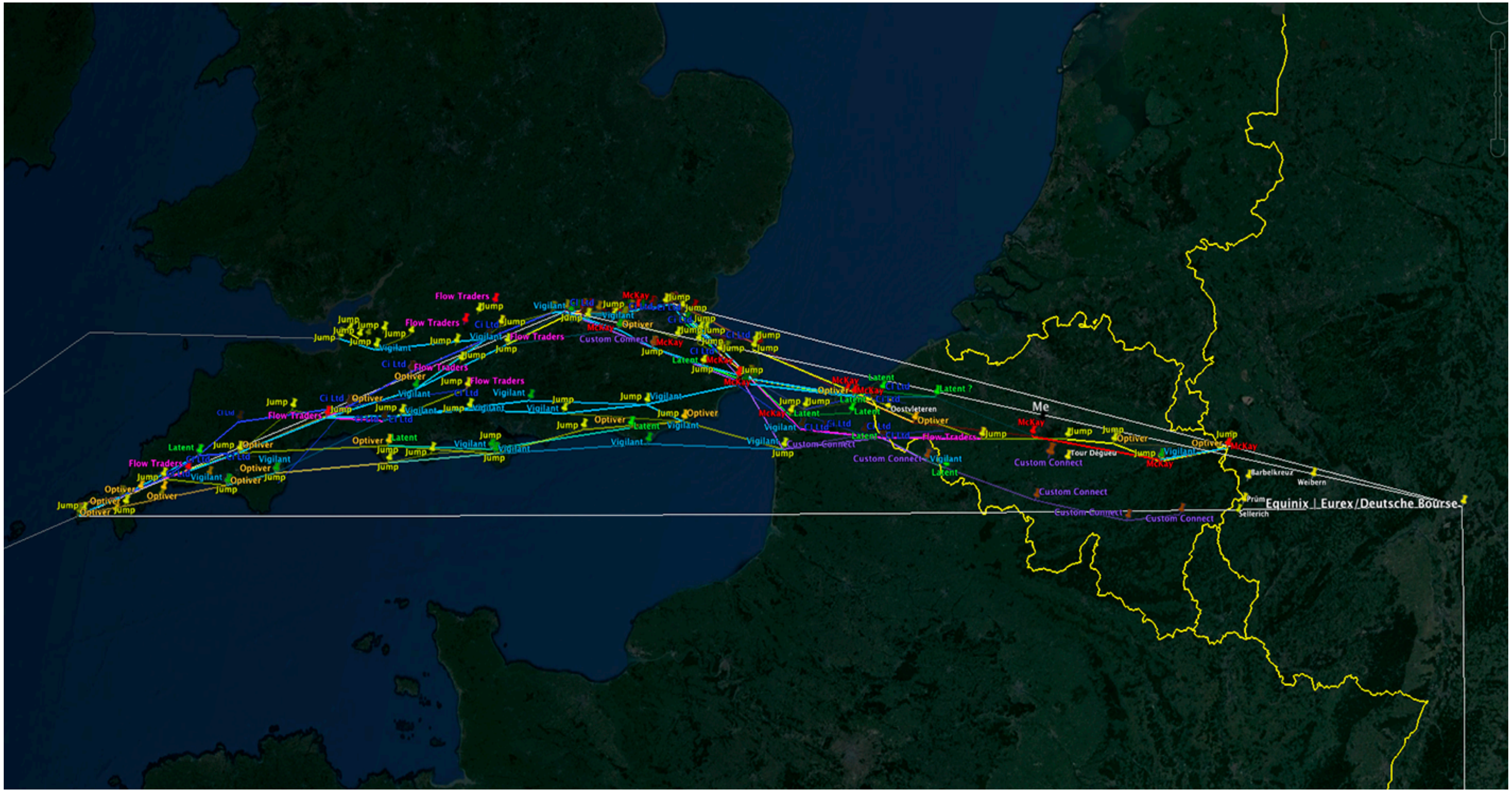


Figure 2. Information transmission latency over time

This figure plots the information transmission latency from June 2017 to July 2017. The period includes 21 trading days before and after a speed-inducing technological upgrade. The vertical bar indicates the technological upgrade, "New T7 Trading Technology", which took effect on July 3, 2017. The sample consists of the 100 most active German stocks cross-listed on XSE and Cboe.

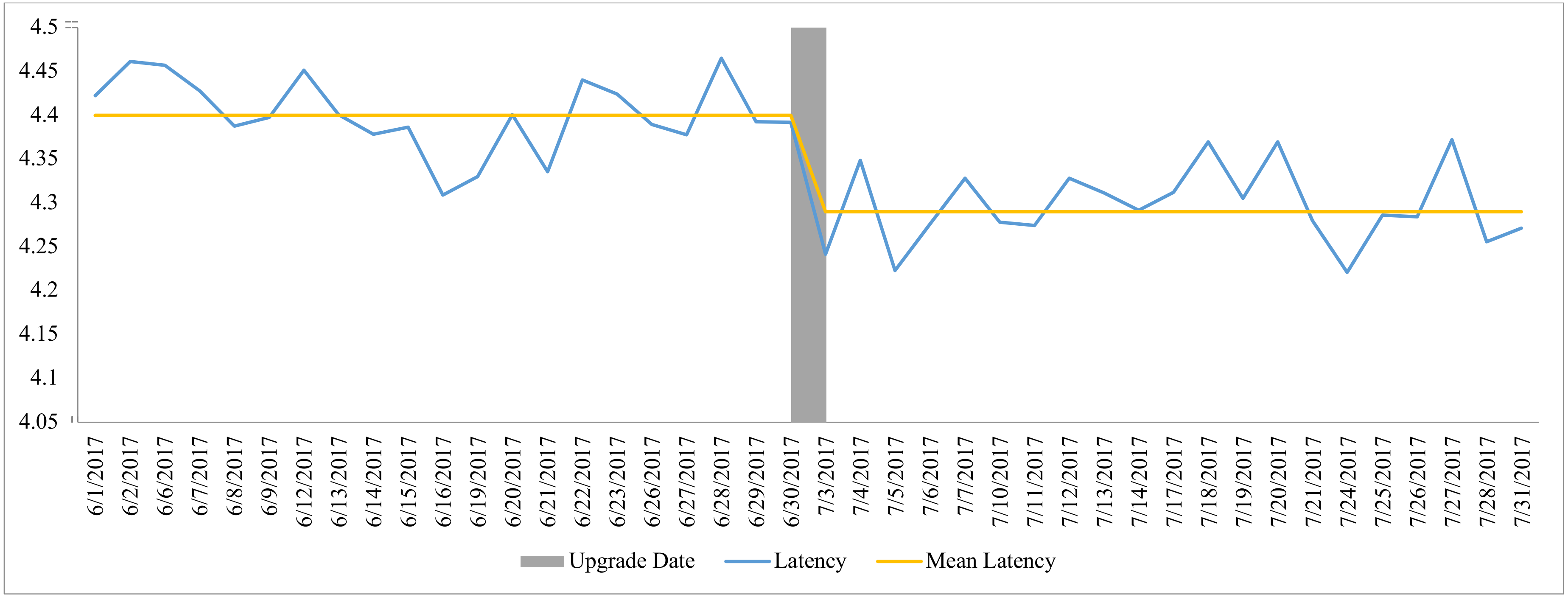
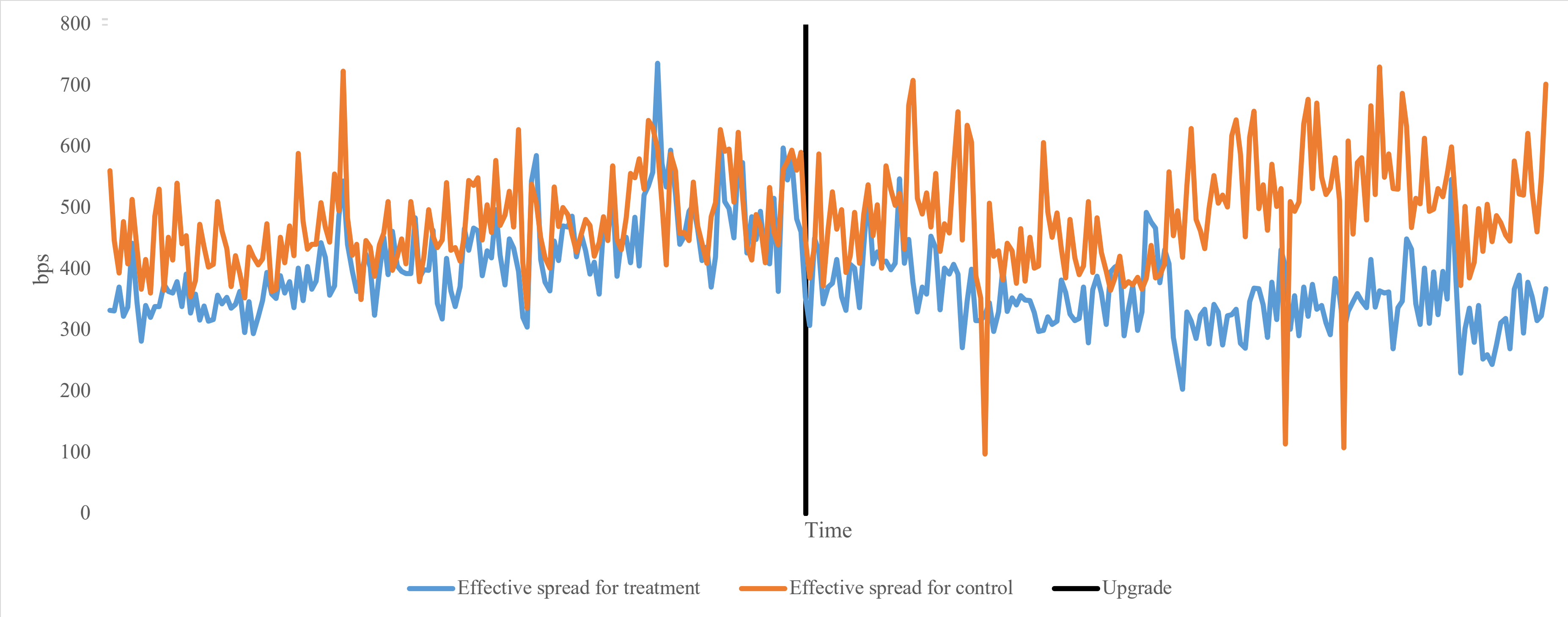


Figure 3. Evolution of outcome variables for treatment and control groups
This figure plots the evolution of two outcome variables, the effective spread and the standard deviation of stock returns prior to and after two technological upgrades on July 3, 2017 and April 9, 2018. The sample period covers [-4; +4 months] intervals around each upgrade. The vertical bar indicates the technological upgrade. The treatment group consists of the 100 most active German stocks cross-listed on XSE and Cboe and the control group includes the 100 stocks listed on Cboe, but ***not*** cross-listed on XSE.

Panel A. Evolution of the effective spread around technological upgrades



Panel B. Evolution of the standard deviation of stock returns around technological upgrades

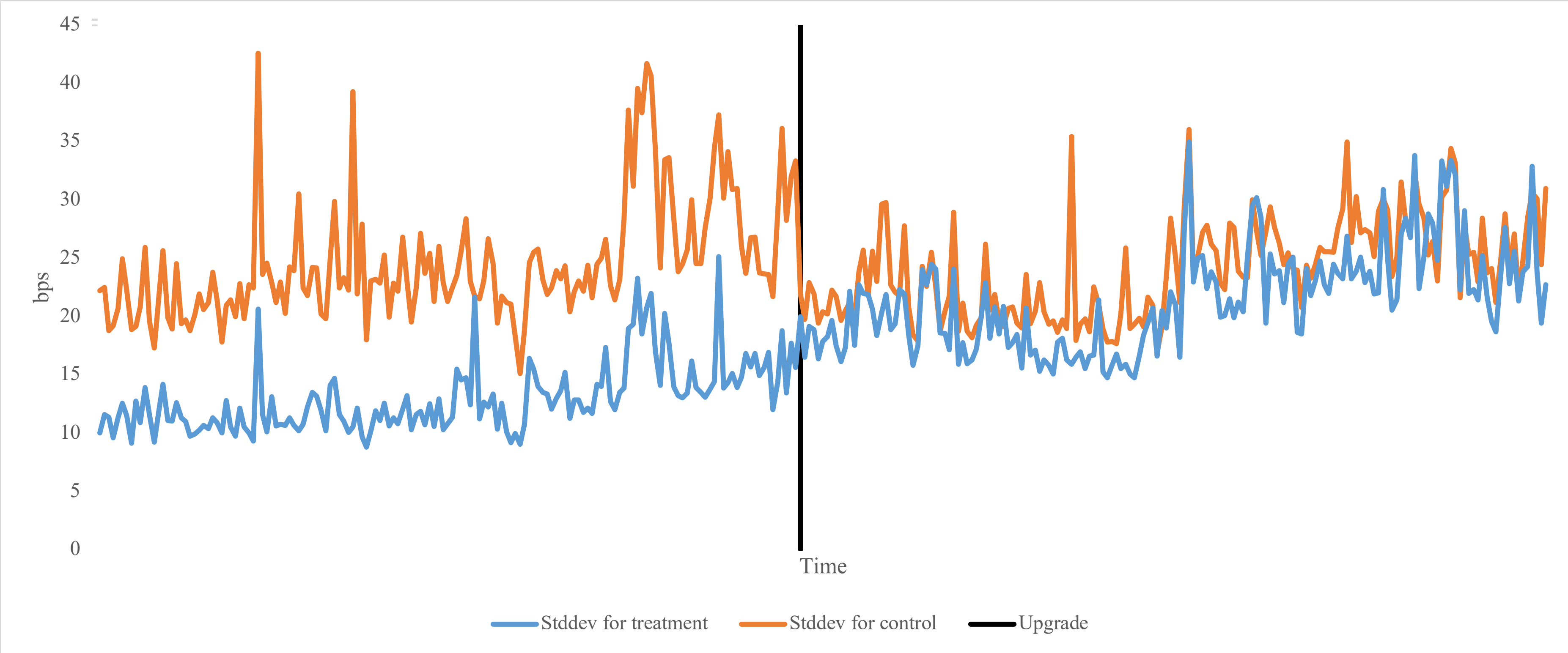


Table 1. Transactions' summary statistics and statistical tests

Panels A and B respectively present trading summary statistics for XSE and Cboe. Panel C reports the statistical tests of the trading summary differences between the XSE and Cboe. The statistical tests conducted are two-sample t-tests and pairwise Wilcoxon-Mann-Whitney tests. The sample consists of the 100 most active German stocks cross-listed on the XSE and Cboe. The sample period covers March 2017 to August 2018. Stocks are classified into quartiles using Euro trading volume.

Panel A

Trading activity: XSE				
	Average trading volume per stock (€'000,000)	Average trading volume per stock (000,000s)	Average transactions per stock (000s)	Average trade size per Stock (€'000)
Full sample	16,263.46	428.56	984.02	14.94
Least active	2,388.44	74.33	335.89	7.31
Quartile 2	4,717.94	145.04	557.78	10.92
Quartile 3	10,556.57	213.05	933.38	14.03
Most active	46,835.87	1,267.65	2,083.09	27.19

Panel B

Trading activity: Cboe				
Full sample	2,739.96	64.09	356.29	6.87
Least active	312.36	10.81	80.25	3.92
Quartile 2	667.55	18.67	165.23	5.72
Quartile 3	1,539.50	31.12	320.37	6.91
Most active	8,440.41	195.75	859.32	10.92

Panel C

Trading activity (Full sample)				
XSE – Cboe	13,523.5***	364.47***	627.73***	8.07***
t-test p-value	< 0.001	< 0.001	< 0.001	< 0.001
W-M-W test p-value	< 0.001	< 0.001	< 0.001	< 0.001

Table 2. Price discovery analysis

This table presents the results for three different price discovery metrics estimating the share of price discovery for XSE and Cboe. *IS* is the information share metric as developed by Hasbrouck (1995), *CS* is the component share metric based on Gonzalo and Granger (1995), and *ILS* is the information leadership share as defined by Putniņš (2013). All estimates are computed based on price samples at the one-second frequency. The sample consists of the 100 most active German stocks cross-listed on XSE and Cboe. The sample period covers March 2017 to August 2018. Stocks are classified into quartiles using Euro trading volume.

	IS	CS	ILS
Full sample	0.69	0.64	0.61
Least active	0.63	0.60	0.56
Quartile 2	0.61	0.58	0.56
Quartile 3	0.68	0.64	0.58
Most active	0.76	0.71	0.61

Table 3. Information transmission latency between XSE and Cboe

This table presents different statistics for the information transmission latency between XSE and Cboe. Panel A reports the number of responses on Cboe to price-changing trades on XSE for different time bins in milliseconds (ms) for the quartiles and full sample of stocks; stocks are classified into quartiles using Euro trading volume. Panel B presents the mean and standard deviation of the information transmission latency between XSE and Cboe for each quartile and the full sample of stocks. Panel C shows the average information transmission latencies for 21 trading days before and after a technological upgrade on July 3, 2017. The statistical tests conducted are two-sample t-tests and pairwise Wilcoxon-Mann-Whitney tests. The sample consists of the 100 most active German stocks cross-listed on XSE and Cboe. The sample period covers March 2017 to August 2018.

Panel A

Speed	Full sample		Least active		Quartile 2		Quartile 3		Most active	
(ms)	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
3	936,646	48.61	63,563	49.05	108,325	46.50	187,528	44.76	577,230	50.39
4	286,962	14.89	19,041	14.69	36,303	15.58	63,498	15.16	168,120	14.68
5	332,286	17.24	21,742	16.78	41,457	17.79	75,439	18.01	193,648	16.91
6	100,435	5.21	6,496	5.01	11,959	5.13	23,531	5.62	58,449	5.10
7	81,733	4.24	5,933	4.58	10,862	4.66	20,686	4.94	44,252	3.86
8	75,895	3.94	5,281	4.08	9,976	4.28	19,924	4.76	40,714	3.55
9	62,679	3.25	4,106	3.17	7,700	3.31	15,834	3.78	35,039	3.06
10	50,364	2.61	3,415	2.64	6,389	2.74	12,517	2.99	28,043	2.45

Panel B

Full sample		Quartile 1 (least active)		Quartile 2		Quartile 3		Quartile 4 (most active)	
Mean (ms)	St. Dev	Mean (ms)	St. Dev	Mean (ms)	St. Dev	Mean (ms)	St. Dev	Mean (ms)	St. Dev
4.39	1.86	4.39	1.87	4.45	1.88	4.55	1.94	4.32	1.83

Panel C

Period	Average latency for the full sample
Before upgrade	4.40
After upgrade	4.30
Difference	0.10***
t-test p value	< 0.001
W-M-W test p value	< 0.001

Table 4. Summary statistics and correlation matrix for explanatory variables

This table reports the summary statistics and correlation matrix for the main variables. Panel A presents the mean and standard deviation of the main variables and Panel B shows the correlation matrix. All variables are computed for the Cboe. $Qspread_{i,t}$ is computed as the difference between ask and bid prices for stock i corresponding to transaction t, $Espread_{i,t}$ is measured as twice the absolute value of the difference between the transaction price and the prevailing bid-ask spread for stock i and transaction t, $AbsCha_{i,t}$ is computed as the absolute value of transaction price differences between the time of transaction t and transaction t-1, $Stddev_{i,t}$ is calculated as the standard deviation of returns for contemporaneous and previous transactions (transactions at time t and t-1) for stock i, , $InvPri_{i,t}$ is the inverse of the transaction price for stock i and transaction t, $lnTV_{i,t}$ is the natural logarithm of trading volume for stock i at time t, $Depth_{i,t}$ is the sum of prevailing bid and ask sizes for stock i corresponding to transaction t and $Momentum_{i,t}$ is the first lag of the stock return for stock i at the time of transaction t (momentum for time t is the stock return at time t-1), $latency_{i,t}$ is the transmission latency between Frankfurt and London for stock i and transaction t and $PRIMP_{i,t}$ is a price impact for stock i at time t and computed as $2q_t(mid_{t+1} - mid_t)$, where q_t is the direction of trade, mid_t and mid_{t+1} are the mid-quotes for transaction t and t+1. The sample consists of the 100 most active German stocks cross-listed on XSE and Cboe. The sample period covers March 2017 to August 2018. Stocks are classified into quartiles using Euro trading volume.

Panel A

Variables	**Full sample**		**Least active**		**Quartile 2**		**Quartile 3**		**Most active**	
	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
$Qspread_{i,t}$(bps)	454.24	1274	717.19	1445	709.86	2202	610.38	1216	289.61	544.66
$Espread_{i,t}$ (bps)	427.25	1190	670.24	1387	666.489	2063	559.01	997.11	275.43	515.22
$AbsCha_{i,t}$ (bps)	327.63	718.26	460.13	806.78	437.37	1145	371.46	629.75	255.59	444.52
$Stddev_{i,t}$ (bps)	13.35	275.99	20.90	140.18	15.90	315.42	30.99	348.32	8.88	271.96
$InvPri_{i,t}$ (bps)	302.16	340.52	363.80	557.58	217.24	134.89	423.11	319.73	307.01	329.44
$lnTV_{i,t}$	3.88	1.30	3.53	1.26	3.57	1.19	3.93	1.23	4.06	1.32
$Depth_{i,t}$	424.83	724.68	267.25	647.72	233.48	304.81	351.47	802.66	535.17	812.43
$Momentum_{i,t}$ (bps)	0.61	276.35	0.45	141.76	0.87	315.81	1.393	349.91	0.46	272.12
$PRIMP_{i,t}$ (bps)	254.01	1.21	366.61	1.97	347.62	1.94	324.98	1.41	197.11	0.74

Panel B

	$Espread_{i,t}$	$Qspread_{i,t}$	$AbsCha_{i,t}$	$Stddev_{i,t}$	$InvPri_{i,t}$	$lnTV_{i,t}$	$Depth_{i,t}$	$Momentum$	$latency_{i,t}$	$PRIMP_{i,t}$
$Espread_{i,t}$	1									
$Qspread_{i,t}$	0.96	1								
$AbsCha_{i,t}$	0.48	0.47	1							
$Stddev_{i,t}$	0.02	0.02	0.02	1						
$InvPri_{i,t}$	-0.16	-0.15	-0.20	0.00	1					

$lnTV_{i,t}$	-0.15	-0.14	-0.18	-0.00	0.47	1				
$Depth_{i,t}$	-0.10	-0.10	-0.12	-0.00	0.41	0.40	1			
$Momentum$	0.01	0.0	0.00	0.00	-0.00	-0.00	0.00	1		
$latency_{i,t}$	0.02	0.02	0.00	0.00	0.00	-0.03	-0.01	0.00	1	
$PRIMP_{i,t}$	0.02	0.02	0.04	0.14	0.01	0.01	0.01	0.15	0.00	1

Table 5. Latency and liquidity

This table reports the coefficient estimates from the following regression model:

$$Spread_{i,t} = \alpha_i + \beta_t + \gamma latency_{i,t} + \sum_{k=1}^{5} \delta_k C_{k,i,t} + \varepsilon_{i,t}$$

where $Spread_{i,t}$ corresponds to one of quoted ($Qspread_{i,t}$) or effective ($Espread_{i,t}$) spread for stock *i* and transaction *t*, α_i and β_t are stock and time fixed effects, $latency_{i,t}$ is the transmission latency between Frankfurt and London for stock *i* and transaction *t*. $C_{k,i,t}$ is a set of *k* control variables, which includes the standard deviation of stock returns ($Stddev_{i,t}$) for stock *i* and transaction *t* as a proxy for volatility, the inverse of price ($InvPri_{i,t}$) for stock *i* and transaction *t*, the natural logarithm of trading volume ($lnTV_{i,t}$) for stock *i* and transaction *t*, market depth ($Depth_{i,t}$) for stock *i* and transaction *t,* and momentum ($Momentum_{i,t}$) for stock *i* and transaction *t*. $Qspread_{i,t}$ is computed as the difference between ask and bid prices for stock *i* corresponding to transaction *t*, $Espread_{i,t}$ is measured as twice the absolute value of the difference between the transaction price and the prevailing bid-ask spread for stock *i* and transaction *t*, $Stddev_{i,t}$ is calculated as the standard deviation of returns for contemporaneous and previous transactions (transactions at time *t* and *t-1*) for stock *i*, $InvPri_{i,t}$ is the inverse of the transaction price for stock *i* and transaction *t*, $lnTV_{i,t}$ is the natural logarithm of trading volume for stock *i* at time *t*, $Depth_{i,t}$ is the sum of prevailing bid and ask sizes for stock *i* corresponding to transaction *t* and $Momentum_{i,t}$ is the first lag of the stock return for stock *i* at the time of transaction *t* (momentum for time *t* is the stock return at time *t-1*). The sample consists of the 100 most active German stocks that are cross-listed in XSE and Cboe. All variables, except $latency_{i,t}$, are computed for the Cboe. Stocks are classified into quartiles using Euro trading volume. The sample period covers March 2017 to August 2018. Standard errors are robust to heteroscedasticity and autocorrelation and t-statistics are reported in parentheses. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

Panel A

	Dependent variable: $\boldsymbol{Qspread_{i,t}}$				
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$latency_{i,t}$	0.988x10^{-3}***	0.112x10^{-3}***	0.111x10^{-3}***	0.166x10^{-3}***	0.656x10^{-3}***
	(25.49)	(6.67)	(7.52)	(12.83)	(26.87)
$Stddev_{i,t}$	0.280x10^{-1}***	0.144***	0.267***	0.381x10^{-1}***	0.139x10^{-1}***
	(9.90)	(6.39)	(12.10)	(4.22)	(8.50)
$InvPri_{i,t}$	0.280x10^{-3}	0.599	-0.475	-2.02	0.214
	(0.01)	(1.15)	(-0.78)	(-1.53)	(1.56)
$lnTV_{i,t}$	0.181x10^{-2}***	0.166x10^{-2}***	0.385x10^{-2}***	0.297x10^{-2}***	0.910x10^{-3}***
	(26.18)	(5.57)	(14.42)	(12.18)	(21.21)
$Depth_{i,t}$	0.162x10^{-5}***	0.743x10^{-5}***	0.340x10^{-5}***	0.137x10^{-4}***	0.397x10^{-6}***
	(10.84)	(12.37)	(4.19)	(12.15)	(5.01)
$Momentum_{i,t}$	0.233x10^{-1}***	0.372x10^{-1}*	0.118x10^{-1}	0.694x10^{-1}***	0.544x10^{-2}***
	(8.46)	(1.85)	(0.59)	(8.10)	(3.35)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes

$\boldsymbol{R^2}$	41.6%	24.8%	20.9%	48.5%	25.9%

Panel B

Dependent variable: $\boldsymbol{Espread_{i,t}}$					
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$latency_{i,t}$	$0.671\text{x}10^{-3}$***	$0.632\text{x}10^{-3}$***	$0.605\text{x}10^{-3}$***	$0.105\text{x}10^{-2}$***	$0.525\text{x}10^{-3}$***
	(18.43)	(4.72)	(4.22)	(8.55)	(22.69)
$Stddev_{i,t}$	$0.248\text{x}10^{-1}$***	0.142***	0.244***	$0.369\text{x}10^{-1}$***	$0.109\text{x}10^{-1}$***
	(9.35)	(7.92)	(11.40)	(4.33)	(7.05)
$InvPri_{i,t}$	$-0.821\text{x}10^{-1}$	$-0.348\text{x}10^{-1}$	$-0.752\text{x}10^{-1}$	-2.32*	0.173
	(-0.42)	(-0.08)	(-0.13)	(-1.87)	(1.33)
$lnTV_{i,t}$	$0.841\text{x}10^{-3}$***	$0.552\text{x}10^{-3}$**	$0.201\text{x}10^{-2}$***	$0.101\text{x}10^{-2}$***	$0.497\text{x}10^{-3}$***
	(12.91)	(2.33)	(7.80)	(4.35)	(12.22)
$Depth_{i,t}$	$0.108\text{x}10^{-5}$***	$0.560\text{x}10^{-5}$***	$0.234\text{x}10^{-5}$***	$0.116\text{x}10^{-4}$***	$0.197\text{x}10^{-7}$
	(7.70)	(11.77)	(2.99)	(10.94)	(0.26)
$Momentum_{i,t}$	$0.229\text{x}10^{-1}$***	$0.169\text{x}10^{-1}$	$-0.241\text{x}10^{-1}$	$0.740\text{x}10^{-1}$***	$0.559\text{x}10^{-2}$***
	(8.85)	(1.07)	(-1.25)	(9.14)	(3.63)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
$\overline{\boldsymbol{R^2}}$	40.9%	29.9%	19.7%	47.5%	25.5%

Table 6. Price impact and latency: a test of the "adverse selection avoidance" channel

This table reports the coefficient estimates from the following regression model:

$$PRIMP_{i,t} = \alpha_i + \beta_t + \gamma latency_{i,t} + \sum_{k=1}^{6} \delta_k C_{k,i,t} + \varepsilon_{i,t}$$

where $PRIMP_{i,t}$ corresponds to the price impact for stock *i* and transaction *t*, α_i and β_t are stock and time fixed effects, $latency_{i,t}$ is information transmission latency between Frankfurt and London. $PRIMP_{i,t} = 2q_t(mid_{t+1} - mid_t)$, where q_t is the direction of trade, mid_t and mid_{t+1} are the mid-quotes for transaction *t* and *t+1*. $C_{k,i,t}$ is a set of *k* control variables, which includes the standard deviation of stock returns ($Stddev_{i,t}$) for stock *i* and transaction *t* as a proxy for volatility, the effective spread ($Espread_{i,t}$) for stock *i* and transaction *t* as a proxy for liquidity, the inverse of price ($InvPri_{i,t}$) for stock *i* and transaction *t*, the natural logarithm of trading volume ($lnTV_{i,t}$) for stock *i* and transaction *t*, market depth ($Depth_{i,t}$) for stock *i* and transaction *t*, and momentum ($Momentum_{i,t}$) for stock *i* and transaction *t*. $Stddev_{i,t}$ is calculated as the standard deviation of returns for contemporaneous and previous transactions (transactions at time *t* and *t-1*) for stock *i*, $Espread_{i,t}$ is measured as twice the absolute value of the difference between the transaction price and the prevailing bid-ask spread for stock *i* at time *t*, $InvPri_{i,t}$ is the inverse of the transaction price for stock *i* at time *t*, $lnTV_{i,t}$ is the natural logarithm of trading volume for stock *i* and transaction *t*, $Depth_{i,t}$ is the sum of prevailing bid and ask sizes for stock *i* corresponding to transaction *t* and $Momentum_{i,t}$ is the first lag of the stock return for stock *i* and transaction *t* (momentum for transaction *t* is the stock return transaction *t-1*). The sample consists of the 100 most active German stocks cross-listed on XSE and Cboe. All variables, except $latency_{i,t}$, are computed for the Cboe. Stocks are classified into quartiles using Euro trading volume. The sample period covers March 2017 to August 2018. Standard errors are robust to heteroscedasticity and autocorrelation and t-statistics are reported in parentheses. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

	Dependent variable: $PRIMP_{i,t}$				
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$latency_{i,t}$	0.971x10^{-3}**	0.243x10^{-2}	0.108x10^{-2}*	-0.429x10^{-3}	0.333x10^{-2}***
	(2.18)	(0.89)	(1.73)	(-1.26)	(3.10)
$Momentum_{i,t}$	0.502***	-8.426***	-1.059***	0.191x10^{-1}	1.358***
	(15.68)	(-26.33)	(-3.65)	(0.84)	(19.17)
$InvPri_{i,t}$	1.241	-18.942**	7.948	3.971**	-10.334
	(0.51)	(-2.27)	(0.89)	(2.08)	(-0.95)
$Espread_{i,t}$	-0.964x10^{-1}***	-0.325x10^{-1}	-0.115***	-0.159***	-0.470x10^{-1}***
	(-10.86)	(-0.56)	(-3.60)	(-11.52)	(-3.44)
$Stddev_{i,t}$	9.111***	-14.958	-22.525***	12.895***	4.677***
	(277.62)	(-41.40)	(-69.73)	(564.21)	(62.65)
$lnTV_{i,t}$	0.382x10^{-2}***	0.194x10^{-2}	0.571x10^{-2}	0.349x10^{-2}***	0.495x10^{-2}**
	(4.82)	(0.41)	(1.46)	(5.83)	(2.45)
$Depth_{i,t}$	0.435x10^{-6}	0.591x10^{-6}	-0.491x10^{-5}	0.191x10^{-5}*	-0.143x10^{-4}
	(0.25)	(0.06)	(-0.42)	(1.73)	(-1.54)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes

Time fixed effects	Yes	Yes	Yes	Yes	Yes
$\overline{R^2}$	14.1%	27.7%	7.4%	22.9%	14.1%

Table 7. Latency and volatility

This table reports the coefficient estimates from the following regression model:

$$Volatility_{i,t} = \alpha_i + \beta_t + \gamma latency_{i,t} + \sum_{k=1}^{5} \delta_k C_{k,i,t} + \varepsilon_{i,t}$$

where $Volatility_{i,t}$ corresponds to either absolute value of price change ($AbsCha_{i,t}$) or the standard deviation of stock returns ($Stddev_{i,t}$), α_i and β_t are stock and time fixed effects, $latency_{i,t}$ is the information transmission latency between Frankfurt and London and $C_{k,i,t}$ is a set of *k* control variables, which includes the effective spread ($Espread_{i,t}$) for stock *i* and transaction *t* as a proxy for liquidity, the inverse of price ($InvPri_{i,t}$) for stock *i* at time *t*, the natural logarithm of trading volume ($lnTV_{i,t}$) for stock *i* and transaction *t*, market depth ($Depth_{i,t}$) for stock *i* and transaction *t,* and momentum ($Momentum_{i,t}$) for stock *i* and transaction *t. $AbsCha_{i,t}$* is computed as the absolute value of transaction price differences between the time of transaction *t* and transaction *t-1*, $Stddev_{i,t}$ is calculated as the standard deviation of returns for contemporaneous and previous transactions (transactions *t* and *t-1*) for stock *i*, $Espread_{i,t}$ is measured as twice the absolute value of the difference between the transaction price and the prevailing bid-ask spread for stock *i* and transaction *t*, $InvPri_{i,t}$ is the inverse of the price for stock *i* and transaction *t*, $lnTV_{i,t}$ is the natural logarithm of trading volume for stock *i* and transaction *t*, $Depth_{i,t}$ is the sum of prevailing bid and ask sizes for stock *i* corresponding to transaction *t,* and $Momentum_{i,t}$ is the first lag of the stock return for stock *i* and transaction *t* (momentum for transaction *t* is the stock return for transaction *t-1*).The sample consists of the 100 most active German stocks that are cross-listed in XSE and Cboe. All variables, except $latency_{i,t}$, are computed for the Cboe. Stocks are classified into quartiles using Euro trading volume. The sample period covers March 2017 to August 2018. Standard errors are robust to heteroscedasticity and autocorrelation and t-statistics are reported in parentheses. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

Panel A

	Dependent variable: $AbsCha_{i,t}$				
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$latency_{i,t}$	- 0.699x10^{-4}***	- 0.297x10^{-3}***	- 0.274x10^{-3}***	0.142x10^{-4}	- 0.544x10^{-4}***
	(-3.20)	(-3.63)	(-3.49)	(0.21)	(-2.81)
$Espread_{i,t}$	0.129***	0.106***	0.117***	0.126***	0.173***
	(297.96)	(60.75)	(101.04)	(148.27)	(221.64)
$InvPri_{i,t}$	- 0.104	0.387	- 0.463	- 0.722	- 0.833x10^{-1}
	(-0.89)	(1.53)	(-1.43)	(-1.06)	(-0.77)
$lnTV_{i,t}$	0.522x10^{-3}***	0.826x10^{-3}***	0.568x10^{-3}***	0.902x10^{-3}***	0.344x10^{-3}***
	(13.39)	(5.72)	(4.01)	(7.16)	(10.12)
$Depth_{i,t}$	- 0.101x10^{-5}***	- 0.634x10^{-6}**	- 0.856x10^{-6}**	- 0.276x10^{-5}**	- 0.924x10^{-6}**
	(-12.03)	(-2.18)	(-1.99)	(-4.77)	(-14.71)
$Momentum_{i,t}$	- 0.342x10^{-2}**	- 0.158x10^{-1}*	- 0.241x10^{-1}**	- 0.258x10^{-2}	- 0.244x10^{-2}*
	(-2.21)	(-1.65)	(-2.29)	(-0.60)	(-1.89)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes

Time fixed effects	Yes	Yes	Yes	Yes	Yes
$\overline{\boldsymbol{R^2}}$	41.8%	34.5%	28.6%	49.4%	30.1%

Panel B

	Dependent variable: $\boldsymbol{Stddev_{i,t}}$				
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$latency_{i,t}$	- 0.193x10^{-4}** (-1.94)	- 0.252x10^{-4} (-1.18)	- 0.269x10^{-4}* (-1.91)	- 0.279x10^{-4} (-1.24)	- 0.128x10^{-4}*** (-9.10)
$Espread_{i,t}$	0.185x10^{-2}*** (9.35)	0.363x10^{-2}*** (7.92)	0.237x10^{-2}*** (11.40)	0.124x10^{-2}*** (4.33)	0.399x10^{-2}*** (7.05)
$InvPri_{i,t}$	0.430x10^{-1} (0.80)	0.289x10^{-2} (0.04)	- 0.150** (-2.57)	0.109 (0.48)	0.102 (1.30)
$lnTV_{i,t}$	0.928x10^{-5} (0.52)	0.343x10^{-4} (0.91)	0.159x10^{-4} (0.62)	- 0.298x10^{-4} (-0.71)	0.201x10^{-4} (0.82)
$Depth_{i,t}$	- 0.665x10^{-7}* (-1.73)	- 0.370x10^{-8} (-0.05)	- 0.719x10^{-7} (-0.93)	0.281x10^{-7} (0.14)	- 0.781x10^{-7}* (-1.72)
$Momentum_{i,t}$	- 0.668x10^{-1}*** (-94.41)	- 0.152*** (-60.93)	- 0.618x10^{-1}*** (-32.67)	- 0.179*** (-123.03)	- 0.156x10^{-1}*** (-16.83)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
$\boldsymbol{R^2}$	17.8%	25.3%	23.5%	24.8%	22.9%

Table 8. Aggressive trading and latency: a test of the "aggressiveness" channel

This table reports the coefficient estimates from the following logit regression model:

$$Aggressiveness_{i,t} = \alpha_i + \beta_t + \gamma latency_{i,t} + \sum_{k=1}^{6} \delta_k C_{k,i,t} + \varepsilon_{i,t}$$

where $Aggressiveness_{i,t}$ is a binary dependent variable for stock *i* and transaction *t*. Specifically, $Aggressiveness_{i,t}$ equals 1 for aggressive trades and 0 otherwise. In order to delineate trades as aggressive or non-aggressive, we first classify trades on the basis of trade direction (buy or sell) using Lee and Ready (1991) algorithm. We then compare the transaction prices with the prevailing best bid (ask) price for sell (buy) transactions. If a transaction price is below (above) or equal to the prevailing best bid (ask) price we classify the sell (buy) transaction as an aggressive trade. α_i and β_t are stock and time fixed effects, $latency_{i,t}$ is the key variable in the model and the information transmission latency between Frankfurt and London. $C_{k,i,t}$ is a set of k control variables, which includes the standard deviation of stock returns ($Stddev_{i,t}$) for stock *i* and transaction *t* as a proxy for volatility, the effective spread ($Espread_{i,t}$) for stock *i* and transaction *t* as a proxy for liquidity, the inverse of price ($InvPri_{i,t}$) for stock *i* and transaction *t*, the natural logarithm of trading volume ($lnTV_{i,t}$) for stock *i* and transaction *t*, market depth ($Depth_{i,t}$) for stock *i* and transaction *t*, and momentum ($Momentum_{i,t}$) for stock *i* and transaction *t*. $Stddev_{i,t}$ is calculated as the standard deviation of returns for contemporaneous and previous transactions (transactions *t* and *t-1*) for stock *i*, $Espread_{i,t}$ is measured as twice the absolute value of the difference between the transaction price and the prevailing bid-ask spread for stock *i* and transaction *t*, $InvPri_{i,t}$ is the inverse of the transaction price for stock *i* and transaction *t*, $lnTV_{i,t}$ is the natural logarithm of trading volume for stock *i* and transaction *t*, $Depth_{i,t}$ is the sum of prevailing bid and ask sizes for stock *i* corresponding to transaction *t* and $Momentum_{i,t}$ is the first lag of the stock return for stock *i* and transaction *t* (momentum for transaction *t* is the stock return for transaction *t-1*). The sample consists of 100 most active German stocks that cross-listed in XSE and Cboe. All variables, except $latency_{i,t}$, are computed for the Cboe. Stocks are classified into quartiles using Euro trading volume. Marginal effects are reported in brackets and they are computed as the mean of marginal effects across stocks. The sample period covers March 2017 to August 2018. Standard errors are robust to heteroscedasticity and autocorrelation and t-statistics are reported in parenthesis. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

	Dependent variable: $\boldsymbol{Aggressiveness_{i,t}}$				
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$latency_{i,t}$	-0.186x10^{-1}***	-0.398x10^{-1}***	-0.276x10^{-1}***	-0.219x10^{-1}***	-0.123x10^{-1}***
	[-0.284x10^{-2}]	[-0.640x10^{-2}]	[-0.427x10^{-2}]	[-0.332x10^{-2}]	[-0.188x10^{-2}]
	(-19.09)	(-11.09)	(-10.10)	(-10.90)	(-9.48)
$Momentum_{i,t}$	0.105	0.651x10^{-1}	-0.378	0.309	0.924
	[0.161x10^{-1}]	[0.105x10^{-1}]	[-0.584x10^{-1}]	[0.469x10^{-1}]	[0.141]
	(0.84)	(0.28)	(-1.23)	(0.56)	(1.26)
$InvPri_{i,t}$	1.691***	0.726***	1.192***	4.165***	3.862***
	[0.259]	[0.117]	[0.184]	[0.632]	[0.588]
	(25.73)	(2.95)	(10.59)	(10.66)	(39.52)
$Espread_{i,t}$	1.196***	1.028***	1.176***	0.786***	4.799***
	[0.183]	[0.164]	[0.182]	[0.119]	[0.730]
	(35.53)	(8.83)	(14.97)	(19.47)	(49.25)

$Stddev_{i,t}$	-0.107* [-0.164×10^{-1}] (-1.95)	1.037 [0.166] (1.42)	-0.322 [-0.498×10^{-1}] (-1.03)	-0.147 [-0.224×10^{-1}] (-1.43)	-0.113 [-0.171×10^{-1}] (-1.60)
$lnTV_{i,t}$	-0.617×10^{-1}*** [-0.945×10^{-2}] (-36.44)	-0.625×10^{-1}*** [-0.100×10^{-1}] (-9.90)	-0.977×10^{-1}*** [-0.151×10^{-1}] (-20.24)	-0.849×10^{-1}*** [-0.129×10^{-1}] (-22.02)	-0.548×10^{-1}*** [-0.834×10^{-2}] (-24.38)
$Depth_{i,t}$	-0.605×10^{-4}*** [-0.926×10^{-5}] (-22.66)	-0.463×10^{-4}*** [-0.742×10^{-5}] (-14.56)	-0.371×10^{-4}*** [-0.575×10^{-5}] (-16.28)	-0.167×10^{-4}*** [-0.254×10^{-4}] (-17.55)	-0.827×10^{-4}*** [-0.125×10^{-4}] (-19.22)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
McFadden R^2	27.2%	31.1%	14.6%	28.2%	25.7%

Table 9. Difference-in-difference estimation of the effects of latency on liquidity

This table examines the relationship between liquidity and latency by exploiting two technological upgrades on July 3, 2017 and April 9, 2018. Specifically, the table reports coefficient estimates from the following regression model, with observations sampled at the daily frequency:

$$DP_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_d + \gamma_2 Treatment_i + \gamma_3 Event_d \times Treatment_i + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d}$$

where $DP_{i,d}$ corresponds to one of two liquidity proxies: quoted ($Qspread_{i,d}$) and effective ($Espread_{i,d}$) spreads. $Qspread_{i,d}$ is the average of the differences between the ask and bid prices corresponding to each transaction, $Espread_{i,d}$ is a daily average, each intraday value is computed as twice the absolute value of the difference between a transaction's price and the prevailing bid-ask spread. $Event_d$ is a dummy taking the value 0 for the pre-upgrade period and one for the post-upgrade period, and $Treatment_i$ is a dummy taking the value 1 for stocks impacted by the upgrade and 0 for stocks not affected by the upgrade. The treatment group consists of the 100 stocks cross-listed on XSE and Cboe and the control group includes the 100 stocks listed on Cboe, but ***not*** cross-listed on XSE. $C_{k,i,d}$ is a set of k control variables, which includes $Momentum_{i,d}$, $InvPri_{i,d}$, $Stddev_{i,d}$, $lnTV_{i,d}$, $TimeT_{i,d}$, $Depth_{i,d}$, $Transactions_{i,d}$ and $Macro_{i,d}$. $Momentum_{i,d}$ is the first lag of daily return for stock *i* on day *d* ($Momentum_{i,d}$ is the return of stock *i* on day *d-1*), $InvPri_{i,d}$ is the inverse of last transaction price for stock *i* on day *d*, $Stddev_{i,d}$ is the standard deviation of transaction prices for stock *i* during day *d*, $lnTV_{i,d}$ is the natural logarithm of trading volume for stock *i* on day *d*, $TimeT_{i,d}$ is a trend variable for each stock *i* starting at 0 at the beginning of the sample period and increasing by one every trading day *d*, $Depth_{i,d}$ is computed as the sum of ask and bid sizes for stock *i* on day *d*, $Transactions_{i,d}$ is the number of transactions for stock *i* on day *d* and $Macro_{i,d}$ is a dummy for stock *i* and takes the value 1 for days *d*s with macroeconomic announcements and 0 otherwise. Stocks are classified into quartiles using Euro trading volume. Firm and time fixed effects are employed, and standard errors are robust to heteroscedasticity and autocorrelation. t-statistics are reported in parentheses. The sample period covers [-4; +4 months] intervals around each upgrade. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

Panel A

	Dependent variable: $\boldsymbol{Qspread_{i,d}}$				
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$Event_d$	0.103x10^{-2}***	0.147x10^{-3}	0.247x10^{-2}***	0.415x10^{-3}***	0.104x10^{-2}***
	(6.06)	(0.31)	(6.27)	(3.65)	(4.17)
$Treatment_i$	-0.209x10^{-2}***	0.399x10^{-3}	-0.135x10^{-2}***	-0.823x10^{-3}***	-0.293x10^{-2}***
	(-19.38)	(1.26)	(-5.45)	(-11.41)	(-16.23)
$Event_d \times Treatment_i$	-0.453x10^{-3}***	-0.189x10^{-3}	-0.184x10^{-2}***	-0.202x10^{-3}**	-0.252x10^{-3}***
	(-2.95)	(-0.44)	(-5.19)	(-1.98)	(-11.12)
$Momentum_{i,d}$	0.154x10^{-2}***	0.560x10^{-4}	0.191x10^{-2}	0.650x10^{-3}**	0.307x10^{-2}***
	(3.55)	(0.05)	(0.72)	(2.34)	(6.11)
$InvPri_{i,d}$	-0.159x10^{-1}***	-0.711x10^{-2}***	-0.313x10^{-1}***	-0.193x10^{-1}***	-0.225x10^{-1}***
	(-22.30)	(-4.63)	(-20.39)	(-17.72)	(-18.59)
$Stddev_{i,d}$	0.299x10^{-3}***	0.672x10^{-3}***	0.834x10^{-3}*	0.212x10^{-3}***	0.669x10^{-4}
	(3.84)	(3.25)	(1.79)	(4.18)	(0.77)
$lnTV_{i,d}$	0.151x10^{-3}***	-0.122x10^{-3}***	0.638x10^{-4}**	0.154x10^{-3}***	0.204x10^{-3}***

	(13.98)	(-3.53)	(2.47)	(19.55)	(13.72)
$TimeT_{i,d}$	-0.486x10^{-5}***	0.318x10^{-6}	-0.695x10^{-5}*	-0.251x10^{-5}**	-0.788x10^{-5}***
	(-3.15)	(0.07)	(-1.94)	(-2.45)	(-3.50)
$Depth_{i,d}$	0.113x10^{-5}***	0.865x10^{-6}***	0.318x10^{-5}***	-0.651x10^{-5}***	0.340x10^{-7}
	(13.80)	(3.23)	(17.48)	(-6.92)	(0.33)
$Transactions_{i,d}$	0.566x10^{-6}***	0.396x10^{-5}***	0.173x10^{-5}***	0.190x10^{-6}***	0.745x10^{-6}***
	(12.70)	(16.85)	(15.54)	(5.84)	(14.17)
$Macro_{i,d}$	-0.218x10^{-3}***	-0.302x10^{-3}	-0.283x10^{-3}	-0.118x10^{-3}**	-0.239x10^{-3}*
	(-2.61)	(-1.30)	(-1.47)	(-2.12)	(-1.95)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
$\overline{R^2}$	36.3%	35.8%	17.7%	38.6%	48.8%

Panel B

	Dependent variable: $\boldsymbol{Espread_{i,d}}$				
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$Event_d$	0.190x10^{-2}***	0.809x10^{-3}*	0.435x10^{-2}***	0.512x10^{-3}**	0.178x10^{-2}**
	(5.45)	(1.95)	(4.40)	(2.06)	(2.47)
$Treatment_i$	-0.436x10^{-2}***	0.284x10^{-2}***	0.748x10^{-3}	-0.151x10^{-2}***	-0.885x10^{-2}***
	(-19.84)	(10.35)	(1.20)	(-9.64)	(-16.83)
$Event_d \times Treatment_i$	-0.977x10^{-3}***	-0.745x10^{-3}**	-0.404x10^{-2}***	-0.184x10^{-3}	0.243x10^{-3}
	(-3.12)	(-1.99)	(-4.52)	(-0.83)	(0.37)
$Momentum_{i,d}$	0.267x10^{-2}***	-0.181x10^{-3}	0.414x10^{-3}	0.125x10^{-2}**	0.518x10^{-2}***
	(3.02)	(-0.19)	(0.06)	(2.06)	(3.53)
$InvPri_{i,d}$	-0.371x10^{-1}***	-0.160x10^{-1}***	-0.847x10^{-1}***	-0.346x10^{-1}***	-0.595x10^{-1}***
	(-25.44)	(-11.99)	(-21.98)	(-14.50)	(-16.87)
$Stddev_{i,d}$	0.106x10^{-2}***	0.629x10^{-3}***	0.743x10^{-3}	0.242x10^{-2}***	0.454x10^{-3}*
	(6.71)	(3.49)	(0.63)	(21.85)	(1.81)
$lnTV_{i,d}$	0.143x10^{-3}***	-0.617x10^{-3}***	-0.445x10^{-3}***	0.249x10^{-3}***	0.377x10^{-3}***
	(6.52)	(-20.53)	(-6.85)	(14.48)	(8.71)
$TimeT_{i,d}$	-0.713x10^{-5}**	-0.162x10^{-5}	-0.422x10^{-5}	-0.409x10^{-5}*	-0.157x10^{-4}**

	(-2.26)	(-0.43)	(-0.47)	(-1.83)	(-2.39)
$Depth_{i,d}$	0.228x10^{-5}***	0.298x10^{-5}***	0.610x10^{-5}***	-0.100x10^{-5}***	0.872x10^{-7}
	(13.69)	(12.79)	(13.36)	(-4.87)	(0.29)
$Transactions_{i,d}$	0.305x10^{-5}***	0.134x10^{-4}***	0.918x10^{-5}***	0.563x10^{-6}***	0.315x10^{-5}***
	(33.56)	(65.47)	(32.93)	(7.91)	(20.60)
$Macro_{i,d}$	-0.208x10^{-3}	-0.401x10^{-3}**	-0.105x10^{-3}	-0.140x10^{-3}	-0.542x10^{-3}
	(-1.22)	(-1.98)	(-0.22)	(-1.15)	(-1.52)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
$\overline{R^2}$	30.3%	31.5%	21.6%	8.9%	9.2%

Table 10. Difference-in-difference estimation of the effects of latency on volatility

This table examines the relationship between volatility and latency around two technological upgrades on July 3, 2017 and April 9, 2018. Specifically, the table reports coefficient estimates from the following regression model using daily frequencies:

$$DP_{i,d} = \alpha_i + \beta_d + \gamma_1 Event_d + \gamma_2 Treatment_i + \gamma_3 Event_d \times Treatment_i + \sum_{k=1}^{8} \delta_k C_{k,i,d} + \varepsilon_{i,d}$$

where $DP_{i,d}$ corresponds to one of two volatility proxies: absolute value of price changes ($AbsCha_{i,d}$) and standard deviation of stock returns ($Stddev_{i,d}$). $AbsCha_{i,d}$ is the absolute difference between the last prices for stock *i* for days *d* and *d-1*, $Stddev_{i,d}$ is the standard deviation of hourly intraday midquote returns for stock *i* during day *d*. $Event_d$ is a dummy taking the value 0 for the pre-upgrade period and 1 for the post-upgrade period, and $Treatment_i$ is a dummy taking the value 1 for stocks that are impacted by the upgrade and 0 for stocks that are not. The treatment group consists of the 100 stocks cross-listed on XSE and Cboe and the control group includes the 100 stocks listed on Cboe, but ***not*** cross-listed on XSE. $C_{k,i,d}$ is a set of *k* control variables, which includes $Momentum_{i,d}$, $InvPri_{i,d}$, $Espread_{i,d}$, $lnTV_{i,d}$, $TimeT_{i,d}$, $Depth_{i,d}$, $Transactions_{i,d}$ and $Macro_{i,d}$. $Momentum_{i,d}$ is the first lag of daily return for stock *i* on day *d* ($Momentum_{i,d}$ is the return of stock *i* on day *d-1*), $InvPri_{i,d}$ is the inverse of last transaction price for stock *i* on day *d*. $Espread_{i,d}$ is a daily average, each intraday value is computed as twice the absolute value of the difference between a transaction's price and the prevailing bid-ask spread. $lnTV_{i,d}$ is the natural logarithm of trading volume for stock *i* on day *d*, $TimeT_{i,d}$ is a trend variable for each stock *i* starting at 0 at the beginning of the sample period and incrementing by one every trading day *d*, $Depth_{i,d}$ is computed as the sum of ask and bid sized for stock *i* on day *d*, $Transactions_{i,d}$ is the number of transactions for stock *i* on day *d*, and $Macro_{i,d}$ is a dummy for stock *i* taking the value 1 for days *d* with macroeconomic announcements and 0 otherwise. Stocks are classified into quartiles using Euro trading volume. Firm and time fixed effects are employed, and standard errors are robust to heteroscedasticity and autocorrelation. t-statistics are reported in parenthesis. The sample period covers [-4; +4] intervals around each upgrade. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

Panel A

Dependent variable: $\boldsymbol{AbsCha_{i,d}}$					
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$Event_d$	-0.987x10^{-2}	-2.832x10^{-2}	-1.552x10^{-2}	1.389x10^{-3}	-0.989x10^{-2}
	(-0.69)	(-0.95)	(-0.57)	(0.39)	(-0.51)
$Treatment_i$	-0.260x10^{-2}***	-0.814x10^{-2}	-0.497x10^{-2}***	-0.444x10^{-2}	-0.282x10^{-2}**
	(-2.88)	(-0.41)	(-2.90)	(-0.19)	(-2.00)
$Event_d \times Treatment_i$	0.255x10^{-2}**	0.172x10^{-2}	0.463x10^{-2}*	0.459x10^{-2}	0.317x10^{-2}*
	(1.98)	(0.64)	(1.89)	(0.14)	(1.82)
$Momentum_{i,d}$	0.313x10^{-2}	0.348x10^{-2}	0.134x10^{-2}	-0.496x10^{-2}	0.341x10^{-2}
	(0.86)	(0.51)	(0.73)	(-0.06)	(0.87)
$InvPri_{i,d}$	-1.418**	0.803	-3.223***	-5.096	-4.981
	(-2.36)	(0.08)	(-3.01)	(-1.47)	(-0.53)
$Espread_{i,d}$	0.616***	0.295	-0.660	0.325***	0.167***
	(3.84)	(0.52)	(-0.31)	(2.93)	(8.00)

$lnTV_{i,d}$	0.117x10^{-3} (1.31)	-0.344x10^{-3} (-1.59)	0.365x10^{-3}** (2.05)	0.172x10^{-3} (0.68)	0.101x10^{-3} (0.88)
$TimeT_{i,d}$	0.262x10^{-4} (0.20)	0.385x10^{-3} (1.44)	-0.413x10^{-4} (-0.17)	-0.159x10^{-3} (-0.49)	-0.479x10^{-4} (-0.27)
$Depth_{i,d}$	-0.862x10^{-6} (-0.13)	0.898x10^{-5} (0.57)	-0.503x10^{-5} (-0.40)	-0.716x10^{-6} (-0.24)	0.315x10^{-6} (0.39)
$Transactions_{i,d}$	-0.177x10^{-6} (-0.05)	-0.291x10^{-4}* (1.76)	-0.130x10^{-5} (-0.17)	-0.134x10^{-6} (-0.01)	-0.312x10^{-6} (-0.76)
$Macro_{i,d}$	-0.999x10^{-3} (-0.14)	-0.183x10^{-3} (-1.26)	0.133x10^{-3} (0.10)	0.560x10^{-3} (0.32)	0.708x10^{-3} (0.75)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
$\overline{R^2}$	25.9%	8.3%	10.6%	7.7%	46.9%

Panel B

	Dependent variable: $Stddev_{i,d}$				
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$Event_d$	0.114x10^{-3} (1.34)	0.152x10^{-3} (0.83)	0.839x10^{-4} (1.27)	0.402x10^{-5} (0.02)	0.206x10^{-3} (0.91)
$Treatment_i$	-0.225x10^{-3}*** (-4.15)	-0.250x10^{-3}** (-2.05)	-0.109x10^{-3}*** (-2.64)	-0.152x10^{-3} (-1.39)	-0.496x10^{-3}*** (-3.02)
$Event_d \times Treatment_i$	0.281x10^{-3}*** (3.65)	0.320x10^{-3}* (1.94)	0.144x10^{-3}** (2.42)	0.357x10^{-3}** (2.32)	0.364x10^{-3}* (1.80)
$Momentum_{i,d}$	-0.122x10^{-3} (-0.56)	-0.124x10^{-3} (-0.29)	-0.214x10^{-3} (-0.48)	-0.281x10^{-3} (-0.67)	-0.152x10^{-3} (-0.33)
$InvPri_{i,d}$	-0.116x10^{-2}*** (-3.19)	-0.967x10^{-3} (-1.63)	-0.622x10^{-3}** (-2.39)	-0.516x10^{-3} (-0.31)	-0.246x10^{-2}** (-2.23)
$Espread_{i,d}$	0.647x10^{-2}*** (6.71)	0.122x10^{-2}*** (3.49)	0.329x10^{-2} (0.63)	0.116x10^{-1}*** (21.85)	0.437x10^{-2}* (1.81)
$lnTV_{i,d}$	0.525x10^{-4}*** (9.69)	0.611x10^{-4}*** (4.54)	0.307x10^{-4}*** (7.11)	0.438x10^{-4}*** (3.64)	0.632x10^{-4}*** (4.69)

$TimeT_{i,d}$	-0.527x10^{-5}*** (-6.80)	-0.615x10^{-5}*** (-3.71)	-0.303x10^{-5}*** (-5.08)	-0.484x10^{-5}*** (-3.12)	-0.725x10^{-5}*** (-3.56)
$Depth_{i,d}$	0.339x10^{-7} (0.82)	0.113x10^{-7} (1.09)	0.151x10^{-7} (0.50)	0.582x10^{-7} (0.41)	0.133x10^{-6} (1.42)
$Transactions_{i,d}$	-0.705x10^{-7}*** (-3.13)	-0.132x10^{-6} (-1.30)	-0.382x10^{-7}** (-2.00)	-0.153x10^{-6}*** (-3.10)	-0.420x10^{-7} (-0.87)
$Macro_{i,d}$	0.880x10^{-4}** (2.09)	0.644x10^{-4} (0.72)	0.380x10^{-4} (1.18)	0.131x10^{-3} (1.56)	0.116x10^{-3} (1.05)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
$\overline{R^2}$	29.5%	35.2%	47.9%	31.1%	26.9%

Table 11. Expected return and the trade-off between higher liquidity and volatility effects low latency
This table reports the coefficient estimates of three specifications of the following regression model:

$$ER_{i,t} = \alpha_i + \beta_t + \gamma_1 Stddev_{i,t} + \gamma_2 Espread_{i,t} + \gamma_3 Stddev_{i,t} * D_{latency,i,t} + \gamma_4 Espread_{i,t} * D_{latency,i,t} + \gamma_5 latency_{i,t} + \sum_{k=1}^{4} \delta_k C_{k,i,t} + \varepsilon_{i,t}$$

where $ER_{i,t}$ is the expected return for stock *i* and transaction *t*, α_i and β_t are stock and time fixed effects, $Stddev_{i,t}$ is the standard deviation of returns for stock *i* and transaction *t*, $Espread_{i,t}$ is effective spread for stock *i* and transaction *t*, $latency_{i,t}$ is the information transmission latency between Frankfurt and London, and $C_{k,i,t}$ is a set of *k* control variables, which includes the market depth ($Depth_{i,t}$) for stock *i* and transaction, the inverse of price ($InvPri_{i,t}$) for stock *i* and transaction *t*, the natural logarithm of trading volume ($lnTV_{i,t}$) for stock *i* and transaction *t* and dummy for sell transactions ($D_{i,t}^{sell}$). In Panel A, $D_{latency,i,t}$ is a dummy equalling 1 during periods which information is transmitted by using microwave connection ($latency_{i,t} \leq 4ms$) for stock *i*, in Panel B, $D_{latency,i,t}$ is a dummy equalling 1 during periods which information is transmitted by using both microwave and fibre optic connections ($latency_{i,t} \leq 6ms$) for stock *i* and in Panel C, $D_{latency,i,t}$ is a dummy equalling 1 during periods which information is transmitted by using only non-microwave connections ($latency_{i,t} \geq 4ms$) for stock *i*. $ER_{i,t}$ is computed as the mean of the previous 60 transaction intervals (*t*) returns for stock *i*, $Stddev_{i,t}$ is calculated as the standard deviation of returns for the contemporaneous and previous transactions (transactions *t* and *t-1*) for stock *i*, $Espread_{i,t}$ is measured as twice the absolute value of the difference between the transaction price and the prevailing bid-ask spread for stock *i* and transaction *t*, $Depth_{i,t}$ is the sum of prevailing bid and ask sizes for stock *i* corresponding to transaction *t*, $InvPri_{i,t}$ is the inverse of the price for stock *i* and transaction *t,* and $lnTV_{i,t}$ is the natural logarithm of trading volume for stock *i* and transaction *t,* $D_{i,t}^{sell}$ is a dummy equalling 1 for sell transactions. Sample consists of the 100 most active German stocks that cross-listed on XSE and Cboe. All variables, except $latency_{i,t}$, are computed for the Cboe. The sample period covers March 2017 to August 2018. Standard errors are robust to heteroscedasticity and autocorrelation and t-statistics are reported in parentheses. *, ** and *** correspond to statistical significance at the 0.10, 0.05 and 0.01 levels respectively.

Panel A

	Dependent variable: $ER_{i,t}$				
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$Stddev_{i,t}$	0.350x10^{-2}***	0.198x10^{-1}***	0.104x10^{-2}***	0.529x10^{-2}***	0.388x10^{-2}***
	(33.01)	(55.05)	(2.99)	(16.44)	(7.63)
$Espread_{i,t}$	0.323x10^{-2}***	0.650x10^{-4}	-0.225x10^{-2}	0.423x10^{-2}***	0.179x10^{-2}***
	(3.08)	(0.03)	(-1.15)	(3.76)	(3.49)
$Stddev_{i,t} * D_{latency,i,t}$	0.366x10^{-2}***	0.928x10^{-1}***	0.141x10^{-2}***	0.388x10^{-2}*	0.163x10^{-1}***
	(3.60)	(4.80)	(6.96)	(1.93)	(7.49)
$Espread_{i,t} * D_{latency,i,t}$	-0.398x10^{-2}***	0.347x10^{-2}	0.742x10^{-3}	-0.611x10^{-2}***	-0.212x10^{-1}***
	(-3.94)	(1.57)	(0.38)	(-3.22)	(-5.32)
$latency_{i,t}$	-0.203x10^{-2}	0.180x10^{-2}	-0.810x10^{-2}**	-0.538x10^{-2}	0.547x10^{-2}
	(-1.20)	(0.54)	(-2.46)	(-1.64)	(1.49)
$Depth_{i,t}$	-0.130x10^{-2}	-0.477x10^{-2}**	0.290x10^{-2}	-0.449x10^{-2}**	0.438x10^{-3}

	(-1.36)	(-2.42)	(1.61)	(-2.43)	(0.21)
$InvPri_{i,t}$	-4.150***	-2.041***	-4.296***	-7.002***	-3.756***
	(-5.44)	(2.74)	(-5.14)	(-4.24)	(-3.80)
$lnTV_{i,t}$	0.696x10^{-2}***	0.151x10^{-1}***	0.154x10^{-1}***	-0.234x10^{-2}	0.364x10^{-3}
	(3.27)	(3.46)	(3.71)	(-0.57)	(0.08)
$D_{i,t}^{sell}$	-0.208x10^{-2}**	-0.529x10^{-2}***	-0.227x10^{-2}	-0.330x10^{-2}**	-0.405x10^{-2}**
	(-2.50)	(-3.15)	(-1.41)	(-2.05)	(-2.29)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
$\overline{R^2}$	42.3%	50.1%	40.9%	38.1%	40.1%

Panel B

	Dependent variable: $ER_{i,t}$				
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$Stddev_{i,t}$	0.454x10^{-2}***	0.184x10^{-1}***	0.338x10^{-2}***	0.256x10^{-2}***	0.357x10^{-2}***
	(26.08)	(42.61)	(8.02)	(6.14)	(6.32)
$Espread_{i,t}$	0.490x10^{-2}***	0.127x10^{-1}***	-0.561x10^{-2}	0.197x10^{-2}***	0.261x10^{-2}***
	(3.20)	(3.78)	(-1.57)	(4.72)	(3.13)
$Stddev_{i,t} * D_{latency,i,t}$	0.502x10^{-2}***	0.233x10^{-1}***	0.397x10^{-2}***	0.326x10^{-1}***	0.108x10^{-1}***
	(4.02)	(7.67)	(-11.97)	(9.74)	(3.28)
$Espread_{i,t} * D_{latency,i,t}$	-0.494x10^{-2}***	-0.117x10^{-1}***	0.309x10^{-2}	-0.187x10^{-2}***	-0.102x10^{-1}***
	(-3.27)	(-3.61)	(0.89)	(7.21)	(-3.71)
$latency_{i,t}$	-0.113x10^{-2}	-0.218x10^{-2}	-0.123x10^{-1}***	0.851x10^{-2}	0.184x10^{-2}
	(-0.67)	(-0.65)	(-3.69)	(0.62)	(0.50)
$Depth_{i,t}$	-0.131x10^{-2}	-0.467x10^{-2}**	0.294x10^{-2}	-0.455x10^{-2}**	0.388x10^{-3}***
	(-1.37)	(-2.37)	(1.63)	(-2.46)	(0.19)
$InvPri_{i,t}$	-4.150***	-2.041***	-4.295***	-7.004***	-3.757***
	(-5.04)	(-2.73)	(-5.14)	(-4.24)	(-2.81)
$lnTV_{i,t}$	0.687x10^{-2}***	0.165x10^{-1}***	0.148x10^{-1}***	0.266x10^{-2}	0.481x10^{-3}
	(3.22)	(3.74)	(3.58)	(0.65)	(0.11)
$D_{i,t}^{sell}$	-0.207x10^{-2}**	-0.519x10^{-2}***	-0.228x10^{-2}	-0.327x10^{-2}**	-0.409x10^{-2}**

	(-2.50)	(-3.09)	(-1.43)	(-2.03)	(-2.31)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	42.5%	50.3%	40.9%	39.1%	40.1%

Panel C

Dependent variable: $ER_{i,t}$					
	Full sample	Least active	Quartile 2	Quartile 3	Most active
$Stddev_{i,t}$	0.460x10^{-2}***	0.157x10^{-1}***	0.223x10^{-2}***	0.330x10^{-2}***	0.435x10^{-2}***
	(16.01)	(27.41)	(3.88)	(5.86)	(6.66)
$Espread_{i,t}$	0.274x10^{-2}***	0.750x10^{-2}	0.152x10^{-2}***	0.684x10^{-2}	0.869x10^{-3}**
	(3.16)	(1.37)	(2.78)	(1.32)	(2.31)
$Stddev_{i,t} * D_{latency,i,t}$	-0.184x10^{-2}***	0.500x10^{-3}	-0.239x10^{-2}***	-0.235x10^{-2}***	-0.185x10^{-2}***
	(-7.63)	(0.43)	(-4.76)	(-4.70)	(-3.97)
$Espread_{i,t} * D_{latency,i,t}$	0.358x10^{-2}***	-0.511x10^{-2}	0.328x10^{-2}**	0.105x10^{-1}**	0.108x10^{-1}***
	(3.54)	(-0.96)	(2.38)	(2.07)	(3.28)
$latency_{i,t}$	0.279x10^{-2}	0.224x10^{-2}	-0.137x10^{-2}	0.294x10^{-2}	0.637x10^{-2}
	(1.57)	(0.70)	(-0.44)	(0.94)	(0.85)
$Depth_{i,t}$	-0.132x10^{-2}	-0.473x10^{-2}**	0.295x10^{-2}	0.455x10^{-2}**	0.414x10^{-3}
	(-1.38)	(-2.40)	(1.63)	(-2.46)	(0.20)
$InvPri_{i,t}$	-4.151***	-2.039**	-4.297***	-7.005***	-3.757**
	(-5.45)	(-2.71)	(-5.14)	(-4.24)	(-2.28)
$lnTV_{i,t}$	0.667x10^{-2}***	0.158x10^{-1}***	0.151x10^{-1}***	-0.269x10^{-2}**	-0.278x10^{-4}***
	(3.13)	(3.59)	(3.64)	(-0.65)	(-0.01)
$D_{i,t}^{sell}$	-0.206x10^{-2}***	-0.515x10^{-2}***	-0.232x10^{-2}	-0.328x10^{-2}**	-0.407x10^{-2}**
	(-2.48)	(-3.07)	(-1.45)	(-2.04)	(-2.30)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	42.3%	50.7%	40.8%	38.1%	40.2%