*Title Page/Author Identifier Page

Market Efficiency in Real Time:

Evidence from Low Latency Activity around Earnings Announcements

Tarun Chordia, and Bin Miao

October 2019

Abstract

The literature has used small samples to show that fast trading or low latency trading (LLT) improves efficiency at extremely high frequencies. However, it is not clear whether LLT driven high frequency improvements in efficiency can impact corporate decision making and investor risk sharing or hedging, which are low frequency processes. This paper uses a comprehensive cross-sectional and time-series sample to provide evidence that LLT enhances efficiency around earnings announcements. Low latency traders trade aggressively at the time of the earnings announcements, such that the information in earnings surprises is quickly incorporated into prices and the post-announcement drift is reduced.

Key words: low-latency trading, market efficiency, earnings announcement, post-earnings announcement drift

JEL Classification: M41; G14;

Contacts

	Chordia	Miao
Voice:	1-404-727-1620	852-2766-3294
Fax:	1-404-727-5238	852-2330-9845
E-mail:	Tarun.Chordia@emory.edu	Bin.Miao@polyu.edu.hk
Address:	Goizueta Business School Emory University Atlanta, GA 30322	School of Accounting and Finance Hong Kong Polytechnic University Kowloon, Hong Kong

* We thank Ekkehart Boehmer, Jonathan Brogaard, Maureen O'Hara, and participants at the 3rd Sydney Market Microstructure Meeting for their helpful comments. We thank Frank Hatheway at Nasdaq OMX for providing the high-frequency trading dataset

Market Efficiency in Real Time:
Evidence from Low Latency Activity around Earnings Announcements

Abstract

The literature has used small samples to show that fast trading or low latency trading (LLT) improves efficiency at extremely high frequencies. However, it is not clear whether LLT driven high frequency improvements in efficiency can impact corporate decision making and investor risk sharing or hedging, which are low frequency processes. This paper uses a comprehensive cross-sectional and time-series sample to provide evidence that LLT enhances efficiency around earnings announcements. Low latency traders trade aggressively at the time of the earnings announcements, such that the information in earnings surprises is quickly incorporated into prices and the post-announcement drift is reduced.

Key words: low-latency trading, market efficiency, earnings announcement, post-earnings announcement drift

JEL Classification: M41; G14;

The social question for high-frequency trading—like all of finance, really—is whether it screws up markets or makes them more efficient and "liquid."

It's especially hard to see why high-frequency trading is needed. Price discovery every millisecond doesn't seem necessary to guide corporate investment or individual risk sharing and hedging.

- Cochrane (2013)

Information is increasingly being released to, interpreted by, and traded on by computers. The impetus for algorithmic trading has come from regulation and advances in technology. Regulation National Market System (Reg NMS) has implemented trade through and market access rules that have integrated the previously fragmented US markets. Dramatic improvements in technology have allowed computer algorithms to dynamically monitor multiple trading venues and strategically submit orders. These algorithms emphasize speed, and as a result, trade latency has declined to milliseconds. The increasing prevalence of low latency trading (LLT) has led to questions about the welfare implications of investing huge sums to achieve sub-second speeds.[1]

The welfare implications of LLT are still being debated.[2] Budish et al. (2015) and Biais et al. (2015) point to the socially wasteful arms race as low latency traders (LLTs) expend ever greater resources to reduce latency.[3] On the other hand, Jovanovic and Menkveld (2016) argue that low latency traders (LLTs) face lower adverse selection costs due to their ability to quickly update quotes, and thus improve gains from trade through their greater willingness to provide liquidity. Chordia et al.

[1] In one example of the LLT arms race, Spread Networks constructed a $300 million high-speed fiber optic cable between Chicago and New York to reduce the round-trip time for messages by 0.003 seconds.

[2] Chordia et al. (2013) have provided a discussion of the different issues related to the welfare implications of high-speed trading.

[3] Further, the popular press has focused on the costs and externalities imposed by LLTs on other market participants. For instance, Lewis (2014) has argued that the markets are "rigged" in favor of the high-speed traders. Calls for regulations that blunt the speed advantage of LLTs abound.

(2018) have argued that increasing competition amongst the LLTs has reduced the degree of externality imposed by LLTs on other market participants.

Since a rigorous welfare analysis from the perspective of a social planner is impossible, empirical studies have explored different welfare aspects of LLT. A number of studies show that LLT improves market quality through increased liquidity and lower short-term volatility (Chordia, Roll, and Subrahmanyam, 2011, Hendershott et al. 2011, Hasbrouck and Saar 2013, and Hendershott and Riordan 2013). Furthermore, Brogaard et al. (2014) find evidence that high frequency traders (HFTs)[4] facilitate price discovery by trading in the direction of permanent price changes and against transitory pricing errors.[5] This strand of literature responds to the concern raised in the first quote above from Cochrane (2013).

While there is broad agreement in the literature that LLT improves efficiency, these improvements in efficiency are documented at extremely high frequencies. Since the great majority of investors have longer investment horizons and corporate disclosures are not made at a millisecond frequency, the question raised in the second quote from Cochrane (2013) is this: Does the increase in liquidity and market efficiency obtain at the frequency of corporate decision making and investor risk sharing and hedging? This is the first paper to provide evidence of LLT-driven

[4] We use LLT to refer to any computer-assisted low-latency trading activity. As such, HFT is a subset of LLT, as specifically defined by the Security and Exchange Commission's (SEC's) concept release on equity market structure (34-61358). We will use the term "HFTs" only for LLTs that fit the SEC definition. Algorithmic trading (AT) refers to the use of computer algorithms to automatically make trading decisions (Hendershott et al. 2011), and thus encompasses both LLT and HFT.

[5] Other papers documenting improvements in market quality due to LLT include the following. Chaboud,et al. (2014) find that LLT improves price efficiency through lower return autocorrelations and fewer arbitrage opportunities and Conrad et al. (2015) find that LLT activity leads prices to more closely resemble a random walk. Carrion (2013) finds that prices incorporate market-wide return information more quickly on days with high HFT participation. Hagströmer and Nordén (2013) show that HFTs reduce short term volatility. Brogaard et al. (2017) show that HFTs supply liquidity and thus help stabilize prices even during periods of extreme price movements.

improvements in market efficiency for time horizons that are relevant to corporate decision making and to long-term investors.

Of particular interest to long-term investors – where "long-term" is broadly defined to include all non-LLT investors – is whether LLT facilitates firms' fundamental information being incorporated into prices. As O'Hara (2015) notes, "…in the high frequency world, it is not clear that information-based trading necessarily relates to fundamental information." LLTs have investment horizons much shorter than a day and rarely carry positions overnight. Their algorithms are designed to respond to market events in the millisecond environment and capture fleeting profit opportunities created by intraday price fluctuations. Therefore, it remains unclear whether the LLT-driven improvement in market efficiency documented at high frequencies also obtains at lower frequencies and when information events are unambiguously identified.

In addition, some recent studies argue that LLT could even harm the informativeness of stock prices, due to algorithms that piggyback and front-run investors with private information. As a result of the reduced payoffs from costly information acquisition activity, fewer investors choose to get informed and prices become less informative about fundamental value. For instance, Weller (2018) finds that several indicators of algorithmic trading (AT) activity, such as cancel-to-trade ratio and odd-lot volume ratio, are negatively associated with the amount of earnings announcement information anticipated by pre-announcement prices. Similarly, Lee and Watts (2018) examine an exogenous shock to AT caused by the SEC's "Tick Size Pilot" experiment and find that an increase in tick size reduces AT and improves the ability of pre-announcement stock returns to predict the news of the upcoming earnings release.

On the other hand, characteristics of popular LLT strategies suggest there are multiple channels through which LLT could positively impact the pricing efficiency of existing firm-specific information. First, LLTs have become the de facto market maker in major exchanges, and there is general agreement in the literature that LLT market making enhances market liquidity and reduces trading costs (Menkveld 2013, O'Hara 2015). Lower transaction cost encourages informed trading, which leads to fundamental information, such as earnings news, being more quickly incorporated into prices (Ng et al. 2008, Chordia et al. 2009).

Second, in addition to passive market-making, LLTs also routinely take the active side of trading, and employ various directional trading strategies built around their speed advantage. These aggressive LLT strategies, such as cross-market arbitrage or reacting to news releases, facilitate faster incorporation of information into prices. For example, as discussed in Jones (2013), in the event of major information releases, some LLT firms electronically parse the news release and automatically trade on the signal inferred from textual analysis of the content. News providers can even perform textual analyses of the news and sell the extracted trading signals to LLT firms, saving them additional milliseconds of precious time. [6]

In addition to directly trading on news signal, LLTs also trade on order flow signal. In such "order anticipation strategies" LLTs analyze the pattern of order flows to infer the existence of any large buyer or seller, and profit from the price momentum created by the underlying trades (see SEC 2010). For example, immediately following earnings announcement, an institutional investor determines that the company's earnings is highly persistent based on comprehensive analysis of the quarterly result, and decides to buy a large number of shares at the prevailing market

[6] Chordia et al. (2018) analyze the impact of Reuters's sale of access to the University of Michigan's Consumer Sentiment Index to LLTs two seconds before wide release.

price. Aggressive LLT activity in this setting could magnify the price impact of the trades and cause the private information of the institutional investor to be more quickly reflected in prices.

Finally, LLT strategies are implemented using algorithms that are not subject to human traders' bounded rationality, such as disposition effect or limited attention, which has been cited as major causes for the market's failure to efficiently react to new information (Frazzini 2006, Hirshleifer et al. 2009). For instance, using a limited sample based on the NASDAQ HFT dataset, Chakrabarty et al. (2015) find some evidence that HFT improves the market's response to earnings announcements during low-attention periods.

In this study, we provide the first large sample evidence in the literature that LLT improves the efficiency of market reaction to earnings news. More specifically, we examine LLT around quarterly earnings announcements over the sample period January 2008 through December 2017. Following Hasbrouck and Saar (2013), we use strategic runs as a proxy for LLT.[7] This measure of daily low-latency activity, LLT, is cross-sectionally correlated, positively with trading volume and firm size and negatively with different measures of the bid-ask spread and the price impact of trades.

LLT is averaged over two days, day 0 and day 1, where day 0 is the earnings announcement day (day after the announcement day) if information is released during (after) trading hours. Standardized earnings surprise (SUE) is measured as the actual earnings per share minus the median analyst forecast, standardized by the stock price at the end of the fiscal quarter for which earnings are announced. For the lowest LLT

[7] A number of studies have used the Nasdaq HFT data, which identifies a subset of HFT trades over the sample period 2008-2009, for a sample of 120 randomly selected stocks. Given that we wish to examine a larger sample of firms over a longer sample period, we do not use the Nasdaq HFT data for our main tests. However, in Section 3.6 we do use the Nasdaq HFT data to check the robustness of the results for the LLT liquidity demanding trades.

decile, the two-day abnormal return[8] differential around earnings announcements between the highest and the lowest SUE deciles is 6.3%. On the other hand, for the highest *LLT* decile the return differential between the highest and the lowest SUE deciles amounts to 12.4%, an increase of almost 100%. In other words, the market reaction to earnings surprise increases with low latency trading.

Further, we examine the post-earnings-announcements-drift (PEAD) for high and low *LLT*. PEAD is proxied by the cumulative abnormal return over 60 trading days (CAR60) following the earnings announcement. For the lowest *LLT* decile, the CAR60 differential between the highest and the lowest SUE deciles amounts to 4.7% while for the highest *LLT* decile, the CAR60 differential between the highest and the lowest SUE deciles is a statistically insignificant -0.8%. Thus, the PEAD decreases with LLT, and this effect persists for a prolonged period of up to a year after announcement. Additionally, the earnings announcement impact is robust to using different proxies for LLT, including: (i) the total number of limit orders submitted and (ii) fraction of orders cancelled within 100 milliseconds.

The degree of LLT and the size of investment in technology is a choice made by fast traders in the presence of retail and institutional investors, analysts, firm disclosure choice, market regulations, etc. In this complex equilibrium it is hard to ascertain causality from LLT to efficiency. For instance, the fact that LLT is most active in large and liquid stocks raises the concern of reverse causality in that fast traders could choose to trade in stocks that are already efficiently priced. Also, given that LLTs, when supplying liquidity, dislike information asymmetries, they would prefer to trade in firms with transparent disclosure policies or firms that are followed by many analysts. In addition, there is the concern that there could be unobserved

[8] Abnormal returns are obtained by adjusting the raw returns for size, book-to-market and momentum as in Daniel et al. (1997).

firm characteristics (an omitted variable problem) that drive both LLT and efficiency. For identification purposes, we conduct additional tests that exploit an exogenous shock caused by the adoption of the autoquote system that substantially increased algorithmic trading on NYSE.[9] Using a difference-in-differences research design, we find that the reduced trading latency significantly increases market efficiency by facilitating the quick incorporation of earnings information into prices.

To understand the underlying mechanism driving market efficiency, we compute a signed measure of *LLT* that can be interpreted as net quoting activity by LLTs in the direction of the earnings surprise. The results based on this signed measure show that market efficiency is higher when LLTs aggressively search for liquidity in the direction of the earnings surprise. This aggressive trading results in a higher price impact at the time of the earnings announcements and a lower PEAD.

We also provide some early evidence that LLT enhances market reaction to unscheduled firm-specific information events. In particular, we examine SEC filings of insider purchases and announcements of stock-financed acquisition of private target, both constitute positive news to the announcing firms, as suggested by prior literature. We find that market reaction is more positive for both events with higher LLT activity during the announcement window.

Our study makes an important contribution to the literature on market reaction to earnings announcements. The earnings response coefficient (ERC), which is estimated by the magnitude of immediate price reaction to standardized unexpected earnings, has been widely used as a measure of earnings quality in empirical accounting research (Dechow et al. 2010). Relatedly, abnormal return volatility and trading volume are customarily used to measure the overall information content of

[9] See Hendershott, Jones, and Menkveld (2011).

earnings announcements (Beaver 1968, Landsman and Maydew 2002, Landsman et al. 2012, Beaver et al. 2018). When drawing inference based on these measures, researchers have been careful to control for well-known determinants, such as accounting choice, audit quality, leverage, and firm fundamentals, but have largely overlooked the role of market microstructure. Our results show that LLT is an important determinant of the cross-sectional variation in market reaction to earnings news. In addition, these results suggest that the fast-changing landscape of equity trading could be partially responsible for recent years' dramatic increase in return volatility at earnings announcements documented in Beaver et al. (2018).

Our study also contributes to the PEAD literature. Since its discovery in the seminal study by Ball and Brown (1968), PEAD has intrigued researchers for decades.[10] Various theories have been proposed to explain the cause of the market's apparent underreaction to earnings news. For example, Bernard and Thomas (1990) argue that it is driven by investors failing to fully appreciate the persistence of earnings (see also Ball and Bartov 1996, Burgstahler et al. 2002, and Soffer and Lys 1999), while Hirsheleifer, Lim, and Teoh (2009) show that limited investor attention is another significant contributor. The literature is also actively debating why the mispricing has not been arbitrated away. Prior studies have highlighted the role of market imperfections such as transaction cost (Bernard and Thomas 1989, Bhushan 1994, Ng et al. 2008, Chordia et al. 2009) and arbitrage risk (Mendenhall 2004). We provide new insights into this anomaly from the perspective of the changing structure of modern markets. We show that one mechanism by which LLTs improve efficiency around earnings announcements is by their aggressive search for liquidity in the direction of the earnings surprise.

[10] See Kothari (2001) for an extensive review of the early literature, and Richardson et al. (2010) for a survey of more recent studies.

Finally, our study contributes to the HFT literature. Similar to Rogers et al. (2017), we examine HFT's trading on firm-specific news. But unlike Rogers et al., who find that HFTs take advantage of their speed and early access to SEC filings to trade on the insider trading information before it becomes available to other market participants, we show that HFT also speed up the process of stock price incorporating information that is publicly available to all market participants.

2. Measuring low-latency trading activity

2.1 The Hasbrouck and Saar (2013) measure

We use the empirical measure developed in Hasbrouck and Saar (2013) as our main proxy for low-latency trading activity. This measure is based on the intensity of "strategic runs", which are long series of linked messages that result from the dynamic order submission and cancellation strategies employed by low-latency traders. More importantly, the measure only requires the NASDAQ trade message data that are publicly available and can be constructed for a wide cross-section of firms over a relatively long time-period. It therefore offers a significant advantage over alternative measures for large sample asset pricing studies.

We obtain the order-level data on NASDAQ from the TotalView-ITCH dataset. In this dataset, each limit order submitted to NASDAQ is identified by a unique order number, and all subsequent events for the order, including partial or full executions or cancellations, can be traced by the same order number. The TotalView-ITCH dataset provides real-time information about executions and orders and are comprised of time- sequenced messages (time stamped to the millisecond) that describe the history of the limit order book. Messages are one of four types: (i) addition of a displayed order to the book, (ii) cancellation of a displayed order, (iii) execution of a displayed order against a new marketable limit order, and (iv) the execution of a non-displayed order.[11] Note that the submission and cancellation of non-displayed limit orders cannot be observed.

Following Hasbrouck and Saar (2013), we link a new displayed limit order (marketable or non-marketable) to an earlier cancelled order if the new order is submitted within 100 milliseconds of the earlier order cancellation and has the same direction (buy or sell)[12] and quantity. We keep only long "runs" with at least 10 linked orders and assign a weight to each run based on its time-in-force, or the timestamp of the last message minus the timestamp of the first message of the run. Our proxy for the low-latency trading activity (LLT_t) during the regular trading hours (9:30:00~16:00:00) of stock-trading day t is defined as the number of time-weighted runs:

$$LLT_t = \frac{1}{2.34 \times 10^7} \sum_{j=1}^{N} T_{jt} \, , \tag{1}$$

where T_{jt} is time-in-force in milliseconds for run j and N corresponds to the number of runs on day t. We standardize by 2.34×10^7, which is the total number of milliseconds each trading day.

Panel A of Table 1 presents the summary statistics of LLT for a broad sample of more than 9.7 million stock-day observations over a period of 2,517 trading days from January 2008 to December 2017.[13] The sample includes all US common stocks (share code 10 and 11) that are traded on NASDAQ, with an average of 3,924 stocks each trading day. The statistics reported in the table are time-series averages of the cross-sectional statistics over the corresponding periods.

---

[11] Displayed orders are visible to all while non-displayed order are invisible. The priority for execution against an incoming marketable limit order follows price, visibility and time.

[12] The dataset provides information for whether the order submission refers to buy or sell orders. As shown by Hasbrouck and Saar (2013), buy (sell) orders result in rapid changes in the bid (ask) quote.

[13] We begin the sample period after the full implementation of Reg NMS in October 2007.

The mean *LLT* over the full sample is 6.979. The median is lower at 5.119. The right skewed distribution is likely due to clustering of low-latency traders among large and liquid stocks. Since *LLT* is the total time-weighted number of runs from market open to close, a mean of about seven suggests that at any point in time within the regular trading hours there are, on average, about seven runs that are simultaneously active for stocks traded on NASDAQ. There is a significant variation in *LLT* across firms, as indicated by the large standard deviation of 7.246 and interquartile range of 7.620. There is also some temporal variation in market-level low-latency activity over the 10 years spanned by our sample, with the annual mean *LLT* peaking at 8.876 in 2014. But the year-over-year changes display no clear pattern.

Panel B of Table 1 reports the distribution of *LLT* partitioned by firm size. We assign each stock to a size decile according to its market capitalization at the close of the previous trading day. The size deciles are updated daily, and the tabulated statistics are averages of all trading days covered by our sample. The table reveals a strong positive association between firm size and low-latency trading activity. Both mean and median *LLT* increase monotonically from the lowest to the highest size deciles, with an average marginal change of 1.863 and 1.787 across adjacent deciles, respectively. Notably, the lower quartile of *LLT* for the lowest size decile is 0, suggesting that at least one quarter of small firm-days have no LLT activity. This is in strong contrast to the largest firms, which, on average, have almost 18 simultaneously active runs.

2.2 LLT and market liquidity

A number of papers (listed in the introduction) have shown that LLT improves market quality through increased liquidity and lower volatility. However, these studies are based on restricted datasets that include small subsets of firms and short time periods. For instance, using a sample that includes the 500 largest stocks listed on NASDAQ and 44 trading days that are selected to cover both normal and volatile market conditions, Hasbrouck and Saar (2013) find that increased low-latency trading activity, as measured by time-weighted number of strategic runs, is associated with narrower bid-ask spreads, larger displayed depth in the limit order book, and lower short-term return volatility. We report the relation between *LLT* and various trading intensity and market liquidity indicators using our more comprehensive sample. In particular, we examine the following empirical measures that capture different dimensions of market quality:

1. *Order Traffic*: total number of orders submitted to NASDAQ during regular trading hours (TotalView-ITCH).
2. *High-frequency Order Cancellations*: proportion of orders that are cancelled within 100 milliseconds of submission. (TotalView-ITCH)
3. *Shares Volume*: number of shares traded on all exchanges. (CRSP)
4. *Quoted Spread*: time-weighted bid-ask spread over a trading day. Bid-ask spread is national best bid minus national best ask, and divided by the midpoint of the NBBO quotes. (Daily TAQ)
5. *Effective Spread*: dollar-volume-weighted average effective spread of all transactions within a trading day. Effective spread is $\frac{2D(P-M)}{M}$, where D is indicator variable that equals to +1 if the trade is a buy and -1 if the trade is a sell. P is transaction price, and M is midpoint of the prevailing NBBO quote. (Daily TAQ)
6. *Price Impact*: dollar-volume-weighted average price impact of all transactions within a trading day. Price impact is $\frac{2D_t(M_{t+5}-M_t)}{M_t}$, where D_t is indicator variable that equals to +1 if trade t is a buy and -1 if the trade is a sell. M_t is

midpoint of the prevailing NBBO quote for trade *t*, and M_{t+5} is midpoint of NBBO quote 5 minutes after trade *t*. (Daily TAQ)

For variables that require trade and quote data, we use the Daily TAQ database to ensure measurement accuracy (Holden and Jacobsen 2014). All trades are signed using the Lee and Ready (1991) algorithm.

Panel C of Table 1 shows that *LLT* is highly correlated with the total number of limit order submissions and the intensity of high-frequency order cancellations on NASDAQ. More importantly, *LLT* is positively correlated with trading volume, and negatively correlated with all three measures of bid-ask spread and price impact of trade. These results suggest that increased low-latency activity is associated with better liquidity in the market, which is consistent with the findings from prior studies.[14]

3. LLT and the efficiency of market reaction to earnings news

3.1 The earnings announcement sample

The sample of earnings announcements is collected from the merged Compustat/CRSP/IBES databases. We start with all non-missing quarterly earnings announcement dates between January 2008 and December 2017 in Compustat. If the announcement date information is also available in I/B/E/S, we follow DellaVigna and Pollet (2009) and Hirshleifer et al. (2009) and use the earlier of the two dates as the event date. We further require non-missing data for calculating key test and control variables and remove foreign firms or firms with closing stock price below $1 before the earnings announcement. The final sample consists of 92,164 quarterly earnings announcements from 4,522 unique firms.

[14] In the internet appendix, we use the Flash Crash of May 6, 2010 to further validate our *LLT* measure.

The descriptive statistics of this sample are presented in Panel A of Table 2. *LLT* measures low-latency activity during earnings announcements, and is defined as the average of *LLT* on day 0 and day 1, where day 0 is the announcement day.[15] The mean and median *LLT* for the earnings announcement sample are 8.794 and 7.154, respectively, both of which are substantially higher than the corresponding full sample statistics reported in Table 1 (6.979 and 5.119). The unusual low-latency activity during earnings announcements is clearly depicted in Figure 1a, which plots the median daily *LLT* of our sample firms within a 61-day window and is centered on the earnings announcement day. LLT activity becomes significantly more pronounced during the announcement window and then quickly declines to normal within a few days after the announcement. In addition, Figure 1b shows that the proportion of strategic runs that ended with a trade also increases substantially, suggesting that, around announcements, a larger proportion of limit orders submitted by LLTs get filled. These patterns are consistent with the fact that many low latency strategies are designed to profit from increased volatilities in the market around earnings announcements.

The surprise in the earnings announcement is measured by standardized unexpected earnings (*SUE).* It is defined as the actual earnings per share (EPS) minus median analyst forecast of EPS, divided by stock price at the end of the fiscal quarter for which earnings is announced. We obtain both actual and forecast EPS from I/B/E/S to ensure consistency in definition of earnings, and winsorize *SUE* at 1% and 99% to mitigate the impact of outliers.[16] The market's immediate reaction to earnings news is denoted *EARET*, the return of the announcing firm minus the return on its size,

[15] Because LLT is constructed to capture trading activity during regular hours, for earnings announcements made after market hour, we define the following trading day as day 0. We use the timestamp in I/B/E/S to identify after-hour announcements.
[16] Winsorization does not affect our regression results since we use the decile rankings of *SUE*.

book-to-market, and momentum-matched portfolio over day 0 and day 1, as suggested by Daniel et al. (1997). The post-announcement return is denoted *CAR60*, and is defined as the buy-and-hold return of the announcing firm over the window [2 ,61], minus its matching portfolio return over the same period.[17] We use a 60-day window for our main analysis, and check for sensitivity to alternative return accumulation windows in Section 3.3.2.

Prior research finds that market reaction to earnings announcement is affected by a number of firm characteristics (Chambers and Penman 1984, Bartov et al. 2000, Hirshleifer et al. 2009). Recall from Panel A of Table 1 that *LLT* increases with firm size. Thus, characteristics such as firm size, institutional ownership, and analyst following may also be among the determinants of low-latency trading activity at earnings announcements, and therefore are likely to be strongly correlated with *LLT*. To evaluate the incremental effect of the *LLT* measure, we examine the following firm characteristics which will be included as control variables in our regression analysis:

1. *Firm Size (MV)*: market value of equity at the end of earnings announcement quarter. Note that the actual announcement is made after the end of the quarter.
2. *Book to Market Ratio* (*BTM*): book value of equity at the end of quarter *t-1* divided by market value of equity at the end of quarter *t*, where quarter *t* is the earnings announcement quarter.
3. *Share Turnover (TOVER)*: average monthly share turnover (trading volume divided by shares outstanding) over a 12-month period ending at the end of earnings announcement quarter.

[17] The results are similar when using raw returns or size adjusted returns or Fama and French (2015) factor adjusted returns with the factor loadings calculated over the past 250 days of daily returns.

4. *Liquidity (ILLIQ)*: Amihud (2002)'s illiquidity measure calculated using daily stock returns and volume data over the 12-month period ending at the end of earnings announcement quarter.
5. *Analyst Coverage (NUMEST)*: number of analysts following the firm at the end of earnings announcement quarter.
6. *Institutional Ownership (INST)*: proportion of shares held by institutional investors at the end of earnings announcement quarter.
7. *Earnings Persistence (PERS)*: coefficient β from the model: $EPS_t = \alpha + \beta \cdot EPS_{t-4} + \varepsilon$, estimated using the 16 quarters preceding the earnings announcement quarter.
8. *Earnings Volatility* (*EPSVOL*): standard deviation of seasonally-adjusted quarterly EPS changes over the 16 quarters preceding the earnings announcement quarter.
9. *Reporting Lag (REPLAG):* number of calendar days between the fiscal quarter end and date of earnings announcement.
10. *Investor Attention* (*NCEA*): number of concurrent earnings announcements.
11. *Net Quarterly Buying by Institutional Investors (ΔINST)*: change in institutional ownership during the quarter of earnings announcement.
12. *Net short-selling (ΔSHORT):* change in short interest during the month of earnings announcement.

Panel A of Table 2 reports the summary statistics of these variables and their correlations with *LLT*. As expected, *LLT* is highly correlated with size, book-to-market ratio, shares turnover, liquidity, and analyst following, suggesting low-latency traders tend to favour large, liquid, growth stocks with transparent information environment. *LLT* is also strongly correlated with institutional holding, since many low-latency trading algorithms are designed to interact with institutional order flow. In comparison, the correlations between LLT and earnings quality variables (*PERS, REPLAG,* and *EPSVOL*) are much lower. Finally, LLT is not significantly correlated with the number of concurrent earnings announcements (*NCEA*), consistent with the expectation that computer algorithms will not be distracted by extraneous events in the market.

3.2 Market reaction to earnings news

Our first test of whether LLT affects the pricing of earnings information examines the market's reaction to earnings announcements. We run the following panel regression:

$$EARET = \beta_0 + \beta_1 DSUE + \beta_2 DSUE * DLLT + \beta_3 DLLT + Controls + Fixed\ Effects + \varepsilon\ . \qquad (2)$$

In equation (2), *DSUE* and *DLLT* are the within-quarter decile rankings of *SUE* and LLT, respectively. We use decile rankings for their robustness to outliers and the ease of interpreting regression coefficients. Our key test variable is the interaction term $DSUE \times DLLT$. If LLT facilitates pricing of earnings news, the coefficient β_2 should be significantly positive, indicating stronger market reaction to earnings announcements when low-latency traders are more actively posting quotes. Conversely, a significantly negative β_2 would suggest that LLT activity in aggregate impedes the price discovery process. The main variables of interest, *DSUE* and *DLLT*, are both standardized to range between 0 and 1, and therefore the coefficient on *DSUE* can be approximately interpreted as the difference in the announcement returns between the top *SUE* decile and the bottom *SUE* decile for firms in the bottom *LLT* decile. The coefficient on the interaction term $DSUE \times DLLT$ thus represents the difference in the magnitudes of market reaction to earnings news between the firms in the top and bottom LLT deciles.

To reliably estimate the impact of LLT on earnings news, we implement five nested specifications of the regression model (2). We start with a univariate model that regresses $EARET$ on $DSUE$ to show the average earnings response coefficient (ERC) for the full sample. We then estimate our baseline model of LLT's impact on ERC by including $DLLT$ and the interaction term $DSUE \times DLLT$. Next we add the list of variables detailed in the previous section to control for time-varying firm characteristics, and include firm fixed effects to capture the effect of any unobserved time-invariant characteristics. Finally, in our most stringent model specification, we further include interactions between $DSUE$ and all control variables and time fixed effects (detailed below). In Panel A of Table 2 we see that LLT is highly correlated with certain firm characteristics such as size, liquidity, and analyst coverage. Controlling for the interaction between SUE and these variables in the regression is thus useful for testing the incremental impact of LLT on market reaction to earnings news.

In all model specifications we also include year, month, and day of the week fixed effects (time fixed effects). The year fixed effects should remove any business cycle related impact over time. The month fixed effects account for seasonality and differences in fiscal year-ends. Day of the week fixed effects account for management choice in the timing of the earnings announcements. For instance, DellaVigna and Pollet (2009) show that investors pay less attention to earnings announced on Fridays and managers may choose to announce poor earnings on Fridays. The standard errors are two-way clustered by firm and calendar date of the earnings announcement since the residuals may be correlated across firms due to correlated shocks or for a firm over time.

Panel B of Table 2 presents the results. In model 1, the coefficient on $DSUE$ is 0.089 (t-statistic = 55.08), indicating a two-day return differential of 8.9% between the best and the worst earnings results. The univariate model (with time fixed effects) has an adjusted-R^2 of 9.2%, reflecting the impact of earnings surprises on announcement returns. Model 2 shows that the market reaction to earnings news varies across LLT deciles. For firms with the lowest LLT activity at earnings announcement, the return differential between top and bottom SUE deciles is 6.3% (t-statistic = 28.99). In contrast, a significantly stronger market reaction is observed for firms in the top LLT decile, as indicated by the positive coefficient of 0.061 (t-statistic = 11.75) on the interaction term $DSUE \times DLLT$. Adding the two coefficients gives an ERC of 12.4% for high LLT earnings announcements, which is almost twice as large as that for the low LLT group. The coefficient on $DLLT$ is -0.034 (t-statistic = -13.05), which suggests that for the lowest SUE decile with a negative earnings surprise, the return differential across the highest and lowest LLT is -3.4%. In other words, higher LLT activity leads to quick incorporation of the negative earnings information into prices.

Models 3 and 4 further show that controlling for firm characteristics and firm fixed effects has little impact on the LLT results. The adjusted-R^2 increases marginally between Model 2 and Model 3 suggesting that there is not much information in the control variables in the presence of firm fixed effects. The last column of Panel B shows that even after interacting $DSUE$ with the control variables and the time fixed effects, the coefficients on $DSUE \times DLLT$ remain strongly significant. Note that due to the large number of interaction terms, the interpretation of the coefficients on $DSUE$ and $DSUE \times DLLT$ in Model 5 is not as straightforward as in Model 2. Despite this, the result does indicate that the positive impact of LLT on market reaction to earnings news is not subsumed by other drivers of earnings announcement returns.[18]

3.3 Post-earnings announcement drift (PEAD)

3.3.1 Impact of LLT on PEAD

As attested by the longstanding ERC literature, the strength of market reaction to earnings news is influenced by a myriad of economic factors, such as the discount rate and quality of the reported earnings (Collins and Kothari 1989; Easton and Zmijewski 1989; Kormendi and Lipe 1987). Since the market reaction result does not speak only to the pricing efficiency of earnings information, we also examine the post-earnings-announcement returns for more reliable inferences. Our test is motivated by the post-earnings-announcement-drift (PEAD) literature, which has commonly relied on the magnitude of the drift to estimate the extent of mispricing caused by the market's underreaction to earnings news (e.g., Bartov et al. 2000, Hirshleifer et al. 2009). If LLT improves (reduces) the pricing efficiency of earnings information, we should observe weaker (stronger) PEAD for earnings announcements with high LLT activity. We test this prediction using the following panel regression:

$$CAR60 = \beta_0 + \beta_1 DSUE + \beta_2 DSUE \times DLLT + \beta_3 DLLT + Controls + Fixed\ Effects + \varepsilon \,. \quad (3)$$

Panel C of Table 2 again presents five nested model specifications to more clearly illustrate the marginal effect of the different specifications. The introduction of the controls, fixed effects, and the interaction terms follows the pattern in Panel B. In

[18] While our result is robust to interacting *SUE* with all the control variables, we note that this model specification seems to overfit the data and suffer from severe multicollinearity problem. For example, the variance inflation factor (VIF) reaches alarming values of 30.69 and 83.26 for some of the interaction terms in the regression, and an astounding 320.12 for the standalone *DSUE* variable.

Model 1, the coefficients on *DSUE* is significantly positive at 0.021 (t-statistic = 7.04), indicating that for the overall sample, the difference in the 60-day post announcement returns between the highest and the lowest *SUE* stocks is an economically significant 2.1%. In contrast, *DSUE* has a larger coefficient of 0.047 (t-statistic = 9.23) in Model 2, suggesting that mispricing of earnings information is more severe for firms with low LLT activity. The coefficient on the interaction term $DSUE \times DLLT$ is significantly negative at -0.059 (t-statistic = -7.07), suggesting the underreaction to earnings news is mitigated when low-latency traders are more active during earnings announcements. Adding the two coefficients together shows that the coefficient on *DSUE* for the highest *LLT* decile is -0.012. Note that because *DLLT* is a continuous variable bounded between 0 and 1, rather than a dichotomous variable that takes value of 0 or 1, the coefficient on *DSUE* for the top *LLT* decile subsample will be slightly different from -0.012. To verify that underreaction to earnings news is non-existent for announcements with the highest LLT activity, we estimate the PEAD regression separately for the top *LLT* decile subsample and find a statistically insignificant coefficient of -0.008 (t-statistic = -0.93) on *DSUE*, as reported in the bottom row of Panel C. Also, in Model 2 the coefficient on *DLLT* is 0.036 (t-statistic = 7.25), which suggests that for the lowest *SUE* decile, the *CAR60* differential across the highest and lowest *LLT* is 3.6%. In other words, higher LLT activity leads to quick incorporation of the negative earnings information into prices and, thus, a lower PEAD.

The remaining columns of Panel C show that these results are generally robust to including control variables, firm fixed effects, and various interaction terms in the regression.

In summary, our results are economically and statistically significant in the presence of the control variables and the interaction of *DSUE* with the control variables, suggesting that the effect of LLT on the price reaction to earnings announcements and PEAD is distinct from the empirical regularities documented in the literature thus far.

3.3.2 Different measurement windows for PEAD

Following Bernard and Thomas (1989) we have used a 60-day post-announcement period to measure PEAD. Existing theories of PEAD, however, do not provide any guidance on how the drift should be measured and some recent studies find that the drift may persist for much longer (Doyle et al. 2006). To verify that our results are robust to alternative horizons of the drift, we examine returns over different periods from 30 to 251 trading days after the announcement. As before, all raw returns are adjusted by their matching portfolio returns based on size, book-to-market, and momentum. Table 3 presents the results. For ease of interpretation we focus on coefficients from the baseline model reported in Panel A. In Panel B we show that the main effect, albeit weaker, is significant for the most part in the extended model that includes the control variables, firm fixed effects, and interaction terms.

Panel A of Table 3 shows that LLT significantly reduces the size of PEAD across all five measurement windows. The coefficient on $DSUE$ increases monotonically with the length of the return accumulation window, suggesting that for low LLT firms, the drift extends over a prolonged period of up to one year after the earnings announcement. The sum of the coefficients on $DSUE$ and $DSUE \times DLLT$ remains close to 0 regardless of the measurement window, indicating that for announcements with the highest LLT activity, earnings information is correctly priced and no predictable post-announcement return is observed.

Thus, LLT reduces the size of PEAD and improves efficiency for up to a year. This is important because, in contrast to the existing studies that measure efficiency at very high frequencies, this time frame of a year is more consistent with the frequency of corporate decision making and investor risk sharing and hedging.

3.4 Portfolio analysis

Overall, the regression results from the market reaction and the post-announcement return tests provide consistent evidence that increased LLT is beneficial to the pricing of earnings information correctly. To more clearly illustrate the economic significance of LLT's impact on pricing efficiency, in this section we examine a portfolio-based, long-short trading strategy that explores the interaction between earnings news and low-latency trading. At the beginning of each month from February 2008 to December 2017, we assign each stock into one of the 5 x 5 independently sorted portfolios based on the *SUE* and *LLT* of its most recent earnings announcement during the past three months.[19] We then calculate the equally-weighted portfolio return for the month, and estimate the alpha from the Fama-French (2015) five-factor model that includes market (MKTRF), size (SMB), value (HML), operating profitability (RMW), and investment (CMA),[20] using the entire time-series of 119 months.[21]

Table 4 reports the monthly alphas for each of the 25 portfolios and various long-short portfolios. The statistical significance of the alpha estimates is based on Newey-West corrected standard errors.[22] The top row of the table shows that a portfolio that is long the high *SUE* stocks and short the low *SUE* stocks generates an average alpha of 0.48% per month during our sample period. However, the

[19] One concern with independent sorts is whether the portfolios have sufficient number of stocks. The minimum (maximum) average number of stocks across the 25 portfolios are 47 (154). Therefore, the portfolios in our sample are well-diversified.

[20] The monthly factor returns are downloaded from Professor Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[21] We use delisting returns from CRSP. If delisting return is missing and the delisting is performance-related, we assume a delisting return of -30%. (Shumway 1997, Beaver et al. 2007)

[22] We use 3-lags in the Newey-West adjustment because each earnings announcement is linked to three subsequent monthly returns.

profitability of the SUE strategy varies significantly across the LLT portfolios. For stocks within the lowest LLT quintile, the monthly alpha from the long-short SUE portfolio is 1.27%, or about 16% annualized. In contrast, for the highest LLT quintile, the monthly long-short portfolio alpha reduces to a statistically insignificant -0.06%. The difference in profitability of the long-short SUE portfolios between the two extreme LLT groups is highly significant at 1.32% (t-statistic = 3.30), again suggesting that increased LLT activity has an economically important impact on improving the efficiency of the market's reaction to earnings news.

3.5 Endogeneity

In the introduction we have discussed the potential concern of reverse causality and the omitted variable problem. We now use the exogenous technological change on the NYSE to address the endogeneity issues. Hendershott et al. (2011) show that the autoquote system introduced in early 2003 significantly increased algorithmic trading activity on the NYSE. We use this exogenous shock to trading latency as our identification strategy to test for whether LLT drives improvements in market efficiency around earnings announcements. In particular, we employ a difference-in-differences (diff-in-diff) research design using NYSE-listed firms as the treatment group and their NASDAQ-listed peers as the control group, and compare the changes in market reaction to earnings news and post-earnings announcement drift from pre- to post-autoquote period by estimating the following regression model:

$$EARET\ or\ CAR60 = \beta_0 + \beta_1 DSUE + \beta_2 DSUE * NYSE + \beta_3 DSUE * POST + \beta_4 DSUE \times NYSE \times POST + \beta_5 NYSE + \beta_6 POST + \beta_7 NYSE * POST + Controls + Fixed\ Effects + \varepsilon\ . \quad (4)$$

In equation (4), the dependent variable is either (i) the 2-day earnings announcement return (*EARET*) for market reaction analysis, or (ii) the 60-day post-announcement return (*CAR60*) for PEAD analysis. *NYSE* is an indicator variable that is 1 for firms listed on NYSE, and 0 for NASDAQ-listed firms. $POST$ is another indicator variable that is 1 for earnings announcements after May 2003, and 0 for announcements before January 2003. As discussed in detail in Hendershott et al. (2011), the NYSE started to phase in the autoquote system in January 2003 and completed the process in May 2003. We therefore exclude all earnings announcements made between January and May of 2003 from our sample for a clean identification of the treatment effect. The triple-interaction term $DSUE \times NYSE \times POST$ is our main variable of interest, and its coefficient β_4 captures the effect of LLT on market efficiency.

In a diff-in-diff test the treatment and control firms should not differ systematically prior to receiving the treatment. To control for differences in firm fundamentals, we match NYSE firms to their NASDAQ peers by industry, book-to-market ratio, and firm size. We require each matched pair to be from the same Fama-French 30 Industry and with differences in book-to-market ratio and market value of equity not exceeding +/- 10%. Industry, book-to-market, and size are measured at the end of December 2002.

Table 5 reports the diff-in-diff results. For robustness, we use two alternative sample periods: 24 or 36 months before and after the exogenous shock. The introduction of autoquotes on NYSE had a strong positive impact on the immediate market reaction to earnings news (β_4 = 0.025 or 0.016, t-statistic = 2.20 or 1.82, depending on sample period). Further, the introduction of autoquotes significantly reduced the magnitude of the post-earnings-announcement drift (β_4 = -0.076 or -0.073, t-statistic = -2.26 or -2.56, depending on sample period). Taken together, these results provide evidence on the beneficial impact of LLT on the efficient incorporation of earnings news into prices.

To mitigate the concern that the increased efficiency we documented above is the result of NYSE and NASDAQ firms responding differently to an overall trend of increasing price responsiveness to earnings announcement, we perform a falsification test by shifting our “event” window to a different time period. To ensure that the actual autoquote event does not contaminate the pseudo-event analysis, we assign our pseudo-event window to be three-years (two-years) before or after the autoquote implementation period for the 36-month (24-month) sample and re-run the diff-in-diff regressions with the pseudo-events. The results, presented in Table IA.1 of the Internet Appendix, show that the previously observed empirical regularity surrounding the adoption of autoquote disappears: there does not appear to be any discernible systematic change surrounding the pseudo-events. The coefficient on the triple-interaction variable is statistically significant in only one out of the eight regressions, but with a wrong sign. These results are thus consistent with the parallel trend assumption being satisfied.

While the implementation of NYSE autoquote provides a clean setting for studying the impact of algorithmic trading, this event happened in early 2000, and technology, regulation, and market structure have all seen significant changes since then. The concern is that the above results may not generalize to the more recent trading environment. To provide corroborating evidence from more recent periods, another identification we have used is the technology enhancement implemented on NASDAQ in April and May of 2010. This technological improvement reduced the latency of submitting and processing orders on NASDAQ from microseconds to nanoseconds (Gai et al. 2013). Once again, we use a difference-in-differences research design and match each NASDAQ-listed firm to its NYSE-listed peer on size, industry, and book-to-market ratio.[23] The results are reported in Table IA.2 of the Internet Appendix. We find that this exogenous shock to LLT significantly increased the magnitude of the immediate market reaction to earnings news for NASDAQ-listed firms relative to their NYSE-listed peers. It also had a negative but statistically insignificant effect on the post-announcement drift. One concern is that due to the small size of firms on Nasdaq, the matching on firm size reduces the sample size considerably. When we relax the matching requirement and match only on industry and book-to-market ratio, the sample size increases by more than three times. The market reaction result remains strong and the PEAD effect becomes more pronounced with the diff-in-diff coefficient in the 24 month regression, being statistically significant at 10% level. Overall, the results from this Nasdaq technological change are supportive of the positive impact of LLT on the efficient incorporation of earnings news into prices. However, we note that this event happened after Reg NMS was implemented. Therefore a stock's listing venue may no longer dominate its trading. To the extent that partitioning the sample by listing venue does not cleanly identify the treatment group, this result needs to be interpreted with caution.

In summary, in the above tests we find consistent results that LLT facilitates timely incorporation of earnings information into prices. While these results provide further support for the beneficial effect of LLT on market efficiency, we acknowledge the possibility that other considerations, such as managers' strategic disclosure policy in response to LLT, could also affect the observed results. We leave detailed examination of these alternative channels to future research.

3.6 Direction of LLT

[23] Industry, book-to-market and size are measured at the end of March 2010.

The results thus far provide robust evidence that *aggregate* low-latency activity at earnings announcements improves price efficiency with regard to earnings information. To better understand the underlying mechanism of this effect, we now examine how the direction of low-latency activity helps incorporate earnings news into prices. Specifically, we define a signed LLT measure based on the difference between the time-weighted number of buy-runs and sell-runs:

$$LLT\_SIGN = \frac{1}{2.34 \times 10^7}\left[\left(\sum_{j=1}^{N} T_j^{Bid}\right) - \left(\sum_{k=1}^{M} T_k^{Ask}\right)\right] \times D, \quad (5)$$

where T_j^{Bid} is time-in-force for buy-run j in milliseconds at the bid price, T_k^{Ask} is time-in-force for sell-run k at the ask price, and D is a dummy variable equal to 1 if *SUE* >= 0, and -1 if *SUE* < 0.

Since the difference in the time-in-force for buy and sell runs is signed conditional on earnings news, *LLT_SIGN* can be interpreted as the net quoting activity by low latency firms in the same direction as the earnings surprise. For instance, if *SUE* < 0, then a positive *LLT_SIGN* corresponds to an excess of sell quoting activity i.e., posting and cancelling of offer quotes as the low latency traders seek to sell. With *SUE* < 0, a negative *LLT_SIGN* would reflect posting and cancelling of bid quotes as the low latency traders supply liquidity to traders looking to sell. To the extent that net order imbalance during earnings announcements is mostly in the direction of earnings surprise, a large and positive *LLT_SIGN* may also be viewed as a proxy for the aggressiveness by LLTs in response to earnings news. This is consistent with Hasbrouck and Saar (2013) who argue that the runs-based measure of LLT "is not restricted to solely capturing liquidity-supplying trades despite being comprised mostly of limit orders."

Panel A of Table 6 shows that the sample mean and median of *LLT_SIGN* are -0.020 and 0, respectively, suggesting LLTs' quoting activity is on average balanced.

However, there is a substantial cross-sectional variation in the quoting activities, as indicated by the large standard deviation of 1.196. This shows that LLTs are primarily liquidity suppliers in some earnings announcements but aggressive consumers of liquidity in other announcements. This significant variation allows us to test for any differential effects of the two trading strategies on market efficiency. Panel B of Table 6 shows that *LLT_SIGN* is negatively correlated with *SUE* and *EARET*, suggesting LLTs tend to trade more aggressively when firms report bad news at earnings announcements. This result is consistent with directional LLTs strategies exploiting short-term price volatility, as bad news announcements tend to generate larger volatility in the market.

Panels C and D of Table 6 report the results of the market reaction and the PEAD tests, respectively. As before *DSUE* and *DLLT_SIGN* are the within quarter decile rankings of *SUE* and *LLT_SIGN* and both *DSUE* and *DLLT_SIGN* are standardized to range between 0 and 1. Also, we use the same control variables, firm fixed effect, time fixed effects, and the interaction of *DSUE* with the controls and time fixed effects as in Table 2.

The coefficient on the interaction term $DSUE \times DLLT\_SIGN$ in Model 1 in Panel C is significantly positive (0.044, t-statistic = 9.19), indicating that the reaction to earnings news is stronger when LLTs are more aggressive in their quote updates in the direction of earnings surprise. Moreover, this result remains robust after controlling for other firm characteristics, various fixed effects, and the interaction terms. Panel D shows that the magnitude of the drift decreases when LLTs quote more aggressively. For example, in Model 1 the PEAD for announcements with lowest *LLT_SIGN* is 2.9% and reduces to 1.4% for the highest *LLT_SIGN* group.

Again, this result is not sensitive to including the controls, the fixed effects, and the interaction terms.

Thus, earnings information is more efficiently incorporated into prices when low-latency traders aggressively update their quotes to be able to trade in the direction of earnings surprises.

For robustness, we next examine the trading activity of 26 HFT firms surrounding 937 quarterly earnings announcements of 104 stocks that are covered by the Nasdaq HFT dataset.[24] For each stock-trading day, we estimate the net demand for liquidity by HFTs by the net HFT order imbalance (*HFTOI*) in the direction of earnings surprise. In particular, we define *HFTOI* as $HFT^{BUY} - HFT^{SELL}$ if the announced earnings meet or beat market expectation (good news), and HFT^{SELL} - HFT^{BUY} otherwise. HFT^{BUY} is total HFT buy volume on the liquidity demand side minus total HFT buy volume on the liquidity supply side, while HFT^{SELL} is total HFT sell volume on the liquidity demand side minus total HFT sell volume on the liquidity supply side. In each case, we require that the other side of the trade be a non-HFT, i.e., we eliminate any trade where both sides of the trade are HFTs. The daily median *HFTOI* within a 61-day window, centered on earnings announcement day, is plotted in Figure 2. The HFTs' net demand for liquidity increases during earnings announcements as they trade in the direction of earnings surprise, resulting in net order imbalance of almost 2000 shares per day in our sample. Given that HFTs and most other low-latency traders typically carry close to zero inventory overnight,

[24] The Nasdaq data provide trading activity of 26 HFT firms on the Nasdaq exchange. It includes 120 stocks selected by size and covers all trading days in 2008 and 2009, as well as the Feb 22 – 26, 2010. See Brogaard et al. (2014) for details about this dataset.

Figure 2 suggests that LLTs trade aggressively around earnings announcements. Their trading thus leads to faster incorporation of earnings information into prices.[25]

3.7 Additional Analysis

3.7.1 NASDAQ-listed stocks

Our sample covers mainly the post-Reg NMS period, which is characterized by a proliferation of market centers and increasing fragmentation of order low. As the TotalView-ITCH dataset captures only trading activity on NASDAQ, a potential concern, therefore, is that the low-latency activities at other trading venues may be systematically different from those on NASDAQ, and hence our *LLT* variable provides only a partial, or even biased, view of the complete market. To address this issue, we conduct additional analysis of market reaction to earnings news for a subsample of stocks with a primary listing on NASDAQ. Another advantage of examining NASDAQ-listed stocks is that most of earnings announcements are made outside regular trading hours, and as a result the opening auctions may play a significant role in the price discovery process. Since these auctions happen only at the primary listing exchange, the NASDAQ-listed stocks could provide a cleaner setting to study the impact of LLT on market efficiency at earnings announcements.

As shown in Table IA.3 of the Internet Appendix, with a sample of 46,232 earnings announcements made by firms listed on NASDAQ, we continue to find strong results that LLT improves the market efficiency of incorporating earnings information, and these results are consistent for both the initial price reaction as well as the PEAD.

3.7.2 Alternative measures of LLT

[25] In a related study, Bhattacharya et al. (2018) examine a similar earnings announcement sample covered by the Nasdaq HFT dataset, and find a stronger market reaction to unexpected earnings when *aggregate* HFT volume is high (defined as accounting for more than 7% of total trading volume). Our analysis of *signed* HFT volume thus complements their finding by showing that it is the liquidity-demanding trades that drives the stronger market reaction.

The *LLT* measure based on strategic runs has been shown to be highly correlated with high-frequency trading in Hasbrouck and Saar (2013). In our own analysis, we also find that *LLT* is correlated with various market quality indicators and firm characteristics in consistent ways as would be expected from a high quality empirical proxy of low latency activity. Nonetheless, we now examine two additional measures of low-latency trading to test whether the positive impact of LLT on market efficiency documented in our study is sensitive to these alternative proxies.

According to the 2010 SEC Concept Release on Market Structure (SEC 2010), a defining characteristic of high-frequency trading is "the submission of numerous orders that are cancelled shortly after submission". Following this description, we define two variables that capture the order submission intensity and high-frequency order cancellations during earnings announcements. The first variable, *NORDER*, counts the total number of (marketable or non-marketable) limit orders submitted to NASDAQ during regular trading hours. The second variable, *HFOCR*, or high-frequency order cancel rate, calculates the percentage of limit orders that are cancelled within 100 milliseconds of submission.[26] Similar to *LLT*, both of the new measures are constructed from the NASDAQ TotalView-ITCH dataset and therefore can be applied in large sample analysis. Recall from Panel C of Table 1 that both *NORDER* and *HFOCR* are highly correlated with *LLT*, consistent with both being proxies of the same underlying construct. As before we use the decile rankings of *NORDER* and *HFOCR* in the regression. Their effect on market pricing of earning information is presented in Table 7. Panel A reports the baseline model and Panel B shows the extended model with all controls included.

[26] The results are robust if we use 200 milliseconds or 300 milliseconds. However, note that this measure misses any cancellations by LLTs outside of 100 or 200 or 300 milliseconds.

Panel A of Table 7 documents a stronger market reaction to earnings news and a smaller post-announcement drift for announcements with high-volume of order submissions. It also shows a similar pattern for high-frequency order cancellations. When more orders are cancelled within 100 milliseconds of submission, the market's immediate reaction to the announcement is stronger and delayed reaction is weaker, suggesting less underreaction to earnings information and hence more efficient prices. In Panel B the PEAD results are statistically insignificant with the introduction of the interaction terms, while the market reaction results remain robust. Overall, the results reported in this section suggest that, as an empirical proxy for LLT, the Hasbrouck and Saar (2003) strategic runs measure seems superior to the simpler measures such as *NORDER* or *HFOCR*. While easy to construct, these measures can be prone to measurement errors. For example, *DNORDER* counts orders submitted by both fast and slow traders, while *HFOCR* ignores the order resubmissions by LLTs.

4. Unscheduled information releases

Thus far, we have robust evidence that LLT improves market efficiency around earnings announcements. Since earnings announcements are mostly pre-scheduled, giving traders ample time to get prepared, it is unclear whether the positive impact of LLT also extends to information events that are largely unexpected. In this section we provide initial evidence that LLT also improves the price responsiveness to unscheduled information release. In particular, we examine market reaction to filings of insider purchases with the SEC[27] and announcements of stock-financed acquisition of private target. Prior literature shows that both events convey significant information to investors with clear implications for prices. (Rogers et al. 2017, Louis and Sun 2010, Brochet 2010, Chang 1998)

[27] Following Rogers et al. (2017), we examine insider purchases rather than sales because purchases are more informative.

4.1 Insider trading filings

Panel A of Table 8 describes our insider trading sample. The sample includes 117,365 Form 4 filings of insider purchases for 4,990 unique firms from January 2008 to December 2017. LLT is average number of time-weighted strategic runs over day 0 and 1, where day 0 is the filing date, and $FRET$ is size-book-to-market-momentum adjusted abnormal return over the two-day event window. The sample mean of LLT is 8.746, significantly higher than the daily mean of 6.979 over the sample period (Panel A Table 1), indicating enhanced LLT activity in response to the filings. $FRET$ is slightly positive at 0.3%, consistent with insider purchases on average are perceived as good news by investors.

We test LLT's impact on market reaction to the insider trading filings using the following regression model:

$$FRET = \beta_0 + \beta_1 DLLT + Controls + Fixed\ Effects + \varepsilon \tag{5}$$

Consistent with the earnings announcement regressions, we use monthly decile ranks of *LLT*, *DLLT*, as the main regressor, for its robustness to outliers and ease of interpretation. This also remove the temporal trend in the raw variable because firms are independently ranked within each calendar month. Following Brochet (2010), we control for transaction details including number of shares purchased by insiders (*TRADE_SIZE*), recent insider purchases within the last 10 days (*RECENT_TRADE*), reporting lag between transaction date and filing date (*REPORT_LAG*), and whether the insider purchase is identified as a pre-planned trade pursuant to Rule 10b5-1 (*RULE10B5*). We also control for time-varying firm characteristics such as firm size (*MV*), book-to-market ratio (*BTM*), loss dummy (LOSS) indicating whether the firm suffered a loss over the most recent fiscal year, R&D spending (R&D), an indicator variable for existence of company policy restricting insider trading (*RESTRICT*), and year, month and day of the week fixed effects in the regression. We further include firm fixed effects to control for the impact of time-invariant firm characteristics.

The regression results are reported in Panel B of Table 8. The coefficient on our key variable of interest, $DLLT$, is significantly positive at 0.007 (t-statistic = 9.25), indicating a more favourable reaction to insider purchase filings with higher LLT activity at the time of filing. In economic terms the differential filing return across the LLT deciles amounts to a two day return of 0.7%. Since insider purchases in general convey good news, the result suggests that LLT is associated with higher price responsiveness to insider trading information.

To address the concern that heightened low-latency activity might cause prices to over-react to the insider trading filings, we estimate the impact of LLT on the post-filing return reversal as follows:

$$CAR60F = \beta_0 + \beta_1 FRET + \beta_2 FRET \times DLLT + \beta_3 DLLT + Controls + Fixed\ Effects + \varepsilon \quad (6)$$

where *CAR60F* is the abnormal return over a 60-day window starting on the second day after the filing date. Panel C of Table 8 shows that the coefficient on $FRET$ is -0.185 (t-statistic = -8.05), indicating a significant return reversal for filings with low LLT. More importantly, the coefficient on the interaction term $FRET \times DLLT$ is a positive 0.109 (t-statistic = 2.49), suggesting that the post-filing return reversal, which reflects the initial overreaction to the filings, is actually mitigated by LLTs.

4.2 Merger and Acquisition (M&A) announcements

The prior literature has shown that the price reaction to an acquirer's announcement of an M&A deal is complicated, and largely depends on the financing method and target firm characteristics. (Travlos 1987, Chang 1998, Louis and Sun

2010) For example, Chang (1998) find that in stock bids, bidders experience positive announcement returns when the target is privately held, but negative returns if the target is publicly traded. On the other hand, there is no abnormal market reaction to announcement to cash bids regardless of the type of the target.

Following this literature, we separately examine LLT's impact on the bidder's announcement return of stock bids for private and public targets. Specifically, we estimate the following regression model separately for the private target subsample and the public target subsample.

$$RET\_ANN = \beta_0 + \beta_1 Log(LLT) + Controls + Fixed\ Effects + \varepsilon \qquad (6)$$

The dependent variable, *RET_ANN*, is the bidder's abnormal return over the two-day announcement window (0, 1), where day 0 is the announcement date of the stock bid. As before, abnormal return is adjusted by its size, book-to-market, and momentum matched portfolio return, and *LLT* is averaged over day 0 and 1. Due to the limited sample size, we use log-transformed *LLT*, rather than cross-sectional decile ranks of LLT, in the regression. Following Louis and Sun (2010), we control for relative deal size (*REL_SIZE*), bidder's characteristics including firm size (*MV*), book-to-market ratio (*BTM*), institutional ownership (*INST*), analyst coverage (*NUMEST*), and abnormal stock returns over the past three month (*RET_P3M*), as well as time and industry fixed effects.[28]

Our sample is collected from the SDC - Mergers and Acquisitions database. We start with all deals that are at least 50% financed by stock and announced between January 2008 and December 2017. After removing observations with missing data, the final sample includes 263 deals with private target and 460 deals with public target. The summary statistics are presented in Panel A of Table 9. Consistent with

[28] We cannot include firm fixed effects as most firms appear only once in our M&A sample.

prior findings, acquirers on average experience positive announcement returns (5.20%) when bidding for privately held targets, and negative returns (-1.20%) when bidding for public targets. Bidders for public targets see significantly higher LLT activity during the announcement window than bidders for private targets (10.123 vs. 6.779), although this could be due to the substantial difference in firm size between the two groups ($10.09 billion vs. $2.01 billion).

Panel B of Table 9 reports the regression results. For the private target subsample, the coefficient of *Log(LLT)* is significantly positive at 6.63 (t-statistic = 2.41). In economic terms, a one standard deviation change in *Log(LLT)* results in a two day announcement return of 5.6%. To the extent that stock bids for private targets represent good news for bidding firms, this result suggest LLT is associated with stronger market reaction to this information. On the other hand, the coefficient on *Log(LLT)* is not significant at conventional level for the public target sample. Finally, we also examine post-announcement return reversals and, as Panel C of Table 9 shows, there is no evidence of LLT-driven overreactions to the M&A announcements.

5. Conclusions

In recent years, financial markets have changed dramatically due to technological advances and regulation. One important development is the advent of fast trading. This paper examines the impact of low latency trading (LLT) on earnings announcements which are pre-scheduled as well as the unscheduled insider filings and the corporate merger and acquisition (M&A) announcements. In the case of earnings, LLT increases the initial price reaction at the time of the announcements and decreases the subsequent drift thereby leading to improvements in price efficiency.

News related to insider trading and M&As is also quickly and accurately incorporated into prices in the presence of LLT.

The literature on fast trading has used a rather limited cross-sectional and time-series sample to show that LLT improves market efficiency at high frequencies. However, the question remains whether short-term improvements in market quality and market efficiency really matter for corporate decisions and investor risk sharing and hedging. Another contribution of this paper is to show that low latency trading facilitates pricing of accounting information and improves market efficiency for time horizons that are relevant to the great majority of investors.

While this paper has exploited exogenous technological shocks to ascertain causality for earnings announcements, the identification of instrumental variables for other announcements is left for future work as is the search for more easily computable proxies for LLT.

References

Amihud, Yakov, 2002. "Illiquidity and Stock Returns: Cross-section and Time-series Effects." *Journal of Financial Markets* 5 (1): 31-56.

Ball, R., Bartov, E., 1996. “How Naïve is the Stock Market’s Use of Earnings Information?” *Journal of Accounting and Economics* 21, 319-337.

Ball, R., Brown, P., 1968. “An Empirical Evaluation of Accounting Income Numbers.” *Journal of Accounting Research* 6, 159-177.

Bartov, E., Radhakrishnan, S., Krinsky, I., 2000. “Investor Sophistication and Patterns in Stock Returns After Earnings Announcements.” *The Accounting Review* 75, 43-63.

Beaver, W., 1968. “The Information Content of Annual Earnings Announcements.” *Journal of Accounting Research* 6: 67-92.

Beaver, W., McNichols, M., Price, R., 2007. “Delisting Returns and Their Effect on Accounting-based Market Anomalies.” *Journal of Accounting and Economics* 43, 341-368.

Beaver, W., McNichols, M., Wang, Z., 2018. “The Information Content of Earnings Announcements: New Insights from Intertemporal and Cross-sectional Behavior.” *Review of Accounting Studies* 23: 95-135.

Bernard, V.L., Thomas, J.K., 1989. “Post-earnings-announcement Drift: Delayed Price Response or Risk Premium?” *Journal of Accounting Research* 27, 1-36.

Bernard, V.L., Thomas, J.K., 1990. “Evidence that Stock Prices Do Not Fully Reflect the Implications of Current Earnings for Future Earnings.” Journal of Accounting and Economics 13, 305-340.

Bhattacharya, N., Chakrabarty, B., Wang, X., 2018. “Earnings Announcements in High Speed Markets: Do High Frequency Traders Bring Fundamental Information into Prices?” Working paper, Southern Methodist University.

Bhushan, R., 1994. “An Informational Efficiency Perspective on the Post-earnings-announcement Drift.” *Journal of Accounting and Economics* 18, 45-65.

Biais, Bruno, Thierry Foucault, and Sophie Moinas. 2015. “Equilibrium Fast Trading.” *Journal of Financial Economics* 116 (2): 292-313.

Brochet, F., 2010. “Information Content of Insider Trades before and after the Sarbanes-Oxley Act.” *The Accounting Review* 85 (2): 419-446.

Brogaard, Jonathan, Terrence Hendershott, and Ryan Riordan. 2014. “High-Frequency Trading and Price Discovery.” *Review of Financial Studies* 27 (8): 2267-2306.

Brogaard, Jonathan, Ryan Riordan, Andriy Shkilko, Konstantin Sokolov, Allen Carrion, and Thibaut Moyaert. 2017. "High Frequency Trading and Extreme Price Movements." *Journal of Financial Economics* 124(3): 486-502.

Budish, Eric, Peter Cramton, and John Shim. 2015. " The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response." *The Quarterly Journal of Economics*, 130(4), pp.1547-1621.

Burgstahler, D., Jiambalvo, J., Shevlin, T., 2002. “Do Stock Prices Fully Reflect the Implications of Special Items for Future Earnings?” *Journal of Accounting Research* 40, 585- 612.

Carrion, Allen. 2013. “Very Fast Money: High-Frequency Trading on the NASDAQ.” *Journal of Financial Markets* 16 (4): 680–711.

Chaboud, Alain P., Benjamin Chiquoine, Erik Hjalmarsson, and Clara Vega. 2014. “Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market.” *The Journal of Finance* 69 (5): 2045–84.

Chang, S., 1998. “Takeovers of Privately Held Targets, Methods of Payment, and Bidder Returns.” *Journal of Finance* 53 (2): 773-784.

Chakrabarty, Bidisha, Pamela Moulton, and Xu Wang. 2015. "Attention Effects in a High-Frequency World." *Working paper,* Saint Louis University.

Chambers, Anne E., and Stephen H. Penman, 1984, "Timeliness of Reporting and the Stock Price Reaction to Earnings Announcements." *Journal of Accounting Research* 22, 21-47.

Chordia, Tarun, Amit Goyal, Bruce Lehmann, and Gideon Saar. 2013. "High-frequency Trading." *Journal of Financial Markets* 16 (4): 637-645.

Chordia, T., Goyal, A., Sadka, G., Sadka, R., Shivakumar, L., 2009. “Liquidity and the Post-Earnings-Announcement-Drift.” *Financial Analyst Journal* 65, 18-32.

Chordia, Tarun, Clifton Green, and Badrinath Kottimukkalur. 2018. "Rent Seeking by Low Latency Traders: Evidence from Trading on Macroeconomic Announcements." *Review of Financial Studies* 31, 4650-4687.

Chordia, Tarun, Richard Roll and Avanidhar Subrahmanyam, 2011, “Recent Trends in Trading Activity and Market Quality.” *Journal of Financial Economics* 101, 243-263.

Cochrane, John, 2013, “Finance: Function Matters not Size.” *Journal of Economic Perspectives* 27, 29-50.

Collins, Daniel W., and S. P. Kothari, 1989, "An Analysis of Intertemporal and Cross-sectional Determinants of Earnings Response Coefficients." *Journal of Accounting and Economics* 11, 143-181.

Conrad, Jennifer S., Sunil Wahal, and Jin Xiang. 2015. "High Frequency Quoting, Trading, and the Efficiency of Prices." *Journal of Financial Economics* 116 (2): 271-291.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers. 1997. "Measuring Mutual Fund Performance with Charateristic-based Benchmarks." *The Journal of Finance* 52 (3): 1035-1058.

Dechow,. P., Ge., W., Schrand, C., 2010. "Understanding Earnings Quality: A Review of the Proxies, their Determinants and their Consequences." *Journal of Accounting and Economics* 50: 344-401.

DellaVigna, S., Pollet, J., 2009. "Investor Inattention and Friday Earnings Announcements." *Journal of Finance* 64, 709-749.

Doyle, J.T., Lundholm, R.J., Soliman, M.T., 2006. "The Extreme Future Stock Returns Following I/B/E/S Earnings Surprises." *Journal of Accounting Research* 44, 849-887.

Easton, Peter D., and Mark E. Zmijewski, 1989, "Cross-sectional Variation in the Stock Market Response to Accounting Earnings Announcements." *Journal of Accounting and Economics* 11, 117-141.

Fama, Eugene F., and Kenneth R. French, 2015, "A Five-factor Asset Pricing Model." *Journal of Financial Economics* 116, 1-22.

Frazzini, A., 2006. "The Disposition Effect and Underreaction to News." *Journal of Finance* 61 (4): 2017-2046.

Gai, Jiading, Chen Yao, and Mao Ye. 2013. "The Externalities of High-Frequency Trading." Working paper, University of Illinois.

Hagströmer, Björn, and Lars Nordén. 2013. "The Diversity of High-Frequency Traders." *Journal of Financial Markets* 16 (4), 741-770.

Hasbrouck, Joel, and Gideon Saar. 2013. "Low-Latency Trading." *Journal of Financial Markets* 16 (4): 646–79.

Hendershott, Terrence, Charles M. Jones, and Albert J. Menkveld. 2011. "Does Algorithmic Trading Improve Liquidity?" *The Journal of Finance* 66 (1): 1–33.

Hendershott, Terrence, and Ryan Riordan. 2013. "Algorithmic Trading and the Market for Liquidity." *Journal of Financial and Quantitative Analysis* 48 (4): 1001–24.

Hirshleifer, D., Lim, S., Teoh, S., 2009. "Driven to Distraction: Extraneous Events and Underreaction to Earnings News." *Journal of Finance* 64, 2289-2325.

Holden, Craig W., and Stacey Jacobsen. 2014. "Liquidity Measurement Problems in Fast, Competitive Markets: Expensive and Cheap Solutions," *The Journal of Finance* 69 (4): 1747-1785.

Jones, C., 2013. “What Do We Know about High-Frequency Trading?” Working paper, Columbia University

Jovanovic, Boyan, and Albert J. Menkveld. 2016. "Middlemen in Limit Order Markets." *Working Paper.*

Kirilenko, Andrei, Albert S. Kyle, Mehrdad Samadi, and Tugkan Tuzun. 2017." The Flash Crash: The Impact of High Frequency Trading on an Electronic Market." *Journal of Finance* 72 (3): 967-998.

Kormendi, R., and Lipe, R., 1987. “Earnings Innovations, Earnings Persistence, and Stock Returns.” *Journal of Business* 60: 323-345.

Kothari, S.P., 2001. “Capital Markets Research in Accounting.” *Journal of Accounting and Economics* 31, 105-231.

Landsman, W., Maydew, E., 2002. “Has the Information Content of Quarterly Earnings Announcements Declined in the Past Three Decades?” *Journal of Accounting Research* 40: 797-808.

Landsman, W., Maydew, E., Thornock, J., 2012. “The Information Content of Annual Earnings Announcements and Mandatory Adoption of IFRS.” *Journal of Accounting and Economics* 53: 34-54.

Lee, Charles, and Mark J. Ready. 1991. "Inferring Trade Direction from Intraday Data." *The Journal of Finance* 46 (2): 733-746.

Lee, C., and Watts, E., 2018. “Tick Size Tolls: Can a Trading Slowdown Improve Price Discovery?” Working paper, Stanford University

Lewis, Michael. 2014. "Flash Boys: A Wall Street Revolt." *W. W. Norton & Company, New York.*

Louis, H., and Sun, A., 2010. “Investor Inattention and the Market Reaction to Merger Announcements.” *Management Science* 56 (10): 1781-1793.

Mendenhall, R., 2004. “Arbitrage Risk and Post-earnings-announcement Drift.” *Journal of Business* 77, 875-894.

Menkveld, Albert J. 2013. "High Frequency Trading and the New Market Makers." *Journal of Financial Markets*, 16(4), 712-740.

Ng, J., Rusticus, T., Verdi, R., 2007, “Implications of Transactions Costs for the Post-earnings-announcement Drift.” *Journal of Accounting Research* 46: 661-696.

O’Hara, M., 2015. “High Frequency Market Microstructure.” *Journal of Financial Economics* 116: 257-270.

Richardson, S., Tuna, I., Wysocki, P., 2010. "Accounting Anomalies and Fundamental Analysis: A Review of Recent Research Advances." *Journal of Accounting and Economics* 50: 410-454

Rogers, J., Skinner, D., Zechman, S., 2017. "Run EDGAR Run: SEC Dissemination in a High-Frequency World." *Journal of Accounting Research* 55 (2): 459-505.

Securities and Exchange Commission, 2010. "Concept Release on Equity Market Structure"

Shumway, T. 1997. "The Delisting Bias in CRSP Data." *Journal of Finance* 52 (1): 327-340.

Soffer, L., Lys, T., 1999. "Post-earnings announcement Drift and the Dissemination of Predictable Information." *Contemporary Accounting Research* 16, 305-331.

Travlos, N., 1987. "Corporate Takeover Bids, Methods of Payment, and Bidding Firms' Stock Returns." *Journal of Finance* 42 (4): 943-963.

Weller, B., 2018. "Does Algorithmic Trading Reduce Information Acquisition?" *Review of Financial Studies* 31: 2184-2226.

Figure 1: Low-latency Activity Surrounding Quarterly Earnings Announcements

This figure plots the median daily low-latency activity during a 61-day window surrounding the earnings announcements. The sample includes an average of 91,908 stocks on each day. Day 0 is the earnings announcement day. *LLT* is a measure of low-latency activity based on the strategic runs measure developed by Hasbrouck and Saar (2013), defined as the time-weighted number of runs with at least 10 messages over the entire regular trading hours of a day. Figure 1a plots the total number of runs, and Figure 1b plots the proportion of runs that ends with a trade. The sample period is from January 2008 to December 2017.

Figure 1a

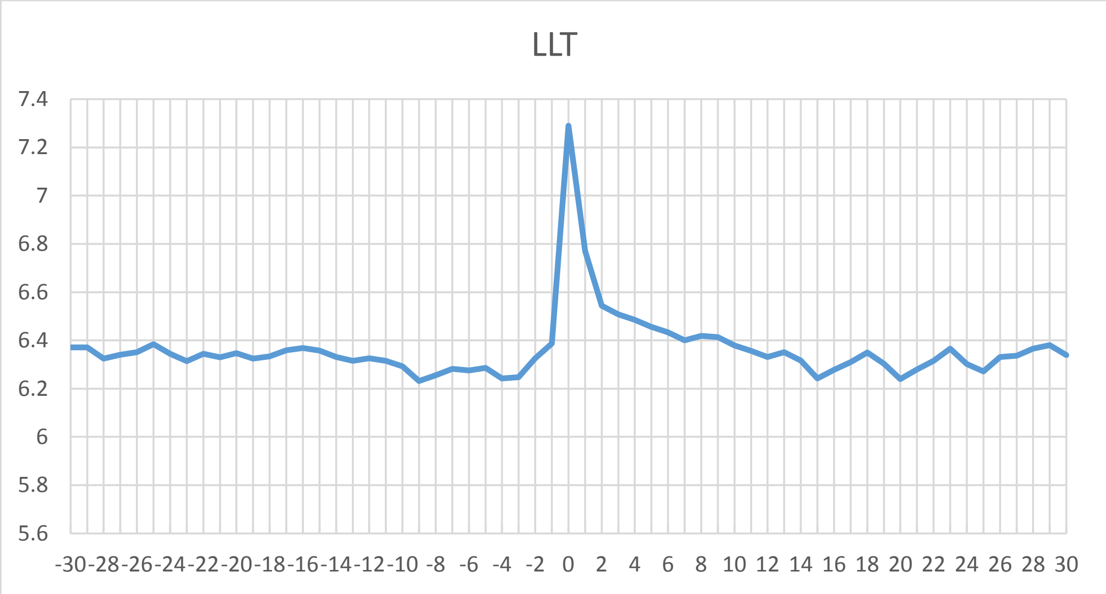

Figure 1b

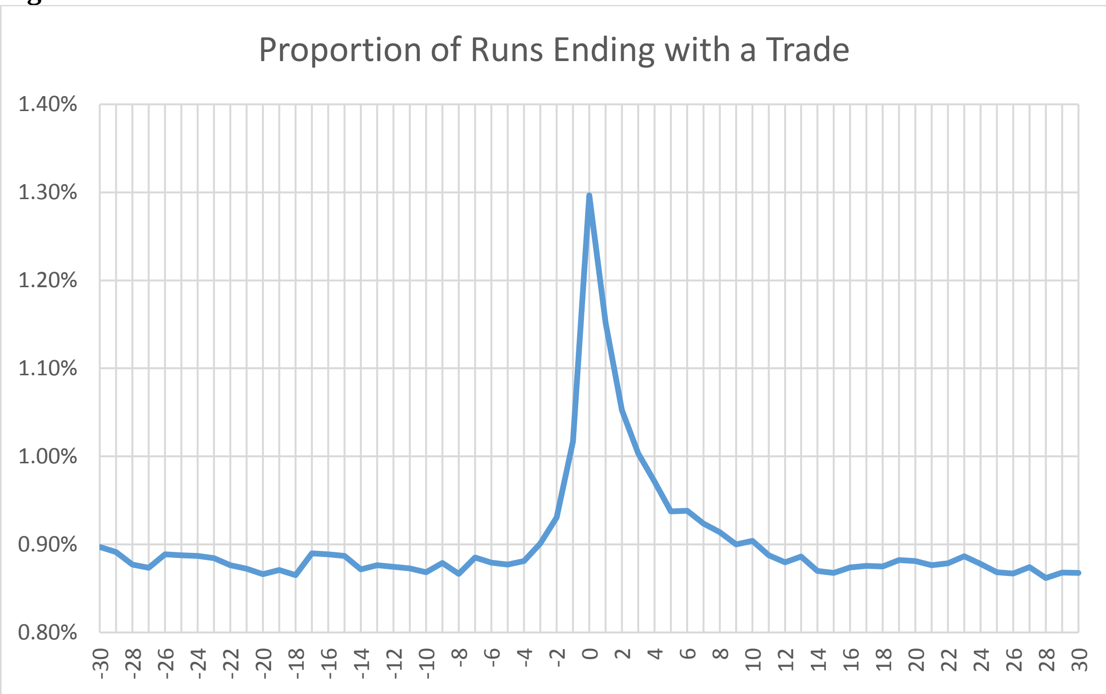

Figure 2: HFT Demand for Liquidity Surrounding Earnings Announcements

This figure plots the daily net demand for liquidity from HFT firms during a 61-day window surrounding the earnings announcements. The sample is based on the Nasdaq HFT dataset and includes 937 quarterly earnings announcements from 104 unique firms. Day 0 is the earnings announcement day. Net liquidity demand by HFT is defined as $HFT^{BUY} – HFT^{SELL}$ if $SUE >= 0$, and HFT^{SELL} - HFT^{BUY} if $SUE < 0$. HFT^{BUY} is buy volume with HFT on the liquidity demand side minus buy volume with HFT on the liquidity supply side. HFT^{SELL} is sell volume with HFT on the liquidity demand side minus sell volume with HFT on the liquidity supply side. We consider only trades where only one side of the trade is an HFT. The other side of the trade is a non-HFT. The sample period is from January 2008 to December 2009, and the last week of February 2010.

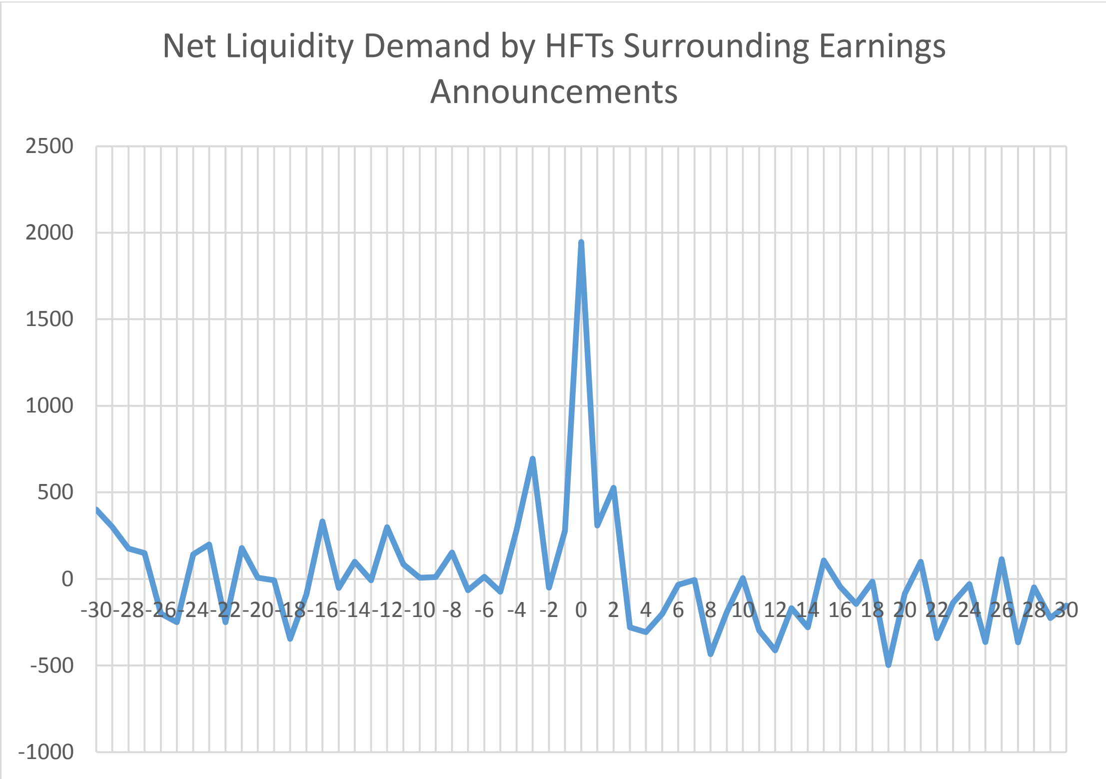

Table 1: Descriptive Statistics of *LLT*

This table presents the descriptive statistics of *LLT*, our main proxy for low-latency trading based on the strategic runs measure developed by Hasbrouck and Saar (2013). *LLT* is defined as the time-weighted number of runs with at least 10 messages during regular trading hours each day. The sample includes 9,727,015 stock-day observations, with an average of 3,865 stocks per day over 2,517 trading days from January 2008 to December 2017. All reported numbers are time series averages of daily cross-sectional statistics. In panel B, each stock is assigned to a size decile according to its closing market capitalization as per the previous trading day. All correlations reported in panel C are statistically significant at 1% level. The variables are defined as follows. *Number of Orders* = number of orders submitted to NASDAQ during regular trading hours. *% of Orders Cancelled within 100ms* = number of orders that are cancelled within 100 milliseconds of submission divided by total number of orders submitted to NASDAQ during regular trading hours. *Shares Traded* = number of shares traded on all exchanges. *Quoted Spread* = $\frac{A-B}{M_1}$, where A is national best bid, B is national best ask, and $M_1 = (A + B)/2$. Daily quoted spread is the time-weighted average over a trading day. *Effective Spread* = $\frac{2D(P-M)}{M}$, where D is indicator variable that equals to +1 if the trade is a buy and -1 if the trade is a sell. P is transaction price, and M is midpoint of the prevailing NBBO quote. Daily effective spread is the dollar-volume-weighted average over a trading day. *Realized Spread* = $\frac{2D_t(P_t-M_{t+5})}{M_t}$, where D_t is indicator variable that equals to +1 if trade at time t is a buy and -1 if the trade is a sell. P_t is transaction price, M_t is midpoint of the prevailing NBBO quote for trade at time t, and M_{t+5} is midpoint of NBBO quote 5 minutes after trade at time t. Daily realized spread is dollar-volume-weighted average over a trading day. *Price Impact* = $\frac{2D_t(M_{t+5}-M_t)}{M_t}$, where D_t is indicator variable that equals to +1 if trade t is a buy and -1 if the trade is a sell. M_{t+5} is midpoint of NBBO quote 5 minutes after trade at time t. Daily price impact is the dollar-volume-weighted average over a trading day. Cancel-to-Trade is count of all cancel messages divided by count of trade messages that are not against hidden orders. Trade-to-Order is sum of trade volume for trades that are not against hidden orders divided by sum of order volume for all add order messages. Odd-lot Ratio is sum of odd lot trade volume divided by sum of trade volume. Trade Size is sum of trade volume divided by count of trade messages.

Panel A: Summary Statistics by Year

Year	Mean	Std Dev	Q1	Median	Q3
2008	5.598	5.541	1.473	4.399	8.025
2009	5.701	6.342	1.703	4.583	7.861
2010	6.226	7.114	2.114	4.946	7.671
2011	7.007	5.671	2.747	6.146	10.545
2012	5.513	4.886	2.077	4.865	7.593
2013	7.004	7.693	1.797	4.389	9.613
2014	8.876	10.952	1.953	4.345	11.670
2015	7.265	7.971	2.099	4.810	10.238
2016	7.948	8.054	2.377	5.702	10.762
2017	8.656	8.230	2.196	7.020	12.767
2008 – 2017	6.979	7.246	2.053	5.119	9.673

Panel B: Summary Statistics of *LLT* by Market Capitalization

MV	Mean	Std Dev	Q1	Median	Q3
1 (Small)	1.224	1.932	0.000	0.413	1.817
2	1.653	2.167	0.011	0.950	2.526
3	2.772	2.793	0.671	2.170	4.042
4	4.417	3.446	2.131	3.828	5.872
5	5.914	4.170	3.291	5.164	7.499
6	6.898	4.439	4.118	6.088	8.613
7	7.953	5.018	4.670	6.901	10.073
8	9.309	6.160	5.187	7.920	11.829
9	11.662	7.006	6.914	10.464	14.651
10 (Large)	17.993	9.343	12.471	16.492	21.205

Panel C: Correlation with Trading and Liquidity Indicators

	Pearson Correlation	Spreaman Rank Correlation
Number of Orders	0.679	0.856
% of Orders Cancelled within 100 ms	0.367	0.553
Shares Traded	0.477	0.756
Quoted Spread	-0.327	-0.736
Effective Spread	-0.280	-0.687
Price Impact	-0.103	-0.329

Table 2: The Efficiency of Market Reaction to Earnings Announcements

Panel A of the table presents the descriptive statistics of firm characteristics for the earnings announcement sample, which includes 92,164 quarterly earnings announcements from January 2008 to December 2017. Panel B presents the coefficient estimates of the regression $EARET = \beta_0 + \beta_1 DSUE + \beta_2 DSUE * DLLT + \beta_3 DLLT + \varepsilon$. Panel C presents the coefficient estimates of the post-earnings announcement drift regression $CAR60 = \beta_0 + \beta_1 DSUE + \beta_2 DSUE * DLLT + \beta_3 DLLT + \varepsilon$. *LLT* is the proxy for low-latency trading based on the strategic runs measure developed by Hasbrouck and Saar (2013). It is defined as the time-weighted number of runs with at least 10 messages over the entire regular trading hours of a day. *LLT* is averaged over day 0 and 1 with day 0 being the earnings announcement date. *SUE* is standardized unexpected earnings, defined as Actual EPS – Median of analyst forecast of EPS, divided by share price at the end of current fiscal quarter. *DLLT* and *DSUE* are within-quarter decile rankings of *LLT* and *SUE*. *EARET* is buy-and-hold abnormal return over day 0 and 1. *CAR60* is the buy-and-hold abnormal return over a 60-day window from day 2 to 61. Abnormal return is raw return minus its size, book-to-market, and momentum matched portfolio return over the same period. *MV* is market value of equity at the end of quarter *t*, where quarter *t* is the fiscal quarter of earnings announcement. *BTM* is book value of common equity (CEQ) at the end of quarter *t-1* divided by market value of equity at the end of quarter *t*. *TOVER* is average monthly share turnover (shares trading volume divided by shares outstanding) over a 12-month period ending at the end of quarter *t*. *ILLIQ* is the Amihud (2002) illiquidity measure estimated using daily data over the 12-month period ending at the end of quarter *t*. *ANALYST* represents the number of analysts following the firm as of the end of quarter *t*. *INST* denotes the proportion of shares owned by institutional investors at the end of quarter *t*. *PERS* is earnings persistence, estimated by the seasonally-adjusted AR(1) coefficient of the following model: $EPS_t = \alpha + \beta \cdot EPS_{t-4} + \varepsilon$, using 16 quarters from quarter *t-16* to *t-1*. *EPSVOL* is earnings volatility, estimated by the standard deviation of seasonally-adjusted quarterly EPS changes over the 16 quarters from quarter *t-16* to *t-1*. *REPLAG* is reporting lag, defined as the number of calendar days between end of quarter *t* and earnings announcement for quarter *t*. *NCEA* is number of concurrent earnings announcements on the earnings announcement day of quarter *t*. *ΔINST* is change in institutional ownership during the earnings announcement quarter. *ΔSHORT* is change in short interest during the earnings announcement month. Within-quarter decile rankings of the independent variables are used in the regressions reported in Panel B and C. Standard errors are two-way clustered by firm and date of earnings announcement. Significance at 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Panel A: Summary Statistics

	Mean	Std Dev	Q1	Median	Q3	Correlation with LTT*
LLT	8.794	7.231	4.196	7.154	11.268	
SUE	-0.001	0.021	-0.001	0.000	0.003	0.049
EARET	-0.001	0.095	-0.041	-0.001	0.039	0.005$
CAR60	-0.004	0.215	-0.099	-0.010	0.078	0.029
|*SUE*|	0.008	0.020	0.001	0.002	0.006	-0.219
|*EARET*|	0.060	0.073	0.017	0.040	0.080	0.081
|*CAR60*|	0.135	0.167	0.040	0.089	0.172	-0.081
Controls						
MV	5.805	21.996	0.237	0.793	2.888	0.637
BTM	0.638	0.535	0.282	0.507	0.821	-0.252
TOVER	1.993	1.848	0.885	1.530	2.509	0.529
ILLIQ	0.362	1.933	0.001	0.003	0.026	-0.675
ANALYST	11.348	9.321	4.000	8.000	16.000	0.621
INST	0.649	0.293	0.459	0.729	0.887	0.385
PERS	0.244	0.488	-0.065	0.146	0.526	0.063
EPSVOL	0.975	2.779	0.121	0.269	0.682	0.050
REPLAG	34.246	14.294	26.000	32.000	38.000	-0.165
NCEA	211.181	129.676	107.000	195.000	310.000	-0.002$
ΔINST	0.001	0.074	-0.014	0.000	0.016	-0.007#
ΔSHORT	0.000	0.010	-0.002	0.000	0.002	0.013

* Spearman rank correlation. All correlations are significant at 1% level except those marked with #, which are significant at 5%, and $, which are not significant at conventional levels.

Panel B: Market Reaction to Earnings Announcements (Dependent variable: *EARET*)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
DSUE	0.089***	0.063***	0.062***	0.063***	0.068***
	(55.08)	(28.99)	(28.92)	(28.63)	(3.23)
DSUE x *DLLT*		0.061***	0.062***	0.069***	0.103***
		(11.75)	(12.01)	(12.77)	(9.10)
DLLT		-0.034***	-0.030	-0.034***	-0.051***
		(-13.05)	(-11.18)	(-11.84)	(-10.67)
Controls	NO	NO	YES	YES	YES
DSUE x *Controls and Time FE*	NO	NO	NO	NO	YES
Firm FE	NO	NO	NO	YES	YES
Year, Month, Day of Week FE (Time FE)	YES	YES	YES	YES	YES
N	92,164	92,164	92,164	92,164	92,164
Adj-R^2	0.092	0.097	0.103	0.180	0.187

Panel C: Post-Earnings Announcement Drift (Dependent variable: *CAR60*)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
DSUE	0.021***	0.047***	0.045***	0.035***	0.068*
	(7.04)	(9.23)	(8.95)	(6.76)	(1.65)
DSUE x *DLLT*		-0.059***	-0.056***	-0.055***	-0.021**
		(-7.07)	(-6.74)	(-6.28)	(-2.00)
DLLT		0.036***	0.027***	0.006	-0.011
		(7.25)	(4.56)	(0.89)	(-1.20)
Controls	NO	NO	YES	YES	YES
DSUE x *Controls and Time FE*	NO	NO	NO	NO	YES
Firm FE	NO	NO	NO	YES	YES
Year, Month, Day of Week FE (Time FE)	YES	YES	YES	YES	YES
N	92,164	92,164	92,164	92,164	92,164
Adj-R^2	0.003	0.004	0.009	0.110	0.112
DSUE Coefficient of Top *LLT* Decile		-0.008 (-0.93)			

Table 3: Alternative Measurement Window of Post-earnings Announcement Returns

The table reports post-earnings announcement drift regression $CAR(n) = \beta_0 + \beta_1 DSUE + \beta_2 DSUE * DLLT + \beta_3 DLLT + \varepsilon$ estimated using alternative windows for measuring post-announcement return. The sample includes 80,801 quarterly earnings announcements from January 2008 to December 2017. *CAR(n)* is buy-and-hold abnormal return over an n-day window starting two days after earnings announcement. Abnormal return is raw return minus its size, book-to-market, and momentum matched portfolio return over the same period. *LLT* is the proxy for low-latency trading based on the strategic runs measure developed by Hasbrouck and Saar (2013). It is defined as the time-weighted number of runs with at least 10 messages over the entire regular trading hours of a day. *LLT* is averaged over day 0 and 1 with day 0 being the earnings announcement date. *SUE* is standardized unexpected earnings, defined as Actual EPS – Median of analyst forecast of EPS, divided by share price at the end of current fiscal quarter. *DLLT* and *DSUE* are within-quarter decile rankings of *LLT* and *SUE*. The decile rankings are standardized to be between 0 and 1. The control variables include size (*MV*), book-to-market ratio (*BTM*), shares turnover (*TOVER*), Amihud (2002) illiquidity measure (*ILLIQ*), institutional ownership (*INST*), analyst following (*ANALYST*), earnings persistence (*PERS*), earnings volatility (*EPSVOL*), reporting lag (*REPLAG*), number of concurrent earnings announcements (*NCEA*), change in institutional ownership (*ΔINST*), and change in short interest (*ΔSHORT).* Standard errors are clustered by firm and date of earnings announcement. Significance at 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Panel A: Baseline Model

	[+2,+31]	**[+2,+61]**	**[+2,+91]**	**[+2,+181]**	**[+2,+251]**
DSUE	0.033***	0.047***	0.056***	0.079***	0.097***
	(9.31)	(9.23)	(8.07)	(7.19)	(6.70)
DSUE x *DLLT*	-0.040***	-0.059***	-0.071***	-0.089***	-0.108***
	(-6.66)	(-7.07)	(-6.10)	(-5.12)	(-4.74)
DLLT	0.029***	0.036***	0.048***	0.062***	-0.071***
	(8.30)	(7.25)	(6.57)	(5.06)	(-4.54)
Controls	NO	NO	NO	NO	NO
DSUE x *Controls and Time FE*	NO	NO	NO	NO	NO
Firm FE	NO	NO	NO	NO	NO
Year, Month, Day of Week FE (Time FE)	YES	YES	YES	YES	YES
N	95,029	92,164	91,153	84720	80,801
Adj-R2	0.005	0.004	0.005	0.008	0.011
DSUE of Top *LLT* Decile	-0.008 (-1.42)	-0.008 (-0.93)	-0.010 (-0.92)	-0.006 (-0.33)	0.001 (0.03)

Panel B: Extended Model

	[+2,+31]	**[+2,+61]**	**[+2,+91]**	**[+2,+181]**	**[+2,+251]**
DSUE	0.012	0.068*	0.101*	0.192**	0.246***
	(0.44)	(1.65)	(1.91)	(2.39)	(2.60)
DSUE x *DLLT*	0.010	-0.021**	-0.030**	-0.017	-0.058**
	(1.42)	(-2.00)	(-2.28)	(-0.86)	(-2.46)
DLLT	-0.01**	-0.011	-0.015*	-0.055***	-0.057***
	(-2.30)	(-1.20)	(-1.84)	(-4.66)	(-3.89)
Controls	YES	YES	YES	YES	YES
DSUE x *Controls and Time FE*	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year, Month, Day of Week FE (Time FE)	YES	YES	YES	YES	YES
N	95,029	92,164	91,153	84720	80,801
Adj-R2	0.129	0.112	0.146	0.212	0.263

Table 4: Portfolio Analysis

At the beginning of each month from February 2008 to December 2017, we assign each stock into one of the 5 x 5 portfolios based on independent sorts of *SUE* and *LLT*. *LLT* is the proxy for low-latency trading based on the strategic runs measure developed by Hasbrouck and Saar (2013). It is defined as the time-weighted number of runs with at least 10 messages over the entire regular trading hours of a day. *LLT* is averaged over day 0 and 1 with day 0 being the earnings announcement date. *SUE* is standardized unexpected earnings, defined as Actual EPS – Median of analyst forecast of EPS, divided by share price at the end of current fiscal quarter. *SUE* is from the most recent earnings announcement during the past three months. Alphas with respect to the Fama-French (2015) five-factor model are calculated for the equal-weighted portfolio returns using the entire time-series of 119 months. The table reports the monthly alphas for each of the 25 portfolios and the various hedged portfolios. Newey-West corrected standard errors with 3 lags are used for statistical significance. Significance at 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

	SUE = 1 (Bad News)	2	3	4	*SUE* = 5 (Good News)	*SUE5* - *SUE1* (Good - Bad)
All	-0.23	0.00	0.09	0.18***	0.26	0.48***
LLT = 1 (Low)	-0.47	0.34	0.37	0.41**	0.79**	1.27***
2	-0.09	-0.02	0.27**	0.09	0.69***	0.78***
3	-0.05	0.12	0.05	0.35***	-0.01	0.04
4	0.10	-0.26**	0.08	0.17**	-0.37	-0.47*
LLT = 5 (High)	-0.26	-0.10	-0.03	-0.05	-0.32	-0.06
LLT5 - *LLT1*	0.21	-0.43*	-0.40*	-0.46**	-1.11***	-1.32***

Table 5: The Impact of Low-Latency Trading on Market Efficiency: A Difference-in-differences Analysis

This table presents the difference-in-differences regression results of the impact of low-latency trading on the market's reaction to earnings announcements. The sample includes quarterly announcements made by firms listed on NYSE and their industry-size-book-to-market matched NASDAQ peers during the 24- or 36-month period before and after the introduction of autoquote on NYSE, which happened between January and May of 2003. *NYSE* = 1 if the firm is listed on NYSE, and 0 if listed on NASDAQ. *POST* = 1 if the earnings announcement is made after May 2003, and 0 if before January 2003. *EARET* is buy-and-hold abnormal return over day 0 and 1, with day 0 being the earnings announcement date. *CAR60* is buy-and-hold abnormal return over 60-day window from day 2 to 61. The control variables include size (*MV*), book-to-market ratio (*BTM*), shares turnover (*TOVER*), Amihud (2002) illiquidity measure (*ILLIQ*), institutional ownership (*INST*), analyst following (*ANALYST*), earnings persistence (*PERS*), earnings volatility (*EPSVOL*), reporting lag (*REPLAG*), number of concurrent earnings announcements (*NCEA*), change in institutional ownership (*ΔINST*), and change in short interest (*ΔSHORT).* Standard errors are two-way clustered by firm and date of earnings announcement. Significance at 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

	24 Months		**36 Months**	
	EARET	***CAR60***	***EARET***	***CAR60***
Intercept	0.004	0.010	0.007	-0.067
	(0.28)	(0.19)	(0.59)	(-1.18)
DSUE	0.059***	0.008	0.056***	0.009
	(7.95)	(0.35)	(9.10)	(0.45)
DSUE x *NYSE*	-0.005	0.028	0.000	0.033
	(-0.60)	(1.10)	(-0.04)	(1.52)
DSUE x POST	0.000	0.064**	0.007	0.064***
	(-0.03)	(2.17)	(0.96)	(2.63)
DSUE x NYSE x POST	0.025**	-0.076**	0.016*	-0.073**
	(2.20)	(-2.26)	(1.82)	(-2.56)
NYSE	0.003	-0.018	-0.001	-0.022*
	(0.54)	(-1.27)	(-0.12)	(-1.8)
POST	0.001	-0.049***	-0.004	-0.056***
	(0.15)	(-2.98)	(-0.96)	(-4.29)
NYSE x POST	-0.013**	0.048**	-0.007	0.052***
	(-2.16)	(2.51)	(-1.26)	(3.40)
Controls	YES	YES	YES	YES
Day of Week, Month, and Industry Fixed Effect	YES	YES	YES	YES
N	10,703	10,703	15,564	15,564
Adj-R^2	0.087	0.025	0.085	0.022

Table 6: Direction of LLT

This table examines the impact of aggressive low-latency trading on returns to earnings news announcements. *LLT* is the proxy for low-latency trading based on the strategic runs measure developed by Hasbrouck and Saar (2013). It is defined as the time-weighted number of runs with at least 10 messages over the entire regular trading hours of a day. *LLT_SIGN* captures the liquidity-taking trades of the low latency traders. It is defined as (number of Buy Runs - number of Sell Runs) if *SUE* >= 0, and (number of Sell Runs - number of Buys Runs) if *SUE* < 0. *SUE* is the standardized unexpected earnings, defined as Actual EPS – Median of analyst forecast of EPS, divided by share price at the end of current fiscal quarter. *LLT_SIGN* is computed each day and then averaged over day 0 and day 1 with day 0 being the earnings announcement day. *DLLT_SIGN* and *DSUE* are within-quarter decile rankings of *LLT_SIGN* and *SUE*. Spearman Rank Correlations are reported in Panel B. The dependent variable in Panel C, *EARET* is the buy-and-hold abnormal return over day 0 and 1. The dependent variable in Panel D is *CAR60*, the buy-and-hold abnormal return over a 60-day window from day 2 to 61. Abnormal return is the raw return minus its size, book-to-market, and momentum matched portfolio return over the same period. Control variables include size (*MV*), book-to-market ratio (*BTM*), shares turnover (*TOVER*), Amihud (2002) illiquidity measure (*ILLIQ*), institutional ownership (*INST*), analyst following (*ANALYST*), earnings persistence (*PERS*), earnings volatility (*EPSVOL*), reporting lag (*REPLAG*), number of concurrent earnings announcements (*NCEA*), change in institutional ownership (*ΔINST*), and change in short interest (*ΔSHORT).* Within-quarter decile rankings of the control variables are used in the regressions in Panels C and D. Standard errors are two-way clustered by firm and date of earnings announcement. Significance at 10%, 5%, and 1% is denoted by *, **, and ***, respectively. The sample period is from January 2008 to December 2017.

Panel A: Summary Statistics of *LLT_SIGN* (N=92,164)

	Mean	Std Dev	Q1	Median	Q3
LLT_SIGN	-0.020	1.196	-0.540	0.000	0.515
SUE	-0.001	0.021	-0.001	0.000	0.003
EARET	-0.001	0.095	-0.041	-0.001	0.039

Panel B: Correlation with other firm characteristics

SUE	*EARET*	*CAR60*	|*SUE*|	|*EARET*|
-0.118***	-0.049***	-0.008**	0.042***	0.015***
MV	*BTM*	*INST*	*NANALYST*	*TOVER*
-0.051***	0.021***	-0.025***	-0.050***	-0.028***
ILLIQ	*NCEA*	*REPLAG*	*PERS*	*EPSVOL*
0.054***	0.001	0.013***	0.001	-0.007**
ΔINST	*ΔSHORT*			
-0.004	0.005			

Panel B: Market Reaction to Earnings Announcements (Dependent variable: *EARET*)

Variable	Model 1	Model 2	Model 3	Model 4
DSUE	0.067***	0.068***	0.073***	0.067***
	(22.22)	(22.62)	(24.19)	(3.01)
DSUE x *DLLT_SIGN*	0.044***	0.041***	0.040***	0.041***
	(9.19)	(8.67)	(8.48)	(8.74)
DLLT_SIGN	-0.023***	-0.022***	-0.022***	-0.023***
	(-10.08)	(-9.69)	(-9.37)	(-9.89)
Controls	NO	YES	YES	YES
DSUE x *Controls and Time FE*	NO	NO	NO	YES
Firm FE	NO	NO	YES	YES
Year, Month, Day of Week FE (Time FE)	YES	YES	YES	YES
N	92,164	92,164	92,164	92,164
Adj-R^2	0.094	0.100	0.176	0.182

Panel C: Post-Earnings Announcement Drift (Dependent variable: *CAR60*)

Variable	Model 1	Model 2	Model 3	Model 4
DSUE	0.029***	0.031***	0.020***	0.078
	(5.12)	(5.52)	(3.66)	(1.37)
DSUE x *DLLT_SIGN*	-0.015**	-0.021**	-0.020**	-0.022**
	(-2.01)	(-2.40)	(-2.24)	(-2.48)
DLLT_SIGN	0.007*	-0.010**	0.008*	0.009*
	(1.75)	(2.04)	(1.65)	(1.83)
Controls	NO	YES	YES	YES
DSUE x *Controls and Time FE*	NO	NO	NO	YES
Firm FE	NO	NO	YES	YES
Year, Month, Day of Week FE (Time FE)	YES	YES	YES	YES
N	92,164	92,164	92,164	92,164
Adj-R^2	0.005	0.008	0.110	0.110

Table 7: Alternative Measures of Low Latency Trading

The table presents the market reaction and post-earnings announcement drift regression results using alternative measures of low-latency trading. *NORDER* is number of limit orders submitted to NASDAQ during regular trading hours. *HFOCR* is number of orders that are cancelled within 100 milliseconds of submission divided by total number of orders submitted to NASDAQ during regular trading hours. *SUE* is standardized unexpected earnings, defined as Actual EPS – Median of analyst forecast of EPS, divided by share price at the end of current fiscal quarter. *EARET* is buy-and-hold abnormal return over day 0 and 1 with day 0 being the earnings announcement day. *CAR60* is buy-and-hold abnormal return over 60-day window from day 2 to 61. Abnormal return is raw return minus its size, book-to-market, and momentum matched portfolio return over the same period. *DSUE*, *DNORDER*, *and DHFOCR* are decile rankings of *SUE*, *NORDER*, and *HFOCR*, respectively. Control variables include size (*MV*), book-to-market ratio (*BTM*), shares turnover (*TOVER*), Amihud's illiquidity (*ILLIQ*), institutional ownership (*INST*), analyst following (*ANALYST*), earnings persistence (*PERS*), earnings volatility (*EPSVOL*), reporting lag (*REPLAG*), number of concurrent earnings announcements (*NCEA*), change in institutional ownership (*ΔINST*), and change in short interest (*ΔSHORT).* Standard errors are two-way clustered by firm and date of earnings announcement. *, **, and *** denotes significance at 10%, 5%, and 1%, respectively. The sample period is from January 2008 to December 2017.

Panel A: Baseline Model

	Dep.Var. = EARET		Dep.Var. = CAR60	
DSUE	0.067***	0.075***	0.046***	0.037***
	(31.68)	(33.54)	(9.23)	(7.68)
*DSUE * DNORDER*	0.055***		-0.063***	
	(10.15)		(-7.32)	
DNORDER	-0.026***		0.041***	
	(-10.09)		(7.97)	
*DSUE * DHFOCR*		0.031***		-0.035***
		(8.65)		(-4.37)
DHFOCR		-0.008***		0.024***
		(-4.34)		(4.63)
Controls	No	No	No	No
DSUE x *Controls and Time FE*	No	No	No	No
Firm FE	No	No	No	No
Year, Month, Day of Week FE (Time FE)	YES	YES	YES	YES
N	92,164	92,164	92,164	92,164
Adj-R^2	0.096	0.094	0.005	0.004

Panel B: Extended Model

	Dep.Var. = ***EARET***		Dep.Var. = ***CAR60***	
DSUE	0.026	0.082***	0.070	0.068
	(1.25)	(3.75)	(1.26)	(1.21)
*DSUE * DNORDER*	0.224***		-0.026	
	(7.14)		(-1.11)	
DNORDER	-0.070***		-0.033**	
	(-7.21)		(-2.12)	
*DSUE * DHFOCR*		0.026***		-0.005
		(6.75)		(-0.49)
DHFOCR		-0.001		-0.006
		(-0.61)		(-0.98)
Controls	YES	YES	YES	YES
DSUE x *Controls and Time FE*	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year, Month, Day of Week FE (Time FE)	YES	YES	YES	YES
N	92,164	92,164	92,164	92,164
Adj-R^2	0.192	0.183	0.112	0.111

Table 8: LLT and Market Reaction to Insider Trading

This table examines the impact of low-latency trading on market reaction to Form 4 filings of insider purchases. Panel A of the table presents the summary statistics of the insider trading sample, which includes 117,365 Form 4 filings from January 2008 to December 2017. Panel B presents the market reaction regression $FRET = \beta_0 + \beta_1 DLLT + Controls + \varepsilon$. Panel C presents the post-filing return reversal regression $CAR60F = \beta_0 + \beta_1 FRET + \beta_2 FRET \times DLLT + \beta_3 DLLT + Controls + Fixed\ Effects + \varepsilon$. LLT is the proxy for low-latency trading based on the strategic runs measure developed by Hasbrouck and Saar (2013). It is defined as the time-weighted number of runs with at least 10 messages over the entire regular trading hours of a day. *LLT* is averaged over day 0 and 1 with day 0 being the Form 4 filing date. *DLLT* is within-month decile ranks of LLT. *FRET* is buy-and-hold abnormal return over day 0 and 1 with day 0 being the Form 4 filing day. *CAR60F* is abnormal return over a 60-day window from day 2 to 61. Abnormal return is raw return minus its size, book-to-market, and momentum matched portfolio return over the same period. The control variables include shares purchased by insiders divided by total shares outstanding (*TRADE_SIZE*), shares purchased by insiders within the last 10 days (*RECENT_TRADE*), reporting lag between transaction date and filing date (*REPORT_LAG*), market value of equity (*MV*), book-to-market ratio (*BTM*), indicator variable for accounting loss in the most recent fiscal year (*LOSS*), indicator variable for positive R&D expense during the most recent fiscal year (*R&D*), indicator variable for existence of company policy restricting insider trading, measured by more than 75% of all insider trading happening within 30 days after earnings announcement in a year (*RESTRICT*), indicator variable for insider purchases identified as pre-planned trade pursuant to Rule 10b5-1 (*RULE10B5*). Within-month decile ranks of all continuous variables are used in the regression. Significance at 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Panel A: Summary Statistics

	Mean	**Std Dev**	**Q1**	**Median**	**Q3**
LLT	8.746	8.433	3.308	6.512	11.529
FRET	0.003	0.047	-0.014	0.000	0.016
CAR60F	-0.001	0.223	-0.100	-0.009	0.082
TRD_SIZE	0.001	0.002	0.000	0.000	0.001
RECENT_TRD	0.000	0.007	0.000	0.000	0.000
REPORT_LAG	5.919	53.097	1.000	2.000	4.000
MV	7.946	32.245	0.247	1.087	3.917
BTM	0.591	0.487	0.248	0.464	0.793
LOSS	0.267	0.442	0.000	0.000	1.000
XRD	0.463	0.499	0.000	0.000	1.000
RESTRICT	0.161	0.367	0.000	0.000	0.000
RULE10B5	0.043	0.203	0.000	0.000	0.000

Panel B: Market Reaction Regressions

Dependent Variable =	***FRET***
DLLT	0.007***
	(9.25)
TRADE_SIZE	0.002***
	(2.89)
RECENT_TRADE	0.001*
	(1.89)
REPORT_LAG	-0.004***
	(-7.59)
MV	-0.016***
	(-8.19)
BTM	0.010***
	(9.88)
LOSS	0.001*
	(1.81)
R&D	0.002
	(1.23)
RESTRICT	0.001**
	(2.53)
RULE10B5	0.000
	(-0.51)
Firm Fixed Effects	YES
Year, Month, and Day of Week Fixed Effect	YES
N	117,365
Adj-R^2	0.090

Panel C: Post-Filing Return Reversal Regressions

Dependent Variable =	***CAR60F***
FRET	-0.185***
	(-8.05)
FRET x DLLT	0.109**
	(2.49)
DLLT	-0.044***
	(-12.16)
TRADE_SIZE	0.001
	(0.45)
RECENT_TRADE	-0.002
	(-0.74)
REPORT_LAG	0.002
	(0.85)
MV	-0.315***
	(-36.15)
BTM	0.070***
	(14.94)
LOSS	0.009***
	(4.08)
R&D	0.010
	(1.29)
RESTRICT	0.002
	(0.75)
RULE10B5	0.002
	(0.61)
Firm Fixed Effects	YES
Year, Month, and Day of Week Fixed Effect	YES
N	117,365
Adj-R^2	0.090

Table 9: LLT and Market Reaction to M&A Announcement

This table examines the impact of low-latency trading on market reaction to acquiring firm's announcements of M&A deals. Panel A of the table presents the summary statistics of the M&A sample, which includes 723 deals from January 2008 to December 2017. Panel B presents the market reaction regression: $RET\_ANN = \beta_0 + \beta_1 LogLLT + Controls + \varepsilon$. Panel C presents the post-announcement return reversal regression: $CAR60MA = \beta_0 + \beta_1 RET\_ANN + \beta_2 RET\_ANN \times DLLT + \beta_3 DLLT + Controls + Fixed\ Effects + \varepsilon$. LLT is the proxy for low-latency trading based on the strategic runs measure developed by Hasbrouck and Saar (2013). It is defined as the time-weighted number of runs with at least 10 messages over the entire regular trading hours of a day. *LLT* is averaged over day 0 and 1 with day 0 being the announcement date. *Log(LLT)* is natural logarithmic of (1+*LLT*). *RET_ANN* is buy-and-hold abnormal return over day 0 and 1 with day 0 being the announcement day. *CAR60MA* is abnormal return over a 60-day window from day 2 to 61. Abnormal return is raw return minus its size, book-to-market, and momentum matched portfolio return over the same period. The control variables include relative deal size as a proportion of acquiror's market capitalization (*REL_SIZE*), market capitalization (*MV*), book-to-market ratio (*BTM*), institutional ownership (*INST*), analyst coverage (*NUMEST*), abnormal return during the 3-month period before announcement (*RET_P3M*). Standard errors in Panel B and C are clustered by announcement date. Significance at 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Panel A: Summary Statistics

	Stock Bids for Private Target (N = 263)			**Stock Bids for Public Target (N = 460)**		
	Mean	**Median**	**Std Dev**	**Mean**	**Median**	**Std Dev**
RET_ANN	0.052	0.018	0.197	-0.012	-0.015	0.085
CAR60MA	-0.056	-0.047	0.215	-0.019	-0.022	0.159
LLT	6.779	4.777	7.099	10.123	7.822	9.635
Log(LLT)	1.719	1.754	0.837	2.058	2.177	0.884
REL_SIZE	1.232	0.320	3.185	0.670	0.451	0.676
MV	2.009	0.290	8.671	10.092	0.911	36.266
BTM	0.649	0.596	0.507	0.627	0.602	0.384
INST	0.418	0.446	0.332	0.545	0.620	0.313
NUMEST	4.795	3.000	6.293	7.207	5.000	7.793
RET_P3M	0.003	-0.006	0.327	0.032	0.012	0.182

Panel B: Market Reaction Regressions

	Stock Bids for Private Target	***Stock Bids for Public Target***
Intercept	3.509	3.931
	(0.36)	(0.78)
Log(LLT)	6.631**	0.922
	(2.41)	(0.83)
REL_SIZE	1.843	1.403
	(1.51)	(1.05)
Log(MV)	-1.095	-0.465
	(-1.09)	(-0.66)
BTM	2.004	-3.502*
	(0.40)	(-1.75)
INST	-4.37	-3.384*
	(-0.86)	(-1.80)
Log(NUMEST)	-3.362**	0.487
	(-2.24)	(0.88)
RET_P3M	-18.137***	-8.966***
	(-3.19)	(-2.96)
Industry Fixed Effects	YES	YES
Year, Month, and Day of Week Fixed Effect	YES	YES
N	263	460
Adj-R^2	0.306	0.173

Panel C: Post-Announcement Return Reversal Regressions (Dependent Variable = *CAR60MA*)

	Stock Bids for Private Target	***Stock Bids for Public Target***
Intercept	-0.043	-0.050
	(-0.38)	(-0.52)
RET_ANN	-0.231	-0.278
	(-0.88)	(-0.81)
RET_ANN x Log(LLT)	0.184	0.257
	(1.54)	(1.57)
Log(LLT)	-0.030	0.019
	(-1.09)	(1.32)
REL_SIZE	-0.003	-0.022*
	(-0.47)	(-1.78)
Log(MV)	0.008	-0.009
	(0.77)	(-1.16)
BTM	-0.027	-0.010
	(-0.61)	(-0.35)
INST	0.098*	0.005
	(1.85)	(0.16)
Log(NUMEST)	-0.002	0.033***
	(-0.09)	(2.86)
RET_P3M	0.009	-0.001
	(0.16)	(-0.02)
Industry Fixed Effects	YES	YES
Year, Month, and Day of Week Fixed Effect	YES	YES
N	263	460
Adj-R^2	0.215	0.179

Internet Appendix A

LLT and the Flash Crash of May 6, 2010

We use the Flash Crash of May 6, 2010 to further validate our measure of low latency trading. The Flash Crash which saw major US stock indices plunging nearly 10% in a matter of minutes and quickly recovering most of the losses before the end of the trading day, focused attention on high frequency trading (HFT). While subsequent investigations generally conclude that HFT did not trigger this market event it did exacerbate the dramatic price and volatility changes (Kirilenko, Kyle, Samadi and Tuzun, 2017). Various accounts of the Flash Crash have blamed major HFT firms for unplugging their computers and withdrawing from the market, thereby exacerbating price volatility during the crash.

Since HFTs are an important subset of the traders that employ low-latency strategies our *LLT* measure should also capture the presence of HFTs in the market. Hasbrouck and Saar (2013) provide some initial evidence on this relation by showing that *LLT* is highly correlated with estimates of high-frequency trading using the NASDAQ-constructed dataset. In this section, we explore the unique setting of the (alleged) absence of HFT during the Flash Crash to conduct an additional validation test on using the strategic runs as an empirical proxy for LLT activity. Our research design is to examine the intraday variation in aggregate *LLT* at market level on May 6, 2010, and check for any significant decrease during the crash. Figure IA.1 plots the intraday pattern of total number of time-weighted runs on NASDAQ sampled at 10-minute intervals from 7am to 8pm. The trading day starts with limited but slowly increasing LLT activity during the pre-market open hours. When the market opens at 9.30am, *LLT* immediately rises and jumps to the level of more than 13,000 runs per 10 minutes. It remains relatively stable at this level until 2pm, when it starts to increase and reaches a peak of more than 19,000 runs during the 2.30 ~ 2.40 pm interval. In the next 20 minutes, *LLT* drops sharply – by more than 60% to about 7,500 runs. It starts to stabilize at 3pm and remains at that level till market closes at 4pm. The timing of the key turning points in the intraday *LLT* pattern coincides almost perfectly with the Flash Crash. Below we provide a description of the "2010 Flash Crash" entry on Wikipedia:

"On May 6, 2010, U.S. stock markets opened and the Dow was down, and trended that way for most of the day on worries about the debt crisis in Greece. At 2:42 p.m., with the Dow down more than 300 points for the day, the equity market began to fall rapidly, dropping an additional 600 points in 5 minutes for a loss of nearly 1,000 points for the day by 2:47 p.m. Twenty minutes later, by 3:07 p.m., the market had regained most of the 600-point drop."[29]

The fact that the timing of the Flash Crash coincides with the changes in the strategic runs, lends strong support to the construct validity of *LLT* as a proxy for trading intensity by low latency traders.

[29] https://en.wikipedia.org/wiki/2010_Flash_Crash

Figure IA.1: Low-latency Activity on May 6, 2010

The figure plots the intraday change of low-latency activity on May 6, 2010. Low-latency activity is measured by total number of time-weighted runs within each 10-minute interval across all stocks traded on NASDAQ.

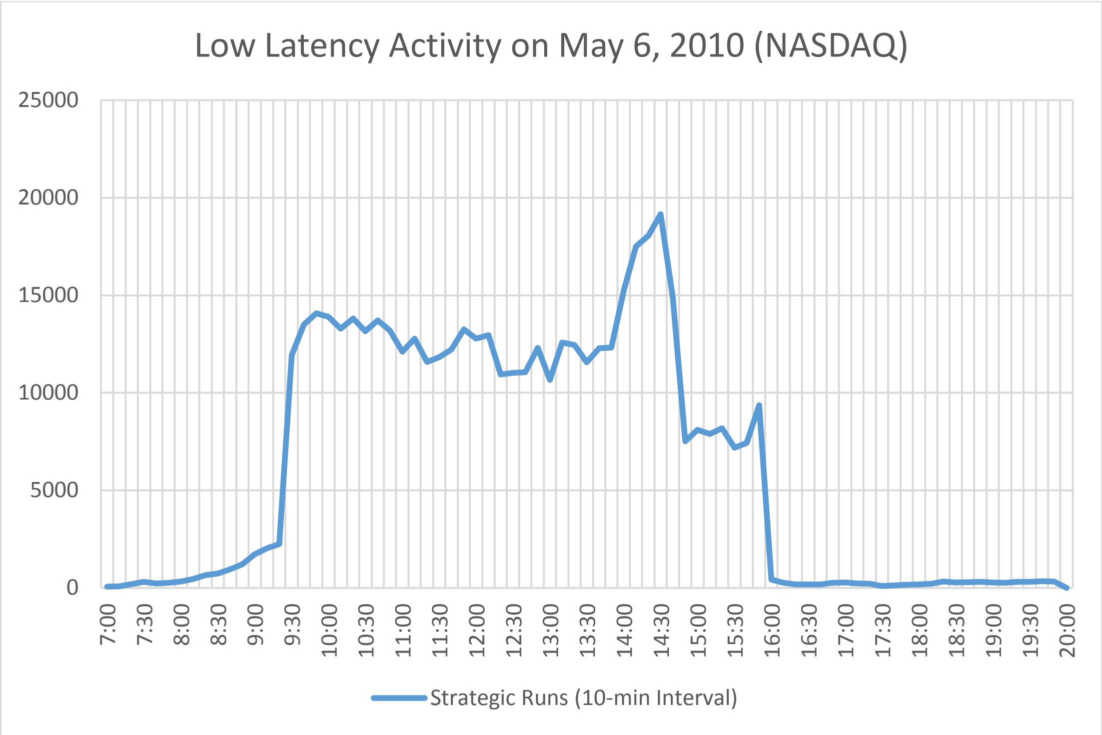

Table IA.1: Falsification Test of the Difference-in-differences Analysis

This table presents the difference-in-differences regression results of the impact of low-latency trading on the market's reaction to earnings announcements. The sample in Panel A includes quarterly announcements made by firms listed on NYSE and their industry-size-book-to-market matched NASDAQ peers during the 36-month period before and after the pseudo-event period, which is set to January to May of 2000 in the left column, and January to May of 2006 in the right column. The sample in Panel B includes quarterly announcements made by firms listed on NYSE and their industry-size-book-to-market matched NASDAQ peers during the 24-month period before and after the pseudo-event period, which is set to January to May of 2001 in the left column, and January to May of 2005 in the right column. *NYSE* = 1 if the firm is listed on NYSE, and 0 if listed on NASDAQ. *POST* = 1 if the earnings announcement is made after the end of the pseudo-event period, and 0 if before the start of the pseudo-event period. *EARET* is buy-and-hold abnormal return over day 0 and 1, with day 0 being the earnings announcement date. *CAR60* is buy-and-hold abnormal return over 60-day window from day 2 to 61. The control variables include size (*MV*), book-to-market ratio (*BTM*), shares turnover (*TOVER*), Amihud (2002) illiquidity measure (*ILLIQ*), institutional ownership (*INST*), analyst following (*ANALYST*), earnings persistence (*PERS*), earnings volatility (*EPSVOL*), reporting lag (*REPLAG*), number of concurrent earnings announcements (*NCEA*), change in institutional ownership (*ΔINST*), and change in short interest (*ΔSHORT*). Standard errors are two-way clustered by firm and date of earnings announcement. Significance at 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Panel A: Pseudo Event Date Leads/Lags Actual Event Date by 36 Months

	Pseudo Event = January 2000		***Pseudo Event = January 2006***	
	EARET	***CAR60***	***EARET***	***CAR60***
Intercept	-0.015	-0.029	0.004	-0.072**
	(-1.45)	(-0.62)	(0.29)	(-2.25)
DSUE	0.057***	0.053**	0.072***	0.051***
	(9.60)	(2.40)	(10.94)	(3.83)
DSUE x *NYSE*	-0.006	0.001	0.001	-0.025
	(-0.94)	(0.04)	(0.15)	(-1.48)
DSUE x POST	-0.002	-0.021	0.038***	-0.016
	(-0.22)	(-0.71)	(3.55)	(-0.76)
DSUE x NYSE x POST	0.013	-0.001	0.011	0.038
	(1.28)	(-0.02)	(0.84)	(1.35)
NYSE	0.000	-0.017	0.002	0.013
	(0.03)	(-1.44)	(0.47)	(1.34)
POST	-0.004	0.032**	-0.016***	0.007
	(-0.84)	(2.25)	(-2.98)	(0.59)
NYSE x POST	0.000	0.013	-0.009	-0.021
	(0.07)	(0.78)	(-1.31)	(-1.29)
Controls	YES	YES	YES	YES
Day of Week, Month, and Industry Fixed Effect	YES	YES	YES	YES
N	16,325	16,325	16,158	16,158
Adj-R^2	0.060	0.017	0.134	0.014

Panel B: Pseudo Event Date Leads/Lags Actual Event Date by 24 Months

	Pseudo Event = January 2001		***Pseudo Event = January 2005***	
	EARET	***CAR60***	***EARET***	***CAR60***
Intercept	0.009	0.022	-0.002	-0.040
	(0.54)	(0.34)	(-0.17)	(-1.15)
DSUE	0.068***	0.054	0.069***	0.036***
	(9.35)	(1.33)	(10.64)	(2.78)
DSUE x *NYSE*	-0.010	0.013	0.000	-0.030
	(-1.12)	(0.30)	(-0.02)	(-1.61)
DSUE x POST	-0.018*	-0.027	0.019**	-0.018
	(-1.92)	(-0.52)	(1.99)	(-1.02)
DSUE x NYSE x POST	0.018	-0.008	0.000	0.049**
	(1.59)	(-0.14)	(-0.01)	(2.09)
NYSE	0.001	-0.026	-0.002	0.018
	(0.17)	(-1.2)	(-0.4)	(1.54)
POST	0.003	0.005	-0.014***	0.009
	(0.54)	(0.18)	(-3.02)	(0.85)
NYSE x POST	-0.004	0.026	0.004	-0.012
	(-0.57)	(1.00)	(0.72)	(-0.88)
Controls	YES	YES	YES	YES
Day of Week, Month, and Industry Fixed Effect	YES	YES	YES	YES
N	10,214	10,214	12,189	12,189
Adj-R^2	0.056	0.011	0.132	0.019

Table IA.2 The Impact of LLT on Market Efficiency:
Analysis of Nasdaq System Upgrade

This table presents the difference-in-differences regression results of the impact of an upgrade in order processing speed on Nasdaq on the market reaction to earnings announcements. The sample includes quarterly announcements made by firms listed on NASDAQ and their industry-size-book-to-market matched NYSE peers during the 24 or 36-month period before and after NASDAQ's system upgrade, which happened during April and May of 2010. *NASD* = 1 if the firm is listed on NASDAQ, and 0 if listed on NYSE. *POST* = 1 if the earnings announcement is made after May 2010, and 0 if before April 2010. *EARET* is buy-and-hold abnormal return over day 0 and 1 with day 0 being the earnings announcement day. *CAR60* is buy-and-hold abnormal return over 60-day window from day 2 to 61. The control variables include size (*MV*), book-to-market ratio (*BTM*), shares turnover (*TOVER*), Amihud (2002) illiquidity measure (*ILLIQ*), institutional ownership (*INST*), analyst following (*ANALYST*), earnings persistence (*PERS*), earnings volatility (*EPSVOL*), reporting lag (*REPLAG*), number of concurrent earnings announcements (*NCEA*), change in institutional ownership (*ΔINST*), and change in short interest (*ΔSHORT).* In Panel A the Nasdaq and NYSE firms are matched on industry, size and the book-to-market ratio while in Panel B Standard errors are two-way clustered by firm and date of earnings announcement. *, **, and *** denotes significance at 10%, 5%, and 1%, respectively.

Panel A: Matched on Industry, Size, and Book-to-market

	24 Months		**36 Months**	
	EARET	***CAR60***	***EARET***	***CAR60***
Intercept	-0.027	0.045	-0.034	0.004
	(-0.85)	(0.96)	(-1.33)	(0.11)
DSUE	0.127***	0.009	0.123***	0.019
	(14.67)	(0.28)	(16.85)	(0.77)
DSUE x *NASD*	-0.017	0.032	-0.015	0.011
	(-1.51)	(0.94)	(-1.61)	(0.44)
DSUE x POST	-0.039***	0.001	-0.040***	-0.013
	(-4.05)	(0.01)	(-4.86)	(-0.48)
DSUE x NASD x POST	0.028**	-0.029	0.030***	-0.007
	(2.17)	(-0.77)	(2.85)	(-0.24)
NASD	0.007	-0.018	0.007	-0.007
	(1.15)	(-0.86)	(1.33)	(-0.41)
POST	0.014**	0.011	0.016***	0.015
	(2.5)	(0.47)	(3.48)	(0.86)
NASD x POST	-0.011*	0.012	-0.015**	0.000
	(-1.7)	(0.55)	(-2.54)	(0.01)
Controls	YES	YES	YES	YES
Day of Week, Month, and Industry Fixed Effect	YES	YES	YES	YES
N	12,878	12,878	18,601	18,601
Adj-R^2	0.145	0.018	0.150	0.013

Panel B: Matched on Industry and Book-to-market

	24 Months		36 Months	
	EARET	***CAR60***	***EARET***	***CAR60***
Intercept	-0.053***	0.069**	-0.051***	0.019
	(-3.97)	(2.18)	(-4.64)	(0.75)
DSUE	0.135***	-0.01	0.122***	0.008
	(16.27)	(-0.49)	(18.49)	(0.56)
DSUE x *NYSE*	-0.038***	0.051**	-0.027***	0.027*
	(-4.16)	(2.38)	(-3.69)	(1.66)
DSUE x POST	-0.049***	0.031	-0.037***	0.005
	(-5.15)	(1.3)	(-4.9)	(0.27)
DSUE x NYSE x POST	0.038***	-0.044*	0.024***	-0.017
	(3.64)	(-1.78)	(2.91)	(-0.85)
NYSE	0.017***	-0.044***	0.011**	-0.025**
	(3.27)	(-3.47)	(2.57)	(-2.57)
POST	0.022***	-0.005	0.016***	0.012
	(3.98)	(-0.39)	(3.89)	(1.1)
NYSE x POST	-0.018***	0.036**	-0.011**	0.009
	(-3.1)	(2.42)	(-2.43)	(0.78)
Controls	YES	YES	YES	YES
Day of Week, Month, and Industry Fixed Effect	YES	YES	YES	YES
N	45,673	45,673	66,492	66,492
Adj-R^2	0.135	0.014	0.135	0.010

Table IA.3 The Efficiency of Market Reaction to Earnings Announcements of NASDAQ-listed Stocks

Panel A of the table presents the descriptive statistics of firm characteristics for the earnings announcement sample, which includes 46,232 quarterly earnings announcements made by firms listed on NASDAQ from January 2008 to December 2017. Panel B presents the coefficient estimates of the regression $EARET = \beta_0 + \beta_1 DSUE + \beta_2 DSUE * DLLT + \beta_3 DLLT + \varepsilon$. Panel C presents the coefficient estimates of the post-earnings announcement drift regression $CAR60 = \beta_0 + \beta_1 DSUE + \beta_2 DSUE * DLLT + \beta_3 DLLT + \varepsilon$. LLT is the proxy for low-latency trading based on the strategic runs measure developed by Hasbrouck and Saar (2013). It is defined as the time-weighted number of runs with at least 10 messages over the entire regular trading hours of a day. LLT is averaged over day 0 and 1 with day 0 being the earnings announcement date. *SUE* is standardized unexpected earnings, defined as Actual EPS – Median of analyst forecast of EPS, divided by share price at the end of current fiscal quarter. *DLLT* and *DSUE* are within-quarter decile rankings of *LLT* and *SUE*. *EARET* is buy-and-hold abnormal return over day 0 and 1. *CAR60* is the buy-and-hold abnormal return over a 60-day window from day 2 to 61. Abnormal return is raw return minus its size, book-to-market, and momentum matched portfolio return over the same period. *MV* is market value of equity at the end of quarter *t*, where quarter *t* is the fiscal quarter of earnings announcement. *BTM* is book value of common equity (CEQ) at the end of quarter *t-1* divided by market value of equity at the end of quarter *t*. *TOVER* is average monthly share turnover (shares trading volume divided by shares outstanding) over a 12-month period ending at the end of quarter *t*. *ILLIQ* is the Amihud (2002) illiquidity measure estimated using daily data over the 12-month period ending at the end of quarter *t*. *ANALYST* represents the number of analysts following the firm as of the end of quarter *t*. *INST* denotes the proportion of shares owned by institutional investors at the end of quarter *t*. *PERS* is earnings persistence, estimated by the seasonally-adjusted AR(1) coefficient of the following model: $EPS_t = \alpha + \beta \cdot EPS_{t-4} + \varepsilon$, using 16 quarters from quarter *t-16* to *t-1*. *EPSVOL* is earnings volatility, estimated by the standard deviation of seasonally-adjusted quarterly EPS changes over the 16 quarters from quarter *t-16* to *t-1*. *REPLAG* is reporting lag, defined as the number of calendar days between end of quarter *t* and earnings announcement for quarter *t*. *NCEA* is number of concurrent earnings announcements on the earnings announcement day of quarter *t*. *ΔINST* is change in institutional ownership during the earnings announcement quarter. *ΔSHORT* is change in short interest during the earnings announcement month. Within-quarter decile rankings of the independent variables are used in the regressions reported in Panel B and C. Standard errors are two-way clustered by firm and date of earnings announcement. Significance at 10%, 5%, and 1% is denoted by *, **, and ***, respectively.

Panel A: Summary Statistics

	Mean	Std Dev	Q1	Median	Q3	Correlation with LTT*
LLT	7.853	7.071	3.618	6.383	9.872	
SUE	-0.065	59.808	-0.002	0.000	0.003	0.062
EARET	-0.001	0.103	-0.045	-0.001	0.043	0.014
CAR60	-0.009	0.222	-0.113	-0.015	0.080	0.028
|*SUE*|	0.934	59.800	0.001	0.003	0.008	-0.238
|*EARET*|	0.064	0.080	0.019	0.044	0.087	0.145
|*CAR60*|	0.144	0.169	0.044	0.098	0.188	-0.066
Controls						
MV	2.543	13.521	0.154	0.405	1.163	0.676
BTM	0.671	0.649	0.277	0.523	0.860	-0.345
TOVER	1.849	1.887	0.685	1.341	2.380	0.603
ILLIQ	1.216	9.911	0.002	0.010	0.058	-0.708
ANALYST	9.203	8.343	4.000	7.000	12.000	0.623
INST	0.592	0.305	0.359	0.645	0.857	0.476
PERS	0.229	0.866	-0.076	0.123	0.486	0.047
EPSVOL	34.616	1480.970	0.104	0.228	0.565	0.001$
REPLAG	34.587	14.680	26.000	33.000	39.000	-0.101
NCEA	210.806	128.743	107.500	193.000	309.000	0.031
ΔINST	0.002	0.075	-0.013	0.000	0.017	0.018
ΔSHORT	0.000	0.009	-0.002	0.000	0.002	0.013

* Spearman rank correlation. All correlations are significant at 1% level except those marked with $, which are not significant at conventional levels.

Panel B: Market Reaction to Earnings Announcements (Dependent variable: *EARET*)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
DSUE	0.093***	0.054***	0.053***	0.053***	0.096***
	(39.75)	(17.84)	(17.78)	(16.50)	(3.05)
DSUE x *DLLT*		0.090***	0.091***	0.100***	0.123***
		(10.84)	(11.11)	(11.68)	(5.53)
DLLT		-0.045***	-0.037***	-0.042***	-0.053***
		(-11.76)	(-8.89)	(-10.44)	(-5.87)
Controls	NO	NO	YES	YES	YES
DSUE x Controls and Time FE	NO	NO	NO	NO	YES
Firm FE	NO	NO	NO	YES	YES
Year, Month, Day of Week FE (Time FE)	YES	YES	YES	YES	YES
N	46,232	46,232	46,232	46,232	46,232
Adj-R^2	0.084	0.092	0.099	0.192	0.197

Panel C: Post-Earnings Announcement Drift (Dependent variable: *CAR60*)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
DSUE	0.027***	0.060***	0.057***	0.049***	-0.052
	(6.76)	(8.86)	(8.58)	(6.96)	(-0.66)
DSUE x *DLLT*		-0.077***	-0.075***	-0.075***	-0.042**
		(-6.28)	(-6.07)	(-5.75)	(-2.03)
DLLT		0.046***	0.027***	0.003	-0.014
		(6.63)	(3.18)	(0.34)	(-1.10)
Controls	NO	NO	YES	YES	YES
DSUE x Controls and Time FE	NO	NO	NO	NO	YES
Firm FE	NO	NO	NO	YES	YES
Year, Month, Day of Week FE (Time FE)	YES	YES	YES	YES	YES
N	46,232	46,232	46,232	46,232	46,232
Adj-R^2	0.008	0.009	0.015	0.113	0.115

Internet Appendix B

LLT and Market Activity Indicators Calculated from MIDAS Data

In response to the Flash Crash of May 6, 2010, the Securities and Exchange Commission (SEC) created the Market Information Data Analytics System (MIDAS) in January 2013, in an effort to modernize the agency's technology for collecting and analyzing market data.[30] MIDAS collects data, time-stamped to the microsecond, from the consolidated tapes as well as separate proprietary feeds provided by each of the 13 national stock exchanges, which allows the SEC to have a complete and near real-time view of the dynamics of the entire market. Select daily summary statistics by individual security and exchange of the raw data have been made available for public access, and these datasets have been employed in recent academic research to measure algorithmic trading (AT) activity in the equity market. (e.g. Weller 2018, Lee and Watts 2018)

Panel A of Table IB.1 presents the correlation structure between *LLT* and four measures of AT constructed from MIDAS data: cancel-to-trade (*CTT*), trade-to-order (*TTO*), odd-lot ratio (*OL*), and trade size (*TS*), all as defined in Weller (2018). The sample includes over 5.4 million stock-day observations and spans 1,507 trading days from January 2012 to December 2017. The correlations are estimated cross-sectionally for each trading day, and then averaged over the sample period.[31] Because *TTO* and *TS* are defined to be inversely related to AT, we multiply both variables by -1 for ease of interpretation.

As the table shows, *OL* and *TS* are both positively, albeit weakly, correlated with *LLT*. In contrast, the two measures of order cancellation rate, *CTT* and *TTO*, are

[30] https://www.sec.gov/marketstructure/midas.html#.XXs9G2kzYuU

[31] We report Spearman rank correlation for its robustness to extreme values produced by the ratio variables.

both negatively correlated with *LLT* at economically significant magnitudes of -0.193 and -0.196, respectively. This somewhat surprising pattern highlights a key limitation of the summary MIDAS data: *CTT* and *TTO* measures the frequency of *all* canceled orders, regardless of the duration, while LLT strategies are typically characterized by "the submission of numerous orders that are cancelled shortly after submission" (SEC 2010). Since a significant proportion of orders are submitted by non-LLT traders and canceled only after a non-trivial duration,[32] *CTT* and *TTO* as proxies for low-latency activity may be noisy, or even systematically biased. Consistent with this conjecture, Panel A of Table IB.1 shows that *CTT* and *TTO* are both negatively correlated with the proportion of high-frequency cancellations (orders cancelled within 100 milliseconds of submission), but positively correlated with low-frequency cancellations (orders cancelled 300 milliseconds or longer after submission).[33] The table further shows that *CTT* and *TTO* are positively correlated with illiquidity as measured by bid-ask spreads and the price impact, which appears to contradict the consensus finding in the literature that algorithmic trading and LLT is generally associated with improved liquidity in the equity market. See, for example, Hendershott, Jones, and Menkveld (2011) and Hasbrouck and Saar (2013).

In addition, both the odd-lot ratio and the trade size are also noisy measures of LLT. While LLTs often submit small sized orders in order to ascertain the state of the limit order book, so do retail traders, especially when the price of a stock is high. For instance, with Amazon trading over $1725 on 9/27/2019, a purchase of a round lot of 100 shares would cost over $172,500. While small trade sizes were essentially the province of retail traders prior to decimalization in 2001, in recent years with the

[32] For example, MIDAS statistics show that in the fourth quarter of 2017, the proportion of limit orders that are cancelled within 100 milliseconds (1 second) of submission is 41% (57%) for large-cap stocks, 29% (41%) for mid-cap stocks, and 17% (25%) for small-cap stocks.

[33] Order duration is calculated using Nasdaq TotalView ITCH data.

advent of algorithmic trading even institutions are breaking up their trades and trading smaller quantities to disguise their trades.[34] LLTs are also posting smaller quantities at tighter spreads. Thus, order sizes are also noisy measures of LLT.

In Panels B and C of Table IB.1 we show that interaction term $DSUE \times DLLT$ remains statistically and economically significant for both the market reaction and the PEAD regressions even when the interactions between *DSUE* and *DCTT, DTTO, DOL*, and *DTS* are introduced in turn into the panel regressions of Table 2. While the MIDAS based variables are easily obtainable, we suggest caution in their use as they are not unambiguous proxies for LLT. Overall, the strategic runs measure, *LLT*, as suggested by Hasbrouck and Saar (2011) seems to be the best available proxy for LLT for tests that require a large cross-section and time-series of the data.

[34] See Chordia, Roll and Subrahmanyam (2011) for the trend in trading volumes and order sizes.

Table IB.1 MIDAS Variables

This table describes the LLT measures derived from MIDAS data. Panel A presents the correlation between the MIDAS variables and LLT and various measures of liquidity. Panel B presents the coefficient estimates of the regression $EARET = \beta_0 + \beta_1 DSUE + \beta_2 DSUE * DLLT + \beta_3 DLLT + controls + \varepsilon$. Panel C presents the coefficient estimates of the post-earnings announcement drift regression $CAR60 = \beta_0 + \beta_1 DSUE + \beta_2 DSUE * DLLT + \beta_3 DLLT + controls + \varepsilon$. *LLT* is the proxy for low-latency trading based on the strategic runs measure developed by Hasbrouck and Saar (2013). It is defined as the time-weighted number of runs with at least 10 messages over the entire regular trading hours of a day. *SUE* is the standardized unexpected earnings, defined as Actual EPS – Median of analyst forecast of EPS, divided by share price at the end of current fiscal quarter. *DLLT* and *DSUE* are within-quarter decile rankings of *LLT* and *SUE*. *EARET* is the buy-and-hold abnormal return over day 0 and 1. *CAR60* is the buy-and-hold abnormal return over a 60-day window from day 2 to 61. Abnormal return is the raw return minus its size, book-to-market, and momentum matched portfolio return over the same period. Cancel-to-Trade (*CTT*) is count of all cancel messages divided by count of trade messages that are not against hidden orders. Trade-to-Order (*TTO*) is sum of trade volume for trades that are not against hidden orders divided by sum of order volume for all add order messages. Odd-lot Ratio (*OL*) is sum of odd lot trade volume divided by sum of trade volume. Trade Size (*TS*) is sum of trade volume divided by count of trade messages. *TTO* and *TS* are multiplied by -1. *DCTT*, *DTTO*, *DOL*, *DTS* are within-quarter decile rankings of *CTT*, *TTO*, *OL*, and *TS*. Control variables include size (*MV*), book-to-market ratio (*BTM*), shares turnover (*TOVER*), Amihud (2002) illiquidity measure (*ILLIQ*), institutional ownership (*INST*), analyst following (*ANALYST*), earnings persistence (*PERS*), earnings volatility (*EPSVOL*), reporting lag (*REPLAG*), number of concurrent earnings announcements (*NCEA*), change in institutional ownership (*ΔINST*), and change in short interest (*ΔSHORT).* Within-quarter decile rankings of the control variables are used in the regressions. Significance at 10%, 5%, and 1% is denoted by *, **, and ***, respectively. The sample period is from January 2012 to December 2017.

Panel A: Correlations

	Cancel-to-Trade	Trade-to-Order	Odd-lot Ratio	Trade Size
LLT	-0.193	-0.196	0.077	0.089
Number of Orders	-0.153	-0.137	0.147	0.115
% of Orders Cancelled	0.765	0.677	0.176	0.077
% of Orders Cancelled within 100 ms	-0.157	-0.172	0.015	0.014
% of Orders Cancelled after 300 ms	0.200	0.197	-0.015	-0.019
Quoted Spread	0.225	0.162	-0.165	-0.079
Effective Spread	0.143	0.053	-0.245	-0.135
Price Impact	0.039	-0.080	-0.177	-0.121

Panel B: Market Reaction Regressions (Dependent Variable = *EARET*)

	(1)	(2)	(3)	(4)
DSUE	0.155***	0.150***	0.119***	0.121***
	(6.61)	(6.38)	(5.06)	(5.15)
*DSUE*DLLT*	0.092***	0.086***	0.104***	0.109***
	(16.07)	(14.91)	(18.09)	(19.12)
DLLT	-0.053***	-0.05***	-0.057***	-0.061***
	(-14.79)	(-13.87)	(-15.86)	(-16.92)
*DSUE*DCTT*	-0.087***			
	(-20.34)			
DCTT	0.065***			
	(24.32)			
*DSUE*DTTO*		-0.09***		
		(-20.94)		
DTTO		0.067***		
		(24.41)		
*DSUE*DOL*			-0.026***	
			(-5.77)	
DOL			0.038***	
			(11.84)	
*DSUE*DTS*				-0.035***
				(-8.21)
DTS				0.04***
				(12.38)
Controls	YES	YES	YES	YES
*DSUE*Controls and Time FE*	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year, Month, Day of Week FE (Time FE)	YES	YES	YES	YES
N	52,421	52,472	52,448	52,421
Adj-R^2	0.205	0.205	0.198	0.198

Panel C: PEAD Regressions (Dependent Variable = *CAR60*)

	(1)	(2)	(3)	(4)
DSUE	0.122**	0.121**	0.127***	0.123**
	(2.47)	(2.46)	(2.59)	(2.51)
*DSUE*DLLT*	-0.066***	-0.069***	-0.069***	-0.064***
	(-5.52)	(-5.71)	(-5.79)	(-5.39)
DLLT	0.028***	0.029***	0.025***	0.024***
	(3.67)	(3.83)	(3.39)	(3.28)
*DSUE*DCTT*	-0.007			
	(-0.78)			
DCTT	-0.017***			
	(-3.01)			
*DSUE*DTTO*		-0.015*		
		(-1.72)		
DTTO		-0.017***		
		(-3.03)		
*DSUE*DOL*			-0.021**	
			(-2.20)	
DOL			-0.032***	
			(-4.88)	
*DSUE*DTS*				-0.026***
				(-2.88)
DTS				-0.032***
				(-4.84)
Controls	YES	YES	YES	YES
*DSUE*Controls and Time FE*	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year, Month, Day of Week FE (Time FE)	YES	YES	YES	YES
N	52,421	52,472	52,448	52,421
Adj-R^2	0.139	0.140	0.140	0.140