Earnings Announcements and Attention Effects in a High-Frequency World

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Abstract

How does limited attention affect stock prices following earnings announcements in today's computer-driven financial markets? We examine the effects of limited attention using a dataset that separately identifies trades made by high-frequency traders (HFTs, or computers) versus non-high-frequency traders (human decision-makers). Using six attention proxies, we find pricing inefficiencies lower by 64% to 100% when HFTs trade following low-attention earnings announcements. An event study of an exogenous shock to algorithmic trading suggests that computerized trading causally reduces low-attention effects. Price efficiency improvements are more closely tied to HFT liquidity demand than supply, consistent with HFTs improving efficiency by processing and aggressively trading on the information in low-attention announcements.

JEL classification: G02, G10, G14, M40, M41

Keywords: Earnings announcements, limited attention, high-frequency trading, price efficiency

1. Introduction

A large body of literature documents that limited attention of financial market participants can affect stock pricing around earnings announcements through various channels. Hirshleifer, Lim, and Teoh (2009) posit that on days when many firms announce their earnings, investors are distracted and able to pay less attention to individual earnings announcements. They find that price responses to earnings surprises on such "busy days" are less efficient than on days when there are fewer earnings announcements. DellaVigna and Pollet (2009) similarly find that price responses to earnings surprises in Friday announcements are less efficient than to earnings announcements made on other weekdays, which they attribute to investors being distracted by the upcoming weekend. Michaely, Rubin, and Vedrashko (2016b) find that managers try to hide bad news by announcing it on Fridays, and they find that Friday announcements have the largest post-earnings announcement drift (PEAD).[1] Chakrabarty and Moulton (2012) identify a different channel – market makers' limited attention – that affects stock liquidity. They find that on days when stocks assigned to one market maker have earnings announcements, there is a reduction in the liquidity of the non-announcing stocks handled by the same market maker. Together these studies show that decision-makers' limited attention and the need to allocate this scarce resource across competing information sources affect prices.

The common motivation for this literature is that *human* decision-makers' attention is a limited resource. But the direct participation of human decision-makers in the trading process has been diminishing over time. In the past several years, equity markets have witnessed a revolutionary shift in the technology and speed of trading. Order submissions and executions now occur in sub-second increments. These are speeds that humans cannot even register, let alone react to.[2] Technological advances have facilitated the proliferation of high-frequency trading, a trading paradigm in which computers trade using algorithms with pre-programmed logic. An estimated 40 to 60 percent of all trades in stocks, derivatives, and foreign currencies across all financial markets can be attributed to high-frequency trading (Sussman, 2012). In the U.S. equity markets, over 50 percent of all trades are such high-frequency trades (Brogaard, Hendershott, and Riordan, 2014). By all measures, high-frequency traders play a large role in the current trading

[1] Michaely, Rubin, and Vedrashko (2016a) offer an alternative explanation for under-reaction to Friday announcements based on firm characteristics.
[2] For example, the latest trading hardware (chip) prepares a trade in 740 billionths of a second; by comparison, the blink of an eye takes about one-third of a second. For further discussion of advances in computerized trading, see http://blogs.wsj.com/marketbeat/2011/06/14/wall-streets-need-for-trading-speed-the-nanosecond-age/.

landscape. Since these machines are not subject to limited attention, we ask: How does limited attention affect stock price reactions to earnings news in today's computer-driven markets?

Recent work by DeHaan, Shevlin, and Thornock (2015) provides an interesting segue into this issue. DeHaan et al. (2015) find that attention to earnings announcements is no lower on Fridays than on other days of the week. This result is in contrast to studies by DellaVigna and Pollet (2009) and Michaely et al. (2016b), who document lower attention to Friday announcements. While DeHaan et al. (2015) do not explore the reasons for this reversal of the previously documented Friday inattention phenomenon, they mention the possibility that the trading technology of modern markets may be at least partially responsible.[3]

In this paper, we test whether attention constraints still affect stock price adjustments following earnings announcements in a world where high-frequency trading plays a large role. Corporate earnings announcements are events that are generally newsworthy and have been found to attract varying levels of investor attention in prior studies (e.g., DellaVigna and Pollet, 2009; DeHaan et al., 2015). The attention literature suggests that human traders have limited attention or cognitive capacity and therefore tend to under-react to certain earnings announcements. In contrast, we would not expect high-frequency traders (HFTs), which trade based on pre-programmed computer algorithms, to suffer from human attention constraints. Furthermore, the growing HFT literature suggests that high-frequency trading leads to faster incorporation of information into prices (e.g., Brogaard et al., 2014), and HFT algorithms are known to parse textual news such as earnings announcements from pre-processed news feeds (e.g., Gross-Klussman and Hautsch, 2011). In our context, this suggests that in a world where HFTs play a large role in trading, price reactions to low-attention earnings surprises may be more efficient.

Since it is not possible to directly measure how much attention investors pay to an announcement, the literature on attention in financial markets has generated a number of proxies to indirectly measure attention based on trading volume, event characteristics, or investor actions. Studies using volume-based attention metrics (e.g., Corwin and Coughenour, 2008) reason that higher trading volume indicates greater attention and, conversely, lower volume indicates binding attention constraints. This interpretation implicitly assumes that all trading originates from human decision-makers. But since total trading volume in today's markets arises from HFTs (which trade based on pre-programmed algorithms that are not subject to attention constraints) as well

[3] See DeHaan et al.'s (2015) footnote 4, which alludes to undistracted arbitrageurs and algorithmic traders.

as human decision-makers, volume-based attention proxies may be misleading. Thus we rely on attention proxies that are based on event characteristics or investor actions. Specifically, we use the following non-volume proxies to identify low-attention earnings announcements: (1) days on which there are multiple announcements, as in Hirshleifer et al. (2009); (2) announcements after which analysts are slow to incorporate earnings news into their earnings forecasts, similar to DeHaan et al. (2015); (3) announcements that are made on Fridays, as in DellaVigna and Pollet (2009); (4) announcements that are accompanied by many non-earnings-related news stories, which are potentially distracting (Miller, 2002); (5) announcements that are made on days with lower download volume of financial reports from the Securities and Exchange Commission's (SEC's) Electronic Data Gathering, Analysis, and Retrieval (EDGAR) facility, similar to DeHaan et al. (2015); and (6) announcements that are accompanied by low Google search volume, as in Da, Engelberg, and Gao (2011).[4] To some extent these proxies capture the richness of the information environment surrounding an earnings announcement in addition to different angles of attention per se. Because these proxies capture different aspects of the underlying attention phenomenon, we also construct an aggregate attention measure that defines events as low-attention if they are classified as such by many of the individual proxies.

Our study requires information about when HFTs are involved in trades. Standard public databases, such as the New York Stock Exchange (NYSE) Trade and Quote (TAQ) database, do not identify trader types. This study is made possible by a unique dataset provided by the NASDAQ exchange that identifies the counterparties to each trade as HFTs or non-HFTs for NYSE- and NASDAQ-listed firms. Using this HFT database and our large set of attention proxies, in our main analysis we examine whether price efficiency differs for low-attention earnings announcements with versus without high-frequency trading. We find that in the presence of HFTs, both short-term and long-term price efficiency are higher using our aggregate attention proxy as well as several of the individual proxies. For example, while earnings announcements that occur on days with many announcements generally have short-term cumulative abnormal returns that are significantly less responsive to earnings surprises, this effect is reduced by 64% when HFTs are active in trading on the low-attention announcements. For the longer horizon, we find that PEAD following low-attention earnings announcements is significantly lower when HFTs participate, with PEAD completely eliminated under some low-attention proxies.

[4] Details of the attention proxies and their construction are provided in Section 3.

An important challenge for our study is establishing causality. Since HFTs endogenously choose when and which stocks to trade, our main findings could reflect either HFTs reducing price inefficiencies through their trading or HFTs choosing to trade on earnings announcements with greater price efficiency. We test small and large stocks separately to show that our results are not simply due to HFTs' preference for large stocks, which typically experience less attention-based inefficiency. Unfortunately, there is no exogenous shock to high-frequency trading during our main sample period, 2008-2009. However, there is a well-known shock to computerized trading in 2003, when the NYSE introduced automated quoting (Autoquote), greatly facilitating HFTs and other algorithmic trading. Compared to the prior system of specialists manually updating quotes, Autoquote provides much quicker feedback to computerized traders like HFTs. Autoquote's phased introduction thus serves as an instrument that allows us to examine causality (as in Hendershott, Jones, and Menkveld, 2011). We find that the introduction of Autoquote significantly reduces the pricing inefficiencies associated with low-attention earnings announcements, suggesting a causal relationship, with computerized traders reducing the price inefficiencies previously documented for low-attention earnings announcements.

Finally, we investigate whether the documented improvements in price efficiency are more closely associated with (i) HFTs supplying liquidity to non-HFTs who want to trade on the earnings information, or (ii) HFTs themselves incorporating earnings information into prices through their liquidity demand. We find that typically HFT liquidity demand and supply both account for a larger fraction of total trading on low-attention announcement days. Further investigation reveals that the improvements in price efficiency are more closely tied to low-attention announcements for which HFTs' liquidity demand relative to their supply is abnormally high. This finding suggests that it is HFTs' ability to process and trade quickly on information (such as textual news feeds about earnings announcements) that contributes more strongly to the improvement in price efficiency around low-attention earnings announcements.

These findings make several contributions to the literature. First and most important, we advance the study of limited attention into modern financial markets. Prior studies that found limited attention affecting stock price responses to earnings news were conducted before HFTs gained prominence, and we find that the attention effect is diminished in the presence of HFTs. We do not claim that limited attention no longer plays any role in financial markets; after all, trading decisions made by humans still account for a large portion of total trading volume.

However, with non-human traders accounting for a significant proportion of trading, it is important to understand whether anomalies linked to limited attention are dissipating in recent times. Our finding that these anomalies are attenuated in an environment with non-human decision-makers (HFTs) implicitly supports the original attribution of these mis-pricings to human attention constraints.

Second, this work is related to recent papers that study how the profitability of anomalies changes over time (e.g., McLean and Pontiff, 2016). Chordia, Subrahmanyam, and Tong (2014) find that several capital market anomalies have attenuated in recent years as market liquidity and trading activity have risen, facilitating more arbitrage activity. Other studies find that the declining profitability of the accruals anomaly is attributable to an increase in liquidity (Mashruwala, Rajgopal, and Shevlin, 2006) and a rise in hedge fund trading (Green, Hand, and Soliman, 2011). Our study contributes to this literature by showing how the rise of the machines (HFTs), which is both facilitated by and contributes to enhanced liquidity and trading activity, may reduce human-attention-based anomalies.

Third, our study suggests that the rise of HFTs has rendered aggregate trading volume a less useful indicator of times when traders are paying less attention. We find that HFTs account for a larger share of trading volume during many low-attention times. Thus researchers using trading-volume-based proxies for attention constraints may fail to find significant results because the changes in activity levels of HFTs and non-HFTs may (at least partially) offset each other.

Finally, our study contributes to the literature on high-frequency trading and price efficiency beyond the market microstructure focus on seconds and sub-seconds. By relating HFT to earnings response coefficients and PEAD, our work moves away from the very-short-horizon pricing efficiency focus, towards longer time windows that are more associated with capital allocation consequences (Lev, 1989). Our study suggests that HFTs play a beneficial role in making prices more efficient around low-attention earnings announcements, times when stocks have been shown to have particularly inefficient price responses to earnings surprises. This result complements the existing literature on high-frequency trading, which catalogs several ways in which HFTs can lead to better market quality in the very short term, including improved liquidity, lower transactions costs, and greater price efficiency. To the best of our knowledge this study is the first to examine the interplay between high frequency trading and limited investor attention.

The remainder of the paper is organized as follows. Section 2 provides background on high-frequency trading and limited attention in financial markets. Section 3 describes our sample, data sources, and key trading and attention measures. Section 4 presents our tests of price efficiency and HFT participation around low-attention earnings announcements. Section 5 investigates whether price efficiency is more closely associated with HFTs demanding or supplying liquidity. Section 6 presents robustness checks, and Section 7 concludes. Appendix A defines all of our variables. Appendix B presents an illustration of how the high-frequency trading measures are calculated.

2. Background on high-frequency trading and limited attention

We first discuss the institutional background on high-frequency trading and its role in financial markets. We then discuss the academic evidence to date on the role of human attention constraints in markets.

2.1 HFT: Definition, growth, and effects

The SEC's Concept Release on Equity Market Structure (2010) recognizes that high-frequency trading is one of the most significant market structure developments in recent years. It notes that, "[b]y any measure, HFT is a dominant component of the current market structure and likely to affect nearly all aspects of its performance."[5] Although there is no strict definition of high-frequency trading, the following characteristics are generally attributed to it (SEC, 2014):[6]

- Use of high speed algorithms for generating, routing, executing and/or canceling orders.
- Use of co-location services and individual data feeds offered by exchanges and vendors to minimize network and other latencies.
- Very short timeframes for establishing and liquidating positions.
- High volume order submission followed in quick succession by cancellations.
- Ending the trading day in as close to a flat position as possible (that is, not carrying significant overnight positions).

[5] Securities Exchange Act Release No. 34-61358, 75 FR 3594, 3606 (January 21, 2010) ("Concept Release").
[6] The first two characteristics can also apply to sophisticated non-HFT traders, such as institutional traders using smart order-routing technology to optimize their order executions. It is the last three characteristics that distinguish HFTs in particular.

High-frequency trading began in early 2000 and has grown rapidly to become a dominant player in today's markets. In U.S. equities, estimates of high-frequency trading come mainly from two private research firms: Rosenblatt Securities and the Tabb Group. Estimates from Rosenblatt Securities indicate that about 67% of all domestic stock trades between 2008 and 2011 were executed by HFTs.[7] In terms of volume, HFTs accounted for a trading volume of about 3.25 billion shares per day in 2009. The Tabb Group estimates that high-frequency trading revenue was about $7.2 billion in 2009.[8]

The growth of high-frequency trading has attracted increasing focus from regulators, the media, and academic researchers. The 2010 SEC concept release on equity market structures (SEC, 2010), the Foresight Project on the Future of Computer Trading in Financial Markets (BIS, 2011), and the MiFID II proposal are all regulatory efforts to understand the impact of high-frequency trading's growth on market quality. In one of the first academic studies to examine the impact of computerized trading on market quality, Hendershott, Jones, and Menkveld (2011) find that algorithmic trading improves several measures of market liquidity – reducing spreads, reducing adverse selection, and enhancing the informativeness of quotes. Brogaard et al. (2014) find that HFTs improve price discovery in U.S. equities, a finding that Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) confirm for the foreign exchange market, where increased HFT activity reduces arbitrage opportunities and return autocorrelations.

In contrast to these positive effects, some recent studies suggest that HFT activity may not be an unmitigated blessing. In examining the Flash Crash of May 2010, Kirilenko, Kyle, Samadi, and Tuzun (2015) find that although HFTs did not trigger the crash, they exacerbated price movements that day. Biais, Foucault, and Moinas (2015) build a theoretical model which shows that high levels of HFT activity can generate market exclusion for slower traders and create negative externalities. In sum, the net effect of HFTs on markets is yet to be established. Amidst this ongoing debate on the impact of HFTs, this study focuses on an unexplored issue surrounding HFTs: whether and how the effects of limited attention on price efficiency following earnings announcements have changed with the rise of high-speed machine trading.

[7] Matthew Philips, "How the Robots Lost: High-Frequency Trading's Rise and Fall," Bloomberg BusinessWeek, June 6, 2013, available at http://www.businessweek.com/articles/2013-06-06/how-the-robots-lost-high-frequency-tradingsrise-and-fall.
[8] Larry Tabb, "No, Michael Lewis, the US Equities Market Is Not Rigged," TABB Group, March 31, 2014, available at http://blogs.wsj.com/moneybeat/2014/04/01/larry-tabb-no-mr-lewis-the-markets-are-not-rigged/

2.2 Investor attention in financial markets

Limited attention is a human attribute, and historically the primary decision-makers in financial markets have been human traders, including institutional portfolio managers, individual (retail) investors, and human market makers such as specialists. A large body of research documents the effects of attention as a scarce cognitive resource in economic decisions (Kahneman, 1973). For example, studies show that limited cognitive capacities can explain the use of heuristics in decision-making (Gabaix, Laibson, Moloche, and Weinberg, 2006) and under-reaction to information (Hong and Stein, 1999). Bali, Peng, Shen, and Tang (2014) find that limited investor attention drives long-term return predictability following liquidity shocks. Such under-reaction has asset pricing consequences and leads to predictable price patterns, including reduced speed of price adjustment (Peng, 2005), prices that do not fully impound all available public information (Huberman and Regev, 2001), under-reaction to earnings announcements (Hirshleifer et al., 2009), and failure to fully respond to profits and losses disclosed in corporate communications (Balakrishnan, Bartov, and Faurel, 2010). In recent work, Chen, Jeremias, and Panggabean (2016) find that the visual attention of managers can affect their judgment and decision-making processes.

The delay in processing, or under-reaction to, information as a result of limited attention becomes especially prominent when there are attention-grabbing events or when multiple stimuli demand attention. Barber and Odean (2008) find that investors more frequently buy stocks that come to their attention due to news announcements, ignoring non-news-making investment opportunities. Graham and Kumar (2006) find that certain investors tend to trade securities following specific events that attract attention, such as dividend initiations. Lee (1992) directly infers that small investors' buy decisions are associated with news events that bring these securities to their attention.

Earnings announcement days are times of increased information in the markets (Beaver, 1968; Brown, Hillegeist, and Lo, 2009), and stocks with earnings announcements generally attract more attention (Aboody, Lehavy, and Trueman, 2010). Several studies examine the impact of limited attention around earnings announcements. Hirshleifer et al. (2009) examine days with multiple announcements and find that the immediate stock price and volume reactions to a firm's earnings surprise is weaker, and PEAD is stronger, when a greater number of earnings announcements by other firms are made on the same day. Chakrabarty and Moulton (2012) find that market makers' limited attention reduces liquidity for stocks when other stocks covered by the same market maker have earnings announcements.

DeHaan et al. (2015) find that managers try to take advantage of predictable variations in attention by releasing bad news in periods of low attention. The issue of strategically timing news to exploit expected patterns of attention constraints is also explored by DellaVigna and Pollet (2009), who find that Friday earnings announcements have a lower immediate stock price response and a higher delayed response in addition to a lower abnormal volume response to earnings surprises than non-Friday announcements. Patell and Wolfson (1982) and Michaely et al. (2016b) find that worse earnings news tends to be released on Fridays and after regular trading hours.

3. Sample, data, and measures

In this section we discuss our sample and the construction of our high-frequency trading variables and attention proxies. In addition to the sources listed below, we obtain basic stock data from CRSP and Compustat. Appendix A details all of our variable definitions, calculations, and data sources.

3.1 Sample construction

Our key data on HFT and non-HFT activity are obtained from a dataset provided by NASDAQ.[9] The NASDAQ dataset includes 120 stocks, selected through a stratified random sampling procedure to reflect the dispersion in market capitalization of the universe of all firms listed on NASDAQ and NYSE. The sample includes all trades in these 120 stocks that occur on the NASDAQ exchange in 2008 and 2009.

IBES and Compustat are the two most widely used databases to identify earnings announcement dates. We begin with the NASDAQ sample of 120 stocks, identify their earnings announcements dates from IBES, and match these announcements in Compustat. This gives us 960 announcements, 937 (98%) of which have the same date in both databases. We delete two announcements where the dates in the two databases are more than 30 days apart. For the remaining 21 announcements, we verify the correct announcement date manually by examining company press releases and newswire reports. This gives us a sample of 958 earnings announcements (937 initially matched plus 21 verified by news sources).

[9] This dataset has been used in other academic studies e.g., Brogaard et al. (2014) and Carrion (2013). It is provided under a non-disclosure agreement.

Recent work by DeHaan et al. (2015) suggests that mixed results in the earnings literature may be attributable to challenges in identifying the precise time of announcements. Bradley, Clarke, Lee, and Ornthanalai (2014) find that IBES timestamps are not always accurate. Since our study relies on announcement times in addition to their dates, we use two additional sources to verify the announcement times: Wall Street Horizon (WSH), which provides institutional traders with corporate event data, and Factiva, a leading source of business newswires.[10]

Of the 958 announcements in our sample, 781 (82%) have the same date and time in WSH and IBES/Compustat. There are nine earnings announcements that are either not covered by WSH or have different dates in WSH and IBES/Compustat. We verify the date for these announcements using Factiva. For another 168 announcements, the dates match in WSH and IBES/Compustat but the reported times differ by one minute or more. For these cases we use Factiva to verify the announcement time. For 130 of these announcements Factiva agrees with the WSH or IBES/Compustat time, and we use that time. For the remaining 38 announcements, we use the earliest timestamp among Factiva, WSH, and IBES/Compustat as the announcement time. We thus arrive at timestamps for all 958 of the earnings announcements in the sample as filtered so far.

We impose the following additional filters to arrive at our final sample: (i) exclude one announcement made on a non-trading day; (ii) exclude two announcements with no trading in the NASDAQ dataset; (iii) exclude four stocks with no trading after announcement time on any of their earnings announcement dates; (iv) exclude 13 stocks that have no high-frequency trading after announcement time on any of their announcement dates; (v) exclude 75 announcements with no trades after their announcement time. After imposing these filters, we are left with 103 stocks and 745 earnings announcements. These 103 stocks have over 542 million trades, for a total volume exceeding 105 billion shares and a dollar volume of about $3.9 trillion in 2008-2009.

3.2 HFT measures

Each trade is the result of the interaction between two counterparties, one of which demands liquidity (a marketable order that immediately takes liquidity from the opposite side of the order book) and the other which supplies liquidity (the limit order that is sitting in the order book). NASDAQ identifies the liquidity demander and supplier in each trade as a high-frequency trader (H) or non-high-frequency trader (N). NASDAQ attaches the HFT and non-HFT identifiers

[10] The Wall Street Horizon data are provided under a non-disclosure agreement.

based its information about the identity of each trader (which is not publicly disseminated). NASDAQ makes this determination based on the firms' trading styles and also on the firms' website descriptions. The characteristics of firms that have been identified as HFTs generally follow the SEC's identification of HFTs, as outlined in Section 2.1.

For each trade, in addition to ticker symbol, date, time, price, share volume, and buy/sell indicator, NASDAQ provides one of four possible trader-type classifications:

- HH: Both the liquidity demander and supplier for the trade are HFTs;
- HN: The liquidity demander is an HFT, the liquidity supplier is a non-HFT;
- NH: The liquidity demander is a non-HFT, the liquidity supplier is an HFT; and
- NN: Both the liquidity demander and supplier for the trade are non-HFTs.

From these classifications we construct three measures of high-frequency trading and two measures of the interactions between HFTs and non-HFTs (as in Brogaard et al., 2014). Our first measure, HFT^{All}, captures the percentage of daily share volume that HFTs represent in each stock each day, taking into account both sides of each trade (liquidity demand and liquidity supply). It is calculated as:

$$HFT^{All} = (2*HH + HN + NH) / (2*\text{Total Volume}) , \tag{1}$$

The numerator in Equation (1) captures the shares demanded and supplied by HFTs, and the denominator reflects the total number of shares demanded and supplied in total (which is equal to two times volume, since each trade involves a demander and a supplier).[11]

Our next two measures capture the extent to which HFTs demand and supply liquidity in each stock. They are calculated as:

$$HFT^{D} = (HH + HN) / \text{Total Volume} , \tag{2}$$

$$HFT^{S} = (HH + NH) / \text{Total Volume} . \tag{3}$$

Finally, we create two measures of the interaction between HFTs and non-HFTs, distinguishing between which trader type is demanding versus supplying liquidity in these interactions. They are calculated as follows:

$$HN\% = HN / \text{Total Volume} , \tag{4}$$

$$NH\% = NH / \text{Total Volume} . \tag{5}$$

[11] We obtain qualitatively similar results using HFT participation defined as (HH+HN+NH)/Total Volume, as in Carrion (2013).

Panels A and B of Table 1 present descriptive statistics for our sample stocks and high-frequency trading, demand, and supply as well as interaction measures for these stocks.[12] The cross-sectional statistics in Panel A show that the sample of stocks is diverse; this is by design, as NASDAQ intentionally provides these data on a sample of stocks evenly spread across the different market capitalizations. Over the two-year sample period, nearly all of the stocks have eight regular earnings announcements (mean number of announcements is 7.98). Panel B shows that HFTs represent 28.8% of trading volume on average. Consistent with prior literature (e.g., Carrion, 2013), we find that total HFT demand (32.8%) exceeds supply (24.7%). When trading with non-HFTs, HFTs are more often on the liquidity demanding side (24.9%) than on the liquidity supplying side (16.8%).

[Table 1 here]

3.3 Attention proxies

To identify low-attention earnings announcements we employ six non-volume-based proxies for low attention derived from the prior literature. We note that these six proxies are not necessarily independent of each other, but rather are related measures designed to capture the underlying phenomenon of low investor attention. We examine their correlation at the end of this section.[13]

Our first proxy for low-attention earnings announcements is those that occur on the same day that many other earnings announcements are released, dubbed "busy" days. Hirshleifer et al. (2009) find that investors tend to underreact to earnings announcements released on a busy day. We define Busy Day announcements as those with an above-quarterly-median number of earnings announcements released on the same day. For example, if the median number of earnings announcements per day is 200 in the first quarter of 2008, all earnings announcements in that quarter that occur on days with more than 200 announcements are designated as low-attention under the *Busy Day* measure.

Our second proxy for low-attention earnings announcements is those with slow analyst speed, similar to DeHaan et al. (2015). Analyst speed is the speed (inverse of day count) with

[12] Because of market clearing, HFT and non-HFT trading in each category (overall, demand, and supply) sum to 100%, so non-HFT trading percentages are simply 100% minus HFT trading percentages.
[13] We do not use earnings announcements that are released after the market close as a proxy for low attention because Jiang et al. (2012) find that earnings announcements made after the market close have more efficient price reactions and a high degree of informational efficiency. We examine post-close earnings announcements in our robustness checks (see Section 6).

which analysts incorporate earnings news into their forecasts. We collect from IBES all analyst forecast updates within 20 days of a firm's earnings announcement. We then calculate the number of weekdays between the earnings announcement and each analyst forecast update (*j*), take the average, and calculate the analyst updating speed as:

$$AnalystSpeed = -1 * ln\left(\frac{1}{j}\sum_{j=1}^{J}\left[1 + Weekdays\ until\ forecast\ update_j\right]\right). \quad (6)$$

We define *Slow Analyst Speed* announcements as those with a below-quarterly-median analyst speed.

Our third proxy for low-attention earnings announcements is those that occur on a *Friday*, when traders may be distracted by the upcoming weekend (DellaVigna and Pollet, 2009).

Our fourth low-attention proxy is a measure of news distraction. We posit that just as investors may be distracted when there are many different firms announcing earnings on the same day (Hirshleifer et al., 2009), investors may also be distracted from a firm's earnings announcement when there are many non-earnings-related stories about the same firm on the same day as the earnings announcement. Firms may recognize this potential distraction: Miller (2002) finds that firms strategically release other discretionary disclosures with their earnings news. From Dow Jones Newswires (via Factiva), we hand-collect the number of new stories for each firm on each of its earnings announcement days, and within those we count the number of stories that are specifically about the firm's earnings announcement. We define Distracting News as *ln(All Stories+1) – ln(Earning Stories+1)* and define *High News Distraction* announcements as those that occur on days with an above-quarterly-median number of Distracting News.

Our fifth proxy for low-attention earnings announcements is based on the number of downloads of financial filings from the SEC's EDGAR online system, which hosts financial filings by public companies.[14] DeHaan et al. (2015) find that abnormal EDGAR download volume is a good proxy for investor attention. Similar to DeHaan et al. (2015), we compute abnormal EDGAR download volume as follows:

$$EDGAR\ downloads = ln(EDGAR_t) - ln(\tfrac{1}{5}\textstyle\sum_{w=1}^{5} EDGAR_w)\ , \quad (7)$$

where the first term is the natural log of EDGAR download volume on the day of interest, and the second term is the natural log of the average EDGAR download volume for the same weekday

[14] The EDGAR download data are analyzed in Drake, Roulstone, and Thornock (2014), and we thank the authors for sharing the data with us.

over the prior five weeks. We define *Low EDGAR* announcements as those with a below-quarterly-median abnormal EDGAR download volume.

Our sixth proxy for low-attention earnings announcements is low Google search volume. Prior research shows that the search frequency in Google (the Search Volume Index, abbreviated SVI) is a good proxy for investor attention (e.g., Da et al., 2011; DeHaan et al., 2015; Drake, Roulstone, and Thornock, 2012). To construct our Google SVI variable, we proceed as follows. From Google Trends, we obtain the daily and weekly SVI values for each stock in our sample. We use tickers instead of company names as our search terms to ensure that we capture results that relate to the search for financial information for a firm (Da et al., 2011). The SVI numbers are ranked values that denote the relative popularity of a search term in the period (day or week) of the query. Google does not provide the raw search numbers for any search term; instead it first normalizes the raw search values by the overall internet search volume (popularity of that term vis-à-vis all other search terms) and then scales the normalized numbers by the highest value of the search term in the period. The normalization and scaling of the SVI numbers complicate comparison of these numbers across periods, as illustrated by Madsen and Niessner (2014). To make daily SVIs comparable across months, we follow Madsen and Niessner's adjustment procedure and scale the daily SVIs (SVI_d) with the weekly SVIs (SVI_w) as follows:

$$SVI = SVI_d * SVI_w / 100 . \qquad (8)$$

We use the natural log of (1+SVI) as our Google search volume variable. We define *Low Google Search* announcements as those with a below-quarterly-median Google search volume. Following the literature, we exclude tickers that are common words (e.g., COST and GAS), as their search volume is inflated by searches unrelated to the stock of interest; this filter removes 12 sample firms. For an additional 33 of our sample tickers Google Trends returns no results because of sparse search volume. This is a common issue in research using the SVI measure. For example, only 56% of the firm-week observations in Da et al.'s (2011) Russell 3000 stock sample have a non-null SVI. In total, we are able to calculate the SVI measure for 58 of our 103 sample stocks (about 56% of our sample stocks). Thus our sample size is severely reduced when we use the Low Google Search proxy for limited attention.

Panel C of Table 1 presents descriptive statistics related to our six attention proxies. Of the 745 earnings announcements in our sample, 60 (8%) occur on Fridays, similar to the 7.6% DeHaan et al. (2015) find in their sample of earnings announcements from 2000 to 2011. On average there are about 233 other earnings announcements on the day that one of our sample earnings announcements occurs, and the standard deviation of 152 announcements is large. The average time between an earnings announcement and the average analyst forecast update is 2.6 trading days, with a median of 2 days and a standard deviation of 1.5 days. The resulting analyst speed measure has a mean of -0.88 with a standard deviation of 0.39.[15] For comparison, DeHaan et al. (2015) report mean analyst speed of -0.96 and standard deviation of 0.54 for their sample. The average firm has 1.95 non-earnings news stories on earnings announcement days, with a standard deviation of 3.68. On average 137 financial filings are downloaded from the SEC's EDGAR database per earnings announcement day, with a standard deviation of 175. The Google search volume index also displays wide variations over our sample of earnings announcements.

We do not expect the six attention proxies to be independent of each other, as they are all related to the same underlying phenomenon of investor attention. Thus a natural question is whether the six attention proxies all identify the same earnings announcements as low-attention events. Table 2 displays the pairwise correlations between announcements identified as low-attention by the six attention proxies.

[Table 2 here]

While several of the pairwise correlations are significant, most are below 10%, suggesting that the six proxies for low attention capture different aspects of attention. For example, low-attention announcements under the Busy Day measure are uncorrelated with those identified under the Slow Analyst Speed measure (correlation of -0.003, *p*-value of 0.932), showing that slow analyst updates are not merely due to a heavy load of announcements all being released on the same day. The negative correlation between proxies such as Friday and Busy Day are not surprising, given the small number of Friday announcements in recent years (e.g., DeHaan et al., 2015). The insignificant correlations between Low Google Search and the other attention proxies are likely due to the large number of announcements for which the Google SVI variable cannot be calculated.

To capture these different aspects of attention jointly, we construct an Aggregate low-attention proxy using five of our six attention metrics. We exclude Low Google Search from the Aggregate measure because the large number of missing observations for Low Google Search

[15] Because the analyst speed measure is a nonlinear (in this case, logarithmic) transformation of the number of days, it is not possible to convert directly between the mean number of days and mean analyst speed, so we report both in the table.

would severely limit the sample size. To construct our Aggregate low-attention metric we proceed as follows. First, we calculate how many of the remaining five proxies identify each earnings announcement as low-attention (so each announcement has an Aggregate score that can range from zero to five, with a score of five meaning that the announcement is labeled low-attention according to all five proxies). Second, within each quarter, we designate all of the announcements that have an Aggregate score above the quarterly median as low-attention announcements. For example, General Electric's earnings announcement on April 11, 2008, is categorized as low-attention by the Slow Analyst Speed, Friday, and High News Distraction proxies, giving it an Aggregate score of three. Since this is above the median Aggregate score of two in the second quarter of 2008, the April 11, 2008 General Electric announcement is marked as low-attention under the Aggregate measure.

4. High-frequency trading and price efficiency

We are interested in whether high-frequency trading is associated with more efficient price reactions around low-attention earnings announcements. In the first two subsections we examine the immediate price response and the long-term price drift around low-attention earnings announcements with versus without high-frequency trading, using our main sample of trading data from 2008-2009 that identifies high-frequency trading. In the third subsection, we address the issue of causality by (i) investigating the links between stock size, attention effects, and high-frequency trading in our main 2008-2009 sample, and (ii) examining an exogenous shock to computerized trading in 2003.

4.1 Immediate price response

Distraction or low attention has been shown to reduce investor reaction (short-term cumulative abnormal returns) to earnings surprises. If HFTs step in and trade during low-attention periods, this inefficient response of stock prices to earnings announcements may be attenuated. We ask whether low-attention earnings announcements with HFTs experience more efficient reactions to earnings surprises than similar earnings announcements without HFTs.

We begin with the Aggregate measure of low attention and then test each attention measure separately with the exception of the Friday low-attention proxy. We are unable to test the Friday low-attention proxy separately because HFTs trade on all but one of the Friday earnings announcements, providing too little variation to examine.[16] We run regressions of the following form:

$$\begin{aligned} CAR_{i,t,t+1} = {} & \alpha + \beta_1 LowAttn_{i,t} + \beta_2 HighUE_{i,t} + \beta_3 HFT_{i,t} \\ & + \beta_4 LowAttn_{i,t} \cdot HighUE_{i,t} + \beta_5 LowAttn_{i,t} \cdot HFT_{i,t} + \beta_6 HighUE_{i,t} \cdot HFT_{i,t} \\ & + \beta_7 LowAttn_{i,t} \cdot HighUE_{i,t} \cdot HFT_{i,t} \\ & + \sum_{j=1}^{J} \gamma_j \, Control_{j,i,t} + \sum_{j=1}^{J} \delta_j \, Control_{j,i,t} \cdot HighUE_{i,t} + \varepsilon_{i,t} \ , \end{aligned} \tag{9}$$

where $CAR_{i,t,t+1}$ is the two-day cumulative abnormal return for stock i from earnings announcement day t to day $t+1$; $LowAttn_{i,t}$ is equal to one if the earnings announcement falls into the low-attention category given the proxy being used, else zero; $HighUE_{i,t}$ is equal to one if the announcement has above-median unexpected earnings, else zero.[17] Unexpected earnings is computed as (Earnings – Analyst consensus forecast) / Price, as in DeHaan et al. (2015), DellaVigna and Pollet (2009), and Hirshleifer et al. (2009).[18] $HFT_{i,t}$ is equal to one if there is HFT trading following the earnings announcement on day t, else zero; we use an indicator variable rather than the percentage of high-frequency trading because HFTs endogenously choose how much to trade on a given announcement (Biais, Foucault, and Moinas, 2015).[19] $Control_{j,i,t}$ includes market capitalization and earnings surprise volatility over the prior four years (both as in DellaVigna and Pollet, 2009). We include month and year indicators to control for differences in return sensitivity across quarters and within a quarter. All controls are interacted with $HighUE_{i,t}$, and standard errors are clustered by announcement day to control for correlation of returns on the same day, as in DellaVigna and Pollet (2009).

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[16] We note that this lack of variability is caused by HFTs trading (rather than HFTs not trading) during Friday earnings announcements, which is in itself consistent with our conjecture that HFTs are less likely to be distracted from trading on Fridays.
[17] The NASDAQ sample is made available for 120 stocks for two years, which limits the number of earnings announcements in our sample and precludes using the finer quantile distinctions of earlier studies, which had the benefit of larger samples. For example, DellaVigna and Pollet use decile indicators for unexpected earnings. Since our sample is too small to use deciles, we use an above/below median split. To ensure the robustness of our results, we examine another definition of earnings surprises in Section 6.
[18] Kothari (2001) points out that analyst forecasts are believed to be "a better surrogate for the market's expectations than time-series forecasts" (page 153).
[19] For example, if stock i has an earnings announcement at 10:00 am on day t, the variable $HFT_{i,t}$ is equal to one if stock i has any trades involving HFT between 10:00 am and midnight on day t, else zero. Using a fixed two-hour period after the announcement, rather than the rest of the day, or a cut-off for HFTs representing at least 5% of volume yields identical inference; see robustness checks in Section 6.

The main estimate of interest is the coefficient on the three-way interacted term $LowAttn_{i,t}*HighUE_{i,t}*HFT_{i,t}$. This coefficient captures the marginal response of the cumulative abnormal return to high unexpected earnings in low-attention earnings announcements when HTFs are trading. If cumulative abnormal returns are more responsive to unexpected earnings on low-attention announcements with HFTs trading, we should see a positive coefficient on the three-way interacted term. Table 3 presents the regression results.

[Table 3 here]

Using the Aggregate attention proxy, in the first column, the coefficient estimate for the triple interaction term *LowAttn*HighUE*HFT* is positive (0.160) and significant (*p*-value of 0.001), indicating that earnings announcements identified as low-attention by the aggregate metric have greater short-term stock price response to earnings surprises when they have high-frequency trading. The negative marginal effect of low attention without HFT (the coefficient of -0.149 on *LowAttn*HighUE*) is consistent with the findings in the previous literature that earnings surprises during low-attention times garner lower short-term stock price responses, as distracted investors under-react to earnings surprises. Figure 1 graphs the marginal effects with and without HFTs for all of the attention proxies in Table 3.

[Figure 1 here]

Figure 1 shows that the effect of low-attention on earnings announcements is generally attenuated when HFTs are trading, leading to less under-reaction than occurs on low-attention announcements without HFTs. The effect is statistically significant for the Aggregate, Busy Day, Slow Analyst Speed, and Low EDGAR attention proxies, with the reductions ranging from 64% for the Busy Day proxy (dividing the marginal HFT effect, *LowAttn*HighUE*HFT*, by the classic attention effect without HFTs, *LowAttn*HighUE*, or 0.057/-0.089 = -64%) to over 100% for the Aggregate proxy. Results for the High News Distraction and Low Google Search proxies are insignificant. Statistical power of the tests to detect significance is likely the main problem for the Low Google Search proxy, as the Google search volume index is available for only 56% of our sample stocks.

4.2 Long-term price drift

The results documented in the previous section suggest that the inefficiency in short-term price responses to unexpected earnings in low-attention announcements is tempered when HFTs participate in trading. We would expect that the greater efficiency of short-term price responses leaves less scope for a longer-term price drift for low-attention earnings announcements with greater HFT participation. To test this, we estimate regressions of the form:

$$
\begin{aligned}
CAR_{i,t+2,t+45} = {} & \alpha + \beta_1 LowAttn_{i,t} + \beta_2 HighUE_{i,t} + \beta_3 HFT_{i,t} \\
& + \beta_4 LowAttn_{i,t} \cdot HighUE_{i,t} + \beta_5 LowAttn_{i,t} \cdot HFT_{i,t} + \beta_6 HighUE_{i,t} \cdot HFT_{i,t} \\
& + \beta_7 LowAttn_{i,t} \cdot HighUE_{i,t} \cdot HFT_{i,t} \\
& + \sum_{j=1}^{J} \gamma_j \, Control_{j,i,t} + \sum_{j=1}^{J} \delta_j \, Control_{j,i,t} \cdot HighUE_{i,t} + \varepsilon_{i,t} \; , \qquad (10)
\end{aligned}
$$

where $CAR_{i,t+2,\,t+45}$ is the cumulative abnormal return for stock *i* from day two to day 45 after the earnings announcement (PEAD), and all other variables are as defined in equation (9). As before, the main coefficient of interest is the coefficient β_7 on the three-way interacted term $LowAttn_{i,t}$*$HighUE_{i,t}$*$HFT_{i,t}$. In this specification, β_7 captures the marginal response of PEAD to high unexpected earnings in low-attention earnings announcements when HFTs are trading. If PEAD is less responsive to unexpected earnings on low-attention announcements with HFTs trading, we should see a negative coefficient on the three-way interacted term. Table 4 presents the regression results.

[Table 4 here]

For earnings announcements categorized as low attention under the Aggregate measure, the coefficient estimate on our main variable of interest, the triple interaction term of *LowAttn*HighUE*HFT*, is negative and significant (coefficient of -0.186 with a *p*-value of .001). This indicates that earnings announcements identified as low-attention by the aggregate metric have lower PEAD following earnings surprises when they have high-frequency trading. The Aggregate PEAD results are driven strongly by Busy Day and Slow Analyst Speed earnings announcements (as in the short-term price efficiency analyses of Table 3) as well as High News Distraction and Low EDGAR announcements. As in the short-term price reaction results (Table 3), the results for the Low Google Search proxy are not significant. Figure 2 graphs the marginal effects with and without high-frequency trading from Table 4.

[Figure 2 here]

Figure 2 shows that the effect of low attention on PEAD is generally attenuated following earnings announcements with high earnings surprises with HFTs trading. Among the five attention proxies with statistically significant effects, the reductions range from 86% for the Low EDGAR proxy to more than 100% for Slow Analyst Speed. Overall, these PEAD results combined with the short-term price reaction results in Table 3 suggest that both the immediate price under-reaction to earnings surprises and PEAD are reduced when HFTs are involved in trading on low-attention earnings announcements.

4.3 Causality

So far we have shown that when HFTs trade on low-attention earnings announcements, the previously documented low-attention-related price inefficiencies are smaller. But that analysis does not establish causality, since HFTs endogenously decide whether to trade on any given earnings announcement. Thus while it may be the case that HFTs reduce inefficiencies through their trading, it is also possible that HFTs simply choose to trade on earnings announcements that have more efficient price reactions, perhaps due to a richer information environment or some other attribute not fully captured by the attention proxies. In the next two subsections we shed light on the question of causality by examining subsamples of large versus small stocks and examining an exogenous change in the NYSE trading system.

4.3.1 Firm size, attention effects, and HFT participation

HFTs are known to have a preference for large stocks (e.g., Brogaard et al., 2014). Thus although we control for firm size in all of our regressions, a natural concern is whether our results are driven by the cross-sectional prevalence of HFTs trading in large stocks, which are already known to have greater price efficiency (Hirshleifer et al., 2009). To address this concern, we divide our sample into small versus large firms (defined as below- and above-median market capitalization) and test each subsample separately using the Aggregate attention proxy. Table 5 presents the results.[20]

[Table 5 here]

Panel A presents the short-term price efficiency results (days *t* to *t+1* relative to the earnings announcement). The coefficient on *LowAttn*HighUE*, the classic attention effect, is significant for small firms (in the first column) but not for large firms (in the second column), consistent with Hirshleifer et al.'s (2009) finding that attention effects are stronger for smaller firms. Notably, the marginal effect of HFTs, captured by the triple-interaction term

[20] The number of observations differs in the small firm and large firm subsamples because of data availability for the regression control variables and individual proxies used to calculate the aggregate proxy.

*LowAttn*HighUE*HFT*, is significant for small firms, suggesting that our results are not driven by large firms alone.

In Panel B we repeat the small firm/large firm subsample analyses for post-earnings-announcement drift (days *t+2* to *t+45* after the earnings announcement). We find that PEAD is higher for stocks with low attention on earnings surprises only among the small firms (significant positive coefficient on *LowAttn*HighUE* for small firms in first column, not for large firms in second column) and that the marginal impact of HFTs reverses the PEAD among small firms. Thus the subsample analyses in both panels indicate that the HFT effect we document in the main study is not merely driven by HFTs trading in large stocks.

4.3.2 Exogenous shock to HFT In 2003 the NYSE automated quote dissemination by introducing Autoquote, creating an exogenous shock that dramatically increased the amount of algorithmic trading, commonly defined as the use of computer algorithms to automatically make trading and order entry and management decisions. High-frequency trading is a type of algorithmic trading, further characterized mainly by short holding periods and low overnight inventories. Hendershott, Jones, and Menkveld (2011) use the exogenous shock of Autoquote to show that algorithmic trading improves stock liquidity. We similarly use this event to establish whether algorithmic trading, which includes high-frequency trading, reduces the effects of limited attention or merely occurs more frequently for earnings announcements with more efficient price reactions. The advantage to this analysis is that it provides a plausibly exogenous shock to high-frequency trading; the disadvantage is that there are no HFT versus non-HFT identifiers in the 2003 data.

The NYSE phased in Autoquote gradually during the first half of 2003, beginning with six stocks on January 29, 2003, rolling out to over 200 stocks during the next two months, and finishing with all remaining stocks on May 27, 2003.[21] We conduct an event study to compare limited attention effects before and after Autoquote is introduced. For the post-event period, we examine each NYSE-listed stock's first earnings announcement after the first trading day with Autoquote.[22] For the pre-event period, we examine each stock's last earnings announcement prior to 45 days before Autoquote is introduced. The 45-day requirement is imposed to ensure that our

[21] We obtain the list of Autoquote activation dates from Terry Hendershott's website: http://faculty.haas.berkeley.edu/hender/.

[22] If the closest earnings announcement does not have all the information required for estimation, we consider the closest subsequent observation for which all information is available. If no suitable earnings announcement is available within 180 days, we drop the observation. This requirement is imposed to capture Autoquote's timely effect while also maximizing sample size.

PEAD tests do not overlap in the pre- and post-event periods.[23] We keep only firms that have both a valid pre-event and a valid post-event earnings announcement. We construct the Aggregate attention measure based on the three attention proxies for which information is available in the 2002-2004 period: Friday, Busy Day, and Slow Analyst Speed. Table 6 presents regression results for the Autoquote event study.

[Table 6 here]

In the first column, the coefficient estimate on the main variable of interest, the triple interaction term of *LowAttn*HighUE*Autoquote*, is positive and significant (coefficient of 0.027 with a *p*-value of .017). This indicates that low-attention earnings announcements with high earnings surprises have a larger short-term price response after the Autoquote introduction. The second column shows that PEAD is also lower for low-attention earnings announcements with high earnings surprises; the coefficient estimate on the triple interaction term of *LowAttn*HighUE*Autoquote* is negative and significant (coefficient of -0.044 with a *p*-value of .012). Taken together, these results suggest a causal relationship between algorithmic trading and the reduction of limited-attention effects.

5. How is high-frequency trading related to improved price efficiency?

So far our results suggest that HFT participation reduces the pricing inefficiencies around low-attention earnings announcements. A question that naturally follows is *how* the trading of HFTs reduces the price inefficiencies. One possibility is that HFTs account for a larger portion of trading when non-HFTs are distracted, in effect "filling in" for the distracted non-HFTs whose absence would otherwise lead to inefficient price reactions. Another possibility is that HFTs process the earnings news (by parsing textual news releases, for example) and aggressively trade on the information by demanding more liquidity than usual, and possibly supplying less (which may or may not lead to an increase in their overall trading percentage). Finally, it may be that HFT presence aids price efficiency primarily through a liquidity supply channel, as HFTs continue to supply liquidity at a time when non-HFTs may not, enabling liquidity-demanding non-HFTs to trade on the earnings news. To distinguish between these possibilities, in this section we first analyze the percentage of trading done by HFTs and then investigate whether the price efficiency

[23] If the closest earnings announcement does not have all the information required for estimation, we look back in time for up to three quarters.

gains documented earlier arise from abnormal HFT liquidity demand or supply. For these tests we return to our main 2008-2009 sample, in which we can identify HFT liquidity demand and supply activity at the trade-by-trade level.

5.1 HFT share of trading volume

It is not obvious a priori whether we should expect HFTs to account for the same fraction of trading on low-attention earnings announcements as on other announcement days. The general intuition of investor inattention is that when human decision-makers (non-HFTs) are inattentive, they trade less. If HFTs largely trade with each other, the withdrawal of non-HFTs could leave them accounting for a larger portion of trading volume on days when non-HFTs are distracted. On the other hand, the decline in non-high-frequency trading may lead to a commensurate decline in high-frequency trading if HFT strategies are mainly tied to non-high-frequency trading – for example, for HFTs that are primarily supplying liquidity to non-HFTs (as in a market-making strategy) or seeking to profit by picking off the limit orders of slower non-HFTs. In such cases we would expect no change in HFTs' percentage of trading. Table 6 compares mean and median trading percentages for HFTs on low-attention versus high-attention earnings announcements, measuring HFT total trading volume (HFT^{All}), demand (HFT^{D}), supply (HFT^{S}), and trades in which HFTs demand liquidity while non-HFTs supply liquidity (HN) and those in which non-HFTs demand and HFTs supply liquidity (NH). All measures are calculated based on trading from the time the earnings announcement is released until midnight the same day.

[Table 7 here]

The results in Table 7 are generally consistent across means and medians and across the five HFT measures within each panel, but the picture varies across the different attention proxies (different panels). When low-attention earnings announcements are defined by the Aggregate proxy (Panel A), Slow Analyst Speed (Panel C), Friday (Panel D), or High News Distraction (Panel E), HFTs appear to account for a significantly higher fraction of trading on low-attention earnings announcement days. Meanwhile, Table 7 reveals no differences in HFT trading percentages for low-attention earnings announcements defined by Low EDGAR (Panel F) and Low Google Search (Panel G).

On Busy Days (Panel B), HFTs account for a significantly lower portion of trading volume, perhaps because HFTs' strong inventory management concerns (Menkveld, 2013; SEC 2014) lead them to trade less in each stock when many stocks offer trading opportunities on the same day. We note that even though HFTs do a smaller proportion of trading on Busy Day than on non-Busy Day earnings announcements, their trading nonetheless leads to a more efficient response to earnings surprises (Tables 3 and 4). The fact that HFTs are associated with improved price efficiency on both Busy Day (when they trade proportionately less) and Slow Analyst Speed announcements (when they trade proportionately more) suggests the need for a deeper examination of how they trade, which we explore in the following section.

5.2 HFT demand versus supply

To better understand how HFTs may contribute to improved price efficiency following low-attention earnings announcements, we analyze HFT liquidity demand versus supply behavior. We focus on abnormal liquidity demand minus supply (rather than simple demand minus supply) because HFTs generally demand more liquidity than they supply (Table 1) and we are interested in how their behavior differs on low-attention earnings announcements. In particular, we define a variable to capture HFT abnormal demand minus supply as follows:[24]

$HFT_{i,t}^{D\text{-}S}$ = 1 if HFT shares demanded minus supplied for stock *i* on earnings announcement day *t* is greater than the mean for stock *i* on non-earnings-announcement days (30 trading days, ending two days before the announcement date); else 0.

We conduct price efficiency tests similar to those in equations (9) and (10), substituting the abnormal HFT demand-supply variable for the simple HFT variable used in the main analyses. We use the Aggregate low attention proxy in these tests. The coefficient estimate of interest in these regressions is the triple-interaction term $LowAttn*HighUE*HFT^{D\text{-}S}$, which captures the incremental effect of high-frequency trading when HFT liquidity demand minus supply is high (compared to occasions when HFT liquidity demand minus supply is low). If the signs on the triple-interaction term are the same as in our main results (Tables 3 and 4), it would suggest that high HFT liquidity demand (relative to supply) drives the main results; opposite signs would suggest that high HFT liquidity supply is more responsible.

[Table 8 here]

The results in Table 8 suggest that the price efficiency effects of HFT arise more from HFT liquidity demand rather than supply. The significantly positive coefficient estimate on the triple-interaction term $LowAttn*HighUE*HFT^{D\text{-}S}$ in the first column (coefficient estimate of 0.058)

[24] Constructing the demand minus supply variable using only the HFT/non-HFT interaction trades HN and NH, described in Section 3, yields identical inference.

shows that when HFTs demand more liquidity relative to what they supply on low-attention earnings surprises, their activity more than offsets the general under-reaction to low-attention earnings surprises (coefficient estimate on *LowAttn*HighUE* of -0.034). A similar picture emerges for PEAD in the second column: The generally positive drift for low attention earnings surprises (coefficient estimate on *LowAttn*HighUE* of 0.087) is offset when HFTs demand more liquidity than they supply (coefficient estimate on $LowAttn*HighUE*HFT^{D\text{-}S}$ of -0.119). Thus it appears that the improved price efficiency around low-attention earnings announcements is more closely related to HFT liquidity demand, consistent with HFTs processing and trading on textual news (as in von Beschwitz, Keim, and Massa, 2015), unencumbered by attention constraints.

6. Robustness checks

Previous studies of the effects of limited investor attention on price efficiency have examined cumulative abnormal returns over various time periods, so we also test the robustness of our results over different time windows. Table 9 replicates the analysis of short-term price reactions to earnings surprises (in Table 3) over one-day (Panel A) and three-day (Panel B) periods.

[Table 9 here]

The results for the Aggregate attention proxy, in the first column, confirm our main results using both one-day (Panel A) and three-day (Panel B) cumulative abnormal returns. The coefficient estimates for the triple interaction term *LowAttn*HighUE*HFT* are positive (0.084 and 0.153) and significant (*p*-values of <0.001 and 0.004, respectively), indicating that earnings announcements identified as low-attention by the Aggregate metric have greater short-term stock price response to earnings surprises when they have high-frequency trading. At the one-day horizon, the coefficient estimates on the three-way interaction term are significant for the Busy Day, Slow Analyst Speed, and High News Distraction attention proxies (Panel A), while the Low EDGAR proxy becomes significant and High News Distraction loses significance at the three-day horizon (Panel B). The Low Google Search proxy continues to show no significant results, as in Table 3. Overall, Table 9 shows that our results for short-term price efficiency are robust to different short-term horizons.

Table 10 replicates the analysis of PEAD (in Table 4) over a 30-day horizon.

[Table 10 here]

The 30-day PEAD results for the Aggregate attention proxy, in the first column, are consistent with our main results. The coefficient estimate for the triple interaction term *LowAttn*HighUE*HFT* is negative (-0.089) and significant (*p*-value of 0.058), indicating that earnings announcements identified as low-attention by the aggregate metric have lower 30-day PEAD when they have high-frequency trading. The individual low-attention proxies based on Busy Days, Slow Analyst Speed, High News Distraction, and Low EDGAR all show significant effects of HFT activity on low-attention announcements with earnings surprises, echoing the findings of Table 4 over the 45-day horizon.

Next, we examine the robustness of our results to alternative measurements of the two key variables in our regressions: high-frequency trading and earnings surprise. In Panel A of Table 11, we define the HFT indicator variable as having the value one if HFTs represent at least five percent of trading volume following the earnings announcement (instead of any positive volume in our main analyses), else zero. In Panel B, we define the HFT indicator variable as having the value one if HFTs trade in the two hours following the earnings announcement (instead of the entire remaining trading day in our main analysis), else zero. Low attention is measured using the Aggregate proxy. The results in both panels are consistent with our main results.

[Table 11 here]

In our main analyses, we follow the limited attention literature (e.g., DellaVigna and Pollet, 2009) in defining earnings surprises based on the difference between reported earnings and analyst forecasts (UE). But recent work such as Lee, Strong, and Zhu (2014) finds that stock prices also respond to the standardized unexpected earnings (SUE) component of earnings announcements. Therefore we replicate our main analyses using SUE as the proxy for earnings surprises; results are presented in Table 12. As in our main analyses, Table 12 shows that the typical short-term under-reaction to high earnings surprises and longer term price drift following low-attention earnings announcements are reduced when HFTs trade.

[Table 12 here]

We also examine whether our results hold for negative earnings surprises. In our main tests, we define *HighUE* as above-median earnings surprises. Since about 71% of the earnings surprises in our sample are positive, 1% are zero, and 28% are negative, *HighUE* captures large positive surprises. To examine whether HFTs also improve price efficiency following negative earnings surprises, we run tests analogous to our main tests, replacing *HighUE* with a variable called *NegUE* that takes the value one for negative unexpected earnings and zero for positive unexpected earnings; observations with unexpected earnings equal to zero are excluded. Consistent with the classic limited attention story, in untabulated results we find that the coefficient on *LowAttn*NegUE* is significantly positive in the two-day CAR regression and significantly negative in the 45-day CAR regression, indicating that following low-attention earnings announcements, prices underreact to (i.e., are less negative) negative earnings surprises in the short run and have greater (more negative) PEAD in the long run. The coefficient on the triple-interaction term *LowAttn*NegUE*HFT* is significantly negative in the short-term CAR regression and significantly positive in the PEAD regression, showing that the low-attention effects are partially offset when HFTs trade. Thus we conclude that HFT participation reduces the classic attention effects for negative as well as positive earnings surprises.

Finally, we conduct a robustness check using post-close earnings announcements, which attract lower investor attention (DeHaan et al., 2015) but also have more efficient price reactions and a high degree of informational efficiency (Jiang, Likitapiwat, and McInish, 2012). Jiang et al. (2012) point out that although volume is lower and fewer investors may be paying attention to post-close earnings announcements, those trades that occur are more informed on average. About 39% of the earnings announcements in our sample are released after the market closes (i.e., between 4:00 pm and midnight). In untabulated results, we find that post-close announcements are not associated with short-term under-reaction to earnings surprises (consistent with Jiang et al., 2012), nor are they associated with higher PEAD. Likewise, we find no significant marginal effects when HFTs trade following post-close announcements. These starkly different results for post-close announcements compared to other low-attention announcements suggest that HFTs enhance price efficiency when low attention would otherwise lead to lower immediate price responses and higher PEAD, but not when investor inattention has no discernable effect on price efficiency (as in post-close announcements).

7. Conclusion

In this study we examine the changing role of attention in modern financial markets, where a large portion of trading is executed by machines using pre-programmed algorithms. The preponderance of these super-fast computers, known as high-frequency traders (HFTs), raises questions about the effects of attention constraints on price efficiency. Previous research has shown that the attention constraints of human traders lead to systematic effects on stock prices. A number of papers have shown that when firms announce earnings at times of low attention, investors generally trade less in those stocks, resulting in inefficient price responses to earnings surprises.

Given that machines are not expected to suffer from limited attention or distraction, does this new type of traders – HFTs – improve price efficiency during earnings announcements with low (human) attention? Using a large set of proxies for investor attention, we answer this question. Our study is made possible by a dataset made available by NASDAQ OMX that identifies trader types as high-frequency and non-high-frequency, a feature not available in standard public datasets.

We employ six attention proxies and an aggregate measure to examine the participation of HFTs around low-attention earnings announcements. We find that the previously documented effects of low attention on stock price efficiency following earnings surprises are lower when HFTs trade. We test both short- and long-term price efficiency and find that high-frequency trading on low-attention announcements is associated with greater stock price responsiveness to earnings surprises and reduced long-term price drift, specifically when human attention constraints cause inefficient reactions to earnings surprises. We examine small and large stocks separately, finding that our results are not driven by the tendencies of HFTs to trade in large stocks and limited attention to mainly affect small stocks. To further address the important issue of causality, we also supplement our main analysis with an event study that examines an exogenous shock to high frequency trading: the introduction of an automated quote dissemination system in 2003. The results from the event study suggest that HFT participation causes the price efficiency improvements around low-attention earnings announcements.

While HFTs are active as both liquidity demanders and liquidity suppliers on low-attention announcements, we find that price efficiency improves more when HFTs are more heavily demanding liquidity. This suggests that it is HFTs' ability to process and trade on earnings news without human distraction that most improves price efficiency. Our results highlight the changing role of attention in modern financial markets and reveal a previously undocumented positive role played by HFTs in the efficient incorporation of earnings information into stock prices.

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Appendix A: Variable sources and definitions

Variable	Data source	Definition
HFT Trading Variables		
HFT^{All}	NASDAQ OMX	(2*HH + HN + NH) / (2*Total Volume)
HFT^{D}	NASDAQ OMX	(HH + HN) / Total Volume
HFT^{S}	NASDAQ OMX	(HH + NH) / Total Volume
HN%	NASDAQ OMX	HN / Total Volume
NH%	NASDAQ OMX	NH / Total Volume
Attention Proxies		
Friday earnings announcements	IBES, Compustat, Wall Street Horizon, Factiva	Derived from IBES variable ANNDAT and Compustat, Wall Street Horizon, and Factiva cross-check
Post-close	IBES, Compustat, Wall Street Horizon, Factiva	Derived from IBES variable ANNTIM and Compustat, Wall Street Horizon, and Factiva cross-check
Busy day	Compustat	Multiple announcements on the same day
Analyst Speed	IBES	$-1 \times ln\left(\frac{1}{j}\sum_{j=1}^{J}[1 + Weekdays\ until\ forecast\ update_j]\right)$
EDGAR downloads	SEC, via authors of Drake, Roulstone, and Thornock (2014)	$ln(EDGAR_t) - ln\left(\frac{1}{5}\sum_{w=1}^{5} EDGAR_w\right)$
Google Search Volume Index (SVI)	http://www.google.com/trends/	*ln* (1+SVI), where SVI = SVI_d * SVI_w / 100, and SVI_d = daily SVI, SVI_w = weekly SVI
News distraction	Factiva	Natural log of the count of (Dow Jones NewsWire stories for firm *i* on day *t*) - Natural log of the count of (Dow Jones NewsWire stories about earnings for firm *i* on day *t*)
Other Main Variables		
Market capitalization	COMPUSTAT	Price*Shares Outstanding
Cumulative abnormal return (CAR)	CRSP/COMPUSTAT	Cumulative abnormal return around earnings announcements in excess of corresponding period Fama-French size and book-to-market 6-portfolio value weighted benchmark return
Unexpected earnings (UE)	CRSP, IBES	(Earnings - Analyst consensus forecast)/Price, with price measured three days prior to earnings announcement
Earnings surprise volatility	CRSP, IBES	Standard deviation of the quarterly unexpected earnings over the prior four years

Appendix B: Illustration of HFT calculations

NASDAQ trader-type classifications: HH = HFT demanding and HFT supplying liquidity; HN = HFT demanding and non-HFT supplying liquidity; NH = non-HFT demanding and HFT supplying liquidity; NN = non-HFT demanding and non-HFT supplying liquidity.

Consider the following set of trades in one stock on one day:

Trade #	NASDAQ Trader-Type Classification	Shares traded	HFT shares demanded + HFT shares supplied
1	HH	100	200
2	HN	200	200
3	NH	300	300
4	NN	400	0
	Totals=	1000	700
	Total shares demanded + shares supplied = 2 x trading volume =	2000	

Variable	Calculation	Value
HFT^{All}	HFT % = (shares demanded by HFT + shares supplied by HFT)/(2 x trading volume):	35%
HFT^{D}	HFT Demand % = (shares with HFT demanding liquidity)/(trading volume):	30%
HFT^{S}	HFT Supply % = (shares with HFT supplying liquidity)/(trading volume):	40%
HN%	HFT Demand with non-HFT Supply % = (HN shares traded)/(trading volume):	20%
NH%	non-HFT Demand with HFT Supply % = (NH shares traded)/(trading volume):	30%

Table 1: Sample descriptive statistics

This table presents descriptive statistics for the sample of 103 NASDAQ stocks over all trading days in 2008 and 2009. In Panel A, means are calculated by stock, and cross-sectional statistics are reported in the table. *Market capitalization* and *Book-to-market ratio* are calculated from quarter-end values; *Price* is the average daily closing price of the stock; *Trading volume* is the average daily NASDAQ trading volume; and *# Earnings announcements* is the number of earnings announcements per stock in the sample period.

Panel B presents descriptive statistics for HFT trading, with means calculated by stock and cross-sectional statistics reported in the table. HFT^{All} measures the percentage of trading volume executed by HFTs; HFT^{D} measures the percentage of trading volume in which HFTs demand liquidity; HFT^{S} measures the percentage of trading volume in which HFTs supply liquidity; *HN%* measures the percentage of trading volume in which HFTs demand and non-HFTs supply liquidity; and *NH%* measures the percentage of trading volume in which non-HFTs demand and HFTs supply liquidity.

In Panel C, the first two lines report the breakdown of all earnings announcements, beginning with the total number of earnings announcements in the sample (*Total*), and then separating out earnings announcements that are made on Fridays (*Friday*). The remaining rows in Panel C present cross-sectional statistics across all earnings announcements for the number of other earnings announcements made on the same day (*# Other earnings announcements*); the speed with which analysts revise their earnings forecasts (*Days until analyst update* and *Analyst speed*); the number of non-earnings news (*News distraction counts and its log-tranformed variable*); the number of financial form downloads from the SEC's EDGAR database (*EDGAR downloads* and the *EDGAR variable);* and *Google search SVI variable,* measured as the log of one plus the Google Search Volume Index scaled for the two-year sample period.

Panel A: Sample stocks	Mean	Median	Std Dev
Market capitalization ($ billion)	19.60	1.83	39.80
Market-to-book ratio	3.35	2.44	3.57
Price	36.47	22.32	50.72
Trading volume (shares million)	2.03	0.36	4.21
# Earnings announcements	7.98	8.00	0.14

Panel B: Trading volume percentages	Mean	Median	Std Dev
HFT^{All}	28.8	27.0	11.8
HFT^{D}	32.8	34.5	11.4
HFT^{S}	24.7	17.1	15.3
HN%	24.9	25.1	8.2
NH%	16.8	12.7	9.7

Panel C: Earnings announcements and attention indicators			
	Total	Fridays	
# Earnings announcements	745	60	
% Earnings announcements	100%	8%	
	Mean	Median	Std Dev
Multiple earnings announcements	233	202	152
Days until analyst update (untransformed)	2.6	2.0	1.5
Analyst speed variable	-0.88	-0.69	0.39
News distraction counts (untransformed)	1.95	0.00	3.68
News distraction variable	0.28	0.00	0.43
EDGAR downloads (untransformed)	137	75	175
EDGAR variable	0.68	0.69	0.61
Google search SVI variable	3.61	3.78	0.77

Table 2: Correlation table for low-attention proxies

This table presents Pearson correlation coefficients between earnings announcements designated as low-attention under the six attention proxies: *Busy Day* signals announcements with an above-median number of announcements released on the same day; *Slow Analyst Speed* signals announcements with below-median analyst speed; *Friday* signals announcements made on Fridays; *High News Distraction* signals announcements with above-median non-earnings-related news; *Low EDGAR* signals announcements that experience below-median abnormal download volume from the SEC's EDGAR database; *Low Google Search* signals announcements that experience below-median Google search volume. P-values are reported in parentheses below the correlation estimates. **, and *** denote significance at the 5% and 1% levels.

	Busy Day	Slow Analyst Speed	Friday	High News Distraction	Low EDGAR
Slow Analyst Speed	-0.003				
	(0.932)				
Friday	-0.205 ***	0.074 *			
	(<0.001)	*(0.063)*			
High News Distraction	-0.120 ***	-0.052	0.031		
	(0.001)	*(0.192)*	*(0.402)*		
Low EDGAR	0.041	-0.012	-0.150 ***	0.041	
	(0.277)	*(0.772)*	*(<0.001)*	*(0.277)*	
Low Google Search	-0.034	0.036	0.078	0.016	-0.010
	(0.473)	*(0.492)*	*(0.104)*	*(0.738)*	*(0.842)*

Table 3: HFT and Short-term price efficiency

This table presents multivariate tests of price efficiency with versus without HFT. The dependent variable is the cumulative abnormal return for stock *i* on earnings announcement days *t* and *t+1*. *Low Attention* is equal to one if the earnings announcement falls into the low-attention category given the proxy being used, else zero; *Aggregate* reflects the combined distribution of Friday, Busy Day, Slow Analyst Speed, High News Distraction, and Low EDGAR earnings announcements. *HFT* is equal to one if there is high-frequency trading in the rest of the day following the earnings announcement, else zero; *HighUE* is equal to one if the announcement has above-median unexpected earnings, else zero. Regressions also include as controls market capitalization and earnings surprise volatility over the prior four years and month and year indicators. All controls are also interacted with HighUE; the intercept, controls, and interacted controls are not reported. P-values (reported in parentheses below coefficient estimates) are based on standard errors that are clustered by announcement day. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Dependent variable = Cumulative abnormal return (CAR) on earnings announcement days *t* to *t+1*						
Low Attention proxy	**Aggregate**	Busy Day	Slow Analyst Speed	High News Distraction	Low EDGAR	Low Google Search
Low Attention	**0.078 *****	0.038	0.059 **	-0.008	0.041	0.059
	(0.002)	*(0.154)*	*(0.018)*	*(0.777)*	*(0.117)*	*(0.144)*
HighUE	**-0.049**	-0.032	0.002	-0.075 *	0.005	0.028
	(0.312)	*(0.506)*	*(0.974)*	*(0.093)*	*(0.925)*	*(0.705)*
HFT	**0.022**	0.003	0.028	-0.001	0.017	0.023
	(0.204)	*(0.902)*	*(0.118)*	*(0.952)*	*(0.438)*	*(0.547)*
Low Attention * HighUE	**-0.149 *****	-0.089 **	-0.152 ***	-0.012	-0.078 *	-0.029
	(0.002)	*(0.033)*	*(<.001)*	*(0.819)*	*(0.053)*	*(0.648)*
Low Attention * HFT	**-0.083 *****	-0.010	-0.073 ***	-0.008	-0.029	-0.076 *
	(0.003)	*(0.695)*	*(0.007)*	*(0.770)*	*(0.280)*	*(0.073)*
HFT * HighUE	**-0.039**	-0.022	-0.053 *	-0.004	-0.041	0.003
	(0.159)	*(0.501)*	*(0.052)*	*(0.886)*	*(0.264)*	*(0.962)*
Low Attention * HighUE * HFT	**0.160 *****	0.057 *	0.155 ***	0.044	0.079 **	0.042
	(0.001)	*(0.085)*	*(<.001)*	*(0.204)*	*(0.032)*	*(0.260)*
Controls (Interacted)	**yes**	yes	yes	yes	yes	yes
# Observations	**566**	679	597	679	642	398

Table 4: HFT and Long-term price efficiency

This table presents multivariate tests of price efficiency with versus without HFT. The dependent variable is the cumulative abnormal return for stock *i* from 2 days after earnings announcement day *t* to 45 days after. Low Attention is equal to one if the earnings announcement falls into the low-attention category given the proxy being used, else zero; *Aggregate* reflects the combined distribution of Friday, Busy Day, Slow Analyst Speed, High News Distraction, and Low EDGAR earnings announcements. *HFT* is equal to one if there is high-frequency trading in the rest of the day following the earnings announcement, else zero; *HighUE* is equal to one if the announcement has above-median unexpected earnings, else zero. Regressions also include as controls market capitalization and earnings surprise volatility over the prior four years and month and year indicators. All controls are also interacted with HighUE; the intercept, controls, and interacted controls are not reported. P-values (reported below coefficient estimates) are based on standard errors that are clustered by announcement day. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Dependent variable = Cumulative abnormal return (CAR) on post-earnings-announcement days *t+2* to *t+45*						
Low Attention proxy	**Aggregate**	Busy Day	Slow Analyst Speed	High News Distraction	Low EDGAR	Low Google Search
Low Attention	**-0.078 ***	-0.076 **	-0.051	-0.011	-0.022	0.057
	(0.057)	*(0.046)*	*(0.208)*	*(0.780)*	*(0.585)*	*(0.335)*
HighUE	**0.065**	0.012	0.088	0.079	-0.036	0.12
	(0.544)	*(0.915)*	*(0.343)*	*(0.424)*	*(0.720)*	*(0.268)*
HFT	**-0.023**	-0.054 *	-0.024	-0.011	-0.022	0.066
	(0.388)	*(0.067)*	*(0.419)*	*(0.652)*	*(0.556)*	*(0.165)*
Low Attention * HighUE	**0.198 *****	0.161 ***	0.142 *	0.103 *	0.147 **	0.004
	(<.001)	*(0.006)*	*(0.052)*	*(0.084)*	*(0.023)*	*(0.965)*
Low Attention * HFT	**0.073 ***	0.083 **	0.078 *	0.007	0.017	-0.102 *
	(0.088)	*(0.035)*	*(0.064)*	*(0.873)*	*(0.700)*	*(0.094)*
HFT * HighUE	**0.032**	0.099 **	0.043	0.022	0.091	-0.051
	(0.499)	*(0.041)*	*(0.355)*	*(0.583)*	*(0.119)*	*(0.521)*
Low Attention * HighUE * HFT	**-0.186 *****	-0.180 ***	-0.172 ***	-0.090 *	-0.127 **	0.034
	(0.001)	*(0.002)*	*(0.009)*	*(0.067)*	*(0.033)*	*(0.362)*
Controls (Interacted)	**yes**	yes	yes	yes	yes	yes
# Observations	**566**	679	597	679	642	398

Table 5: HFT and price efficiency for small versus large firms

This table presents multivariate tests of price efficiency with versus without HFT. The dependent variable is the cumulative abnormal return (CAR) for stock *i* on earnings announcement days *t* and *t+1* in Panel A and day *t+2* to *t+45* in Panel B. *Small Firms* (*Large Firms*) are defined as firms with below-median (above-median) market capitalization. *Low Attention* is equal to one if the earnings announcement falls into the low-attention category under the Aggregate measure, which reflects the combined distribution of Friday, Busy Day, Slow Analyst Speed, High News Distraction, and Low EDGAR earnings announcements. *HFT* is equal to one if there is high-frequency trading in the rest of the day following the earnings announcement, else zero; *HighUE* is equal to one if the announcement has above-median unexpected earnings, else zero. Regressions also include as controls market capitalization and earnings surprise volatility over the prior four years and month and year indicators. All controls are also interacted with HighUE; the intercept, controls, and interacted controls are not reported. P-values (reported in parentheses below coefficient estimates) are based on standard errors that are clustered by announcement day. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A: Cumulative abnormal return (CAR) on earnings announcement days *t* to *t+1*

	Small Firms	Large Firms
Low Attention	0.040	0.013
	(0.268)	*(0.825)*
HighUE	-0.123 *	-0.031
	(0.077)	*(0.774)*
HFT	-0.003	-0.052
	(0.869)	*(0.175)*
Low Attention * HighUE	-0.173 ***	-0.040
	(<.001)	*(0.682)*
Low Attention * HFT	-0.033	-0.005
	(0.413)	*(0.931)*
HFT * HighUE	-0.010	0.032
	(0.723)	*(0.695)*
Low Attention * HighUE * HFT	0.171 ***	0.027
	(0.001)	*(0.397)*
Controls (Interacted)	yes	yes
# Observations	256	310

Panel B: Cumulative abnormal return (CAR) on earnings announcement days *t+2* to *t+45*

	Small Firms	Large Firms
Low Attention	-0.140	-0.054
	(0.152)	*(0.434)*
HighUE	0.067	-0.074
	(0.626)	*(0.535)*
HFT	-0.003	-0.051
	(0.933)	*(0.248)*
Low Attention * HighUE	0.323 **	0.128
	(0.011)	*(0.240)*
Low Attention * HFT	0.178 *	0.060
	(0.085)	*(0.394)*
HFT * HighUE	0.033	0.044
	(0.593)	*(0.617)*
Low Attention * HighUE * HFT	-0.369 ***	-0.121
	(0.002)	*(0.142)*
Controls (Interacted)	yes	yes
# Observations	256	310

Table 6: Autoquote and price efficiency

This table presents multivariate tests of price efficiency for earnings announcements before and after Autoquote is introduced for each NYSE-listed stock. The dependent variable is the cumulative abnormal return (CAR) for stock *i* on earnings announcement days *t* and *t+1* in the first column and day t+2 to t+45 in the second column. *Low Attention* is equal to one if the earnings announcement falls into the low-attention category under the Aggregate measure, which reflects the combined distribution of Friday, Busy Day, and Slow Analyst Speed announcements. *Autoquote* is equal to one if the earnings announcment is after the Autoquote effective day for the stock, else zero; *HighUE* is equal to one if the announcement has above-median unexpected earnings, else zero. Regressions also include as controls market capitalization and earnings surprise volatility over the prior four years and month and year indicators. All controls are also interacted with *HighUE;* the intercept, controls, and interacted controls are not reported. P-values (reported in parentheses below coefficient estimates) are based on standard errors that are clustered by announcement day. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Dependent variable	CAR on earnings announcement days *t* to *t+1*	CAR on earnings announcement days *t+2* to *t+45*
Low Attention	0.003	-0.009
	(0.586)	*(0.390)*
HighUE	0.007	-0.059
	(0.946)	*(0.555)*
Autoquote	0.017	-0.037
	(0.698)	*(0.330)*
Low Attention * HighUE	-0.021 **	0.018
	(0.016)	*(0.242)*
Low Attention * Autoquote	-0.013	0.026 *
	(0.119)	*(0.066)*
Autoquote * HighUE	-0.022	0.048
	(0.659)	*(0.297)*
Low Attention * HighUE * Autoquote	0.027 **	-0.044 **
	(0.017)	*(0.012)*
Controls (Interacted)	yes	yes
# Observations	1922	1922

Table 7: HFT trading on low-attention versus high-attention earnings announcements

This table presents univariate tests of the percentage of trading by HFTs on low-attention earnings announcements versus high-attention earnings announcements. HFT^{All} measures the percentage of trading volume executed by HFTs; HFT^{D} measures the percentage of trading volume in which HFTs demand liquidity; HFT^{S} measures the percentage of trading volume in which HFTs supply liquidity; *HN%* measures the percentage of trading volume in which HFTs demand and non-HFTs supply liquidity; and *NH%* measures the percentage of trading volume in which non-HFTs demand and HFTs supply liquidity. Each panel uses a different measure to identify low-attention (first column) versus high-attention (second column) earnings announcements. Panel A compares earnings announcements flagged as high versus low attention under our Aggregate attention metric. Panel B compares earnings announcements that occur on days with above-median number of other earnings announcements (*Busy*) to those that occur on days with below-median number of other earnings announcements (*Quiet*). Panel C compares earnings announcements with below-median analyst forecast revision speed (*Slow*) to those with above-median speed (*Fast*). Panel D compares earnings announcements that occur on Fridays (*Friday*) to those that occur on other days of the week (*Non-Friday*). Panel E compares earnings announcements with above-median non-earnings-related news (*High News Distraction*) to those with below-median non-earnings news (*Low News Distraction*). Panel F compares earnings announcements with below-median EDGAR download volume (*Low EDGAR*) to those with above-median download volume (*High EDGAR*). Panel G compares earnings announcements with below-median Google search volume (*Low Google*) to those with above-median search volume (*High Google*).

Panel A: Aggregate low-attention vs high-attention earnings announcements

	Low Mean	High Mean	p-value	Low Median	High Median	p-value
HFT^{All}	23.3%	18.7%	0.0012	22.9%	17.8%	0.0013
HFT^{D}	24.1%	20.8%	0.0243	25.9%	20.8%	0.0219
HFT^{S}	22.5%	16.6%	0.0006	17.8%	13.4%	0.0012
HN%	17.7%	16.6%	0.3239	17.8%	17.0%	0.2608
NH%	16.0%	12.3%	0.0032	13.5%	10.5%	0.0034
# Announcements	163	430		163	430	

Panel B: Busy Day versus Quiet Day earnings announcements

	Busy Mean	Quiet Mean	p-value	Busy Median	Quiet Median	p-value
HFT^{All}	18.2%	20.9%	0.0076	17.2%	19.8%	0.0111
HFT^{D}	19.6%	23.6%	0.0004	18.2%	24.4%	0.0004
HFT^{S}	16.8%	18.2%	0.2416	13.5%	14.3%	0.1474
HN%	15.7%	18.4%	0.0035	15.0%	19.1%	0.0014
NH%	12.9%	12.9%	0.9973	10.3%	10.8%	0.4842
# Announcements	344	401		344	401	

Panel C: Slow versus Fast Analyst Speed earnings announcements						
	Slow	Fast		Slow	Fast	
	Mean	Mean	p-value	Median	Median	p-value
HFT^{All}	23.0%	17.6%	0.0000	22.8%	16.9%	0.0000
HFT^{D}	24.9%	19.4%	0.0000	26.8%	18.7%	0.0000
HFT^{S}	21.1%	15.8%	0.0001	16.6%	13.3%	0.0007
HN%	18.8%	15.4%	0.0006	19.5%	15.3%	0.0011
NH%	15.1%	11.9%	0.0017	12.5%	10.2%	0.0028
# Announcements	272	354		272	354	

Panel D: Friday versus non-Friday earnings announcements						
	Friday	Non-Friday		Friday	Non-Friday	
	Mean	Mean	p-value	Median	Median	p-value
HFT^{All}	26.3%	19.1%	0.0001	22.3%	18.3%	0.0002
HFT^{D}	29.2%	21.1%	0.0000	28.3%	21.0%	0.0001
HFT^{S}	23.4%	17.0%	0.0028	17.0%	13.7%	0.0043
HN%	21.7%	16.7%	0.0001	21.6%	16.6%	0.0006
NH%	16.0%	12.7%	0.0377	12.1%	10.4%	0.0240
# Announcements	60	685		60	685	

Panel E: High versus Low News Distraction earnings announcements						
	High Distraction	Low Distraction		High Distraction	Low Distraction	
	Mean	Mean	p-value	Median	Median	p-value
HFT^{All}	23.0%	16.9%	0.0000	22.1%	16.6%	0.0000
HFT^{D}	24.7%	19.3%	0.0000	24.8%	18.6%	0.0000
HFT^{S}	21.3%	14.6%	0.0000	16.7%	11.8%	0.0000
HN%	18.7%	15.9%	0.0020	18.2%	15.8%	0.0017
NH%	15.2%	11.1%	0.0000	12.5%	9.4%	0.0000
# Announcements	334	411		334	411	

Panel F: Low versus High EDGAR download earnings announcements						
	Low EDGAR	High EDGAR		Low EDGAR	High EDGAR	
	Mean	Mean	p-value	Median	Median	p-value
HFT^{All}	19.6%	19.9%	0.8286	18.2%	19.1%	0.7325
HFT^{D}	21.2%	22.5%	0.3050	21.2%	22.9%	0.3094
HFT^{S}	18.0%	17.3%	0.5288	14.3%	13.5%	0.8178
HN%	16.5%	17.9%	0.1300	16.6%	17.9%	0.1704
NH%	13.3%	12.7%	0.5403	10.9%	10.4%	0.7478
# Announcements	350	353		350	353	

Panel G: Low versus High Google Search earnings announcements						
	Low Google Mean	High Google Mean	p-value	Low Google Median	High Google Median	p-value
HFT^{All}	20.7%	20.4%	0.8335	19.8%	19.6%	0.8883
HFT^{D}	23.5%	22.9%	0.6511	24.7%	23.8%	0.5803
HFT^{S}	17.9%	18.0%	0.9361	14.5%	14.0%	0.9185
HN%	18.4%	18.1%	0.8344	18.0%	18.9%	0.5840
NH%	12.8%	13.3%	0.5895	10.9%	11.3%	0.4616
# Announcements	216	219		216	219	

Table 8: HFT demand versus supply and price efficiency

This table presents multivariate tests of price efficiency with versus without abnormal HFT demand versus supply. The dependent variable is the cumulative abnormal return (CAR) for stock *i* on earnings announcement days *t* and *t+1* in the first column and day *t+2* to *t+45* in the second column. *Low Attention* is equal to one if the earnings announcement falls into the low-attention category under the Aggregate measure, which reflects the combined distribution of Friday, Busy Day, Slow Analyst Speed, High News Distraction, and Low EDGAR earnings announcements. $HFT^{D\text{-}S}$ is equal to one if HFT shares demanded minus supplied for stock *i* on earnings announcement day *t* is greater than the median for stock i on non-earnings-announcement days, else zero; *HighUE* is equal to one if the announcement has above-median unexpected earnings, else zero. Regressions also include as controls market capitalization and earnings surprise volatility over the prior four years and month and year indicators. All controls are also interacted with HighUE; the intercept, controls, and interacted controls are not reported. P-values (reported in parentheses below coefficient estimates) are based on standard errors that are clustered by announcement day. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Dependent variable	CAR on earnings announcement days *t* to *t+1*	CAR on earnings announcement days *t+2* to *t+45*
Low Attention	0.002	-0.045 **
	(0.910)	*(0.019)*
HighUE	-0.076 *	0.068
	(0.086)	*(0.482)*
$HFT^{D\text{-}S}$	-0.001	-0.012
	(0.897)	*(0.490)*
Low Attention * HighUE	-0.034	0.087 ***
	(0.134)	*(0.001)*
Low Attention * $HFT^{D\text{-}S}$	0.006	0.068 **
	(0.739)	*(0.027)*
$HFT^{D\text{-}S}$ * HighUE	0.000	0.028
	(0.977)	*(0.268)*
Low Attention * HighUE * $HFT^{D\text{-}S}$	0.058 **	-0.119 ***
	(0.026)	*(0.003)*
Controls (Interacted)	yes	yes
# Observations	566	566

Table 9: HFT and Short-term price efficiency with 1-day and 3-day horizons

This table presents multivariate tests of price efficiency with versus without HFT. The dependent variable is the cumulative abnormal return for stock *k* on earnings announcement day *t* in Panel A and days *t-1* to *t+1* in Panel B. *Low Attention* is equal to one if the earnings announcement falls into the low-attention category given the proxy being used, else zero; *Aggregate* reflects the combined distribution of Friday, Busy Day, Slow Analyst Speed, High News Distraction, and Low EDGAR earnings announcements. *HFT* is equal to one if there is high-frequency trading in the rest of the day following the earnings announcement, else zero; *HighUE* is equal to one if the announcement has above-median unexpected earnings, else zero. Regressions also include as controls market capitalization and earnings surprise volatility over the prior four years and month and year indicators. All controls are also interacted with HighUE; the intercept, controls, and interacted controls are not reported. P-values (reported in parentheses below coefficient estimates) are based on standard errors that are clustered by announcement day. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A: One-day Cumulative Abnormal Return

Dependent variable = Cumulative abnormal return (CAR) on earnings announcement days *t*

Low Attention proxy	**Aggregate**	Busy Day	Slow Analyst Speed	High News Distraction	Low EDGAR	Low Google Search
Low Attention	**0.030** **	0.013	0.017	0.000	0.003	0.010
	(0.024)	*(0.231)*	*(0.142)*	*(0.995)*	*(0.777)*	*(0.551)*
HighUE	**0.010**	-0.013	0.016	-0.036	0.002	0.029
	(0.767)	*(0.684)*	*(0.632)*	*(0.250)*	*(0.949)*	*(0.587)*
HFT	**-0.002**	-0.023 **	-0.003	-0.018 **	-0.022 **	-0.040 ***
	(0.745)	*(0.014)*	*(0.722)*	*(0.018)*	*(0.020)*	*(0.004)*
Low Attention * HighUE	**-0.065** ***	-0.041 **	-0.041 **	-0.012	-0.025	-0.013
	(0.003)	*(0.038)*	*(0.025)*	*(0.513)*	*(0.158)*	*(0.644)*
Low Attention * HFT	**-0.038** **	0.001	-0.031 **	-0.013	0.008	-0.001
	(0.010)	*(0.917)*	*(0.012)*	*(0.330)*	*(0.482)*	*(0.939)*
HFT * HighUE	**-0.007**	0.012	0.001	0.018	0.008	0.045 *
	(0.630)	*(0.503)*	*(0.951)*	*(0.182)*	*(0.648)*	*(0.097)*
Low Attention * HighUE * HFT	**0.084** ***	0.028 *	0.044 **	0.033 *	0.024	0.001
	(<.001)	*(0.089)*	*(0.014)*	*(0.060)*	*(0.110)*	*(0.489)*
Controls (Interacted)	**yes**	yes	yes	yes	yes	yes
# Observations	**566**	679	597	679	642	398

Panel B: Three-day Cumulative Abnormal Return

	Dependent variable = Cumulative abnormal return (CAR) on earnings announcement days *t-1* to *t+1*					
Low Attention proxy	**Aggregate**	Busy Day	Slow Analyst Speed	High News Distraction	Low EDGAR	Low Google Search
Low Attention	**0.067** **	0.046	0.053 *	-0.020	0.034	0.044
	(0.026)	*(0.105)*	*(0.053)*	*(0.466)*	*(0.197)*	*(0.302)*
HighUE	**-0.076**	-0.038	-0.015	-0.091 **	-0.026	-0.042
	(0.131)	*(0.446)*	*(0.764)*	*(0.043)*	*(0.659)*	*(0.571)*
HFT	**0.030** *	0.015	0.033 *	0.005	0.025	0.022
	(0.095)	*(0.496)*	*(0.070)*	*(0.791)*	*(0.254)*	*(0.598)*
Low Attention * HighUE	**-0.127** **	-0.096 **	-0.161 ***	-0.002	-0.059	-0.008
	(0.017)	*(0.033)*	*(<.001)*	*(0.972)*	*(0.200)*	*(0.905)*
Low Attention * HFT	**-0.078** **	-0.016	-0.063 **	0.001	-0.029	-0.060
	(0.015)	*(0.564)*	*(0.033)*	*(0.959)*	*(0.288)*	*(0.190)*
HFT * HighUE	**-0.025**	-0.019	-0.045	0.008	-0.022	0.027
	(0.410)	*(0.595)*	*(0.132)*	*(0.799)*	*(0.600)*	*(0.667)*
Low Attention * HighUE * HFT	**0.153** ***	0.068 *	0.164 ***	0.036	0.064 *	0.021
	(0.004)	*(0.065)*	*(<.001)*	*(0.267)*	*(0.089)*	*(0.384)*
Controls (Interacted)	**yes**	yes	yes	yes	yes	yes
# Observations	**566**	679	597	679	642	398

Table 10: HFT and Long-term price efficiency with 30-day horizon

This table presents multivariate tests of price efficiency with versus without HFT. The dependent variable is the cumulative abnormal return for stock *i* from 2 days after earnings announcement day *t* to 30 days after. *Low Attention* is equal to one if the earnings announcement falls into the low-attention category given the proxy being used, else zero; *Aggregate* reflects the combined distribution of Friday, Busy Day, Slow Analyst Speed, High News Distraction, and Low EDGAR earnings announcements. *HFT* is equal to one if there is high-frequency trading in the rest of the day following the earnings announcement, else zero; *HighUE* is equal to one if the announcement has above-median unexpected earnings, else zero. Regressions also include as controls market capitalization and earnings surprise volatility over the prior four years and month and year indicators. All controls are also interacted with HighUE; the intercept, controls, and interacted controls are not reported. P-values (reported below coefficient estimates) are based on standard errors that are clustered by announcement day. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Dependent variable = Cumulative abnormal return (CAR) on post-earnings-announcement days *t+2* to *t+30*						
Low Attention proxy	**Aggregate**	Busy Day	Slow Analyst Speed	High News Distraction	Low EDGAR	Low Google Search
Low Attention	**-0.008**	-0.008	0.004	-0.007	-0.022	0.014
	(0.813)	*(0.801)*	*(0.901)*	*(0.830)*	*(0.538)*	*(0.699)*
HighUE	**0.093**	0.087	0.076	0.11	0.002	0.137
	(0.250)	*(0.284)*	*(0.272)*	*(0.131)*	*(0.976)*	*(0.142)*
HFT	**-0.007**	-0.024	-0.013	-0.015	-0.016	0.065 *
	(0.745)	*(0.361)*	*(0.573)*	*(0.463)*	*(0.635)*	*(0.093)*
Low Attention * HighUE	**0.110** **	0.046	0.116 **	0.081	0.121 **	0.068
	(0.041)	*(0.349)*	*(0.031)*	*(0.102)*	*(0.021)*	*(0.291)*
Low Attention * HFT	**-0.006**	0.023	0.021	0.009	0.008	-0.034
	(0.864)	*(0.500)*	*(0.520)*	*(0.795)*	*(0.846)*	*(0.385)*
HFT * HighUE	**0.000**	0.031	0.031	0.011	0.056	-0.043
	(0.997)	*(0.458)*	*(0.386)*	*(0.734)*	*(0.241)*	*(0.478)*
Low Attention * HighUE * HFT	**-0.089** *	-0.073 *	-0.145 ***	-0.080 *	-0.086 *	-0.055
	(0.058)	*(0.078)*	*(0.005)*	*(0.058)*	*(0.059)*	*(0.206)*
Controls (Interacted)	**yes**	yes	yes	yes	yes	yes
# Observations	**566**	679	597	679	642	398

Table 11: HFTs and price efficiency under alternative HFT cutoffs

This table presents multivariate tests of price efficiency with versus without HFT using two alternative cutoff points. Panel A indentifies events with HFT trading if HFT trading exceeds 5% of trading volume. Panel B indentifies events with HFT trading if HFTs trade within 2 hours from earnings announcement time. The dependent variable is the cumulative abnormal return (*CAR*) for stock *i* on earnings announcement days *t* and *t+1* in the first column and day *t+2* to *t+45* in the second column. *Low Attention* is equal to one if the earnings announcement falls into the low-attention category under the Aggregate measure, which reflects the combined distribution of Friday, Busy Day, Slow Analyst Speed, High News Distraction, and Low EDGAR earnings announcements. $HFT^{5\%}$ is equal to one if HFT trading exceeds 5% of trading volume after earnings announcment time for stock *i* on earnings announcement day *t*, else zero; HFT^{2hour} is equal to one if HFTs trade within 2 hours from earnings announcement time for stock i on earnings announcement day t, else zero; *HighUE* is equal to one if the announcement has above-median unexpected earnings, else zero. Regressions also include as controls market capitalization and earnings surprise volatility over the prior four years and month and year indicators. All controls are also interacted with HighUE; the intercept, controls, and interacted controls are not reported. P-values (reported in parentheses below coefficient estimates) are based on standard errors that are clustered by announcement day. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A: HFTs trade more than 5% of the trading volume

Dependent variable	CAR on earnings announcement days *t* to *t+1*	CAR on earnings announcement days *t+2* to *t+45*
Low Attention	0.072 ***	-0.062 *
	(<.001)	*(0.053)*
HighUE	-0.052	0.107
	(0.253)	*(0.291)*
$HFT^{5\%}$	0.032 **	-0.007
	(0.045)	*(0.745)*
Low Attention * HighUE	-0.090 **	0.170 ***
	(0.041)	*(<.001)*
Low Attention * $HFT^{5\%}$	-0.083 ***	0.061 *
	(<.001)	*(0.090)*
$HFT^{5\%}$ * HighUE	-0.031	-0.004
	(0.177)	*(0.909)*
Low Attention * HighUE * $HFT^{5\%}$	0.104 **	-0.168 ***
	(0.018)	*(0.001)*
Controls (Interacted)	yes	yes
# Observations	566	566

Panel B: HFTs trade within 2 hours after announcement time

Dependent variable	CAR on earnings announcement days *t* to *t+1*	CAR on earnings announcement days *t+2* to *t+45*
Low Attention	0.024	-0.047
	(0.210)	*(0.207)*
HighUE	-0.078 *	0.076
	(0.095)	*(0.469)*
HFT^{2hour}	0.018	-0.035
	(0.206)	*(0.149)*
Low Attention * HighUE	-0.048 *	0.088 *
	(0.090)	*(0.099)*
Low Attention * HFT^{2hour}	-0.026	0.044
	(0.230)	*(0.257)*
HFT^{2hour} * HighUE	-0.006	0.018
	(0.768)	*(0.605)*
Low Attention * HighUE * HFT^{2hour}	0.061 **	-0.081 *
	(0.026)	*(0.078)*
Controls (Interacted)	yes	yes
# Observations	566	566

Table 12: HFT and price efficiency using alternative unexpected earnings measure

This table presents multivariate tests of price efficiency with versus without HFT. The dependent variable is the cumulative abnormal return (CAR) for stock *i* on earnings announcement days *t* and *t+1* in the first column and days *t+2* to *t+45* in the second column. *Low Attention* is equal to one if the earnings announcement falls into the low-attention category under the *Aggregate* measure, which reflects the combined distribution of Friday, Busy Day, Slow Analyst Speed, High News Distraction, and Low EDGAR earnings announcements. *HFT* is equal to one if there is high-frequency trading in the rest of the day following the earnings announcement, else zero; *HighSUE* is equal to one if the announcement has above-median unexpected earnings, else zero. Regressions also include as controls market capitalization and earnings surprise volatility over the prior four years and month and year indicators. All controls are also interacted with HighSUE; the intercept, controls, and interacted controls are not reported. P-values (reported in parentheses below coefficient estimates) are based on standard errors that are clustered by announcement day. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Dependent variable	CAR on earnings announcement days *t* to *t+1*	CAR on earnings announcement days *t+2* to *t+45*
Low Attention	0.068 **	-0.058
	(0.014)	*(0.239)*
HighSUE	-0.007	0.185 *
	(0.920)	*(0.095)*
HFT	0.038 **	-0.025
	(0.039)	*(0.533)*
Low Attention * HighSUE	-0.095 *	0.119 *
	(0.055)	*(0.066)*
Low Attention * HFT	-0.074 **	0.080
	(0.021)	*(0.122)*
HFT * HighSUE	-0.037	0.041
	(0.227)	*(0.408)*
Low Attention * HighSUE * HFT	0.119 **	-0.148 **
	(0.013)	*(0.013)*
Controls (Interacted)	yes	yes
# Observations	568	568

Figure 1: HFT effects on short-horizon cumulative abnormal returns

This graph depicts the marginal effects on post-earnings-announcement days *t* to *t+1*, comparing the coefficients of interest from regressions in Table 3. *Low Attention * High UE* is the classic low-attention effect, and *Low Attention * High UE * HFT* is the marginal effect of HFT trading on low attention high-earnings-surprise announcements. Asterisks following the low-attention proxy labels indicate that the marginal effect of HFT is significant at the 1% (***), 5% (**), or 10% (*) level.

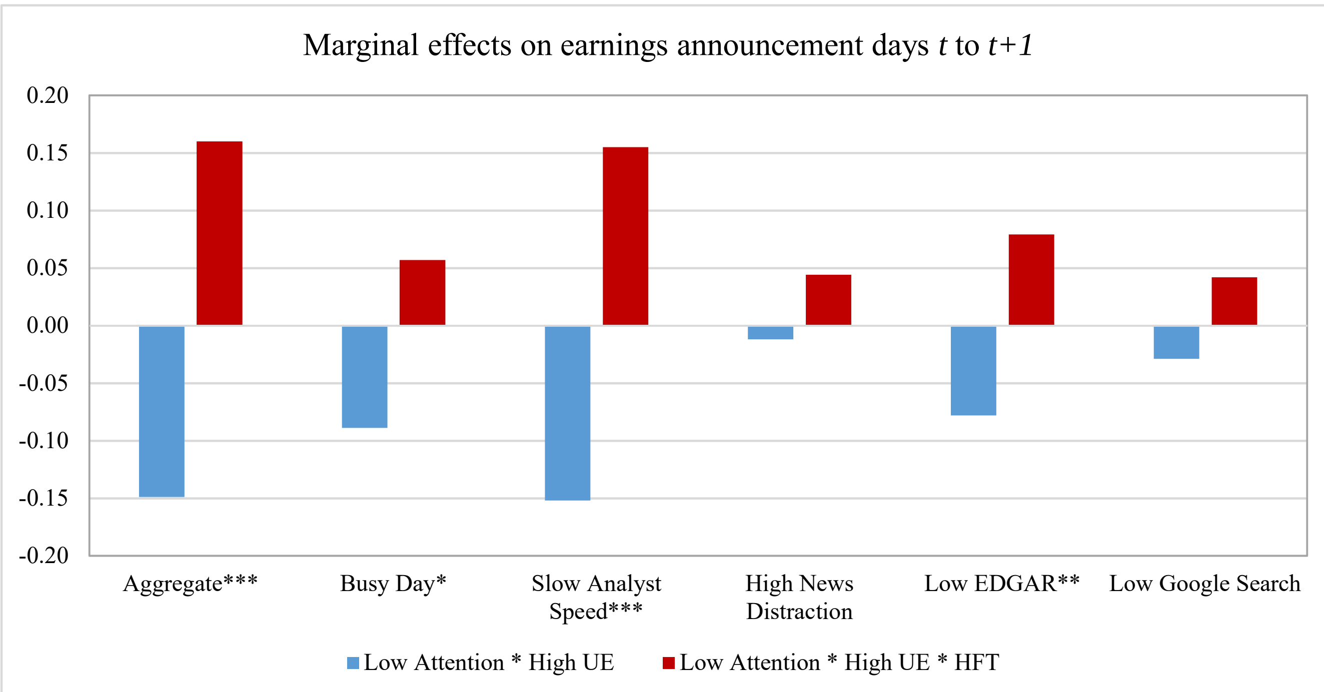

Figure 2: HFT effects on long-horizon cumulative abnormal returns

This graph depicts the marginal effects on post-earnings-announcement days *t+2* to *t+45* ,comparing the coefficients of interest from regressions in Table 4. *Low Attention * High UE* is the classic low-attention effect, and *Low Attention * High UE * HFT* is the marginal effect of HFT trading on low attention high-earnings-surprise announcements. Asterisks following the low-attention proxy labels indicate that the marginal effect of HFT is significant at the 1% (***), 5% (**), or 10% (*) level.