Tick Size Tolls: Can a Trading Slowdown Improve Price Discovery?

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October 9, 2018

Abstract

This study examines how an increase in tick size affects algorithmic trading (AT), fundamental information acquisition (FIA), and the price discovery process around earnings announcements (EAs). Leveraging the SEC's randomized "Tick Size Pilot" experiment, we show a tick size increase results in a universal decline across four commonly-used proxies for AT. This decrease in AT is accompanied by a sharp drop in abnormal volatility and volume around EAs. More importantly, we find causal evidence of increased FIA in the pre-announcement period. Specifically, we show that with a larger tick size: (a) treatment firms' pre-announcement returns better anticipate next quarter's standardized unexpected earnings (SUEs); (b) their pre-announcement returns capture more of their total returns; (c) they experience an increase in EDGAR web traffic in the days leading up to EAs; and (d) they exhibit a drop in price synchronicity with index returns. Taken together, our evidence shows that while an increase in tick size reduces AT and abnormal market reaction *after* EAs, it also increases FIA activities *prior to* EAs. (*JEL: M40, M41, G12, G14*)

Keywords: Earnings Announcements, Information Acquisition, Market Efficiency, Tick Size Pilot, Algorithmic Trading

We would like to thank David Larcker, Joseph Piotroski, Lisa De Simone, and seminar participants at Stanford University for helpful feedback and discussion. All errors are our own.
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1 Introduction

As part of the 2012 Jumpstart Our Business Startups (JOBS) Act, Congress directed the SEC to study the effect of a change in tick size on liquidity provision and market quality for small-capitalization stocks (e.g., SEC, 2013). In JOBS, legislators expressed concern that a larger tick size is needed to provide sufficient incentive for liquidity provision for smaller-capitalization stocks. By increasing the minimum increment used in quoting and trading of securities, legislators hope to encourage additional market-maker support, and thus improve liquidity for these stocks. To test for these effects, and to assess other potential unexpected consequences, the SEC directed FINRA and the national securities exchanges to develop and implement an experimental pilot program.

The resulting randomized controlled experiment, commonly referred to as the "Tick Size Pilot" (TSP) program, began in October of 2016. The TSP involved approximately 2,600 exchange traded smaller-capitalization ($3 billion or less) stocks. Over the month of the launch, a larger minimum tick size was phased in, from $0.01 to $0.05, for three different randomized treatment groups of 400 securities each, while a control sample of roughly 1,400 securities continued to trade at a $0.01 tick size.[1] The $0.05 minimum tick size is kept in place for the treatment firms for two years, with the experiment wrapping up in October 2018. In much the same way that the Reg SHO Pilot granted researchers unprecedented insights into the effects of short-selling (e.g., Diether, Lee, and Werner, 2009; Boehmer and Wu, 2013), the Tick Size Pilot presents researchers with an extraordinary opportunity to study the causal effects of tick size on price discovery and equity market dynamics.

In this paper, we examine how an increase in tick size affects algorithmic trading (AT), fundamental information acquisition (FIA), and the informativeness of prices with respect

[1]The three test groups successively introduce the $0.05 tick size to: quotes only (Group 1); both quotes and trades (Group 2); and, both trades and quotes, plus an additional "displayed order priority" rule (Group 3). This last rule requires market participants to route orders without a meaningfully better price to more transparent venues for execution. Prior studies (e.g. Rindi and Werner, 2017; Chung, Lee, and Rösch, 2018) as well as our own analyses find that the treatment effect on liquidity is economically similar across the three groups of treated firms. Therefore, we combine these three sub-groups and refer to them collectively as the "treated firms."

to earnings news.[2] Most theoretical models predict an increase in tick size will lead to a drop in algorithmic trading. Less clear, however, is whether (and if so, how) an increase in tick size might impact other measures of market quality, such as market liquidity and price efficiency (defined as the informativeness of prices with respect to fundamental information about firm value). We exploit the relatively clean research setting offered by the tick size pilot study to shed new light on these open empirical questions.

Our study is related to, and motivated by, a growing literature on the effect of algorithmic trading (AT) in financial markets. In recent years AT trading (broadly defined as round-trip trades where both legs take place on the same day) has accounted for more than 50 per cent of the reported trading volume in U.S. stock markets. An important, and still unsettled, question is how this high volume of AT impacts the quality of markets, in terms of their depth (i.e., available liquidity) and pricing efficiency. We address this question in three steps. First, we evaluate the effect of a tick size increase on AT activities. Second, we document how a tick size increase impacts trading volume and bid-ask spreads, both during normal trading periods and in the period immediately *after* an earnings news release. Finally, we examine the effect of a tick size increase on the level of FIA activities *prior to* an earnings news release.

Our first set of tests examines how the pilot program impacts AT. Prior studies suggest the minimum tick size should be closely related to the level of AT activity. For example, Chordia, Goyal, Lehmann, and Saar (2013) note that given a larger tick size, algorithmic traders will face higher costs when attempting to step in front of other limit orders. At the same time, a larger tick size reduces the frequency with which quotes need to be updated. This too should lead to an erosion in the value of the speed advantage algorithms have over human traders, and thus a decline in predatory algorithms that take advantage of

[2]We follow Weller (2017) in defining algorithmic trading (AT) as any computer-assisted low-latency trading activity. Prior literature has nominated four empirical proxies for measuring the level of AT activity: the Odd Lot Ratio (OLR; O'Hara, Yao, and Ye, 2014); the Trade-to-Order ratio (TOR; Hendershott, Jones, and Menkveld, 2011); the Cancel-to-Trade ratio (CTR; Hasbrouck and Saar, 2013 and Weller, 2017); and the Average Trde Size (ATS; Conrad, Wahal, and Xiang, 2015; O'Hara et al., 2014). We use all four proxies in our tests.

stale quotations (e.g., Foucault, Röell, and Sandås, 2003). The weight of these arguments suggests we should see a drop in AT activities for the treatment firms in the tick size pilot program.[3] Using four common proxies for the level of AT trading, we confirm these predictions. Specifically, we document a sharp and uniform drop in AT across all four measures. The average daily decline is approximately 11.06% relative to pre-treatment levels, with a further incremental decline in the period surrounding earnings announcements (EAs).[4]

Our second set of tests examines how an increase in tick size impacts bid-ask spreads, trading volume, and return volatility around earnings new releases. Other studies on the TSP program report that treatment firms experience an increase in quoted and effective spreads, as well as depth (e.g., Rindi and Werner, 2017, Albuquerque, Song, and Yao, 2017, and Chung et al., 2018). The combination of an increase in *both* spread and depth leaves the overall directional effect of the pilot on market liquidity ambiguous. We confirm these findings and provide additional evidence on the *abnormal* market reaction to the release of earnings news. It is well understood that earnings new releases are associated with an increase in information asymmetry risk, leading to wider spreads and lower depth as liquidity suppliers seek higher compensation in anticipation of the news release (e.g., Lee, Mucklow, and Ready, 1993). We present evidence that an increase in tick size has a direct impact on these event-related market reactions.

Consistent with other TSP studies, we find a increase in bid-ask spreads of approximately 24 basis points for treated firms during normal trading. We further document no significant change in abnormal bid-ask spreads, suggesting no significant change in event-related information asymmetry costs. Like prior studies, we also find a significant decrease in volume of approximately 18% among treated firms during normal trading. In addition, we show this

[3] As a counter to this argument, Yao and Ye, 2018 present a model in which AT can increase with an increase in the minimum tick size. However, the evidence to date (e.g., Weller, 2017) suggests that the Yao and Ye, 2018 effect is likely to be secondary relative to the effect anticipated by Chordia et al., 2013 and Foucault et al., 2003.

[4] As an aside, our construction of the four AT proxies benefits from the SEC's recently-created MIDAS (Market Information and Data Analytics System) database. Compared to prior studies, these MIDAS-based measures offer sharper identification of the underlying constructs associated with AT.

drop-off in volume is more acute around EAs, as *abnormal* volume for treated firms declines by approximately 38% versus pre-treatment levels. Furthermore, using absolute cumulative abnormal returns (ACAR) as a measure of the market response to earnings, we find that treated firms experience a drop in news-related return volatility of approximately 7% during the first day of the earnings announcement. Taken together, our results on abnormal spread suggest no increase in news-related information asymmetry costs; however, a larger tick size does appear to have a dampening effect on post-announcement price discovery activities, as measured by ACAR and abnormal trading volume.

Our third set of tests explore the implications of a tick size increase for fundamental information acquisition (FIA) activities. Our results thus far show that an increase in tick size decreases the post-announcement market reaction. These findings are broadly supportive of the view that algorithmic traders help facilitate price discovery after news releases (e.g., Brogaard, Hendershott, and Riordan, 2014; Rogers, Skinner, and Zechman, 2017). However, it is possible that the apparent benefits conveyed by AT in the post-announcement period come at a cost. Specifically, elevated AT trading may decrease incentives for investors to engage in longer-term FIA prior to the earnings release. Thus the apparent decrease in price discovery during the post-announcement period may be offset by an increase in pre-announcement FIA. We explore this possibility by examining the effect of the TSP on four different measures of pre-announcement FIA.

A number of recent papers (e.g., Stiglitz, 2014; Han, Khapko, and Kyle, 2014; Weller, 2017) argue that the perceived decline in trading costs attributed to AT (e.g., Hendershott et al., 2011) derives at least partially from the ability of these algorithms to screen order flow and avoid adverse selection. This ability to avoid trading with informed agents, combined with more pernicious activities associated with AT, such as "front-running" and "back-running" algorithms (Yang and Zhu (2017)), has the effect of transferring prospective profits away from fundamental investors. As a result, a striking tension emerges between between price discovery by (1) acquiring new information and by (2) incorporating existing information into prices (Weller, 2017). Although AT may improve price efficiency with respect to *existing* information, their activities may deter information acquisition and diminish price efficiency with respect to *acquirable* information. In the words of Stiglitz (2014): "Better nanosecond price discovery comes at the expense of a market in which prices reflect less well the underlying fundamentals." Our third set of tests evaluate this proposition in the context of the TSP program.

We conduct four specific tests to gauge the treatment effect on pre-announcement FIA. First, using a variant of the future earnings response coefficient (FERC) measure, we examine the ability of pre-announcement returns to anticipate the earnings surprise (i.e., the standardized unexpected earnings, or SUE) in the upcoming quarterly news release. Using a difference-in-difference analysis, we find a statistically reliable increase in the positive correlation between pre-announcement returns and SUEs among treated firms. This finding points to an increase in the ability of pre-announcement returns of treated firms to capture upcoming earnings news. Varying the length of the pre-announcement return window had minimal effect on this result, as it is statistically significant using return windows as short as one trading week before the announcement.

Second, we investigate the effect of the TSP on the volume of web traffic at each firm's home page on SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. EDGAR is the central repository for all mandatory SEC filings and the daily level EDGAR search volume (or ESV) for each firm is a more direct measure of its FIA activities. Our results show that treated firms experience an significant increase in its EDGAR search volume (ESV) in the period leading up to each earnings announcement. This increase in ESV is observed for pre-announcement windows that range from 1 to 20 trading days before the news release.

Third, we examine the effect of the TSP on Weller (2017)'s "jump ratio" (JUMP). This variable is defined as the cumulative return around the earnings announcement (days -1 to +2) divided by the total monthly return up to and including the announcement period (days −21 to +2). As developed in Weller (2017), a higher JUMP implies less of the total information acquisition takes place in the pre-announcement period. Our results show that JUMP ratios are reliably lower for treated firms during the TSP period. This finding again supports the view that a greater proportion of the total value-relevant news is being incorporated prior to the actual earnings release.

Fourth, we examine the effect of an increase in tick size on the price synchronicity of treated firm returns with market index returns. Morck, Yeung, and Yu (2000) propose stock price synchronicity as a measure of price efficiency. In their framework, firms whose returns are more synchronized with market indices (i.e. firms in which a greater proportion of the daily variation in returns is explained by market movements) have lower price efficiency (less informative prices). We compute a price synchronicity measure (SYNCH) for each firm following Morck et al. (2000), and find a reliably negative treatment effect. Again, this evidence supports the view that an increase in tick size leads to greater price efficiency (i.e. more informative prices).

Finally, to close the loop, we show that the pre-announcement price efficiency gains do not appear to come at the expense of lower price efficiency in the post-announcement period. Using both a post-earnings announcement drift (*PEAD*) test and a test that measures the speed of post-EA price discovery (*POST-JUMP*), we find no reduction in the speed of the post-EA price discovery process among treated firms. These post-EA findings, when combined with the pre-EA results, support the view that an increase in tick size can improve the overall efficiency (informativeness) of stock prices with respect to earnings news.

Our results help to reconcile some of the mixed findings in prior TSP studies. For example, using intraday measures of the speed of price discovery, Rindi and Werner (2017) and Chung et al. (2018) conclude that the TSP increases market price efficiency; conversely, Thomas, Zhang, and Zhu (2018) and Albuquerque et al. (2017) largely suggest the opposite, based on the markets' response to news events. Our results provide an explanation for why both results can hold. In general, the TSP is associated with slower incorporation of *existing* information into prices. However, the TSP also increased incentives for fundamental information acquisition. As a result, in the context of earnings news dissemination, some of the price discovery appears to have shifted to the pre-announcement period. Overall, the increase in tick size appears to have a net positive effect on the informativeness of prices. This is a particularly important consideration for regulatory purposes, as the SEC has repeatedly emphasized its duty to uphold the interests of long-term investors, as opposed to short-term traders (e.g., SEC, 2010).

To our knowledge, ours is the first study to establish a direct empirical link between an increase in tick size and an increase in FIA prior to the release of quarterly earnings. The study closest to ours in spirit is Weller (2017). Like us, Weller uses MIDAS data to examine the effect of AT on incentives for information acquisition. However, rather than using the TSP to conduct his tests, Weller employs the lagged firm price as an instrumental variable for differences in AT activity (i.e., higher priced firms, given a constant tick size, will have greater AT trading). By extending his test to the set of treatment and control firms in the TSP, we provide more direct evidence on the causal effect of tick size on FIA. Our JUMP ratio results confirm the main finding in his study in a different setting. In addition, we provide new evidence on the link between tick size and FIA by demonstrating that: (a) the pre-EA returns of treated firms better predict their subsequent SUE, (b) treated firms experience an increase in EDGAR traffic in the pre-EA period, and (c) treated firm returns become less synchronized with index returns.

Our study also contributes to a line of inquiry in accounting that examines the information content of earnings announcements. Beaver, McNichols, and Wang (2018a) report a striking increase in information content of quarter EAs from 1999 to 2016. Other follow-up studies have explored cross-sectional factors contributing to this effect, such as management guidance, analyst forecasts, and disaggregated financial statement line items Beaver, McNichols, and Wang, 2018b, or trading noise and investor over- or under-reaction Thomas et al., 2018. In these studies, the information content of EAs is measured as the variability of stock price revision on the day of the EA relative to variability of prices at other times (essentially our ACAR measure). Our results suggest the sharp increase in ACAR over the past decade might be due to AT activities. Specifically, the rise in AT has had two effects on the observed ACAR variable: (1) a decline in FIA, leading to lower price volatility in non-EA periods (a denominator effect); and (2) a surge in AT after the EA, leading to higher post-EA price volatility (a numerator effect). Viewed in the context of our results, the increase in ACAR reported in prior studies is likely due at least in part to increased AT during earnings announcements. This trend does not necessarily imply earnings news in recent periods contain greater information content than earnings news in earlier periods.

The rest of the paper proceeds as follows. The next section discusses the related literature most pertinent to this study. Section 3 outlines the methodology used throughout this study and gives a brief description of the Tick Size Pilot Program. Section 4 describes the sample construction and data used. The main empirical results of the paper are provided in Sections 5, 6, 7, and 8. Additional tests are presented in Section 9, and Section 10 closes with a discussion of considerations for the interpretation of the results of this study.

2 Related Literature

2.1 ATs and Price Informativeness

Financial markets provide two important asset pricing functions: liquidity and price discovery for incorporating information in prices (O'Hara, 2003). A significant number of prior studies on AT have suggested that algorithmic traders can benefit equity markets along both dimensions. For example, AT has been associated with more rapid incorporation of public information into prices (e.g., Brogaard et al., 2014, Hu, Pan, and Wang, 2017; Rogers et al., 2017; Chakrabarty, Moulton, and Wang, 2017), and increased liquidity through improved quoting efficiency (e.g., Hendershott et al., 2011). The above studies suggest, in the main, that the price informativeness is increasing with algorithmic trading activity.

An important feature of these studies is that they are focused solely on high-frequency measures of market quality. The central research question they address is how well (i.e., how quickly) price incorporates *existing* information. Although this is an important question, particularly in the market microstructure literature, it ignores another key aspect of price informativeness: namely, the issue of how AT may alter incentives for longer-term investors to produce information.[5] If AT increases cost to longer-term investors, less overall information may be produced, leading to less informative prices. As a result, price can be more "informationally efficient" with respect to available information, but less "informative" in the sense that it contains a smaller absolute level of information (Brunnermeier (2005)).

As Weller (2017) observed, traders contribute to price discovery by (1) acquiring new information and (2) incorporating new information into prices. In the context of AT, a number of authors have noted a potential conflict between these two components of price discovery. For example, in advocating AT curtailment, Stiglitz (2014) argues that high levels of AT may dissuade information acquisition by longer-term investors, thus reducing the extent to which prices reflect the "fundamentals" of the economy. A similar argument is made by Griffin, Kelly, and Nardari (2010). Weller (2017) provides empirical support for this potential conflict. Using lagged stock price as a proxy for an instrument for variations in AT activity, the author examines the effect of AT on the incorporation of earnings news. In particular, he develops a "price jump ratio" measure, and documents that the amount of information in prices prior to scheduled announcements decreases by approximately 9 to 13% per standard deviation of AT activity.

[4] In a related study, Rösch, Subrahmanyam, and Van Dijk, 2017 show that the improvement in intraday pricing associated with AT varies over time, and may be systematically related the the funding liquidity available to the algorithmic traders.

[5] Brogaard et al. (2014) acknowledge the possibility that liquidity demanding AT orders surrounding macroeconomic announcements may "impose significant adverse selection on longer-term investors," which may result in welfare gains being small or negative. They note, however, liquidity providing ATs are also present during these times, and the net effect appears to be positive.

In summary, significant extant evidence supports the idea that AT helps improve price discovery after the release of earnings news. However, this faster price discovery in the post-EA period may possibly come at the expense of long-term price efficiency and reduced information acquisition. We directly examine this proposition in the context of the TSP. To the extent that an increase in tick size reduces AT, we posit a reduction in the speed with which the market responds to earnings news, as well as a possible increase in information acquisition activities prior to the earnings release date.

2.2 Tick Size and Market Quality

The extant evidence on the relation between tick size and market quality is, in general, mixed. It is well understood that when the tick size is binding (i.e., when the tick size exceeds the spread that would otherwise be quoted), an increase in tick size will lead, on average, to wider spreads and increased depth (e.g., Harris, 1994; Goldstein and Kavajecz, 2000; Bessembinder, 2003; Jones and Lipson, 2001). However, given *both* wider spreads and greater depth, the net directional effect on overall market liquidity would be ambiguous. This ambiguity is an important motivation behind the design and implementation of the Tick Size Pilot study.

Several studies suggest that the effect of a larger tick size will be heterogeneous across both investor bases and securities. For example, Werner, Wen, Rindi, Consonni, and Buti (2015) models a dynamic limit order book in which rational traders decide whether to demand or supply liquidity, and where liquidity is endogenous. They show that a wider tick size may encourage liquidity provision, reduce spreads, and increase market depth for illiquid stocks while doing the opposite for liquid securities. Seppi (1997) examines the differential impact on different investor types. In his analysis, larger pricing increments are more favorable to institutional traders than retail traders, with larger trades being placed by institutional investors in the presence of larger tick sizes. Jones and Lipson (2001) presents some empirical support for this prediction.

The likelihood of differential effects across investor clienteles is particularly important to our study. A key concern among large institutional investors is the frequent need to practice "stealth trading" (i.e. disguise their order flows to prevent being front-run by algorithmic traders). A larger tick size slows down AT and produces more batched trades that offer less information to other traders about the presence of informed orders. This should in turn lead to lower trading costs for large fundamental investors (Stiglitz, 2014 and Han et al., 2014). In fact, early evidence from the TSP appears support this view, as both Chung et al. (2018) and Rindi and Werner (2017) find that treated firms exhibit a decrease in trading costs for institutional investors and an increase in trading cost for smaller investors (more specifically costs increase for traders who deal in smaller units of shares per order). This shift in trading costs could induce greater FIA, both by increasing the profitability of private information acquisition (i.e., by reducing the trading costs to fundamental traders), and by reducing the opportunity for predatory trading by ATs.

2.3 Studies on the Tick Size Pilot Program

Most TSP studies to date examine the impact of a tick size increase on market liquidity and trading volume. Rindi and Werner (2017) find at the daily level that an increase in tick size causes increases in quoted and effective spreads, as well as depth, with minimal effect on trading volume. Albuquerque et al. (2017) and Chung et al. (2018) confirm the Rindi and Werner (2017) results on spreads and depth, but report an overall decrease in volume.[6] More relevant to our study, both Chung et al. (2018) and Rindi and Werner (2017) find evidence that a tick size increase led to decreased trading costs for institutional investors and increased costs for small investors.

Evidence on how the TSP affects price informativeness is mixed. Rindi and Werner (2017) use an intraday measure of price impact as a proxy for price discovery, and conclude treated

[6]We note that given the on-going nature of the pilot program, different studies have used different cut-off dates when drawing their samples. Some variation in inferences across the studies, for example the differences reported in terms of the impact on trading volume, may be attributable to small differences in the sample used. Our analyses is based on almost the entire pilot period.

firms show an improvement in price informativeness. Chung et al. (2018) provides similar evidence using daily return autocorrelations, return predictability of past order flow changes, and a R^2 based measure. In contrast, Yao and Ye (2018) argue that high-frequency price efficiency decreased for treated firms, based on evidence of a more muted market response around news events.[7] Less related to our study, Thomas et al. (2018) also provide some evidence of a muted market reaction to earnings announcements using the Beaver (1968) abnormal return volatility measure. None of these tests address the impact of a tick size change on incentives for fundamental information acquisition.

Our findings help explain why prices could be simultaneously more efficient (as measured by intraday metrics of the speed of price discovery) while also displaying what appears to be muted reactions to news events. Specifically, we document a muted reaction to earnings announcements *after* the announcement using absolute cumulative abnormal return measures over various calculation periods. However, using both a future earnings response (FERC) based measure and the Weller (2017) jump ratio (JUMP), we show that much of this muted reaction may be attributable to earnings information having already been incorporated into prices *before* the announcement. Our finding of elevated levels of information acquisition through EDGAR and increased firm-specific information (SUE) being incorporated into pre-announcement prices, further support these inferences. Collectively, our results are largely consistent with price efficiency to earnings news actually increasing, despite the muted reaction around EAs.

3 Methodology

3.1 Tick Size Pilot Program

In April of 2012, the JOBS Act was signed into law by Congress in an effort to encourage the funding of small businesses in the United States. The primary purpose was

[7] Note that their focus is on the market response within 10 seconds of a news event.

to increase U.S. economic growth by easing many of the country's securities regulations for small capitalization, emerging growth companies. While the ratification of this regulation had wide-ranging consequences, two are most relevant to this study. First, the passage of JOBS Act mandated the SEC to design a study and report back to Congress on how the 2001 decimalization initiative (i.e. the introduction of a $0.01 tick size in US equity markets) affected liquidity and trading for small capitalization companies. Second, for purposes of this study, it granted SEC permission to re-designate a minimum tick increment in small-capitalization stocks that is greater than $0.01, but less than $0.10.

Pursuant to this mandate, in 2014 the SEC directed FINRA and the national securities exchanges to act jointly in developing a plan to implement an experimental pilot program that, among other things, would widen the quoting and trading increment for small capitalization stocks. The intended purpose of the pilot is to determine whether increasing the minimum tick size for small capitalization securities would increase market making and improve price discovery for these often lightly-traded securities. The resulting "Tick Size Pilot Program" was approved by the SEC on May 6, 2015. It was phased in during October 2016 and is scheduled to last two years.

The program involves approximately 1400 control securities that continue to be traded and quoted in $0.01 increments, and 1200 randomly assigned treatment securities split between three different treatment groups that experience a widening of their quoting and trading increments.[8] Eligible securities for the pilot study include all securities that have a market capitalization of no more than $3 billion, an average closing price of at least $2, and an average trading volume of one million shares or less as determined during a two week pre-pilot collection period. From this subset of securities, test and control groups were selected randomly using a stratified random sampling process. Companies are not able to opt in or out of a particular group and are only removed in the case of M&A activity, a delisting, dropping below $1 a share, or other related events.

[8] For a full description see `https://tinyurl.com/ybvuvyyu`.

During the pilot, Test Group 1 securities are quoted in $0.05 increments but will continue to trade at their current price increments. Test Group 2 securities are quoted and traded in $0.05 increments with certain exceptions for midpoint executions and retail liquidity providing orders. Test Group 3 securities follow the same quoting and trading rules as Test Group 2, with an additional "trade-at" requirement.[9] Rindi and Werner (2017) and Chung et al. (2018), as well as our own analyses, find that none of the results related to traders' incentives for FIA vary across the three treatment sub-groups in an economically meaningful way. Therefore, for parsimony and to increase the power of our tests, we combine the three sub-groups and refer to them collectively as the "treatment firms."

The two-year pilot study officially began on October 3, 2016, but was phased-in gradually over the month of October. By October 31, all treatment firms are fully under the new rules. A timeline of this roll-out process is presented in Figure 1. The pre-treatment and post-treatment periods for our study are selected as depicted in Figure 1. At the completion of the pilot on October 31, 2018, our sample will consist of exactly two-years before the initiation of the pilot, and two-years after the close of its launch month.

3.2 Empirical Tests

As a randomized, controlled experiment the Tick Size Pilot provides an ideal setting to study the causal effect of tick size on algorithmic trading, price discovery and information acquisition in equities markets. In most tests, we implement a standard difference-in-differences design to estimate the average treatment effect (ATE) of an increase in trading increments on various measures of price efficiency, information acquisition, and algorithmic trading.

Unless otherwise noted, we follow prior studies (e.g., Rindi and Werner, 2017) in estimating the following regression for each variable of interest in a pooled sample of treatment

[9] The so-called "trade-at" requirement prevents price matching by a person not displaying at a price of a trading centers best protected bid or offer unless a number of exemptions apply. Specifically, retail orders must be executed with at least $0.0005 price improvement and block size orders, defined as greater than 5,000 shares or $100,000, are exempted from the trade-at prohibition.

firms and control firms (i.e. control firms vs. those in groups G1, G2 or G3):

$$Y_{i,t} = \alpha + \beta_1 Post_t + \beta_2 Treatment_i + \beta_3 Post_t \times Treatment_i + \gamma X_{i,t} + \epsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ is one of the dependent variables of interest, as described in the Appendix, $Post_t$ is an indicator for taking a value of one in the post-treatment period, October 31, 2015, and $Treatment_i$ an indicator of whether the security is a member of groups G1, G2 or G3. The variable $X_{i,t}$ represents a vector of optional control variables discussed in the next section. The estimated average treatment effect (ATE) of an increase in tick size on the dependent variable in this case is β_3. We use this equation to examine the effect of a tick size increase on Algorithmic Trading both during normal trading (Table 2 Panel A) and EAs (Table 2 Panel B). We also use this research design to examine the effect of tick size on bid-ask spreads and volume (Table 3) as well as ACAR (Table 4), information acquisition through EDGAR (Table 6), as well as price synchronicity and the JUMP ratio (Table 7).[10]

We use a slightly different equation to investigate the treatment effect of the tick size pilot on future earnings response coefficients (FERCs). Specifically, we estimate:

$$\begin{aligned} Y_{i,t} = {} & \alpha + \beta_1 Post_t + \beta_2 Treatment_i + \beta_3 SUE_{i,t} + \\ & + \beta_4 Treatment_i \times SUE_{i,t} + \beta_5 Post_t \times SUE_{i,t} + \beta_6 Post_t \times Treatment_i \\ & + \beta_7 Post_t \times Treatment_i \times SUE_{i,t} + \rho SUE_{i,t-1} + \gamma X_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2}$$

where the dependent variable is either the raw (RET) or factor-adjusted (CAR) return of the firm computed over days $t - 60$ to $t - 1$ relative to each quarter t EA. All explanatory variables are as noted above and described in the Appendix, and SUE is the standardized unexpected earnings for firm i in quarter t. The goal of this test is to measure the effect of the TSP treatment on how well pre-EA returns reflect future SUEs. This test is similar in spirit

[10]Note that in some specifications, we replace the $POST$ dummy variable with quarterly fixed effects to ensure our results are not driven by quarterly variations. In all such instances, we also conducted the tests using a $POST$ variable to ensure none of our inferences would differ under the original specification.

to tests in Hirshleifer, Lim, and Teoh (2009) and Dellavigna and Pollet (2009), although the treatment in their studies is related to the timing of earnings news releases. This test is also a quarter-based variant of FERC tests used in other prior studies of price informativeness with respect to earnings (e.g., Drake, Roulstone, and Thornock, 2012; Fernandes and Ferreira, 2009; Clement, Hales, and Xue, 2011).

The coefficient of interest in these regressions is β_7, which captures the average treatment effect on the differential sensitivity of pre-announcement returns to future earnings surprises. To the extent that pre-EA information acquisition increases more for treatment firms, we would expect β_7 to be positive. The results of this test are reported in Table 5.

3.3 Controls and Spillovers

A key advantage of the Tick Size Pilot setting is that it allows us to estimate average treatment effects with little concern for selection issues that would otherwise exist absent a randomized control sample. In our setting, over-usage of control variables may in fact lead to a "bad controls" problem (e.g., Angrist and Pischke, 2009). For instance, while controlling for liquidity or institutional ownership might seem sensible, these variables themselves can be affected by the tick size treatment (e.g., Rindi and Werner, 2017; Albuquerque et al., 2017). Furthermore, the securities in this pilot study are smaller firms by design, and data availability can be an issue when a large set of control variables are added. For these reasons, we generally report one set of results with no control variables.

As a robustness check, we also report results for our tests with a set of control variables in place. Specifically, in tests where we indicate controls were used, the following variables were added to the estimation model: quarterly firm size (the natural logarithm of market capitalization), asset growth, return on assets, and the book-to-market ratio. Each of these variable has been shown to be associated with market reaction to quarterly earnings announcements. In addition, for certain tests (those where the dependent variable is *ACAR, SYNCH, ESV* or *JUMP*), our control variables also include the quintile rank of the absolute value of standardized unexpected earnings (SUE). This variable is intended to control for the size of the earnings surprise, or the amount of potentially acquirable information. None of our main results were affected by the inclusion of these control variables.

Another research design issue is the potential effect of treatment spillovers on control firms. The total effect of a regulatory change consists of direct and indirect effects, but the standard difference-in-difference approach measures only direct effects Boehmer, Jones, and Zhang, 2015. In the case of the TSP, Rindi and Werner, 2017 find that stocks with unchanged tick size nevertheless experienced significant liquidity spillovers. Specifically, as some market makers left stocks trading in decimals for more lucrative pilot stocks, quoted spreads widened for control stocks also in the post-treatment period. Indeed, we also find a spillover effect among control firms, not only in terms of wider bid-ask spreads, but also in terms of a drop in AT activities (see Figure 2). However, in our context, spillovers of this nature only serve to reduce the power of our tests. Our results show that, even with a spillover effect, the treatment firms experienced a steeper decline in AT, ACAR, JUMP, and SYNCH, as well as a greater increase in FERC (future earnings response coefficient) and ESV (EDGAR search volume), relative to the control firms.

4 Data

4.1 Pilot Firms

We obtain the list of securities used in the Tick Size Pilot Program from files at the FINRA website.[11] These files, which are updated daily, identify all securities included in the TSP, firms in each treatment group, as well as any changes made to these lists in the course of the program.[12] Following prior studies (e.g., Rindi and Werner, 2017) we omit securities

[11] `http://www.finra.org/industry/oats/tick-size-pilot-data-collection-securities-files`

[12] These changes include any symbol changes, movements from one pilot group to another, or removal from the Tick Size Pilot. The reasons a firm maybe removed include M&A activities, delisting, or a price decline below $1. When a treatment firm's price drops below $1, it is moved to the control group

that are not common equity (e.g., preferred stocks) or are dropped from the pilot study, due to mergers, de-listings, or price declines below $1.

Panel A of Table 1 presents basic summary statistics on the firms included in the pilot study. As discussed earlier, companies included in this pilot study are typically small-cap stocks, with an average (median) market capitalization of $774.37 ($452.21) million and average total assets of approximately $1.467 billion. Consistent with these companies being emerging growth companies (EGCs), pilot stocks exhibit large, and highly skewed, asset growth – a mean of 15.07% and a median of 5.04%. For the quarterly firm observations used in this study, 49% are treatment firms and 51% control firms.

4.2 Earnings Announcement Data

We obtain quarterly earnings announcement dates and data used in the calculation of fundamental ratios from Compustat. From the universe of earnings announcements, we retain those having an announcement date from October 3, 2014 (two years before the pilot start date) to December 31, 2017, excluding the phase-in period (from October 3 to October 31, 2016). For each analysis in this study, we include all observations where the minimum data needed for estimation is available.

We obtain daily price, volume and return data around each earnings announcement date from the Center for Research in Security Prices (CRSP) and the Fama and French (1992) portfolios used for the construction of expected returns from WRDs. EDGAR server data used for the construction of the EDGAR search volume metric is accessed through the SEC website, and compiled following Ryans (2017).[13] The construction details for variables used in this study are presented in the Appendix. Following prior literature in similar contexts (e.g., Hendershott et al., 2011; Chordia, Subrahmanyam, and Tong, 2014) all continuous variables are winsorized at the 99.5% and .05% level to remove potential data errors and mitigate the impact of outliers.

[13] This is available for free access at `http://www.jamesryans.com/`.

Panel B of Table 1 presents summary statistics for our main variables. With the exception of SUE, $SYNCH$ and $JUMP$, these variables are measured during the EA window (i.e., day 0 to +1). Standardized unexpected earnings (SUEs) are approximately zero, matching prior findings (e.g., Livnat and Mendenhall, 2006). Also as expected, we find CAR is slightly positive and $ACAR$ is a much higher positive number. The median number of non-robot EDGAR downloads (ESV) during a typical EA period is 82. The median relative bid-ask spread for sample firms during an EA is 21.14. The median JUMP ratio is 0.47, indicating that approximately 47% of the total monthly (i.e., days -21 to +2) returns is captured in the EA period (days -1 to +2). Finally, the median $SYNCH$ is -1.94, which corresponds to a median R-squared of approximately 12.5% from a regression of firm returns on index returns.

4.3 Algorithmic Trading Proxies

Our algorithmic trading proxies are constructed from the SEC Market Information Data Analytics System (MIDAS). Launched in January 2013 in response to the so-called "Flash Crash" of 2010, MIDAS provides microsecond stamped, order book information from all major U.S. exchanges. Using this information, the SEC provides daily summary information to investors by security exchange including total volume (order and hidden), odd lot volume, counts of trades and cancellations. In contrast to the market data in TAQ, which only provides information on the national best bid offer (NBBO), MIDAS incorporates quote and cancellation information from the entire order book.

As discussed in Weller (2017), MIDAS data allows researchers to construct significantly improved AT proxies relative to prior studies. For instance, a number of earlier AT studies used the NASDAQ AT proprietary dataset (e.g., Brogaard, Hendershott, and Riordan, 2017b; O'Hara et al., 2014; Carrion, 2013), which covers a short sample period, 2008-2009, and includes only approximately 120 stocks. Similarly, other studies rely on standard TAQ data, which only includes the NBBO, thus omitting the rest of the order book where AT activity may be taking place. Moreover, TAQ data has traditionally ignored odd lot trades, where an increasingly significant amount of AT activity takes place. As a result, prior measures of AT activity based on TAQ data have a significant bias due to odd lot truncation (e.g., O'Hara et al., 2014).

Using SEC MIDAS data, we construct the four AT measures used in Weller (2017) to proxy for the amount of AT activity during our sample period: the trade-to-order ratio, cancel-to-trade ration, odd lot ratio, and average trade size. A brief motivation behind each proxy, in addition to details of the calculation, can be found in the Appendix.

Basic summary statistics for the daily AT proxies are presented in Panel C of Table 1, with a Pearson correlation presented in Panel D. Several interesting insights present themselves. First, odd lot trading, as discussed extensively in O'Hara et al. (2014), makes up a large portion of trading volume in the equity securities used in this study, accounting for approximately 18.91% of all order volume. Daily orders and order-cancellations far exceed actual trading volume, with trade-to-order and cancel-to-trade ratios of 3.51% and 29.30 on average. These numbers are quantitatively similar to those report in Weller (2017), suggesting the presence of substantial AT activity even among these smaller capitalization TSP firms. Finally, while all variables are correlated with each other in the expected direction if driven by algorithmic trading activity, there is substantial individual variation across the proxies, suggesting each may capture a slightly different aspect of, or strategy within, algorithmic trading.

4.4 Data Availability

Due to the on-going nature of the TSP, we conduct our analyses using the latest available data as of the time of writing. Our analyses of the AT proxies using the SEC MIDAS data (Table 2) include all earnings announcements through June 30, 2018. EDGAR log data, used in our EDGAR search volume, or ESV, tests (Table 6), is available through June 30, 2017. This allows us to conduct analyses on all earnings dates up to and including June

29, 2017. Finally, our analyses on variables constructed using CRSP price and volume data (Tables 3, 4, 5, 7, 8 and 9) include all earnings announcements through June 30, 2018. Upon completion of the TSP at the end of October 2018, we will update all of our analyses again using the full sample period.

5 Tick Size and Algorithmic Trading

As a first step in evaluating the impact of a tick size increase on algorithmic trading, Figure 2 presents a time-series plot for each of the four AT proxies discussed in the Appendix. The averages for the treatment and control groups are separately plotted. As we can see across all plots, while algorithmic trading was virtually identical for all firms in the pre-treatment period, a clear divergence in AT activity occurs between treatment and control firms post-treatment. This divergence is evident across all four AT proxies. This evidence suggests that an increase in tick size caused a decrease in algorithmic trading across all four proxies.

To more fully evaluate this result, and to determine average treatment effects, Table 2 presents the estimates of Equation 1 using each of the four AT proxies. For each proxy, two main sets of specifications are run. In Panel A we estimate average treatment effects on daily AT activity (without conditioning on a news event); in Panel B we examine the treatment effect on the average and abnormal AT activity in the 3-day window centered around an earnings announcement. This latter specification is important because it provides insight on whether the treatment effects on AT are more acute during news events. Prior studies report that AT strategies are dynamic and exhibit a tendency to cluster around information events and periods of extreme price movements (e.g., Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov, 2017a; Brogaard et al., 2014). We investigate whether there is an incremental decline in AT in the period immediately surrounding the announcement.

Our results show that an exogenous increase in tick size led to a reduction in algorithmic trading across all four proxies. Focusing first on Panel A of Table 2, the estimated treatment effect of the increase in tick size on algorithmic trading is a decrease in the odd lot ratio of approximately 1.44% and the cancel-to-trade ratio of 4.4 (Columns 1 through 4). Similarly, in Columns 5 through 8 of Panel A in Table 2, the estimated treatment effect is an increase of 0.57% in the trade-to-order ratio and an increase in the average trade size of 4.3 stocks per trade. All estimates are statistically significant at the 1% level and are of similar economic magnitudes regardless of specification used. In terms of economic significance, given pre-treatment sample averages of 17.09%, 2.98%, 98.59 and 35.74 for OLR, TOR, ATS and CTR, respectively, these findings represent an average decrease of 11.06% across all AT proxies relative to pre-treatment levels.

The findings on AT activity around earnings announcements in Panel B of Table 2 are similar. Specifically, across all AT proxies, an increase in tick size appears to have decreased average algorithmic trading during earnings announcements. All estimates are statistically significant at the 1% level, with the exception of $CTR^{[-1,1]}$ which is significant at the 5% level. The average decrease relative to pre-treatment levels across all proxies is 7.70%, which is slightly lower than the results during normal trading as reported in Panel A.[14] Evidently the decrease in news-related AT is slightly less than the decline in AT during non-news days. The results related to abnormal AT activity is broadly consistent with this inference. For example we find a significant increase in *Abn.* $CTR^{[-1,1]}$, suggesting a relative shift in AT towards the EA period. However, the results related to abnormal levels for the other three AT proxies are statistically insignificant.

To summarize, across the four AT metrics, we find a universal decline in AT activity as a result of an increase in tick size. This effect is observed during both normal trading and during EAs. We do not find consistent evidence that AT declines greater during EAs.

[14]Pre-treatment averages for for OLR, TOR, ATS and CTR, respectively, are 16.88%, 4%, 105.83, and 34.56.

6 Trading Activity and Spreads Around Earnings

Prior studies have documented significant increases in quoted and traded spreads, and decreases in trading volume, for firms affected by treatment in the Tick Size Pilot (e.g., Rindi and Werner, 2017; Yao and Ye, 2018; Chung et al., 2018). These prior studies do not condition their results on an earnings news event. Although not the primary purpose of this study, we also document how tick size increases affect spreads and trading volume around earnings announcements.

Panel A of Table 3 reports the results for the effect of tick size on average and abnormal trading volume around EAs. Consistent with prior findings for normal trading days, we find a drop in EA volume for treatment firms after initiation of the TSP. All differences are statistically significant at the 1% level. On average, we observe a decrease of 35.954 to 104.42 thousand shares in daily volume depending on the calculation period. This represents a decrease of 18.2% to 27.3% relative to pre-treatment levels. Abnormal trading volume results suggest the decline in volume is even greater than the drop in normal volume. On average, we observe an incremental decrease of 68.843 thousand shares in the 3-day window (days -1 to 1), representing a drop of 37.36% relative to pre-treatment levels. Similar inferences obtain when looking at abnormal activity in the 5-day window after an EA (days 0 to +5). Overall, we find a significant reduction in trading volume as a result of the TSP treatment, with the effect being even more stronger during EAs. We explore this result further in later sections.

In Panel B of Table 3, we explore the effect of the pilot on daily bid-ask spreads. Given the nature of the treatment, namely increasing the minimum increments of quotation and trading, an increase in bid-ask spreads is at least partly mechanical. However, the economic magnitude of these changes are less obvious for a number of reasons described in Section 2. This is particularly true around earnings announcements. To the extent that AT increases adverse selection costs for slower traders (e.g., Biais, Foucault, and Moinas, 2015; Foucault, Hombert, and Roşu, 2016), a case can be made that a decline in AT may lead to narrower *abnormal* bid-ask spreads around EAs.

Across different EA windows, we find an average daily increase in bid-ask spreads of approximately 24 basis points (statistically significant at the 1% level). These effects are quite comparable to the 22.2 basis point increase on bid-ask spreads during normal trading days reported by Rindi and Werner (2017). Importantly, we find no evidence of any change in abnormal bid-ask spread, suggesting that incremental EA-related information asymmetry costs remained largely the same for the treatment firms.

Overall, the results indicate that average daily traded volume decreased as a result of the increase in tick size, but particularly so in the period immediately surrounding the EA. This result is indicative of a decreased market response to earnings announcements. Moreover, we find that while bid-ask spreads increase around the announcement period for treatment firms, abnormal bid-ask spreads remained largely unchanged, suggesting no significant change in in EA-related adverse selection costs.

7 Tick Size and Price Responses to Earnings News

This section explores how an increase in tick size affects the short-window response to earnings information, as measured by the absolute cumulative abnormal return ($ACAR$) variable. This measurement has a long history in the accounting and finance literature, dating back to Ball and Brown (1968) and Fama, Fisher, Jensen, and Roll (1969). It is commonly used in the evaluation of information events (e.g., Baruch, Panayides, and Venkataraman, 2017; Roll, Schwartz, and Subrahmanyam, 2010). For example, several recent studies find a sharp increase in $ACAR$ around EA dates over the past decade (Beaver et al., 2018a,b) and Thomas et al., 2018). This rise in EA-related $ACAR$ is widely interpreted as a sign that the information content of EAs is on the rise. We explore another explanation: namely that the recent increase in $ACAR$ is related to market decimalization and the rise of AT during EA periods.

Table 4 presents difference-in-difference estimates of the effect of an increase in tick size on absolute cumulative abnormal returns ($ACAR$). As we see from Columns 1 and 2, there is a significant decline in $ACAR$ in the short-term (day 0 to day 1) window. The average treatment effect is a drop in $ACAR$ in the order of 0.406%. Given the sample average $ACAR^{[0,1]}$ is 5.80%, this a drop of approximately 7%. The decline in $ACAR$ appears to persist at least through the first 10 trading days after the earnings announcements.

Figure 3 presents a time-series plot of the average treatment effect from the date of announcement to 30 days after the announcement. This graph illustrates the persistence of these effects and highlights their dynamics over time. Specifically, we see that the treatment effect is immediately detectable on the day of the earnings announcement. The drop in $ACAR$ remains significant even 30 trading days after the announcement. This finding could be interpreted as evidence that the post-EA price discovery process has declined (consistent with Yao and Ye, 2018). Alternatively, it is possible that some of the news that was previously associated with EAs is now already impounded into prices *before* the announcement period, due to an increase in fundamental information acquisition activities. We explore this possibility in the next section.

8 Tick Size and Pre-Earnings Information Acquisition

The evidence to this point shows that the increase in tick size decreased algorithmic trading, and significantly reduced the post-EA response, in terms of both abnormal volume and $ACAR$. Viewed in isolation, this evidence suggests that an increase in tick size reduces price discovery. However, as noted earlier, it is possible that the tick size increase has given fundamental traders more incentive to produce information in the pre-EA period. To examine this possibility, we now investigate the extent to which earnings information is incorporated into price earlier for treatment firms.

8.1 Returns and Future Earnings

If information acquisition increased as a result of an increase in tick size, we should expect pre-announcement returns for treated firms to become more informative with respect to future earnings news. In our first test, we formally test this conjecture by examining the relation between pre-EA returns and the subsequent earnings surprise (as measured by standardized unexpected earnings, or SUE). As discussed in Section 3, this test shares a number of similarities with what is commonly referred to as future earnings response coefficient (FERC) tests in the accounting literature.

Table 5 presents estimates of Equation 2 cumulative returns (either RET, or CAR) in the trading quarter immediately before each earnings announcement to proxy for the amount of pre-EA information priced by the market. All controls are as described in Section . In addition, we include the lagged SUE – i.e., the SUE from the most recent quarter – to control for any potential SUE drift.

As expected, we see a significantly positive coefficient on SUE across all columns and specifications. This reflects the fact that pre-EA returns generally portend the soon-to-be-release earnings surprise. More importantly, across all columns and specifications, we also see a statistically significant and positive coefficient on the $Post \times Treatment \times SUE$ variable. This result show that the cumulative pre-EA returns of treatment firms becomes more correlated with future SUEs during the TSP test period. Estimated effects indicate that one standard deviation increase in SUE in an upcoming announcement (approximately 5.91%), is associated with a 1.17% (1.01%) increase in RET (CAR) in the quarter before the announcement. All estimated effects are statistically significant at the 5% level or higher.

To examine the robustness of this result, Figure 4 depicts the average treatment effect (i.e. the coefficient estimate on $Post \times Treatment \times SUE$ for different start dates. To construct this figure we re-estimate Equation 2 for $CAR^{[T,-1]}$ across various starting dates, $T = -60$ to -1. This figure shows that the average treatment effect is positive for all return accumulation periods starting from $T = -5$ through to $T = -60$, and reliably so for most. In general, these results are consistent with the treatment firms' cumulative abnormal returns in the pre-earnings period capturing more of their upcoming SUE news once the tick size was increased.

In summary, the results of this section largely support the notion that prices in the pre-earnings period became more informative as a result treatment in the Tick Size Pilot. From the period starting approximately three trading months before an earnings announcement to the five-day period before the announcement, cumulative abnormal returns are more positively correlated with future earnings surprises for treatment firms in the post-treatment period.

8.2 Acquisition of Fundamental Information through EDGAR

The prior section provides evidence that an increase in tick size has caused pre-EA returns to become more positively correlated with future earnings surprises. This finding is consistent with an increase in the informativeness of pre-EA prices. In this subsection, we look for direct evidence of increased information acquisition in the pre-EA period by examining user traffic on the firms' EDGAR website.

Table 6 presents estimated effects of treatment in the Tick Size Pilot study on cumulative (non-robotic) EDGAR activity across various starting dates in the period immediately before, and during, each earnings announcement. Assuming treatment led to an increase in information acquisition, we would expect a disproportionate increase web traffic for treatment firms during the TSP period. Specifically, we would expect the estimated coefficient on $Post \times Treatment$ to be positive.

The evidence shows this is indeed the case. The average treatment effects are positive across all estimations and are statistically significant at the 1% level for time periods that begin 20 days or less before the EA (see Columns 3 through 6). During the 20 days leading up to the EA, the EDGAR traffic increases for treatment firms by approximately 4 page views. Most of the increase in EDGAR activity appears to occur closer to the EA date, as the estimated coefficient for the five-day window before the EA (days −5 to −1) is 3.84. These effects are small from an economic perspective, representing just 1 to 4% of pre-treatment averages in the pre-earnings period (Columns 3 through 5), and approximately 2% in the period immediately after earnings (Column 6). However, given numerous other sources of other data available to investors, this metric likely captures only a small portion of the increase in fundamental information acquisition activities.

8.3 Alternative Measures of Information Acquisition

This section explores two additional measures of price informativeness that has been used by past studies. The first of these measures is a variant of the Morck et al. (2000) stock price synchronicity measure, $SYNCH$. Based on the R^2 measure from Roll (1988), this measure captures the extent to which a firm's returns is correlated with index returns. Intuitively, when less firm-specific information is being produced, more of the stock's returns will reflect market-wide information, leading to a higher $SYNCH$ measure. We estimate a price synchronicity measure for each firm-quarter using in daily returns in the three-month period before the earnings announcement (trading days −60 to −1). If treatment firms experienced an increase in pre-EA information acquisition, we would expect to see a decrease in their $SYNCH$.

Columns 1 through 3 of Table 7 presents difference-in-difference analyses of the effect of tick size on stock price synchronicity. In the first two columns we include a *Post* indicator variable; in the third column we include quarterly fixed effects. Across all three specifications, the coefficient on $Post \times Treatment$ is reliably negative, indicating that an increase in tick size had the effect of decreasing stock price synchronicity. All estimates are significant at the 1% level and show similar magnitudes. In terms of economic significance, this decrease represents an approximately 4% drop in synchronicity relative to average pre-treatment levels across all measurement periods.

Our next set of tests is based on the $JUMP$ ratio from Weller (2017). This variable is defined as the cumulative abnormal return during the EA period ($CAR^{[-1,+2]}$) divided by the cumulative abnormal return in the 24 trading days up to and including the EA period ($CAR^{[-21,+2]}$). Intuitively, it quantifies the share of information incorporated into prices before the earnings announcement. $JUMP$ is an inverse measure of price informativeness, because a higher $JUMP$ ratio indicates less information was revealed in pre-EA returns. To the extent that an increase in tick size leads to an increase in pre-EA information acquisition, we would expect to see a decrease $JUMP$ for treated firms.

Columns 4 through 6 of Table 7 report difference-in-difference analyses of the effect of tick size on the JUMP ratio. All estimates are negative, although the statistical significance is only marginal (significant at the 10% in Columns 5 and 6, not significant in Column 4). In economic terms, these estimates suggest an increase in FIA of approximately 4 to 5% versus post-treatment average, a number similar in magnitude to inferences derived from the stock price synchronicity measure. Our findings also qualitatively similar to those reported in Weller (2017), who reports lower $JUMP$ for firms with less AT activities.[15]

To summarize, the results in this section largely mirror those of Sections 8.1 and 8.2. Specifically, we provide evidence that using two additional measures of information acquisition and price efficiency, the Morck et al. (2000) $SYNCH$ measure and the Weller (2017) $JUMP$ measure, that pre-EA prices appear to incorporate more information after a tick size increase. For nearly all specifications considered, average treatment effects show the same thing – an increase in pre-EA information acquisition among treated firms.

9 Post-Announcement Price Discovery

Section 8 results show that additional information is being incorporated into prices in the pre-announcement period. However, we also found a reduction in post-EA response to

[15]The stronger statistical significance of the Weller (2017) $JUMP$ results could be attributed to a number of reasons including: (1) differences in methodology between our study and his which uses a instrumental variable design, and (2) the sample for his tests is derived from a larger sample size than ours with a significantly different set of firms.

earnings news as measured by ACAR and abnormal volume (Sections 6 and 7). Is it possible that the price discovery improvement we found in the pre-EA period is off-set by a decline in post-EA price discovery?

In this section, we close the loop by examining the effect of the TSP program on price discovery in the post-EA period. We do so in two steps: (1) by evaluating the treatment effect on the size of the Post-Earnings Announcement Drift (PEAD), and (2) by examining the extent to which short-window EA returns capture total returns from day 0 to either day +21 or day +60 days (i.e., the *Post-JUMP* ratio).

9.1 Post-Earnings Announcement Drift

Following prior studies (e.g., Bernard and Thomas, 1990; Livnat and Mendenhall, 2006), we use standardized unexpected earnings (SUEs) to proxy for the market's directional surprise to earnings information. For each quarter, we compute a firm's $SUE\ Rank$, defined as its decile ranking based on its most recent SUE. We then examine the effect of treatment in the pilot study on the extent to which $SUE\ Rank$ predicts subsequent cross-sectional returns (i.e., the PEAD phenomenon).

Table 8 presents the results for these analyses. The dependent variable is the cumulative abnormal return from day +2 to day +60 after the EA ($CAR^{[+2,+60]}$). In Column 1, we first establish that PEAD was present for the pilot sample. Using only pre-treatment period data, we find the coefficient estimate on $SUE\ Rank$ is both positive and significant at the 1% level, indicating a significant PEAD in the pilot securities. In Columns 2 through 4, we use three different model specifications to evaluate the treatment effect on the predictive power of $SUE\ Rank$. These regressions are similar to the earlier FERC tests, except the dependent variable is post-EA returns rather than pre-EA returns. The variable of particular interest is the coefficient on the interaction term between $Post, Treatment$ and $SUE\ Rank$.

We find little change in the PEAD effect as a result of the TSP treatment. In all three specifications (Columns 2, 3, and 4), the estimate on the key interaction term is statistically indistinguishable from zero, and economically small. Together with our earlier findings, it appears that an increase in tick size has increased price informativeness prior to EAs without exacerbating the post-EA price drift known as PEAD.

9.2 Post-JUMP Ratios

As a final test, we use a post-EA variant of Weller (2017)'s $JUMP$ ratio to examine the effect of the TSP on the speed of the post-EA price discovery process. To conduct this test, we compute a *POST-JUMP* variable, defined as:

$$POST\text{-}JUMP_{i,t}^{[-1,k]} = \frac{CAR_{i,t}^{(T_0-1,T_0+2)}}{CAR_{i,t}^{(T_0-1,T_0+k)}}$$

where $CAR_{i,t}^{(T_1,T_2)}$ represents the cumulative abnormal return between dates T_1 and T_2, using the Fama and French (1992) model, and T_0 represents the earnings announcement day of firm i in period t. This ratio quantifies the share of price discovery that takes place during the first four days of the announcement period, relative to the total post-announcement return measured k days after the news release. A higher *POST-JUMP* ratio indicates a greater share of the information was incorporated into price during the EA period. In other words, higher *POST-JUMP* is indicative of faster price discovery, and less post-earnings announcement price "drift."

Table 9 reports the *POST-JUMP* results. The dependent variable is either the *POST-JUMP* ratio computed through day +21 (Columns 1 to 3) or day +60 (Columns 4 to 6). In Columns 3 and 6, we include quarterly fixed effects; in the other columns we use a *Post* indicator variable to denote time periods after the launch of the TSP in October 2016. These regressions are analogous to the earlier $JUMP$ tests, except the dependent variable is now post-EA returns rather than pre-EA returns. The variable of particular interest is the coefficient on the interaction term between $Post \times Treatment$.

Across all six specifications, we find no statistically significant change in the *POST-*

JUMP ratio as a result of the TSP treatment. In fact, when *POST-JUMP* is measured to 21 days (Columns 1 to 3), coefficient of interest is positive, indicating an increase in the speed of post-EA price discovery. When *POST-JUMP* is measured to 60 days (Columns 4 to 6), the estimated coefficients small and insignificant. Once again, we find no evidence of a slow-down in the speed of price discovery in the post-EA period.

10 Concluding Remarks

The introduction of decimal pricing in April 2001 laid the groundwork for a chain of events that literally transformed the U.S. equity markets. The one-cent tick size, together with the advent of ultra-fast computers and automated trading platforms, gave rise to algorithmic traders who profit from minute and fleeting price dislocations. Today, although AT has come to dominate daily trading volume, its net effect on market liquidity and price informativeness is still the subject of extensive debates (see SEC, 2014a and SEC, 2014b). These debates reflect the complexity of the unanswered questions surrounding the impact of the one-cent minimum price increment. The SEC ordered a large-scale pilot study precisely because these questions are so difficult to answer absent a randomized controlled experiment.

In this paper, we use the Tick Size Pilot program to examine how an increase in tick size affects algorithmic trading, price discovery, and fundamental information acquisition around earnings announcements. We report four primary findings. First, we provide causal evidence that an increase in tick size significantly deters algorithmic trading activities. Second, we show that this decline in AT is accompanied by what appears to be a considerable reduction in the markets' response to earnings information. Third, we find evidence of an economically significant increase in pre-announcement information acquisition by fundamental investors. Using several different proxies, we show that treated firms experience an increase in FIA activities in advance of the earnings news release. As a result, their pre-EA prices better anticipate (i.e. are more informative about) firms' fundamental news. Finally, to close the loop, we show that these pre-announcement price efficiency gains do not come at the expense of lower price efficiency in the post-announcement period.

Collectively, our results support the existence of a striking tension between price discovery by (1) acquiring new information and by (2) incorporating existing information into prices (Weller, 2017). Although decimalization may have improved price efficiency with respect to *existing* information, it appears to have deterred information acquisition, and thus diminished price efficiency with respect to *acquirable* information. We believe the latter effect, in particular, should be of interest to security market regulators.

Two important considerations come to mind when interpreting the findings of this study. First, we do not have causal evidence that the decline in AT led to the increase in information acquisition. The TSP setting allows us to draw causal inference between an increase in tick size and: (1) a decline in AT, and (2) an increase in FIA. However, while a compelling conceptual case can be made that the documented decrease in AT led to the changes in price efficiency and information acquisition, we cannot completely rule out alternative mechanisms through which an increase in tick size may have caused these FIA effects.

A second consideration is to what extent these results are generalizable to securities outside the tick size pilot. The firms considered in this study are substantially smaller than the general universe of publicly traded firms, and it is unclear whether we should expect similar effects if regulators were to, say, increase tick size for the entire marketplace.

The above considerations aside, we believe the Tick Size Pilot is a powerful setting in which to study how trading costs affect trading incentives and behavior among different market participants. Rarely have we seen a randomized controlled experiment of this scale and duration play out in live trading. Given the importance of the liquidity problem among small capitalization firms, and the increased focus in AT, we have no doubt many more interesting studies will be forthcoming.

A Variable Definitions

A.1 Measures of Information Acquisition, Price Discovery and Earnings Response

Cumulative Abnormal Returns (CAR)

Cumulative abnormal returns are standard measure of the signed market response to earnings, and have a long history in event studies. Following prior studies (e.g., Weller, 2017), we define cumulative abnormal returns as:

$$CAR_{i,t}^{[T_0,T_1]} = \prod_{k=T_0}^{T_1} \left(1 + r_{i,t}^k\right) - \prod_{k=T_0}^{T_1} \left(1 + \mathbb{E}[r_{i,t}^k]\right)$$

where $CAR_{i,t}^{(T_0,T_1)}$ is the cumulative abnormal return from dates T_0 to T_1, $r_{i,t}^k$ is the returns of stock i on day k relative to the earnings date in quarter t, and $\mathbb{E}[r_{i,t}^k]$ is the expected return calculated using the Fama and French (1992) model. Factor loadings are estimated using a 252 trading day window (approximately one calendar year), starting 90 days before the announcement date. Observations with fewer than 60 trading days in the estimation period are dropped. Measured in percent.

Absolute Cumulative Abnormal Returns (ACAR)

The absolute cumulative abnormal return measure of Ball and Brown (1968) and Fama et al. (1969) is a standard measure of the incorporation of information around event dates. Following prior studies, we define the measure to be

$$ACAR_{i,t}^{[T_0,T_1]} = |CAR_{i,t}^{[T_0,T_1]}|$$

where $CAR_{i,t}^{(T_0,T_1)}$ is the cumulative abnormal return from dates T_0 to T_1 using the Fama and French (1992) model and described below. This metric is calculated for each stock i, and announcement period t, for which data is available. Conditional on the information content of earnings being equal, a higher $ACAR$ is associated wither a stronger market response to information events. Measured in percent.

Standardized Unexpected Earnings (SUE)

Unexpected earnings have a long history academic literature as a measure of market surprise (e.g., Ball and Brown, 1968). Bernard and Thomas (1990) use a standardized measure earnings in the study of post-earnings announcement drift (PEAD) which Livnat and Mendenhall (2006) further explores using various calculation of SUE. Following this latter study, standardized unexpected earnings are calculated as

$$SUE_{i,t} = \frac{I_{i,t} - \mathbb{E}[I_{i,t}]}{p_{i,t}}$$

where $I_{i,t}$ is primary earnings per share of firm i in quarter t, $p_{i,t}$ is the price per share form firm i at the end of quarter t, and $\mathbb{E}[I_{i,t}]$ is calculated using a one-year seasonal walk model. Measured in percent.

EDGAR Search Volume (ESV)

A number of recent studies use web traffic on the SEC's EDGAR servers as a direct measure of information acquisition by market participants (e.g., Lee, Ma, and Wang, 2015; Dehaan, Shevlin, and Thornock, 2015). This measure grants insights into how much, and when, financial information of firms is being acquired around earnings. Following prior work (e.g., Drake, Roulstone, and Thornock, 2015), we define cumulative EDGAR pre-earnings announcement search volume as:

$$ESV_{i,t}^{[T_0,T_1]} = \sum_{k=T_0}^{T_1} ESV_{i,t}^{k}$$

where $ESV_{i,t}^{k}$ is defined as total non-robotic EDGAR downloads (across all disclosures) for firm i in announcement quarter t for each day k relative to the earnings date. A higher value of total EDGAR search volume indicates more information acquisition activity.

Price Jump Ratio (JUMP)

Weller (2017) uses the ratio of post-announcement price variation to the total variation before and including earnings to study the effects of algorithmic trading on information acquisition in equities markets. This measure quantifies the share of information acquired and incorporated into securities' prices pre-announcement. Following Weller (2017), we compute the price jump ratio as:

$$JUMP_{i,t} = \frac{CAR_{i,t}^{(T_0-1,T_0+2)}}{CAR_{i,t}^{(T_0-21,T_0+2)}}$$

where $CAR_{i,t}^{(T_1,T_2)}$ represents the cumulative abnormal return between dates T_1 and T_2, using the Fama and French (1992) model, and where T_0 represents the earnings announcement day of firm i in period t. As developed in Weller (2017), a higher price jump ratio implies less information acquisition in the pre-announcement period relative to the post-announcement information set.

Post-Earnings Price Jump Ratio (POST-JUMP)

Using a post-earnings variant of the Weller (2017) price jump ratio, we define the post-earnings price jump ratio to be:

$$POST\text{-}JUMP_{i,t}^{[-1,k]} = \frac{CAR_{i,t}^{(T_0-1,T_0+2)}}{CAR_{i,t}^{(T_0-1,T_0+k)}}$$

where $CAR_{i,t}^{(T_1,T_2)}$ represents the cumulative abnormal return between dates T_1 and T_2, using the Fama and French (1992) model, and T_0 represents the earnings announcement day of firm i in period t. This ratio quantifies the share of price discovery that takes place during the first four days of the announcement period, relative to the total post-announcement return measured k days after the news release. A higher *POST-JUMP* ratio indicates a greater share of the information was incorporated into price during the EA period. In other words, higher *POST-JUMP* is indicative of faster price discovery, and less post-earnings announcement price "drift."

Price Synchroncity (SYNCH)

Roll (1988) proposes an R^2-based price efficiency measure based on the intuitive idea that the less firm-specific information is produced and incorporated into the stocks price, the better a stocks return is approximated by market-wide information. Subsequent studies use a transformation of this metric, stock price "synchronicity" in the study of the amount of firm-specific information in prices. Following Morck et al. (2000), we define the stock price synchronicity measure as:

$$SYNCH_{i,t} = ln\left(\frac{R^2}{1 - R^2}\right)$$

where R^2 is the coefficient of determination from

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \epsilon_{i,t}$$

for earnings date t for firm i. This metric is calculated from day -60 to -1 relative to earnings date t to capture the amount of firm-specific information impounded into prices prior to earnings announcement in quarter t. A lower price synchronicity measure implies more information acquisition by investors in the pre-announcement period.

Trading Activity and Liquidity Variables (VOL, SPD)

Prior studies have noted decreased volume, and increased spreads as a result of increases in trading increments (e.g., Rindi and Werner, 2017). Following prior literature, we look at two standard trading activity variables, daily trading volume and effective spreads. Daily trading volume ($VOL_{i,t}$) is calculated as the total trading volume (from CRSP), measured in thousands of dollars. Daily bid-ask spreads ($SPD_{i,t}$), measured in basis points, are calculated as:

$$SPD_{i,t} = \frac{Ask_{i,t} - Bid_{i,t}}{0.5 \cdot (Ask_{i,t} + Bid_{i,t})}$$

where $Ask_{i,t}$ and $Bid_{i,t}$ are the reported daily ask and bid closing prices, respectively, from CRSP on day t for firm i.

A.2 Algorithmic Trading Proxies

Odd Lot Ratio (OLR)

O'Hara et al. (2014) provide empirical support of the increased use of odd-lot trades in equities (i.e., those quantities of less than 100 shares) from high frequency or algorithmic traders. Following the SEC MIDAS calculations, we calculate the odd lot ratio for stock i on day t as:

$$OLR_{i,t} = \frac{Odd\ Lot\ Volume_{i,t}}{Total\ Trade\ Volume_{i,t}}$$

where $Odd\ Lot\ Volume_{i,t}$ is the sum of all odd lot trade volume and $Total\ Trade\ Volume_{i,t}$ is the sum of all trade volume for all 12 stock exchanges captured by the SEC MIDAS system, excluding the NYSE and AMEX due to data comparability issues with other exchanges. A higher odd lot ratio is associated with greater algorithmic trading activity. Measured in percent.

Trade-to-Order Ratio (TOR)

Hendershott et al. (2011) propose an algorithmic trading proxy based on the number electronic order submissions. This measure is motivated by the propensity for algorithmic traders to submit limit orders as part of slice and dice algorithms. Similarly, Brogaard, Hendershott, and Riordan (2015) use a an AT proxy based on the sum of all submissions and cancellations, divided by the number of executions. Using the inverse of this metric, we define the trade-to-order ratio for stock i on day t as:

$$TOR_{i,t} = \frac{Total\ Trade\ Volume_{i,t}}{Total\ Order\ Volume_{i,t}}$$

where $Total\ Order\ Volume_{i,t}$ is the sum all order volume and $Total\ Trade\ Volume_{i,t}$ is the sum of all trade volume for all 12 stock exchanges captured by the SEC MIDAS system, excluding the NYSE and AMEX due to data comparability issues with other exchanges. A higher trade-to-order ratio is associated with less algorithmic trading activity. Measured in percent.

Cancel-to-Trade Ratio (CTR)

Much of algorithmic traders strategic advantage is in their ability to nearly instantaneously replace their stales quotes with updated quotes based on new market information. This led to a rapid chain of order submissions and cancellations which prior studies have documented to be associated with algorithmic trading activity (e.g., Conrad et al., 2015; Hagströmer and Nordén, 2013; Brogaard et al., 2015). Consistent with this, Hasbrouck and Saar (2013) use the cancellation rate in their AT proxy and Weller (2017) uses the cancel-to-trade ratio. Following this latter study, the cancel-to-trade ratio for stock i on day t is calculated as:

$$CTR_{i,t} = \frac{Count\ of\ Cancels_{i,t}}{Count\ of\ Trades_{i,t}}$$

where $Count\ of\ Cancels_{i,t}$ is the count of all canceled orders and $Count\ of\ Trades_{i,t}$ is the count of all trades for all 12 stock exchanges captured by the SEC MIDAS system excluding the NYSE and AMEX due to data comparability issues with other exchanges. A higher cancel-to-trade ratio is associated with greater algorithmic trading activity.

Average Trade Size (ATS)

One defining characteristic of algorithmic trading is their tendency to slice large, parent orders up into a series of subsequent smaller, child orders (e.g., Conrad et al., 2015; O'Hara et al., 2014). Such behavior is at least partially driven by their desire to break larger, round-lot sized orders into smaller, odd lots(e.g., O'Hara et al., 2014). Following this intuition, we proxy for this sort of behavior with average trade size following the SEC MIDAS definition for stock i on day t:

$$ATS_{i,t} = \frac{Total\ Trade\ Volume_{i,t}}{Count\ of\ Trades_{i,t}}$$

where $Total\ Trade\ Volume_{i,t}$ is the sum of all trade volume and $Count\ of\ Trades_{i,t}$ is the count of all trades for all 12 stock exchanges captured by the SEC MIDAS system excluding the NYSE and AMEX due to data comparability issues with other exchanges.

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Figures and Tables

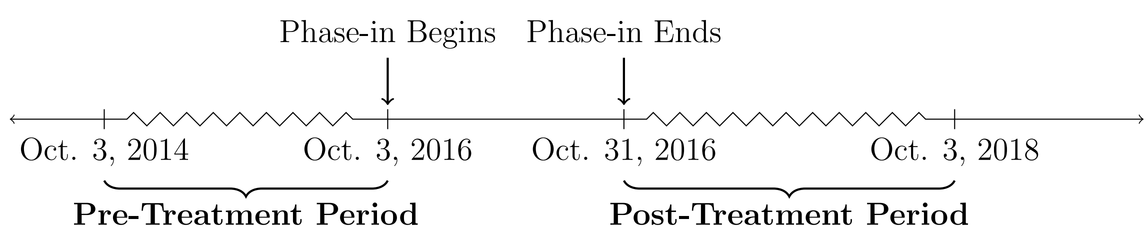


Figure 1
Tick Size Pilot Timeline
This figure presents the timeline for the tick size pilot study which began on October 3, 2016. As shown, we define the pre-treatment earnings announcements to be in the two-year period preceding the pilot start date. The post-treatment earnings announcements are defined to be in the two-years after the pilot's implementation, the duration of the pilot study (subject to data availability), excluding the one-month phase-in period in October 2016.

Table 1
Summary Statistics

Panel A: Pilot Firm Quarterly Descriptives

	$Mean$	SD	$p^{1\%}$	$p^{10\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	N
Mkt. Cap (\$ *MM*)	774.37	832.19	13.24	63.69	452.21	1,134.67	3,631.79	24,979
Assets (\$ *MM*)	1,467.02	2,625.62	11.38	60.46	554.42	1,515.91	14,327.91	25,002
Asset Growth (%)	15.07	48.81	-43.85	-12.90	5.04	16.49	252.92	24,772
EPS	0.15	0.71	-2.20	-0.44	0.14	0.41	2.58	24,993
Treatment	0.49	0.50	0	0	0	1	1	25,013
Control	0.51	0.50	0	0	1	1	1	25,013

Panel B: Earnings Announcement Variable Descriptives

	$Mean$	SD	$p^{1\%}$	$p^{10\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	N
SUE (%)	0.06	5.91	-20.56	-2.55	0.07	0.64	23.70	24,731
$ACAR^{[0,1]}$ (%)	5.80	6.11	0.05	0.54	3.76	7.98	29.78	25,013
$CAR^{[0,1]}$ (%)	0.23	8.30	-24.23	-9.04	0.15	4.00	25.18	25,013
$ESV^{[0,1]}$	97.78	69.53	10	30	82	126	362	19,124
$VOL^{[0,1]}$	493.92	775.54	0.23	8.02	197.69	608.71	4,087.00	25,009
$SPD^{[0,1]}$	72.51	133.15	2.18	5.08	21.14	68.85	728.70	25,009
$SYNCH$	-2.43	1.99	-9.74	-5.00	-1.94	-1.09	0.43	25,010
$JUMP$	0.47	2.67	-9.67	-0.88	0.47	0.97	10.87	24,717

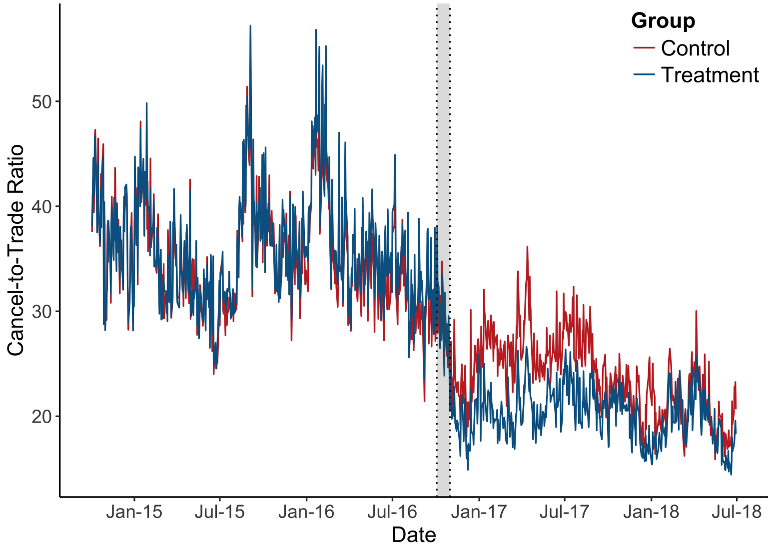
Panel C: Algorithmic Trading Proxy Descriptives

	$Mean$	SD	$p^{1\%}$	$p^{10\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	N
Odd Lot Ratio (*OLR*)	18.91	15.67	0	4.50	16.12	23.68	100	1,504,272
Trade-to-Order Ratio (*TOR*)	3.51	2.64	0	0.72	2.94	4.81	12.50	1,521,691
Cancel-to-Trade Ratio (*CTR*)	29.30	31.50	5.32	9.02	19.98	32.56	179.25	1,474,409
Average Trade Size (*ATS*)	95.50	44.51	28.04	56.95	86.09	105.63	284.88	1,474,135

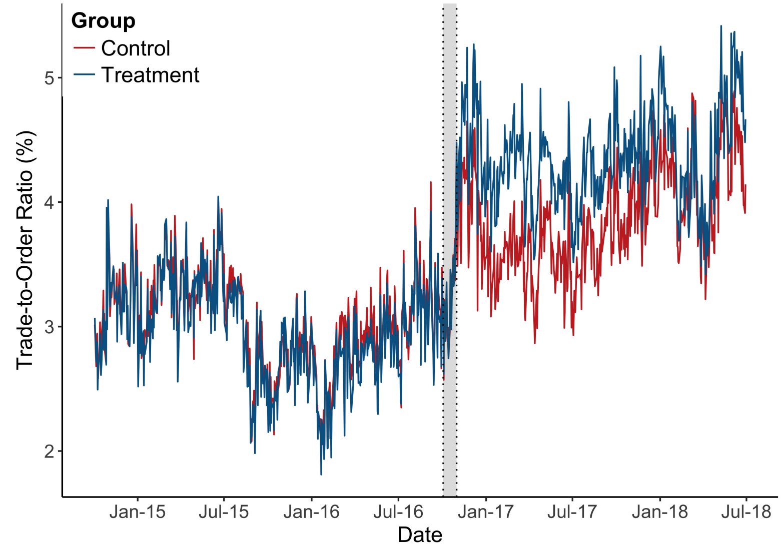
Panel D: Algorithmic Trading Pairwise Correlations

	OLR	TOR	CTR	ATS
Odd Lot Ratio (*OLR*)	1	-0.39	0.18	-0.65
Trade-to-Order Ratio (*TOR*)	-0.39	1	-0.52	0.46
Cancel-to-Trade Ratio (*CLT*)	0.18	-0.52	1	-0.10
Average Trade Size (*ATS*)	-0.65	0.46	-0.10	1

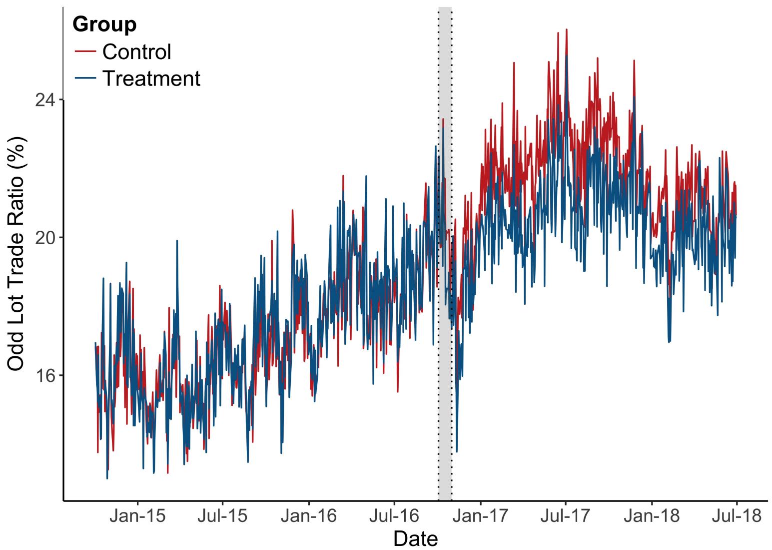
This table reports descriptive statistics on the pilot firm quarterly fundamentals, algorithmic trading proxies, and the earnings response and information measures used throughout this study and described in the Appendix and Section 4. All variables are derived from the sample of securities used in the SEC Tick Size Pilot experiment from the periods of October 3,2014 to October 3, 2018 (subject to data availability). Panel A reports basic summary statistics on fundamentals, and descriptive information of the pilot firms. Panel B reports quarterly summary statistics for the market reactions and information acquisition measures derived from earnings announcements for securities used as part of this study. Panel C reports daily summary statistics for four algorithmic trading proxies derived from the SEC MIDAS database, and Panel D shows the Pearson correlation matrix of all algorithmic trading proxies.



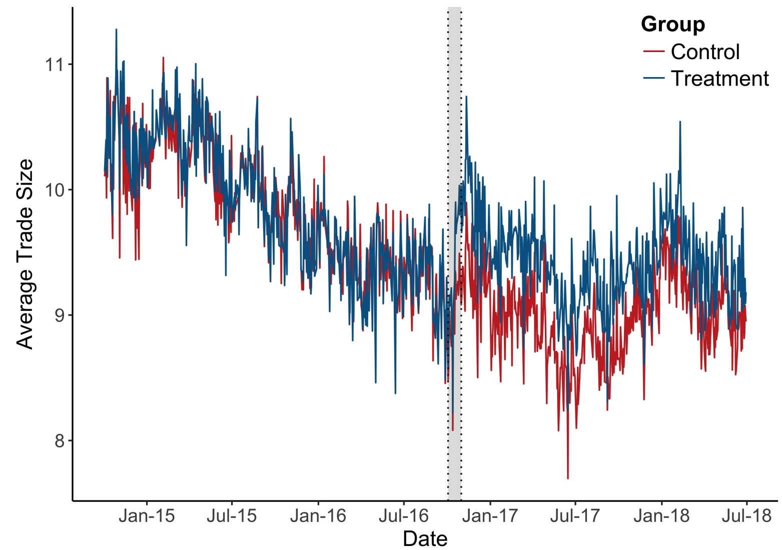
(a) Cancel-to-Trade Ratio (CTR)



(b) Trade-to-Order Ratio (TOR)



(c) Odd Lot Trade Ratio (OLR)



(d) Average Trade Size (ATS)

Figure 2

Time-series of Algorithmic Trading by Treatment/Control

This figure presents the time-series of the equal-weighted averages by treatment group in the SEC Tick Size Pilot Study for the four algorithmic trading proxies described in the Appendix. The shaded area between the dotted lines represents the phase-in period of treatment in the tick size pilot from October 3, 2017 to October 31, 2017.

Table 2
The Effect of Tick Size on Algorithmic Trading

Panel A: Daily Algorithmic Trading

	Dependent variable:							
	Odd Lot Ratio (*OLR*)		*Cancel-to-Trade Ratio* (*CTR*)		*Trade-to-Order Ratio* (*TOR*)		*Average Trade Size* (*ATS*)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	4.509		−11.445		0.840		−8.525	
	(22.266)***		(−21.679)***		(19.979)***		(−12.106)***	
Treatment	0.119	0.124	0.778	0.780	−0.063	−0.065	0.220	0.198
	(0.312)	(0.326)	(0.918)	(0.919)	(−0.951)	(−0.976)	(0.172)	(0.154)
Post × *Treatment*	−1.440	−1.445	−4.407	−4.419	0.566	0.568	4.278	4.303
	(−5.837)***	(−5.868)***	(−6.996)***	(−7.000)***	(10.892)***	(10.931)***	(4.406)***	(4.432)***
Date FEs	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,514,305	1,514,305	1,484,320	1,484,320	1,531,823	1,531,823	1,483,978	1,483,978
Adjusted R^2	0.016	0.026	0.048	0.067	0.049	0.070	0.006	0.016

Panel B: Algorithmic Trading Around Earnings Announcements

	Dependent variable:							
	$OLR^{[-1,1]}$	*Abn.* $OLR^{[-1,1]}$	$CTR^{[-1,1]}$	*Abn.* $CTR^{[-1,1]}$	$TOR^{[-1,1]}$	*Abn.* $TOR^{[-1,1]}$	$ATS^{[-1,1]}$	*Abn.* $ATS^{[-1,1]}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	−0.141	−0.097	−0.249	−1.179	−0.010	0.083	1.509	1.097
	(−0.341)	(−0.581)	(−0.270)	(−2.594)***	(−0.105)	(1.650)*	(0.959)	(1.778)*
Post × *Treatment*	−0.956	0.239	−2.599	2.085	0.611	0.042	2.509	−0.618
	(−5.482)***	(1.239)	(−2.256)**	(3.057)***	(4.709)***	(0.495)	(2.960)***	(−0.983)
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,184	21,182	21,138	21,136	21,240	21,238	21,077	21,073
Adjusted R^2	0.024	0.002	0.058	0.016	0.071	0.014	0.013	0.002

This table presents results from the difference-in-difference analyses of the effect of treatment in the SEC Tick Size Pilot study on algorithmic trading. Calculation of all dependent variables are as described in the Appendix, and represent various proxies for algorithmic trading. Dependent variables of the form $Y^{[T_0,T_1]}$ (*Abn.* $Y^{[T_0,T_1]}$) represent the average (abnormal) value for variable Y from days T_0 to T_1 from the earnings announcement. *Post* is an indicator variable which takes a value of one after the phase-in period of treatment groups, after October 31, 2016. *Treatment* is an indicator variable taking a value of one for those securities assigned to receive treatment in the pilot study (e.g., those assigned to groups G1, G2 or G3) and zero for control firms. All estimates are based on the two-year period surrounding the implementation of the tick size pilot, excluding the phase-in period, as described in Section 4. Two-way cluster robust t-statistics, clustered at the observation level, are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 3
The Effect of Tick Size on Bid-Ask Spreads and Volume

Panel A: Volume

	Dependent variable:				
	$VOL^{[-5,-1]}$	$VOL^{[-1,1]}$	$VOL^{[0,5]}$	$Abn.\ VOL^{[-1,1]}$	$Abn.\ VOL^{[0,5]}$
	(1)	(2)	(3)	(4)	(5)
$Treatment$	15.036	21.304	16.634	7.998	4.121
	$(1.853)^{*}$	(1.113)	(1.099)	(0.628)	(0.481)
$Post \times Treatment$	−35.954	−104.420	−85.556	−68.843	−52.571
	$(-5.934)^{***}$	$(-7.895)^{***}$	$(-7.814)^{***}$	$(-7.183)^{***}$	$(-6.450)^{***}$
Quarter FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	24,635	24,635	24,635	24,635	24,635
Adjusted R^2	0.247	0.191	0.211	0.101	0.095

Panel B: Effective Spread

	Dependent variable:				
	$SPD^{[-5,-1]}$	$SPD^{[-1,1]}$	$SPD^{[0,5]}$	$Abn.\ SPD^{[-1,1]}$	$Abn.\ SPD^{[0,5]}$
	(1)	(2)	(3)	(4)	(5)
$Treatment$	2.314	1.031	1.207	−1.184	−1.087
	(0.616)	(0.263)	(0.321)	(−1.003)	(−1.459)
$Post \times Treatment$	23.616	23.890	24.012	1.510	1.414
	$(12.249)^{***}$	$(11.134)^{***}$	$(12.472)^{***}$	(0.820)	(1.018)
Quarter FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	24,635	24,635	24,635	24,635	24,635
Adjusted R^2	0.357	0.341	0.361	0.002	0.004

This table presents results from the difference-in-difference analyses of the effect of treatment in the SEC Tick Size Pilot study on volume and bid-ask spread. The dependent variables of the form $Y^{[T_0,T_1]}$, are as described in the Appendix, and represent the average value for variable Y from days T_0 to T_1 from the earnings announcement. $Abn.\ Y^{[T_0,T_1]}$ represents the abnormal value of variable Y, defined to be the difference between $Y^{[T_0,T_1]}$ and $Y^{[-2,-22]}$. *Post* is an indicator variable which takes a value of one after the phase-in period of treatment groups, after October 31, 2016. *Treatment* is an indicator variable taking a value of one for those securities assigned to receive treatment in the pilot study (e.g., those assigned to groups G1, G2 or G3) and zero for control firms. All estimates are based on the two-year period surrounding the implementation of the tick size pilot, excluding the phase-in period, as described in Section 4. Two-way cluster robust t-statistics, stock and quarter, are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 4
The Effect of Tick Size on Absolute Cumulative Abnormal Returns

	Dependent variable:					
	$ACAR^{[0,1]}$		$ACAR^{[0,5]}$		$ACAR^{[0,10]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Treatment$	−0.003	0.017	−0.171	−0.112	−0.155	−0.045
	(−0.017)	(0.103)	(−0.929)	(−0.631)	(−0.938)	(−0.304)
$Post \times Treatment$	−0.396	−0.406	−0.407	−0.373	−0.503	−0.492
	(−2.212)**	(−2.248)**	(−1.655)*	(−1.507)	(−2.526)**	(−2.509)**
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	25,013	24,639	25,013	24,639	25,013	24,639
Adjusted R^2	0.007	0.036	0.009	0.053	0.010	0.065

This table presents results from the difference-in-difference analyses of the effect of treatment in the SEC Tick Size Pilot study on absolute cumulative abnormal returns (ACAR) from the day of earnings announcements onward. Calculation of $ACAR^{[0,T]}$ is as described in the Appendix, and represents the unsigned market response to earnings information. *Post* is an indicator variable which takes a value of one after the phase-in period of treatment groups, after October 31, 2016. *Treatment* is an indicator variable taking a value of one for those securities assigned to receive treatment in the pilot study (e.g., those assigned to groups G1, G2 or G3) and zero for control firms. All estimates are based on the two-year period surrounding the implementation of the tick size pilot as described in Section 4, and all control variables are as described in Section 3. Two-way cluster robust t-statistics, by stock and quarter, are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

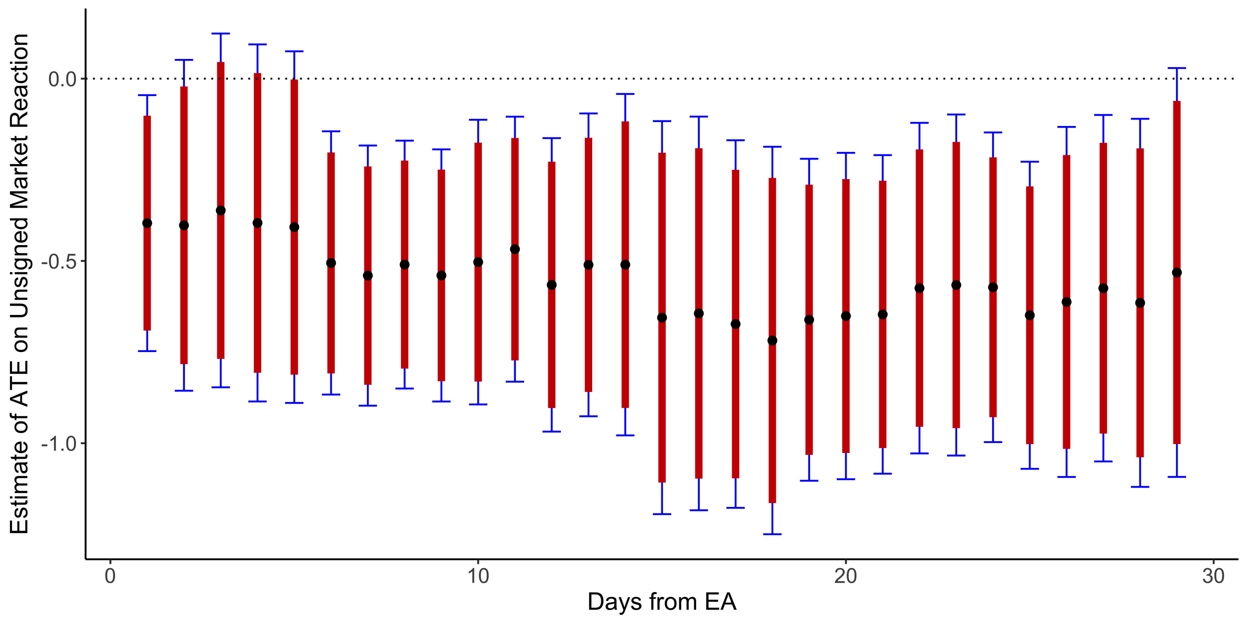


Figure 3
The ATE of Tick Size on Unsigned Market Reactions (Post-EA)
This figure presents the estimates of the average treatment effect (ATE) of tick size on absolute cumulative abnormal returns following earnings announcements. Regressions are run following Equation 1 of the form:

$$ACAR_{i,t}^{[0,T]} = \alpha_t + \delta Treatment_i + \beta Post_t \times Treatment_i + \epsilon_{i,t}$$

where $ACAR_{i,t}^{[0,T]}$ is as described in the Appendix. All independent variables are discussed in Section 3, and all parameter estimates are calculated from the full sample described in Section 4. Black dots represent the estimates of $\hat{\beta}$ are presented for various ending dates, T, represented on the x-axis. The blue and red bars represent the 95% and 90% confidence intervals, respectively, for each estimate calculated using two-way cluster robust standard errors clustered by quarter and stock.

Table 5
The Effect of Tick Size on Future Earnings Response Coefficients

	Dependent variable:					
	$RET^{[-60,-1]}$			$CAR^{[-60,-1]}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	1.318	1.097		0.008	−0.024	
	(0.439)	(0.363)		(0.014)	(−0.041)	
Treatment	−0.306	−0.313	−0.331	−0.036	−0.100	−0.103
	(−2.630)***	(−2.325)**	(−2.014)**	(−0.324)	(−0.697)	(−0.711)
SUE	0.157	0.124	0.100	0.162	0.097	0.096
	(3.405)***	(2.811)***	(1.842)*	(3.757)***	(2.092)**	(2.061)**
$Treatment \times SUE$	−0.039	−0.026	−0.026	−0.024	−0.007	−0.006
	(−0.729)	(−0.518)	(−0.468)	(−0.530)	(−0.182)	(−0.148)
$Post \times SUE$	−0.102	−0.091	−0.080	−0.109	−0.095	−0.094
	(−1.565)	(−1.509)	(−1.196)	(−1.664)*	(−1.550)	(−1.528)
$Post \times Treatment$	1.362	1.354	1.316	1.038	1.014	1.018
	(3.491)***	(3.422)***	(3.444)***	(3.556)***	(3.428)***	(3.383)***
$Post \times Treatment \times SUE$	0.181	0.177	0.198	0.175	0.169	0.171
	(2.336)**	(2.803)***	(2.638)***	(2.327)**	(2.548)**	(2.564)**
Quarter FEs	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Observations	24,731	24,321	24,321	24,731	24,321	24,321
Adjusted R^2	0.005	0.010	0.096	0.003	0.008	0.010

This table presents results from the difference-in-difference analyses of the effect of treatment in the SEC Tick Size Pilot study on the markets response to upcoming earnings announcements. Calculation of *RET* and *CAR* are as described in the Appendix, and represents the signed market response to earnings information. *Post* is an indicator variable which takes a value of one after the phase-in period of treatment groups, after October 31, 2016. *Treatment* is an indicator variable taking a value of one for those securities assigned to receive treatment in the pilot study (e.g., those assigned to groups G1, G2 or G3) and zero for control firms. *SUE* is the standardized unexpected earnings for the quarter of announcement using a random-walk model as described in the Appendix. All estimates are based on the two-year period surrounding the implementation of the tick size pilot as described in Section 4, and all control variables are as described in Section 3. Two-way cluster robust t-statistics, stock and quarter, are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

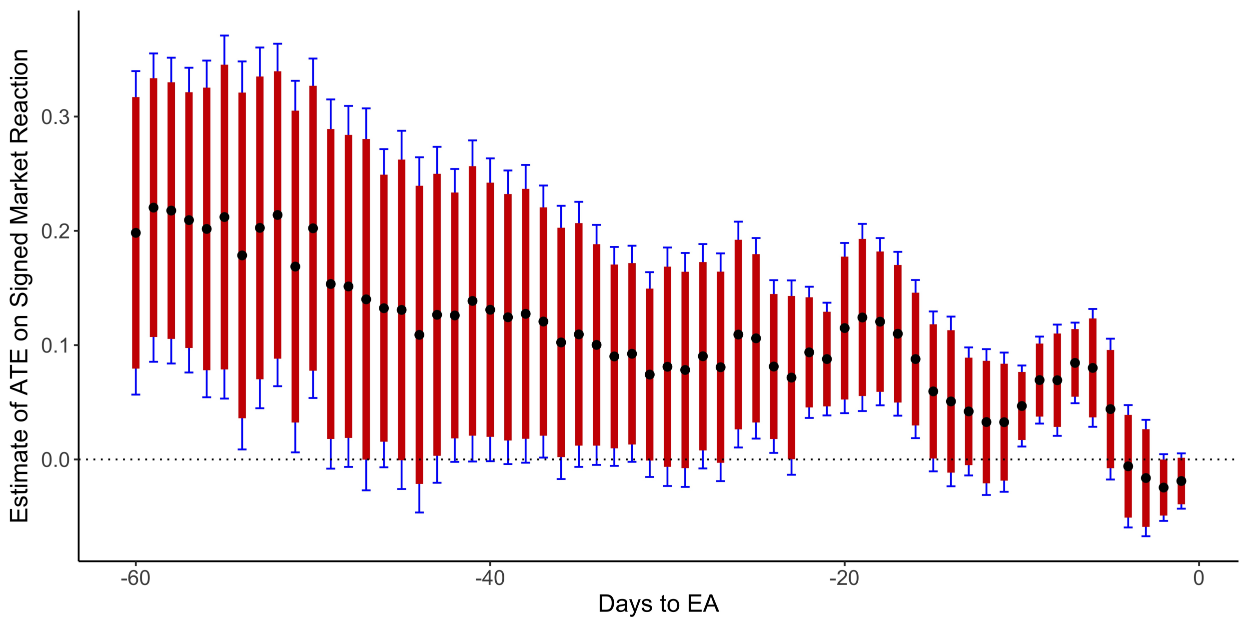


Figure 4
The ATE of Tick Size on Future Earnings Response Coefficients
This figure presents the estimates of the average treatment effect (ATE) of tick size on cumulative abnormal returns preceding earnings announcements. Regressions are run following Equation 2 of the form:

$$\begin{aligned} CAR_{i,t}^{[T,-1]} &= \alpha_t + \beta_1 Treatment_i + \beta_2 SUE_{i,t} + \beta_3 Treatment_i \times SUE_{i,t} \\ &+ \beta_4 Post_t \times SUE_{i,t} + \beta_5 Post_t \times Treatment_i \\ &+ \beta_6 Post_t \times Treatment_i \times SUE_{i,t} + \gamma SUE_{i,t-1} + \epsilon_{i,t} \end{aligned}$$

where $CAR_{i,t}^{[T,-1]}$ is as described in the Appendix. All independent variables are discussed in Section 3, and all parameter estimates are calculated from the full sample described in Section 4. Black dots represent the estimates of $\hat{\beta}_6$ are presented for various calculation starting dates, T, represented on the x-axis. The blue and red bars represent the 95% and 90% confidence intervals, respectively, for each estimate calculated using two-way cluster robust standard errors clustered by quarter and stock.

Table 6
The Effect of Tick Size on Announcement EDGAR Activity

	Dependent variable:					
	$ESV^{[-40,-1]}$	$ESV^{[-30,-1]}$	$ESV^{[-20,-1]}$	$ESV^{[-10,-1]}$	$ESV^{[-5,-1]}$	$ESV^{[-1,1]}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Treatment$	9.702	4.895	4.923	1.223	2.195	2.131
	(0.487)	(0.327)	(0.492)	(0.235)	(0.460)	(0.804)
$Post \times Treatment$	2.736	8.287	4.003	4.220	3.837	2.172
	(0.297)	(1.152)	(2.346)**	(3.422)***	(3.467)***	(4.440)***
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,879	18,879	18,879	18,879	18,879	18,879
Adjusted R^2	0.236	0.227	0.223	0.207	0.195	0.166

This table presents results from the difference-in-difference analyses of the effect of treatment in the SEC Tick Size Pilot study on information acquisition through EDGAR in the period leading up to firm's earnings announcements. Calculation of $ESV^{[T_0,T_1]}$ is as described in the Appendix, and acts as a proxy for the amount of information acquired arounding earnings announcements. *Post* is an indicator variable which takes a value of one after the phase-in period of treatment groups, after October 31, 2016. *Treatment* is an indicator variable taking a value of one for those securities assigned to receive treatment in the pilot study (e.g., those assigned to groups G1, G2 or G3) and zero for control firms. All estimates are based on the two-year period surrounding the implementation of the tick size pilot as described in Section 4, and all control variables are as described in Section 3. Two-way cluster robust t-statistics, stock and quarter, are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 7
The Effect of Tick Size on Alternative Proxies for Pre-announcment Information Acquisition

	Dependent variable:					
	SYNCH			*JUMP*		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	−0.394	−0.511		0.057	0.047	
	(−2.469)**	(−2.969)***		(1.628)	(1.232)	
Treatment	0.010	−0.037	−0.036	0.065	0.067	0.067
	(0.158)	(−0.989)	(−0.931)	(1.603)	(1.658)*	(1.671)*
Post × *Treatment*	−0.080	−0.098	−0.098	−0.091	−0.099	−0.100
	(−3.819)***	(−3.490)***	(−3.313)***	(−1.627)	(−1.697)*	(−1.720)*
Quarter FEs	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Observations	25,010	24,636	24,636	24,717	24,347	24,347
Adjusted R^2	0.012	0.321	0.348	0.000	0.001	0.001

This table presents results from the difference-in-difference analyses of the effect of treatment in the SEC Tick Size Pilot study on information acquisition around earnings announcements using the the Morck et al. (2000) stock price synchronicity measure and the Weller (2017) "jump ratio" measure. Calculation of dependent variables are described in the Appendix, and act as a proxies for the amount of firm-specific information produced and incorporated into a stocks price in the pre-announcement period. *Post* is an indicator variable which takes a value of one after the phase-in period of treatment groups, after October 31, 2016. *Treatment* is an indicator variable taking a value of one for those securities assigned to receive treatment in the pilot study (e.g., those assigned to groups G1, G2 or G3) and zero for control firms. All estimates are based on the two-year period surrounding the implementation of the tick size pilot as described in Section 4, and all control variables are as described in Section 3. Two-way cluster robust t-statistics, stock and quarter, are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 8
The Effect of Tick Size on Post Earnings Announcement Drift

	Dependent variable: $CAR^{[2,60]}$			
	(1)	(2)	(3)	(4)
SUE Rank	0.341	0.352	0.297	0.296
	(3.488)***	(3.135)***	(3.064)***	(3.000)***
Post		−1.507	−1.312	
		(−1.361)	(−1.227)	
Treatment		−0.112	−0.099	−0.102
		(−0.175)	(−0.163)	(−0.164)
Treatment × *SUE Rank*		0.033	0.021	0.022
		(0.473)	(0.317)	(0.325)
Post × *SUE Rank*		0.075	0.073	0.071
		(0.441)	(0.429)	(0.410)
Post × *Treatment*		1.021	0.908	0.874
		(0.906)	(0.828)	(0.779)
Post × *Treatment* × *SUE Rank*		−0.032	−0.009	−0.004
		(−0.204)	(−0.060)	(−0.025)
Quarter FEs	Yes	No	No	Yes
Period	Pre-Treatment	All	All	All
Controls	Yes	No	Yes	Yes
Observations	13,984	24,731	24,639	24,639
Adjusted R^2	0.010	0.004	0.009	0.011

This table presents results from the difference-in-difference analyses of the effect of treatment in the SEC Tick Size Pilot study on the post earnings earnings announcement drift. The dependent variable, $CAR^{[2,60]}$, measures the 60-day post-announcement cumulative abnormal returns, as described in the Appendix. *SUE Rank* is the quarterly decile ranking of standardized unexpected earnings (measured using a random-walk model as described in the Appendix). *Post* is an indicator variable which takes a value of one after the phase-in period of treatment groups, after October 31, 2016. *Treatment* is an indicator variable taking a value of one for those securities assigned to receive treatment in the pilot study (e.g., those assigned to groups G1, G2 or G3) and zero for control firms. All estimates are based on the two-year period surrounding the implementation of the tick size pilot, excluding the phase-in period, as described in Section 4. Two-way cluster robust t-statistics, stock and quarter, are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 9
The Effect of Tick Size on the Relative Incorporation of Post-Earnings News

	Dependent variable:					
	$POST\text{-}JUMP^{[-1,21]}$			$POST\text{-}JUMP^{[-1,60]}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	−0.035	−0.042		0.063	0.053	
	(−0.902)	(−1.068)		(1.309)	(1.128)	
Treatment	−0.011	−0.011	−0.011	−0.077	−0.080	−0.080
	(−0.333)	(−0.347)	(−0.343)	(−1.487)	(−1.523)	(−1.521)
Post × *Treatment*	0.061	0.062	0.063	−0.008	−0.008	−0.009
	(1.139)	(1.174)	(1.187)	(−0.125)	(−0.129)	(−0.138)
Quarter FEs	No	No	Yes	No	No	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Observations	24,672	24,304	24,304	24,822	24,451	24,451
Adjusted R^2	0.000	0.0003	0.0003	0.0003	0.001	0.0005

This table presents results from the difference-in-difference analyses of the effect of treatment in the SEC Tick Size Pilot study on the relative market response between the days immediately around an earnings announcement and the days following it. The dependent variable is a variant of the Weller (2017) "jump ratio" measure. Specifically, *POST-JUMP* is the ratio of the cumulative abnormal return from day -1 to day +2, divided by the cumulative abnormal return from day -1 to day +k, where k is either +21 or +60. A higher *POST-JUMP* ratio indicates faster price discovery in the post announcement period. *Post* is an indicator variable which takes a value of one after the phase-in period of treatment groups, after October 31, 2016. *Treatment* is an indicator variable taking a value of one for those securities assigned to receive treatment in the pilot study (e.g., those assigned to groups G1, G2 or G3) and zero for control firms. All estimates are based on the two-year period surrounding the implementation of the tick size pilot as described in Section 4, and all control variables are as described in Section 3. Two-way cluster robust t-statistics, stock and quarter, are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.