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The effect of tick size on managerial learning from stock prices☆

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A B S T R A C T

We investigate the effect of tick size, a key feature of market microstructure, on managerial learning from stock prices. Using a randomized controlled tick-size experiment, the 2016 Tick Size Pilot Program, we find that a larger tick size increases a firm's investment sensitivity to stock prices, suggesting that managers glean more new information from stock prices to guide their investment decisions as the tick size increases. Consistently, we also find that changes in managerial beliefs, as reflected in adjustments of forecasted capital expenditures, respond more strongly to market feedback under a larger tick size. Additional evidence suggests the following mechanism through which tick size affects managerial learning: a larger tick size reduces algorithmic trading, in turn encouraging fundamental information acquisition. Increased fundamental information acquisition generates incremental information about growth opportunities, macroeconomic factors, and industry factors, with respect to which the market has a comparative information advantage over management.

1. Introduction

It is well known in the accounting and finance literature that stock prices can reveal useful information that is unknown to managers and that managers learn from this information and use it to guide their decision-making (Bond et al., 2012). This managerial-learning perspective motivates Bond et al. (2012) to introduce a new notion of price efficiency, "revelatory price efficiency" (RPE), which captures the extent to which stock prices *reveal* new information to managers. RPE differs from the conventional notion of price efficiency, "forecasting price efficiency" (FPE), which indicates how well stock prices *predict*

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fundamental values and captures the total volume of information in prices. Bond et al. (2012) contend that the value of secondary markets depends on RPE. The greater the volume of new information in stock prices (i.e., higher RPE), the greater the extent to which managers will base their real decisions on stock prices (i.e., more learning) (Edmans et al., 2017).

In this paper, we study the effects of tick size (i.e., a minimum price increment), a key parameter of microstructure, on RPE and managerial learning from stock prices. Our research question is motivated by a recent randomized controlled experiment, the "Tick Size Pilot Program" (TSP), conducted by the US Securities and Exchange Commission (SEC) with the goal of improving market-making, liquidity, and thereby capital formation for small- and mid-capitalization companies by increasing the tick size (e.g., SEC, 2012). Using the TSP, prior studies have examined the effects of tick size on liquidity (e.g., Chung et al., 2020), price behaviors (e.g., Albuquerque et al., 2020; Lee and Watts, 2021), and shareholder monitoring (Ahmed et al., 2020; Li and Xia, 2021). We broaden the scope of this literature by exploring the real effects of tick size from the perspective of managerial learning.

Although evidence in the microstructure literature generally suggests that a larger tick size reduces FPE with respect to existing information (e.g., Holden et al., 2014), the impact of tick size on RPE is ex-ante unclear, for at least two reasons. First, it is unclear how tick size affects information acquisition. On the one hand, a larger tick size reduces general liquidity (Bessembinder, 2003; SEC, 2012; Yao and Ye, 2018), which in turn discourages information acquisition (Holmstrom and Tirole, 1993; Jayaraman and Milbourn, 2012). On the other hand, a larger tick size reduces algorithmic trading (AT) (Lee and Watts, 2021),[1] which in turn encourages fundamental information acquisition (FIA) (Weller, 2017; Lee and Watts, 2021).

Second, it is also unclear whether RPE rises or falls with total information acquisition. For example, Lee and Watts (2021) show that a larger tick size increases the non-robotic search volume on the SEC's Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) for corporate disclosures, which contain information that managers already have. Whether an increase in the acquisition of information that is *known* to managers also implies an increase in the acquisition of information that is *unknown* to managers depends on whether factors that are unknown to managers are complements to or substitutes for known factors (Gao and Liang, 2013; Goldstein and Yang, 2019).[2] Given these complex and opposing economic forces, the impact of tick size on RPE and thereby managerial learning remains an empirical question.

We use the TSP to study the causal effects of tick size on RPE. During the TSP, the SEC randomly selected 1200 stocks (treatment stocks) from the universe of 2399 small- and mid-cap stocks and increased the tick size for those stocks from 1 cent to 5 cents for two years starting in October 2016. The tick size for the remaining 1199 stocks (control stocks) remained unchanged at 1 cent. As the extent of RPE is not directly observable, we follow the learning literature (e.g., Chen et al., 2007; Foucault and Frésard, 2012; Edmans et al., 2017; Jayaraman and Wu, 2019) to infer RPE from the sensitivity of future investment to current q, commonly known as investment$-q$ sensitivity. The underlying intuition is that investment$-q$ sensitivity will be stronger when movements in stock prices are more likely to originate from information that is new to managers than from information that was already known to them (Goldstein et al., 2022). If a larger tick size causes stock prices to convey more (less) information that is new to managers, investment$-q$ sensitivity should increase (decrease).

We find that, during the TSP, investment$-q$ sensitivity rises 0.82% higher for treatment firms than for control firms. This increase in investment$-q$ sensitivity is economically significant, representing a 58% increase relative to the prevailing pre-TSP sensitivity.[3] We also find that treatment and control firms behave similarly before the TSP and that the treatment effect appears only after the implementation of the TSP. In addition, the treatment effect holds when we compare the treatment firms with a set of firms that are similar to the control firms but were not included in the TSP (Rindi and Werner, 2019). Finally, we find no change in the sensitivity of investment to cash flows, which is a non-price measure of investment opportunities. These findings bolster our inference that the increase in investment-q sensitivity is due to the larger tick size.

Although an increase in investment$-q$ sensitivity is consistent with an increase in RPE and managerial learning, it could be driven by other channels. The challenge in ascribing our finding solely to an increase in learning is the absence of a direct proxy for managerial learning (Edmans et al., 2017). We adopt two strategies to support the learning interpretation of our findings. Our first strategy is to provide more direct evidence of learning by examining managerial beliefs reflected in capital expenditure (capex) forecasts made by managers. Even though publicly disclosed capex forecasts are still proxies for managers' internal forecasts, the link between these two types of forecasts is likely to be strong (Hemmer and Labro, 2008; Dichev et al., 2013; Zuo, 2016). Using management capex forecasts, Jayaraman and Wu (2020) show that managers adjust forecasted annual capex in response to the short-window market reaction to their capex forecasts, suggesting that managers revise their beliefs about investment opportunities based on market feedback. Although management capex forecasts are infrequent in the TSP sample, we find a stronger association, during the TSP, between managers' adjustment of forecasted capex and market reaction to capex forecasts in treatment firms than in control firms. This finding suggests that managers glean more

[1] AT is the use of computer algorithms to automatically submit orders and manage those orders after submission (Hendershott et al., 2011).

[2] On the one hand, an increase in the acquisition of information that is *known* to managers may crowd out the acquisition of information that is *unknown* to managers. On the other hand, if traders' comparative information advantage lies in interpreting the implications of corporate disclosures (e.g., Fishman and Hagerty, 1989; Jayaraman and Wu, 2020), acquiring more information that is *known* to managers may lead to an increase in the acquisition of information that is *unknown* to the managers.

[3] Our results are based on small- and mid-cap firms in the TSP, which have less precise internal information (e.g., Doyle et al., 2007; Feng et al., 2009) and therefore have a stronger incentive to learn from the market. We therefore recommend caution when generalizing our results, in particular regarding their economic magnitude, to large firms.

information from stock prices that they use to revise their beliefs as the tick size increases, consistent with the inference of an increase in learning based on investment−q sensitivity.

Our second strategy for reinforcing the learning interpretation of our findings is to investigate the underlying mechanism and show that it runs through managerial learning. The earlier discussion suggests the following mechanism that might be at work: a larger tick size reduces AT and thereby encourages FIA (Lee and Watts, 2021). Increased FIA generates information that is new to managers and consequently enhances managerial learning from stock prices, as reflected in higher investment−q sensitivity. The results of a series of cross-sectional tests are consistent with this learning-based mechanism. We find that the increase in investment−q sensitivity during the TSP is concentrated in treatment firms that experience greater reductions in AT and those that experience a greater increase in non-robotic EDGAR search volume, a common measure of FIA (Lee and Watts, 2021),[4] consistent with the hypothesized roles of AT and FIA.

We also find that the treatment effect of the TSP is concentrated in firms with greater exposure to external factors that operate beyond managers' control. The treatment effect is observed for growth firms, which have greater exposure to growth opportunities, but is absent for value firms. It also concentrates in firms whose earnings co-move more strongly with macroeconomic factors (i.e., Gross Domestic Product and energy prices). Furthermore, during the TSP, non-TSP firms' investments respond more strongly to the stock prices of industry peers in the TSP treatment group but less strongly to the stock prices of industry peers in the TSP control group. These findings suggest that increased FIA under a larger tick size generates additional information about growth opportunities, macroeconomic factors, and industry factors, regarding which the learning literature maintains that the market is more likely to produce information that is unknown to managers (e.g., Bond et al., 2012; Bai et al., 2016; Goldstein et al., 2022).

In our last set of analyses, we assess alternative explanations for the higher investment−q sensitivity during the TSP that we observe. One alternative explanation is that a larger tick size loosens firms' financial constraints, enabling them to vary investment more readily in response to investment opportunities (the financial-constraint channel). The effect of tick size on financial constraints may result from increased market-making by brokers and dealers (SEC, 2012), allowing firms to obtain external financing more easily. We find, however, that the increase in investment−q sensitivity is concentrated in firms that were less financially constrained to begin with. This finding is inconsistent with the financial-constraint channel but consistent with the managerial learning channel, as less constrained firms are better able to adjust investments in response to information contained in stock prices (e.g., Edmans et al., 2017; Jayaraman and Wu, 2019). The increase in investment−q sensitivity during the TSP also holds when controlling for the effects of FPE and shareholder monitoring (Ahmed et al., 2020)—two additional alternative explanations of our baseline results.

To the best of our knowledge, our study is the first to document a plausibly causal effect of tick size on corporate policies via the managerial-learning perspective. In so doing, it broadens the economic consequences of tick size in at least two streams of literature. One stream of the microstructure literature studies the effects of tick size on price efficiency inferred from stock-price behavior (e.g., Rindi and Werner, 2019; Albuquerque et al., 2020; Chung et al., 2020; Lee and Watts, 2021). We extend these studies by inferring price efficiency from managerial beliefs and actions, which provides direct evidence of the real effects of tick size. Another stream of the accounting and corporate finance literature examines the economic consequences of tick size on corporate policies, mainly through the shareholder-monitoring channel (Bharath et al., 2013; Edmans et al., 2013; Norli et al., 2015).[5] For example, two recent studies examine the effects of the TSP on earnings management through the monitoring channel (Ahmed et al., 2020; Li and Xia, 2021). We extend this literature by uncovering a new channel through which tick sizes affect corporate policies—managerial learning from stock prices.

Our study also adds to the learning literature. While evidence of learning is well established (e.g., Chen et al., 2007; Dessaint et al., 2019), less is known about institutional features that facilitate or impede learning (Jayaraman and Wu, 2020). An emerging body of literature shows how features of the corporate information environment, such as insider-trading enforcement (Edmans et al., 2017), mandatory segment disclosure (Jayaraman and Wu, 2019), voluntary capex disclosure (Jayaraman and Wu, 2020), and information-dissemination technologies (Goldstein et al., 2022), facilitate or impede managerial learning. We extend this literature by showing that tick size, a microstructure feature of the secondary financial market, can facilitate or impede managerial learning. Furthermore, while it has long been assumed in the learning literature that managers learn information about macroeconomic trends and industry factors from stock prices (e.g., Bond et al., 2012; Goldstein et al., 2022), there is little evidence to date that confirms this assumption. We document a portfolio of evidence suggesting that such information drives the increase in managerial learning caused by a larger tick size.

Finally, our results contribute to the interplay between market microstructure and financial reporting/disclosure. We show that an increase in the tick size strengthens the feedback effect generated by voluntary capex disclosure (Jayaraman and Wu, 2020). Early studies in this interdisciplinary field show that financial reporting/disclosure affects liquidity (e.g., Lee et al., 1993; Chakrabarty and Moulton, 2012). Recent studies show that innovations in microstructure affect price discovery in

[4] EDGAR search volume is one observable action related to FIA. The learning-based mechanism does not, however, require FIA to be restricted to corporate disclosures on EDGAR.

[5] Gao and Liang (2013) claim that the major difference between the monitoring role and the informational feedback role of stock prices is that each exploits a different type of information. The former relies mainly on backward-looking information in stock prices reflecting managers' past actions, while the latter takes advantage of forward-looking information. Forward-looking information in stock prices in fact often impedes monitoring.

financial reporting/disclosure (e.g., Chordia and Miao, 2020; Bhattacharya et al., 2020). Our findings extend this literature by documenting an impact of microstructure on the role of financial reporting/disclosure in real decisions.

The remainder of the paper is organized as follows: In Section 2, we review the related literature. In Section 3, we describe the institutions of the TSP, our research design, and sample selection. We present the results indicating the effects of tick size on investment−q sensitivity in Section 4 and the results of the tests of managerial learning in Section 5. We address alternative explanations in Section 6 and conclude in Section 7.

2. Related literature

2.1. *Effects of tick size on price efficiency*

The microstructure literature has long examined the effects of tick size on price efficiency. For example, Chordia et al. (2008), Chordia et al. (2014), and Albuquerque et al. (2020) show that a reduction in the tick size improves FPE with respect to existing information.[6] The effects become more nuanced, however, in the presence of information acquisition because tick size affects information acquisition in opposite directions through two distinct channels: the liquidity channel and the AT channel. In the liquidity channel, a larger tick size reduces the overall level of liquidity (Bessembinder, 2003; SEC, 2012; Yao and Ye, 2018), which in turn reduces traders' incentive to acquire fundamental information (Holmstrom and Tirole, 1993; Jayaraman and Milbourn, 2012). In the AT channel, however, a wider tick size reduces AT (Lee and Watts, 2021), which in turn encourages FIA (Weller, 2017). AT constrains FIA because order-anticipation strategies that algorithmic traders employ reduce prospective rents for information acquirers and thereby weaken their incentives to obtain information in the first place (e.g., Stiglitz, 2014; Menkveld, 2016; Baldauf and Mollner, 2020).[7] Lee and Watts (2021) show that, consistent with the AT channel, the non-robotic search volume of corporate filings on SEC EDGAR around earnings announcements, a measure of FIA, increases with tick size during the TSP, while AT decreases at the same time. Relatedly, Rindi and Werner (2019) and Chung et al. (2020) find that price impact, the adverse-selection component of the bid−ask spread, increases to a greater extent for TSP treatment stocks than for control stocks. They interpret their findings as suggesting that traders have stronger incentives to gather and trade on private information when the tick size is larger. We extend these studies by examining whether the increased information acquisition generates information that is new to managers and thereby has a real effect through managerial learning.

2.2. *Managerial learning from stock prices*

Managerial learning from stock prices has recently attracted great interest among accounting researchers (e.g., Zuo, 2016; Jayaraman and Wu, 2019, 2020; Chen et al., 2021). It is now well known that managers might not be aware of all facets of a firm's operations and might look to stock prices to glean new information to guide corporate decisions, such as investment and earnings forecasts (Bond et al., 2012; Zuo, 2016; Edmans et al., 2017).[8] Stock prices provide an ideal mechanism for performing this role as they can aggregate information held by dispersed investors (Hayek, 1945). Less is known, though, about institutional features that facilitate or impede managerial learning (Jayaraman and Wu, 2020). An important stream of literature in accounting and finance thus focuses on how financial reporting and disclosure, which directly affect a firm's information environment, shape managerial learning.

Theoretical work in this literature generates conflicting predictions regarding the effects of disclosures on managerial learning. Gao and Liang (2013) present a model in which corporate value depends on two factors—assets-in-place and growth opportunities—which are affected by a common source of uncertainty. They show that greater disclosure crowds out traders' private information acquisition and therefore reduces RPE. In contrast, Goldstein and Yang (2019) show that disclosure can improve RPE if it pertains to a factor that real decision-makers already know about and when the market is very effective in processing information.

[6] Chordia et al. (2008) and Chordia et al. (2014) show that stock prices follow random walks more closely under a smaller tick size, as indicated by weaker post-decimalization return autocorrelations and short-horizon return predictability. Albuquerque et al. (2020) find a greater increase in price delays in response to news for TSP treatment firms than for control firms. One explanation of these findings is that a smaller tick size improves liquidity, which in turn stimulates arbitrage activity to incorporate existing information into stock prices.

[7] According to SEC (2010), order anticipation "*involves any means to ascertain the existence of a large buyer (seller) that does not involve violation of a duty, misappropriation of information, or other misconduct*" and is widely used by algorithmic traders. For example, algorithmic traders specializing in liquidity provision can avoid adverse selection by employing sophisticated pattern-recognition software to ascertain from publicly available information the existence of a large buyer or seller and then use their speed advantage to cancel their quotes to avoid trading with informed traders (Weller, 2017). Aggressive-side (i.e., liquidity taking) algorithmic traders can also use sophisticated orders to "ping" different market centers in an attempt to locate and trade in front of large buyers and sellers, regardless of whether they are based on fundamental information or liquidity needs. This practice is commonly known as "front-running" (Li, 2014). Some algorithmic traders specialize in inferring fundamental investors' information from their past order flows and exploiting this information by trading ahead of fundamental investors using their speed advantage, a practice defined as "back-running" by Yang and Zhu (2020). These order-anticipation strategies, which are designed to avoid adverse selection and front-/back-run informed traders, reduce prospective rents obtained through information acquisition.

[8] Managers can also learn from other information sources, such as analysts (Martens and Sextroh, 2021) and institutional investors (Zhang, 2021).

Empirically, Jayaraman and Wu (2019) find that mandatory segment disclosure impedes managerial learning, as reflected in reduced investment−q sensitivity, suggesting that more disclosure about what a manager knows dissuades informed traders from impounding information that might be useful to the manager. Consistently, Goldstein et al. (2022) find that greater dissemination of corporate disclosures, generated by the implementation of the EDGAR system in the United States, crowds out investors' private information acquisition and reduces managerial learning from stock prices. Chen et al. (2021) find that managers issue fewer earnings forecasts as options trading on their stocks becomes more active and that, when managers disclose less, options trading has a stronger positive effect on investment−q sensitivity. Chen et al. (2021) argue that managers strategically reduce disclosure to avoid crowding out informed trading. We extend this literature by investigating the role of market microstructure in facilitating or impeding managerial learning. The idea that market microstructure is associated with managerial learning goes back at least to Chen et al. (2007). We contribute to the literature by utilizing the randomized controlled experiment of the TSP that allows for plausibly causal inferences regarding the effect of microstructure on managerial learning.

Dye and Sridha (2002) present another theoretical model where a manager solicits market feedback by voluntarily announcing a new strategy she is considering and then conditioning the decision to implement the new strategy on the extent of the market's price reaction to the announcement. Empirically, Jayaraman and Wu (2020) find that managers adjust their forecasted annual capex according to market reactions to their capex forecasts, indicating active use of voluntary capex disclosures to solicit market feedback. We extend their study by examining the effects of tick size on the market feedback solicited by voluntary capex disclosures.

One consensus view in the learning literature maintains that information that is new to managers most likely concerns external factors that are beyond managers' control, such as macroeconomic conditions, industry competition, and consumer demand (e.g., Dye and Sridha, 2002; Bond et al., 2012). For example, several learning models assume that managers are more likely to learn information about growth opportunities from the market, which requires analysis of these external factors (e.g., Gao and Liang, 2013; Goldstein and Yang, 2019; Goldstein et al., 2022). This assumption is consistent with prior evidence pertaining to the relative accuracy of management and analyst EPS forecasts (Hutton et al., 2012) and managerial learning from industry peers' stock prices (Foucault and Frésard, 2014).[9] We add to this evidence by showing that shocks to market microstructure have a stronger impact on managerial learning in firms where these external factors are more important.

3. Institutions, research design, and sample selection

We use the TSP to study the causal effects of tick size on RPE and managerial learning. In Subsection 3.1, we provide institutional details about the TSP. We discuss the regression specification and variable construction in Subsection 3.2 and sample selection in Subsection 3.3.

3.1. A controlled experiment: the Tick Size Pilot Program

The "Jumpstart Our Business Startups" (JOBS) Act, which was signed into law on April 5, 2012, directed the SEC to conduct a study to "*… Examine the impact that decimalization has had on the number of initial public offerings … [and] the impact that this change has had on liquidity for small and middle capitalization company securities and whether there is sufficient economic incentive to* support *trading operations in these securities in penny increments*" (SEC, 2012). This direction was partly motivated by American lawmakers and regulators who were concerned about the decline in the number of small firms seeking to raise equity capital from public markets over the previous decade (e.g., Doidge et al., 2017) and their conjecture that tick size was responsible for this decline.[10] In response, the SEC directed the Financial Industry Regulatory Authority (FINRA) and the National Securities Exchanges to develop an experimental pilot program. The resulting TSP was approved by the SEC in May 2015.[11]

The TSP included in its scope 2399 stocks, selected from the universe of Regulation National Market System (Reg NMS) securities that satisfy the following criteria[12]: (a) having a price of at least $1.50 on each trading day, a volume-weighted

[9] Hutton et al. (2012) show that analyst forecasts are more accurate than management forecasts when a firm's operations are more extensively exposed to broad macroeconomic factors, such as the business cycle and commodity prices. They argue that analysts have access to macroeconomic expertise as well as a broader perspective that enables them to infer the implications of macroeconomic forecasts for a firm and its customers, suppliers, and competitors. Foucault and Frésard (2014) show that a firm's investment responds not only to its own stock price but also to the prices of its industry peers. They argue that managers learn information about future demand for products and the dynamics of competition in a given industry from the valuations of industry peers.

[10] Supporters of a larger minimum tick size argue that a wider tick for small stocks will generate extra fees for brokerages. In turn, brokerages will use the additional fees to support research on small stocks via increased analyst coverage, which will reduce the cost of capital and improve capital formation for those small stocks (Weild and Kim, 2009; IPO Task Force, 2011; SEC, 2012). In untabulated results, we do not find a significant effect of tick size on analyst coverage during the TSP.

[11] Complete details regarding the TSP can be found at the FINRA website: http://www.finra.org/industry/tick-size-pilot-program.

[12] Rule 600(b) of Reg NMS defines "NMS security" as any security, other than an option, for which trade reports are made available pursuant to an effective transaction reporting plan. In general, NMS securities are stocks listed on national securities exchanges, such as the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and Nasdaq.

average price of at least \$2, and an average daily trading volume of one million or fewer shares during the three-month measurement period starting on April 4, 2016; and (b) maintaining market capitalization below \$3 billion and a closing price higher than \$2 on August 31, 2016, the last day of the measurement period. The SEC announced the list of TSP securities on Sep 3, 2016, randomly assigned 1200 of these stocks to the treatment group, and increased the tick size for their quotes from 1¢ to 5¢ during the TSP.[13] The remaining 1199 stocks were assigned to the control group, for which the tick size remained at 1¢. The two-year TSP officially began on October 3, 2016 and was phased in gradually over the month of October. By October 31, 2016, all treatment stocks were traded fully under the new tick size of 5¢. The TSP ended on September 30, 2018.

3.2. Research design

Our main regression specification, as in equation (1) and estimated on firm-year observations, is a difference-in-differences (DiD) regression where we implement the investment−q regression with interactions involving the treatment effect (Jayaraman and Wu, 2019):

$$\begin{aligned} INV_{i,t+1} = {} & \beta_1 \cdot Q_{i,t} + \beta_2 \cdot TREAT_i \cdot POST_{i,t} + \beta_3 \cdot TREAT_i \cdot Q_{i,t} + \beta_4 \cdot POST_{i,t} \cdot Q_{i,t} \\ & + \beta_5 \cdot TREAT_i \cdot POST_{i,t} \cdot Q_{i,t} + \beta_6 \cdot CF_{i,t+1} + \beta_7 \cdot TREAT_i \cdot CF_{i,t+1} \\ & + \beta_8 \cdot POST_{i,t} \cdot CF_{i,t+1} + \beta_9 \cdot TREAT_i \cdot POST_{i,t} \cdot CF_{i,t+1} + \beta_{10} \cdot INVAST_{i,t} \\ & + Firm_i + Year_t + \varepsilon_{i,t+1} \end{aligned} \tag{1}$$

where $INV_{i,t+1}$ represents firm i's investment in year t+1. As in Chen et al. (2007), we define $INV_{i,t+1}$ as the sum of capital expenditures and R&D expenses scaled by the beginning-of-year book assets (see Appendix for variable definitions). $Q_{i,t}$ represents firm i's normalized stock price, or Tobin's q. It is calculated as the market value of equity plus the book value of assets minus the book value of equity scaled by book assets, all measured at the end of year t (i.e., the beginning of year t+1).

Our coefficient of interest is β_5 on $TREAT_i \cdot POST_{i,t} \cdot Q_{i,t}$. $TREAT_i$ is a dummy variable that takes the value of 1 for firms in the TSP treatment group and 0 for firms in the TSP control group. $POST_{i,t}$ is a dummy variable that equals 1 for the two fiscal years that began during the TSP (i.e., between October 2016 and September 2018), which we refer to as the post-treatment period, and 0 for the two fiscal years that ended before the TSP (i.e., before October 2016), which we refer to as the pre-treatment period. $Q_{i,t}$ is measured under the tick size of 1¢ for both treatment and control firms in the pre-treatment period. In the post-treatment period, $Q_{i,t}$ is measured under the tick size of 1¢ for control firms but under the tick size of 5¢ for treatment firms.

$CF_{i,t+1}$ in equation (1) represents firm i's cash flows in year t+1 (Chen et al., 2007). It is calculated as the sum of net income before extraordinary items, depreciation and amortization, and R&D expenses, scaled by beginning-of-year book assets. We include $CF_{i,t+1}$, $TREAT_i \cdot CF_{i,t+1}$, $POST_{i,t} \cdot CF_{i,t+1}$, and $TREAT_i \cdot POST_{i,t} \cdot CF_{i,t+1}$ in equation (1) to control for the well-documented effects of cash flows on investment (Fazzari et al., 1988). One interpretation of $CF_{i,t+1}$ treats it as a non-price-based measure of investment opportunities (e.g., Edmans et al., 2017; Jayaraman and Wu, 2019). We also control for the inverse of lagged total assets, $INVAST_{i,t}$, to isolate the correlation between $INV_{i,t+1}$ and $Q_{i,t}$ induced by the common scaling variable.

Finally, we include firm fixed effects ($Firm_i$) to control for time-invariant heterogeneity across firms and year fixed effects ($Year_t$) to control for time-varying shocks. The dummy variables $TREAT_i$ and $POST_{i,t}$ are omitted from equation (1) because firm and year fixed effects are included. Following the standard procedure in the literature, we winsorize all unbounded variables at 1% and 99% to mitigate the influence of outliers. Following Jayaraman and Wu (2019), we cluster standard errors at the industry level and present significance for two-tailed tests.

3.3. Data and sample

We collect data from several sources: investment and other financial accounting data come from Compustat, stock prices come from the Center for Research in Security Prices (CRSP), insider trades come from Thomson Reuters' Insiders tables, and management capex forecasts come from I/B/E/S Guidance. To construct our sample for the analyses of investment−q sensitivity, we begin with all NYSE/AMEX/Nasdaq-listed stocks in the TSP from the FINRA website. Following prior studies on investment−q sensitivity (e.g., Chen et al., 2007; Jayaraman and Wu, 2019), we drop firms that operate in the financial (SIC codes 6000−6999) and utility (SIC codes 4200−4299) industries. For the remaining firms, we retain data for fiscal years in the pre- and post-treatment periods. We require a firm-year observation to have a year-end share price higher than \$1, non-missing revenue, and non-missing values for all variables required to estimate investment−q sensitivity. Our main sample consists of 5544 firm-year observations for 766 treatment stocks and 750 control stocks. Table 1 displays summary statistics for the variables in our main sample. The average total investment rate (INV) accounts for 11.24% of beginning total assets. The means of Tobin's q (Q) and cash flows (CF) are 2.20 and 0.09, respectively. We defer the discussion of the remaining variables in Table 1 to subsequent sections when we introduce them formally.

[13] The SEC further divided the 1200 stocks into three test groups, where stocks in test groups 2 and 3 received additional treatments beyond the quote rule. Lee and Watts (2021) do not find any economically meaningful difference in FIA across the three subgroups, and, for the sake of parsimony and to increase the power of their tests, they present the results without dividing the treatment group into subgroups. We follow their approach in our paper.

Table 1
Descriptive statistics for the main sample.

	N	Mean	SD	25%	50%	75%
INV	5544	11.24	14.57	3.00	6.55	13.54
Q	5544	2.20	1.70	1.24	1.64	2.46
CF	5544	0.09	0.17	0.04	0.09	0.15
INVAST	5544	7.81	19.22	0.85	2.33	6.62
CTT	4649	29.18	21.75	15.31	22.53	34.54
OLR	4649	0.40	0.14	0.30	0.39	0.49
TRADESIZE	4649	101.40	39.48	77.17	90.41	112.93
ESV	3951	37.73	20.48	23.50	33.75	47.33
CYCLICALITY	5542	0.21	0.22	0.03	0.13	0.33
ENERGY	5542	0.20	0.21	0.03	0.12	0.31
$1 - R^2$	5510	0.87	0.10	0.81	0.89	0.95
VAR_RATIO	5384	1.14	0.10	1.07	1.12	1.18
FINCONS	4296	0.01	0.05	−0.02	0.01	0.05
$AbsDACC_{MJ}$	1757	0.04	0.04	0.01	0.03	0.05
$AbsDACC_{MDD}$	1753	0.04	0.04	0.01	0.03	0.06

In this table, we present descriptive statistics for the main sample of the Tick Size Pilot Program. All variable definitions are listed in the Appendix.

4. Effects of tick size on investment−*q* sensitivity: evidence from the TSP

In this section, we present our estimation of the treatment effects of tick size on investment−*q* sensitivity. In Panel An of Table 2, we report the results obtained by estimating two specifications of equation (1). For column (1), we estimate a simpler version of equation (1) by dropping the interaction terms involving cash flows (i.e., *TREAT* × *CF*, *POST* × *CF*, and *TREAT* × *POST* × *CF*). For column (2), we estimate the complete specification of equation (1).

The main coefficient of interest is on *TREAT* × *POST* × *Q*, which represents the change in investment−*q* sensitivity of treatment stocks relative to the change in investment−*q* sensitivity of control stocks from the pre-treatment period to the post-treatment period. This coefficient is significantly positive in both columns (1) and (2), indicating a rise in investment−*q* sensitivity following the increase in the tick size. In terms of economic magnitude, the coefficient of 0.82% on *TREAT* × *POST* × *Q* in column (2) corresponds to 58% of the sum of the coefficient of 1.61% on *Q* and the coefficient of −0.19% on *TREAT* × *Q*, which represents the investment−*q* sensitivity of treatment firms in the pre-period. This finding suggests that the investment−*q* sensitivity of treatment firms increases by 58% when the tick size widens from 1 cent to 5 cents. This result is economically significant but also plausible. For example, Foucault and Frésard (2012) find that cross-listing leads to a doubling of investment−*q* sensitivity. Nevertheless, our results are based on small- and mid-cap firms in the TSP and therefore may not be generalizable to large firms.

Turning to other control variables whose coefficients are reported in Panel A of Table 2, the coefficient on *TREAT* × *Q* is not statistically significant, suggesting that investment−*q* sensitivity is similar between treatment and control stocks in the pre-treatment period. This result is consistent with the random assignment of stocks into treatment and control groups by the SEC. The coefficient on *POST* × *Q* is not statistically significant either, suggesting that investment−*q* sensitivity remains unchanged for the control stocks in the post-period. Finally, the coefficient on *TREAT* × *POST* × *CF* is insignificant, suggesting that the sensitivity of investment to cash flows remains unchanged after the increase in the tick size. As a result, the increase in investment−*q* sensitivity of the treatment group is not part of a general trend in which investment becomes more responsive to investment opportunities (Jayaraman and Wu, 2019).

In summary, we find that an increase in the tick size leads to higher investment−*q* sensitivity. To further strengthen this causal inference, we conduct a series of additional analyses. First, to verify the parallel-trends premise that makes the TSP a legitimate shock for causal inferences, in Fig. 1 we illustrate graphically the time trends in investment-*q* sensitivity, estimated separately for treatment and control stocks. To better visualize the pre-treatment trends, we extend the pre-treatment period backwards to include two additional years. Panel A of Fig. 1 presents estimates of investment-*q* sensitivity in dots for treatment firms and diamonds for control firms over the four years (years −4, −3, −2, and −1) before and two years (years 1 and 2) after the implementation of the TSP, along with 90% confidence intervals indicated by dashed lines. Panel B presents the difference in investment-*q* sensitivity between the treatment and control groups for each year. Investment-*q* sensitivity for treatment and control firms track each other closely in the pre-treatment period, suggesting that the “parallel trends” assumption is not violated.[14] Turning to the post-treatment period, investment-*q* sensitivity increases to a greater extent for treatment firms than for control firms in year 1 and to an even greater extent in year 2. Panel B presents the differential effects more sharply. The difference in investment-*q* sensitivity between the two groups seems to bounce around in the pre-treatment period, but at no time is the difference significantly different from 0. In contrast, the difference is statistically

[14] To further confirm the “parallel trends” assumption, we conduct a placebo test and re-estimate equation (1) by defining years −2 and −1 as the pseudo post-treatment period and years −4 and −3 as the pseudo pre-treatment period. In untabulated results, we find an insignificant coefficient on *TREAT* × *POST* × Q in this placebo test, consistent with the parallel trends observed in Fig. 1.

Table 2
Effects of the tick size on Investment−*q* sensitivity.

Panel A: Effects of the Increase in the Tick Size on Investment−*q* Sensitivity

	INV	
	(1)	(2)
Q	1.57***	1.61***
	(0.16)	(0.16)
TREAT × *POST*	−1.84***	−1.43**
	(0.61)	(0.62)
TREAT × *Q*	−0.23	−0.19
	(0.26)	(0.25)
POST × *Q*	−0.05	0.02
	(0.19)	(0.19)
TREAT*× *POST*× *Q	0.96***	0.82***
	(0.30)	(0.29)
CF	1.65	3.66
	(2.06)	(2.86)
TREAT × *CF*	–	1.29
		(4.31)
POST × *CF*	–	−4.62***
		(1.62)
TREAT × *POST* × *CF*	–	−1.10
		(5.00)
INVAST	0.21***	0.21***
	(0.04)	(0.04)
Firm FE	Y	Y
Year FE	Y	Y
Obs.	5544	5544
Adj. R^2	0.80	0.80

Panel B: Robustness Tests of the Effects of Tick Size on Investment−*q* Sensitivity

	INV	
	(1)	(2)
Sample	Alternative Control Group	Quarterly Data
Q	2.43***	0.42***
	(0.42)	(0.14)
TREAT × *POST*	−1.47*	−0.44**
	(0.81)	(0.18)
TREAT × *Q*	−1.02***	−0.15
	(0.28)	(0.10)
POST × *Q*	−0.49	−0.15
	(0.44)	(0.09)
TREAT* × *POST* × *Q	1.24***	0.25**
	(0.42)	(0.10)
CF	7.78	1.89
	(7.72)	(1.51)
TREAT × *CF*	−2.55	0.88
	(7.06)	(2.61)
POST × *CF*	1.33	−0.92
	(7.83)	(1.86)
TREAT × *POST* × *CF*	−6.01	−2.47
	(8.07)	(3.35)
INVAST	0.22***	0.02**
	(0.04)	(0.01)
Firm FE	Y	Y
Year FE	Y	–
Quarter FE	–	Y
Obs.	3885	21,707
Adj. R^2	0.81	0.69

In this table we present results pertaining to the impact of tick size on investment−*q* sensitivity. For Panel A, we compare changes in investment−*q* sensitivity between the treatment and control groups during the TSP. *TREAT* is a dummy variable that takes the value of 1 for firms in the treatment group and 0 for firms in the control group. *POST* is a dummy variable that equals 1 for the two years in the post-treatment period and 0 for the two years in the pre-treatment period. Panel B presents the results of robustness tests. We replicate the regression associated with column (2) of Panel A by replacing the TSP control group with a group of stocks that are similar to the control group but not included in the TSP for column (1) of Panel B and using quarterly data for column (2). All variable definitions are listed in the appendix. Standard errors displayed in parentheses are clustered by industry. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

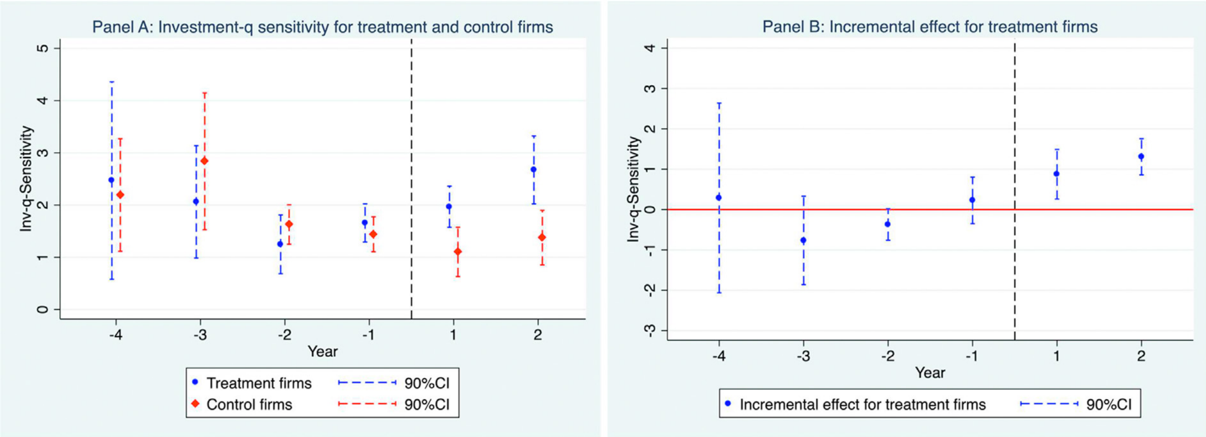

Fig. 1. Time Trends in Investment−*q* Sensitivity. Panel A displays the time trends in investment−*q* sensitivity, estimated separately for treatment and control firms, around the implementation of the TSP. The *x*-axis denotes the year relative to the implementation of the TSP and the y-axis plots the estimates of investment-*q* sensitivity for each year. Years −4 through −1 precede the implementation and years 1 and 2 follow the implementation. The dots and diamonds represent estimates of investment−*q* sensitivity and the dashed vertical lines denote 90% confidence intervals. Panel B displays the difference in investment-*q* sensitivity estimates between treatment and control firms in dots for each year along with 90% confidence intervals in dashed vertical lines.

significant in both years of the post-treatment period. These results not only rule out pre-treatment-period trends but also indicate that the increase in information revealed by prices manifests gradually in investment decisions.

Second, to control for spillover effects that might transmit to the control group (Rindi and Werner, 2019),[15] we examine the robustness of our findings with respect to the selection of the control group. We follow Rindi and Werner (2019) to construct an alternative control group that consists of stocks that are similar to the control stocks but were not part of the TSP because they missed the stock-selection criteria for inclusion in the TSP at the margin.[16] We identify 301 stocks for this alternative control group. We report the results of estimating regression (1) based on this alternative control group in column (1) of Panel B in Table 2. We continue to find an increase in investment−*q* sensitivity for the treatment group, as indicated by the significant positive coefficient of 1.24% on *TREAT* × *POST* × *Q*.[17]

Third, we examine the robustness of the treatment effect of the TSP using quarterly data. The tradition in the literature estimates investment−*q* sensitivity using firm-year observations of Tobin's *q* and investment. In theory, however, investment−*q* sensitivity can also be estimated using firm-quarter observations (Goldstein et al., 2022). We therefore re-estimate regression (1) using quarterly data. We report the results in column (2) of Panel B in Table 2. Consistent with our findings at annual frequency, we find a greater increase in quarterly investment−*q* sensitivity during the TSP for the treatment group than for the control group, as indicated by the significant positive coefficient of 0.25% on *TREAT* × *POST* × *Q*.[18]

5. Tests of managerial learning

In the previous section we show that an increase in the tick size increases investment−*q* sensitivity. We interpret this finding as suggesting that RPE and managerial learning from stock prices increase with the tick size. Learning is not directly observable, though, so it is possible that other factors drive the increase in investment−*q* sensitivity. In this section, we provide two sets of evidence to reinforce our inference on learning. First, we provide more direct evidence of learning by showing that changes in managerial beliefs respond more strongly to market feedback as the tick size increases. Second, we investigate the underlying mechanism through which tick size affects investment−*q* sensitivity and show that this mechanism runs through managerial learning.

[15] Rindi and Werner (2019) show that liquidity in the treatment group of TSP has a spillover effect on liquidity in the control group.

[16] Stated precisely, these stocks have either: (1) a stock price that falls between \$1.50 and \$2.00 and market capitalization that is less than or equal to \$3 billion on August 31, 2016 as well as an average daily share volume that is less than or equal to 1 million shares for the month of August 2016; (2) a stock price of at least \$2.00 and market capitalization of between \$3 and \$6 billion on August 31, 2016 as well as an average daily share volume that is less than or equal to 1 million shares for the month of August 2016; or (3) a stock price of at least \$2.00 and market capitalization that is less than or equal to \$3 billion on August 31, 2016 and an average daily share volume of between 1 and 2 million shares for the month of August 2016.

[17] We note that investment−*q* sensitivity differs between the treatment group and the alternative control group in the pre-treatment period, as indicated by the significant coefficient of −1.02% on *TREAT* × *Q*. This finding suggests that the TSP control group is a better match for the treatment group than the alternative control group. We therefore focus in the following analyses on the comparison between the TSP treatment and control groups.

[18] Recently, Heitzman and Huang (2019) modified the standard investment−*q* sensitivity regression by adding outstanding cash and cash equivalents balance (*CASH*) as an additional explanatory variable. They argue that *CF* in this modified regression measures accounting profits. Building on their specification, we modify regression (1) by adding *CASH*, *TREAT* × *CASH*, *POST* × *CASH*, and *TREAT* × *POST* × *CASH* as additional explanatory variables. In untabulated results, we continue to find a significantly positive coefficient (0.97 with p-value<0.01) on *TREAT* × *POST* × *Q*. In contrast, the coefficients on *TREAT* × *POST* × *CF* and *TREAT* × *POST* × *CASH* are insignificant.

5.1. Effects of tick size on managerial belief

One unique prediction of managerial learning is that managers change their beliefs about investment opportunities according to market feedback, which in turn leads to changes in their actions. While managerial beliefs are unobservable, they can be inferred from management forecasts (Zuo, 2016).[19] Using management capex forecasts, Jayaraman and Wu (2020) show that managers adjust forecasted (or proposed) annual capex according to short-window stock market reactions to capex forecasts. Their finding offers direct evidence of learning by linking changes in managerial beliefs to market feedback. Building on their finding, we predict a stronger positive association between managers' adjustments of forecasted annual capex and market reactions to capex forecasts under a larger tick size if managerial learning increases with the tick size.

To test this prediction, we collect, from I/B/E/S Guidance, annual management capex forecasts issued by NYSE/AMEX/Nasdaq-listed TSP firms over the two-year period before and the two-year period during the TSP. We retain the first capex forecast issued by management for a firm-year, as the market's comparative information advantage over management resides in the longer horizon (Hutton et al., 2012; Zuo, 2016). Following Jayaraman and Wu (2020), we also delete capex forecasts that are issued concurrently with management earnings forecasts. We require a firm to issue capex forecasts in both the pre-

Table 3
The effects of tick size on managerial beliefs.

Panel A: Descriptive statistics

	N	Mean	SD	25%	50%	75%
ADJ_CAPEX	749	0.0197	0.4415	−0.1850	−0.0202	0.0902
CAR	749	0.0025	0.0999	−0.0505	0.0062	0.0565
SIZE	749	1162	916	448	901	1691
PRC	749	32	27	12	23	42
LAG_CAPEX	749	81	114	18	40	96
SURP	749	0.0056	0.9482	−0.1500	0.0200	0.1800
EA_DUM	749	0.66	0.47	0.00	1.00	1.00

Panel B: Effects of the Increase in the Tick Size on the Sensitivity of Changes in Managerial Beliefs to Market Feedback

	ADJ_CAPEX	
	(1)	(2)
CAR	0.254	0.282
	(0.31)	(0.30)
TREAT × *POST*	0.150**	0.158**
	(0.07)	(0.07)
TREAT × *CAR*	−0.404	−0.510
	(0.54)	(0.55)
POST × *CAR*	−0.522	−0.539
	(0.43)	(0.38)
TREAT × ***POST*** × ***CAR***	1.327*	1.447*
	(0.74)	(0.77)
Ln (*SIZE*)	–	0.039
		(0.15)
Ln (*PRC*)	–	0.034
		(0.15)
Ln (*LAG_CAPEX*)	–	−0.185***
		(0.05)
SURP	–	−0.004
		(0.02)
EA_DUM	–	−0.006
		(0.07)
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Obs.	749	749
Adj. R^2	0.39	0.42

In this table we present results pertaining to the impact of tick size on managerial beliefs. In Panel A, we report descriptive statistics for the sample of management capex forecasts issued by TSP firms. In Panel B, we compare changes in the association between revisions of managerial beliefs, as reflected in adjustments of forecasted capex (*ADJ_CAPEX*), and market reactions to management capex forecasts (*CAR*) between the treatment and control groups during the TSP. *TREAT* is a dummy variable that takes the value of 1 for firms in the treatment group and 0 for firms in the control group. *POST* is a dummy variable that equals 1 for management capex forecasts issued in the two years of TSP and 0 for forecasts issued in the two years before TSP. All variable definitions are listed in the appendix. Standard errors displayed in parentheses are clustered by industry. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

[19] Even though publicly disclosed management forecasts are still proxies for managers' internal forecasts of project payoffs, the link between these two types of forecasts is likely to be strong (Hemmer and Labro, 2008; Zuo, 2016). For example, using a large survey with top financial executives, Dichev et al. (2013) find that there is "a tight link between internal and external reporting."

treatment and post-treatment periods. The final sample consists of 749 management capex forecasts issued by 121 treatment firms and 112 control firms.

Panel A of Table 3 presents descriptive statistics for this sample. Our proxy for changes in managerial beliefs is the adjustment of forecasted capex (*ADJ_CAPEX*) defined as the percentage difference between capital expenditures made by a given firm in a given year and the amount forecasted by the firm for the same year (scaled by the latter). *ADJ_CAPEX* has a mean of 1.97% and a standard deviation of 44.15%. The market reaction to capex forecasts (*CAR*) is defined as cumulative abnormal returns (i.e., firm-level returns minus S&P 500 index returns) over the five days surrounding the date of a capex forecast. *CAR* has a mean value of 0.25%, indicating on average a small but positive market reaction, and a standard deviation of around 10%.

To estimate the effects of tick size on the association between *ADJ_CAPEX* and *CAR*, we implement the regression of Jayaraman and Wu (2020) with interactions of the treatment effect:

$$\begin{aligned} ADJ\ CAPEX_{i,a,f} = {} & \beta_1 \cdot CAR_{i,a} + \beta_2 \cdot TREAT_i \cdot POST_{i,a} + \beta_3 \cdot TREAT_i \cdot CAR_{i,a} \\ & + \beta_4 \cdot POST_{i,a} \cdot CAR_{i,a} + \beta_5 \cdot TREAT_i \cdot POST_{i,a} \cdot CAR_{i,a} \\ & + \beta_6 \cdot Ln(SIZE_{i,a-1}) + \beta_7 \cdot Ln(PRC_{i,a-1}) + \beta_8 \cdot Ln(LAG\ CAPEX_{i,a-1}) \\ & + \beta_9 \cdot SURP_{i,a-1} + \beta_{10} \cdot EA\_DUM_{i,a} + Firm_i + Quarter_a + \varepsilon_{i,a,f} \end{aligned} \tag{2}$$

where $ADJ\ CAPEX_{i,a,f}$ refers to the adjustment of the forecasted capex in announcement a for fiscal year f and $CAR_{i,a}$ refers to market reaction to capex forecast announcement a. $TREAT_i$ is a dummy variable that takes the value of 1 (0) for TSP treatment (control) firms. $POST_{i,a}$ is a dummy variable that equals 1 (0) if the capex forecast a is announced during the two-year period after (before) the implementation of TSP. Following Jayaraman and Wu (2020), we also control for additional firm-level characteristics (defined in the Appendix) that may correlate with both *ADJ_CAPEX* and *CAR* as well as firm fixed effects ($Firm_i$) and quarter fixed effects ($Quarter_a$), the latter of which is defined by the quarter in which a capex forecast is issued. Our coefficient of interest is β_5 on $TREAT_i \cdot POST_{i,a} \cdot CAR_{i,a}$. If a larger tick size increases RPE and managerial learning, we expect to observe $\beta_5 > 0$.

Panel B of Table 3 presents the results obtained by estimating regression (2) without control variables in column (1) and those obtained with control variables in column (2). The positive coefficient on $TREAT \times POST \times CAR$ is significant at the 10% level in both columns, indicating a stronger association between adjustments of forecasted capex and market feedback under a larger tick size.[20] We interpret this finding as suggesting that managers glean more information from market reactions to their capex forecasts to revise their beliefs about investment opportunities as the tick size increases, consistent with the inference of an increase in learning based on investment−q sensitivity. We acknowledge, however, that the statistical significance of this finding is somewhat weak given the small sample.

5.2. A learning-based mechanism through which tick size affects investment-q sensitivity

Our discussion in the introduction suggests the following learning-based mechanism through which tick size can affect investment−q sensitivity: a larger tick size reduces AT (Lee and Watts, 2021), which in turn encourages FIA (Weller, 2017; Lee and Watts, 2021). Increased FIA generates information that is new to managers and consequently enhances managerial learning from stock prices, as reflected in higher investment−q sensitivity. In this section we describe a series of cross-sectional tests of this learning-based mechanism that we conducted. Despite the intrinsic limitation that the partitioning variables can be correlated with a host of omitted variables, finding consistent evidence from these cross-sectional tests provides further support for managerial learning.[21]

5.2.1. Algorithmic trading

Our first cross-sectional test examines the role of AT. Lee and Watts (2021) show that AT declines with the tick size during the TSP. If the above hypothesized mechanism holds, we expect the increase in investment−q sensitivity to be concentrated in treatment firms that experience greater reductions in AT. Before testing this prediction, we first confirm the reduction of AT with the tick size in our sample using the standard DiD regressions. We follow Weller (2017) and Lee and Watts (2021) in measuring AT with the cancel-to-trade ratio (*CTT*), the odd-lot ratio (*OLR*), and trade size (*TRADESIZE*). Higher values of *CTT*

[20] Untabulated results show that the coefficient estimate of 0.680 (=0.282−0.510−0.539 + 1.447) on *CAR* for treatment firms during the TSP, based on results reported in column (2), is significantly different from 0, with a p-value of 0.03.

[21] In addition to results tabulated in this section, we also conduct (untabualted) cross-sectional tests based on managers' incentives to learn from stock prices. We find that the higher investment-q sensitivity during the TSP we observe concentrates in treatment firms with larger differences in opinions, as reflected in wider analyst forecast dispersions, and those with less precise internal information, as reflected in lower profitability of insider trades. The former finding is consistent with the prediction of Allen (1993) that learning from stock prices is more valuable when there is wider dispersion of opinions regarding how a firm should be run because the market checks whether a manager's view of the production function is sensible. The latter finding is consistent with the argument in Chen et al. (2007) and Dessaint et al. (2019) that managers rely more heavily on stock prices for their investment decisions when internal information about fundamentals is less precise.

Table 4
The effects of tick size on Investment−q sensitivity: The role of algorithmic trading.

Panel A: Effects of the Increase in the Tick Size on Algorithmic Trading

	(1)	(2)	(3)
	Ln (*CTT*)	*Ln* (*OLR*)	*Ln* (*TRADESIZE*)
TREAT × ***POST***	−0.18***	−0.05***	0.06***
	(0.02)	(0.01)	(0.01)
Firm & Year FE	Y	Y	Y
Obs.	4643	4643	4643
Adj. R^2	0.80	0.80	0.82

Panel B: Cross-sectional Relationship between Increases in Investment−q Sensitivity and Reduced Algorithmic Trading

Variables to partition the treatment group	(1)	(2)	(3)
	CTT	*OLR*	*TRADESIZE*
TREAT_ATDECMORE × ***POST*** × ***Q***	1.33***	0.84**	1.14***
	(0.26)	(0.39)	(0.36)
TREAT_ATDECLESS × ***POST*** × ***Q***	0.18	0.38	0.14
	(0.45)	(0.72)	(0.37)
Controls	Y	Y	Y
Firm & Year FE	Y	Y	Y
Obs.	4814	4814	4814
Adj. R^2	0.82	0.82	0.82

In this table, we present results pertaining to the impact of tick size on algorithmic trading (AT) and the association between changes in AT and changes in investment−q sensitivity. In Panel A, we compare changes in AT between the treatment and control groups in the TSP. *TREAT* is a dummy variable that takes the value of 1 for firms in the treatment group and 0 for firms in the control group. *POST* is a dummy variable that equals 1 for the two years in the post-treatment period and 0 for the two years in the pre-treatment period. Measures of AT include the cancel-to-trade ratio (*CTT*) for column (1), the odd-lot ratio (*OLR*) for column (2), and trade size (*TRADESIZE*) for column (3). In Panel B, we report the results of difference-in-differences regressions of investment−q sensitivity after dividing the treatment group into two subgroups depending on whether AT decreases from the pre-treatment period to the post-period more or less than the cross-sectional median. Specifically, an indicator variable, *TREAT_ATDECMORE* (*TREAT_ATDECLESS*), equals 1 if a firm is in the treatment group and its *CTT* decreases more (less) than the cross-sectional median (column (1)), its *OLR* decreases more (less) than the cross-sectional median (column (2)), or its *TRADESIZE* increases more (less) than the cross-sectional median (column (3)). Control variables (Controls) include *Q*, *TREAT_ATDECMORE* × *Q*, *TREAT_ATDECLESS* × *Q*, *POST* × *Q*, *CF*, *TREAT_ATDECMORE* × *CF*, *TREAT_ATDECLESS* × *CF*, *POST* × *CF*, *TREAT_ATDECMORE* × *POST*, *TREAT_ATDECLESS* × *POST*, *TREAT_ATDECMORE* × *POST* × *CF*, *TREAT_ATDECLESS* × *POST* × *CF*, and *INVAST*. All variable definitions are listed in the appendix. Standard errors displayed in parentheses are clustered by industry. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

and *OLR* or a lower value of *TRADESIZE* indicate more AT.[22] Consistent with Lee and Watts (2021), we find significantly greater reductions in *CTT* and *OLR* and a significantly greater increase in *TRADESIZE* for TSP treatment stocks than for TSP control stocks, as can be seen in Panel A of Table 4.

To test our prediction, we divide the treatment group into two subgroups. *TREAT_ATDECMORE* (*TREAT_ATDECLESS*) is an indicator variable that equals 1 if a firm is in the treatment group and its AT drops from the pre-treatment period to the post-treatment period to a greater (lesser) extent than the cross-sectional median of the treatment group and 0 otherwise.[23] We modify equation (1) to allow the treatment effects to differ between these two subgroups, a design that resembles that used in Jayaraman and Wu (2019):

$$INV_{i,t+1} = \beta_1 \cdot TREAT\,ATDECMORE_i \cdot POST_{i,t} \cdot Q_{i,t} + \beta_2 \cdot TREAT\,ATDECLESS_i \cdot POST_{i,t} \cdot Q_{i,t} + Firm_i + Year_t + \sum Controls + \varepsilon_{i,t} \tag{3}$$

We report the results of estimating equation (3) in columns (1)–(3) of Panel B in Table 4 for *CTT*, *OLR*, and *TRADESIZE*, respectively. While we estimate the full specification of equation (3) here, for the sake of parsimony we tabulate only the results for the relevant variables. Consistent with our prediction, the coefficient on *TREAT_ATDECMORE* × *POST* × *Q* is significantly positive and the coefficient on *TREAT_ATDECLESS* × *POST* × *Q* is insignificant in all three columns.

5.2.2. Fundamental information acquisition

Our second cross-sectional test explores the role of FIA. Lee and Watts (2021) show that FIA increases with the tick size during the TSP. If the learning-based mechanism holds, we expect the increase in investment−q sensitivity to be concentrated in treatment firms that experience a greater increase in FIA. Before testing this prediction, we first confirm their finding of increased FIA in our sample. We follow them in measuring FIA by the non-robotic EDGAR search volume around earnings

[22] These proxies are also widely used in the recent microstructure literature to proxy for one specific type of AT—high-frequency trading—which is known to specialize in order-anticipation strategies (e.g., O'hara et al., 2014; Conrad et al., 2015; Brogaard et al., 2019).

[23] AT falls to a greater extent if *CTT* falls to a greater extent, *OLR* decreases to a greater extent, or *TRADESIZE* increases to a greater extent.

Table 5
The effects of tick size on Investment−*q* sensitivity: The role of fundamental information acquisition.

Panel A: Effects of the Increase in the Tick Size on EDGAR Search Volume		Panel B: Cross-sectional Relationship between Increases in Investment−*q* Sensitivity and Increases in EDGAR Search Volume	
	Ln (ESV)		*INV*
TREAT × ***POST***	0.04**	***TREAT_ESVINCMORE*** × ***POST*** × ***Q***	1.21***
	(0.02)		(0.43)
		TREAT_ESVINCLESS × ***POST*** × ***Q***	0.56
			(0.40)
		Controls	Y
Firm & Year FE	Y	Firm & Year FE	Y
Obs.	3861	Obs.	5056
Adj. R^2	0.77	Adj. R^2	0.80

In this table, we present results pertaining to the impact of tick size on non-robotic EDGAR search volume (*ESV*) and the association between changes in *ESV* and changes in investment−*q* sensitivity. In Panel A, we compare changes in *ESV* between the treatment and control groups in the TSP. *TREAT* is a dummy variable that takes the value of 1 for firms in the treatment group and 0 for firms in the control group. *POST* is a dummy variable that equals 1 for the two years in the post-treatment period and 0 for the two years in the pre-treatment period. In Panel B, we report the results of difference-in-differences regressions of investment−*q* sensitivity after dividing the treatment group into two subgroups depending on whether *ESV* increases from the pre-treatment period to the post-period more or less than the cross-sectional median. Specifically, the indicator variable *TREAT_ESVINCMORE* (*TREAT_ESVINCLESS*) equals 1 if a firm is in the treatment group and its *ESV* increases more (less) than the cross-sectional median. Control variables (Controls) include *Q*, *TREAT_ESVINCMORE* × *Q*, *TREAT_ESVINCLESS* × *Q*, *POST* × *Q*, *CF*, *TREAT_ESVINCMORE* × *CF*, *TREAT_ESVINCLESS* × *CF*, *POST* × *CF*, *TREAT_ESVINCMORE* × *POST*, *TREAT_ESVINCLESS* × *POST*, *TREAT_ESVINCMORE* × *POST* × *CF*, *TREAT_ESVINCLESS* × *POST* × *CF*, and *INVAST*. All variable definitions are listed in the appendix. Standard errors displayed in parentheses are clustered by industry. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

announcements (*ESV*).[24] Consistent with Lee and Watts (2021), we find a significantly greater increase in *ESV* for treatment stocks than for control stocks during the TSP, as can be seen in Panel A of Table 5.

To test our prediction, we divide the treatment stocks into two subgroups. *TREAT_ESVINCMORE* (*TREAT_ESVINCLESS*) is an indicator variable that equals 1 if a firm is in the treatment group and its *ESV* increases from the pre-treatment period to the post-treatment period to a greater (or lesser) extent than the cross-sectional median of the treatment group and 0 otherwise. We then estimate regression (3) by replacing *TREAT_ATDECMORE* and *TREAT_ATDECLESS* with *TREAT_ESVINCMORE* and *TREAT_ESVINCLESS*. We present the results of this regression in Panel B of Table 5. Consistent with our prediction, the coefficient on *TREAT_ESVINCMORE* × *POST* × *Q* is significantly positive and the coefficient on *TREAT_ESVINCLESS* × *POST* × *Q* is insignificant.[25]

5.2.3. Types of Information that is new to managers

One key assumption of the learning-based mechanism is that increased FIA under a larger tick size generates additional information that is new to managers. While such information is not directly observable, the learning literature generally agrees that information about growth opportunities, macroeconomic factors, and industry-wide factors is more likely to be new to managers (see the literature review in Section 2.2). In the third set of cross-sectional tests, we show that these types of information drive the increase in investment−*q* sensitivity under a larger tick size.

5.2.3.1. Growth opportunities. We first examine whether the increased FIA generates new information about growth opportunities. Bai et al. (2016) and Goldstein et al. (2022) argue that managers are more likely to learn from outsiders about growth opportunities than about assets in place, as the former depend more heavily on industry prospects or market conditions. Therefore, if the tick size increases investment−*q* sensitivity through the managerial-learning channel, we expect the higher investment−*q* sensitivity for TSP treatment stocks to concentrate in growth firms, to which information about growth opportunities is more valuable. To test this prediction, we follow Goldstein et al. (2022) in partitioning treatment stocks into growth and value stocks. *TREAT_GROWTH* (*TREAT_VALUE*) is an indicator variable that equals 1 if a firm is in the treatment group and its average market-to-book ratio of equity in the pre-treatment period is above (below) the cross-sectional median of the treatment group and 0 otherwise. We then estimate regression (3) by replacing *TREAT_ATDECMORE* and *TREAT_ATDECLESS* with *TREAT_GROWTH* and *TREAT_VALUE*. Panel A of Table 6 presents the results of this regression. The coefficient on *TREAT_GROWTH* × *POST* × *Q* is significantly positive while that on *TREAT_VALUE* × *POST* × *Q* is statistically insignificant, which is consistent with the interpretation that additional information about growth opportunities is acquired and becomes impounded into stock prices under a larger tick size.

5.2.3.2. Macroeconomic information. We next examine macroeconomic information. As macroeconomic information is more valuable to firms whose fundamentals have greater exposure to macroeconomic factors (e.g., Hutton et al., 2012), we expect

[24] EDGAR search volume is widely used in the accounting literature to measure FIA (e.g., Drake et al., 2015; Dechow et al., 2016; Bozanic et al., 2017), as most FIA activities are not directly observable.

[25] We obtain *ESV* from James Ryan, who provides detailed descriptions of the data in Ryans (2017). As *ESV* data ends in the middle of 2017, the sample for Panel A of Table 5 is smaller than our main sample as it covers only the first year in the post-period. We are still able, however, to calculate the change in *ESV* from the pre-treatment period to the post-period for the majority of firms in the main sample. So the sample size for Panel B is larger than that for Panel A.

Table 6
Types of information driving the effects of tick size on Investment−q sensitivity.

Panel A: Cross-sectional Variation in Increases of Investment−q Sensitivity with Growth Opportunities

	INV
TREAT_GROWTH* × *POST* × *Q	0.95***
	(0.24)
TREAT_VALUE* × *POST* × *Q	0.41
	(0.67)
Controls	Y
Firm & Year FE	Y
Obs.	5544
Adj. R^2	0.80

Panel B: Cross-sectional Variation in Increases of Investment−q Sensitivity with Exposure to Macroeconomic Factors

	INV	
	(1)	(2)
Macroeconomic exposure proxy	*CYCLICALITY*	*ENERGY*
TREAT_HIGHMACRO* × *POST* × *Q	1.28***	1.19***
	(0.41)	(0.37)
TREAT_LOWMACRO* × *POST* × *Q	0.05	0.32
	(0.71)	(0.56)
Controls	Y	Y
Firm & Year FE	Y	Y
Obs.	5542	5542
Adj. R^2	0.80	0.80

Panel C: Effects of the Increase in the Tick Size on the Sensitivities of a Non-Pilot Stock's Investment to the Stock Prices of its Pilot Industry Peers

	INV
Q	2.55***
	(0.57)
$Q_{TREATPEER}$	0.15
	(0.97)
$Q_{CONTROLPEER}$	0.69
	(1.49)
POST × *Q*	−0.58
	(0.45)
***POST* × $Q_{TREATPEER}$**	1.92**
	(0.77)
***POST* × $Q_{CONTROLPEER}$**	−1.16*
	(0.68)
CF	1.85
	(2.49)
$CF_{TREATPEER}$	6.36**
	(2.65)
$CF_{CONTROLPEER}$	0.46
	(0.60)
POST × *CF*	−10.02**
	(3.98)
POST × $CF_{TREATPEER}$	8.09
	(10.30)
POST × $CF_{CONTROLPEER}$	−0.43
	(0.72)
INVAST	0.16***
	(0.03)
Firm & Year FE	Y
Obs.	6849
Adj. R^2	0.75

In this table we present the results of tests in which we explore the types of information that drive increases in investment−q sensitivity under a larger tick size. In Panel A, we report the results of difference-in-differences regressions of investment−q sensitivity after dividing the TSP treatment group into two subgroups, growth firms (*TREAT_GROWTH* = 1) and value firms (*TREAT_VALUE* = 1), depending on whether a firm's average market-to-book ratio of equity in the pre-treatment period is above or below the cross-sectional median. In the increase in investment–q sensitivity in TSP to concentrate in those firms if more macroeconomic information is acquired and impounded into stock prices under a larger tick size. To test this prediction, we follow Hutton et al. (2012) in measuring a firm's macroeconomic exposure by the extent to which a firm's earnings co-move with Gross Domestic Product (*CYCLICALITY*) or energy prices (*ENERGY*). A higher *CYCLICALITY* or *ENERGY* value indicates greater macroeconomic exposure.

We next divide the treatment group into two subgroups. *TREAT_HIGHMACRO* (*TREAT_LOWMACRO*) is an indicator variable that equals 1 if a firm is in the treatment group and its average *CYCLICALITY* or *ENERGY* in the pre-treatment period is above (below) the cross-sectional median of the treatment group and 0 otherwise. We then estimate regression (3) by replacing *TREAT_ATDECMORE* and *TREAT_ATDECLESS* with *TREAT_HIGHMACRO* and *TREAT_LOWMACRO*. Panel B of Table 6 presents the results of this regression for *CYCLICALITY* and *ENERGY*. For both measures of macroeconomic exposure, we find a significantly positive coefficient on *TREAT_HIGHMACRO* × *POST* × *Q* and a statistically insignificant coefficient on *TREAT_LOWMACRO* × *POST* × *Q*, which is consistent with the interpretation that more macroeconomic information is acquired and impounded into stock prices under a larger tick size.

5.2.3.3. Industry information. Finally, we examine industry-wide information. If more industry-wide information is acquired and impounded into the prices of TSP treatment firms, we expect managers of those firms' industry peers to learn more from their stock prices, leading to an increase in the sensitivity of peer firms' investments to treatment firms' stock prices. To test this prediction, we collect a sample of NYSE/AMEX/Nasdaq-listed stocks that are not part of the TSP and refer to them as non-TSP firms. We require a non-TSP firm to have at least one TSP treatment peer firm and one TSP control peer firm in the same two-digit SIC industry for each year in the pre- and post-treatment period. We estimate the effects of TSP treatment firms' tick size on the sensitivity of non-TSP firms' investment to TSP treatment firms' stock prices using the following regression (Foucault and Frésard, 2014):

$$\begin{aligned} INV_{j,t+1} = {} & \beta_1 \cdot Q_{j,t} + \theta_1 \cdot Q_{j,TREATPEER,t} + \gamma_1 \cdot Q_{j,CONTROLPEER,t} + \beta_2 \cdot POST_{j,t} \cdot Q_{j,t} \\ & + \theta_2 \cdot POST_{j,t} \cdot Q_{j,TREATPEER,t} + \gamma_2 \cdot POST_{j,t} \cdot Q_{j,CONTROLPEER,t} \\ & + \beta_3 \cdot CF_{j,t+1} + \theta_3 \cdot CF_{j,TREATPEER,t+1} + \gamma_3 \cdot CF_{j,CONTROLPEER,t+1} \\ & + \beta_4 \cdot POST_{j,t} \cdot CF_{j,t+1} + \theta_4 \cdot POST_{j,t} \cdot CF_{j,TREATPEER,t+1} \\ & + \gamma_4 \cdot POST_{j,t} \cdot CF_{j,CONTROLPEER,t+1} + INVAST_{j,t} + Firm_j + Year_t + \varepsilon_{j,t+1} \end{aligned} \tag{4}$$

where $INV_{j,t+1}$ represents non-TSP firm j's investment in year $t+1$, $Q_{j,t}$ represents its Tobin's q at the end of year t, and $Q_{j,TREATPEER,t}$ ($Q_{j,CONTROLPEER,t}$) represents the average Tobin's q for non-TSP firm j's industry peers in the TSP treatment (control) group at the end of year t. Cash-flow variables, $CF_{j,t+1}$, $CF_{j,TREATPEER,t+1}$, and $CF_{j,CONTROLPEER,t+1}$, are defined similarly. All other variables are defined in the same way as in regression (1).

Our coefficient of interest is θ_2 on *POST* × $Q_{TREATPEER}$. We include *POST* × $Q_{CONTROLPEER}$ to control for trends that might appear in investment-to-peer-q sensitivity over our sample period. The contrast between θ_2 on *POST* × $Q_{TREATPEER}$ and γ_2 on *POST* × $Q_{CONTROLPEER}$ in regression (4) serves effectively as a DiD test for the effects of tick size on learning from peers' stock prices. We report the results of estimating regression (4) in Panel C of Table 6. Consistent with our prediction, we find a significant positive coefficient on *POST* × $Q_{TREATPEER}$, suggesting that managers in non-TSP firms learn more industry-level information from stock prices of TSP treatment peer firms after the latter experience an increase in the tick size. In contrast, the coefficient on *POST* × $Q_{CONTROLPEER}$ is significantly negative ($p < 0.10$), suggesting that the positive coefficient on *POST* × $Q_{TREATPEER}$ does not reflect a general increasing trend in investment-to-peer-q sensitivity. This finding is consistent with the intuition suggested in Foucault and Frésard (2014) that learning from one peer's stock price diminishes as another peer's stock price becomes more informative.

6. Alternative explanations

In this section, we discuss our examination of alternative explanations of the effects of tick size on investment–q sensitivity. Ruling out these alternative explanations further supports the learning interpretation of our findings.

Panel B, we report the results of difference-in-differences regressions of investment–q sensitivity after dividing the treatment group into two subgroups depending on whether a firm's exposure to macroeconomic factors is above or below the cross-sectional median. Specifically, the indicator variable *TREAT_HIGHMACRO* (*TREAT_LOWMACRO*) equals 1 for treatment firms with pre-treatment macroeconomic exposure above (below) the cross-sectional median. The proxy for macroeconomic exposure is *CYCLICALITY*, the co-movement between earnings and GDP, in column (1) and *ENERGY*, the co-movement between earnings and energy prices, in column (2). In Panel C, we present results indicating the changes in the sensitivities of a non-Pilot stock's investment to its own q, to the average q of its peers in the TSP treatment group ($Q_{TREATPEER}$), and to the average q of its peers in the TSP control group ($Q_{CONTROLPEER}$). A non-Pilot stock is a stock that is not included in either the TSP treatment group or the TSP control group. *POST* is a dummy variable that equals 1 for the two years in the post-treatment period and 0 for the two years in the pre-treatment period. Control variables (Controls) in Panel A include *Q*, *TREAT_GROWTH* × *Q*, *TREAT_VALUE* × *Q*, *POST* × *Q*, *CF*, *TREAT_GROWTH* × *CF*, *TREAT_VALUE* × *CF*, *POST* × *CF*, *TREAT_GROWTH* × *POST*, *TREAT_VALUE* × *POST*, *TREAT_GROWTH* × *POST* × *CF*, *TREAT_VALUE* × *POST* × *CF*, and *INVAST*. Control variables for Panel B are the same as those for Panel A except that we replace *TREAT_GROWTH* (*TREAT_VALUE*) with *TREAT_HIGHMACRO* (*TREAT_LOWMACRO*). All variable definitions are listed in the appendix. Standard errors displayed in parentheses are clustered by industry. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Tests of alternative explanations.

Panel A: Controlling for Forecasting Price Efficiency

	INV	
	(1)	(2)
FPE =	*Ln* $(1 - R^2)$	*Ln* $(\lvert VAR\_RATIO - 1 \rvert)$
TREAT × ***POST*** × ***Q***	0.73**	0.78**
	(0.33)	(0.32)
TREAT × *POST* × *CF*	1.50	−2.10
	(5.57)	(5.67)
FPE	1.18	−0.21
	(1.73)	(0.27)
FPE × *Q*	2.50***	−0.04
	(0.81)	(0.10)
FPE × *CF*	−57.31***	1.73
	(10.90)	(1.23)
Controls	Y	Y
Firm & FE	Y	Y
Obs.	5506	5369
Adj. R^2	0.80	0.81

Panel B: Cross-sectional Variation with Financial Constraints

	INV
TREAT_HIGHFINCONS × ***POST*** × ***Q***	−0.15
	(0.35)
TREAT_LOWFINCONS × ***POST*** × ***Q***	0.91***
	(0.30)
Controls	Y
Firm FE	Y
Year FE	Y
Obs.	4296
Adj. R^2	0.83

Panel C: Controlling for Shareholder Monitoring

	INV	
	(1)	(2)
AbsDACC=	*Ln* $(AbsDACC_{MJ})$	*Ln* $(AbsDACC_{MDD})$
TREAT × ***POST*** × ***Q***	1.87***	2.05***
	(0.65)	(0.65)
TREAT × *POST* × *CF*	−0.74	−2.06
	(3.73)	(3.98)
AbsDACC	−0.21	0.45
	(0.30)	(0.33)
AbsDACC × *Q*	0.28***	0.13
	(0.10)	(0.16)
AbsDACC × *CF*	−1.84**	−3.83**
	(0.78)	(1.59)
Controls	Y	Y
Firm & FE	Y	Y
Obs.	1735	1731
Adj. R^2	0.80	0.80

In this table we present results obtained by examining alternative explanations for the effects of tick size on investment−*q* sensitivity. Panel A presents the results of the impact of tick size on investment−*q* sensitivity after controlling for the effects of forecasting price efficiency (FPE). We use two measures of FPE: return non-synchronicity $(1 - R^2)$ and the absolute deviation of the intraday variance ratio from 1 $(\lvert VAR\_RATIO - 1 \rvert)$. *TREAT* is a dummy variable that takes the value of 1 for firms in the treatment group and 0 for firms in the control group. *POST* is a dummy variable that equals 1 for the two years in the post-treatment period and 0 for the two years in the pre-treatment period. Panel B presents the results of difference-in-differences regressions of investment−*q* sensitivity after dividing the treatment group into two subgroups. *TREAT_HIGHFINCONS* (*TREAT_LOWFINCONS*) equals 1 for treatment firms with pre-treatment financial constraints (*FINCONS*) above (below) the cross-sectional median. Panel C presents the results of the impact of tick size on investment−*q* sensitivity after controlling for the effects of shareholder monitoring. We use two proxies for shareholder monitoring based on findings in Ahmed et al. (2020): the magnitude of discretionary accruals based on the modified Jones model ($AbsDACC_{MJ}$) and that based on the modified Dechow and Dichev model ($AbsDACC_{MDD}$). Control variables (Controls) in Panel A and C include *Q*, *TREAT* × *Q*, *POST* × *Q*, *CF*, *TREAT* × *CF*, *POST* × *CF*, *TREAT* × *POST*, and *INVAST*. Control variables (Controls) in Panel B include *Q*, *TREAT_HIGHFINCONS* × *Q*, *TREAT_LOWFINCONS* × *Q*, *POST* × *Q*, *CF*, *TREAT_HIGHFINCONS* × *CF*, *TREAT_LOWFINCONS* × *CF*, *POST* × *CF*, *TREAT_HIGHFINCONS* × *POST*, *TREAT_LOWFINCONS* × *POST*, *TREAT_HIGHFINCONS* × *POST* × *CF*, *TREAT_LOWFINCONS* × *POST* × *CF*, and *INVAST*. All variable definitions are listed in the appendix. Standard errors displayed in parentheses are clustered by industry. ***, **, and * denote two-tailed significance at the 1%, 5%, and 10% levels, respectively.

6.1. Forecasting price efficiency

The first alternative explanation for the increase in investment−q sensitivity is rising FPE, rather than rising RPE, during the TSP. To rule out this alternative explanation, we follow Edmans et al. (2017) to add controls for both FPE and its interactions with Q and CF to regression (1). We measure FPE in two ways. Return non-synchronicity ($1 - R^2$), as in Edmans et al. (2017) and Lee and Watts (2021), is calculated as 1 minus the R^2 from a firm-specific regression of a firm's stock returns on market returns. When a firm's stock returns co-move with the market to a lesser extent (i.e., higher $1 - R^2$), its stock price conveys more firm-specific information, indicating higher FPE. Our second measure, the absolute deviation of the intraday variance ratio from 1 ($|VAR\_RATIO - 1|$), is widely used in the microstructure literature to measure price efficiency (e.g., Lo and MacKinlay, 1988; Chordia et al., 2008). *VAR_RATIO* is calculated as the ratio of five times the variance of 1-min mid-quote returns to the variance of 5-min mid-quote returns. When the stock price is efficient and follows a random walk, the variance in the stock return is a linear function of the length of the measurement window. As a result, the closer *VAR_RATIO* is to 1 (i.e., lower $|VAR\_RATIO - 1|$), the more closely the stock price follows a random walk, indicating higher FPE. Panel A of Table 7 displays the results of regression (1) after controlling for these two measures of FPE and their interaction terms. $TREAT \times POST \times Q$ remains significantly positive in both columns, suggesting that the effect of tick size on investment−q sensitivity is not driven by an increase in FPE.

6.2. Financial constraints

The second alternative explanation concerns financial constraints. It is possible that a larger tick size promotes market-making by brokers and dealers for small stocks (SEC, 2012), enabling them to obtain external financing more easily. A loosening of financial constraints allows firms to vary their investments more readily in response to investment opportunities. Through this financial-constraint channel, a larger tick size should also increase the sensitivity of investment to non-price measures of investment opportunities, not only q, contrary to the finding we report in Section 4. To further rule out this alternative explanation, we conduct another cross-sectional test and report the results here. If the effect of tick size operates through loosening financial constraints, it should be stronger in firms that were more financially constrained to begin with. In contrast, the learning explanation predicts that the effect should be stronger in firms that were less constrained, as these firms are better able to adjust investments in response to increased information in stock prices (Luo, 2005; Chen et al., 2007; Bakke and Whited, 2010; Edmans et al., 2017; Jayaraman and Wu, 2019).

To test the competing abovementioned predictions, we use the 10-K text-based financial constraint measure (*FINCONS*) developed by Hoberg and Maksimovic (2015).[26] We divide the treatment group into two subgroups. *TREAT_HIGHFINCONS* (*TREAT_LOWFINCONS*) is an indicator variable that equals 1 if a firm is in the treatment group and its *FINCONS* in the pre-treatment period is above (below) the cross-sectional median of the treatment group and 0 otherwise. We then estimate regression (3) by replacing *TREAT_ATDECMORE* and *TREAT_ATDECLESS* with *TREAT_HIGHFINCONS* and *TREAT_LOWFINCONS*, respectively. We report the results of this regression in Panel B of Table 7. Consistent with the learning channel but inconsistent with the financial-constraint channel, the coefficient on $TREAT\_LOWFINCONS \times POST \times Q$ is significantly positive while that on $TREAT\_HIGHFINCONS \times POST \times Q$ is statistically insignificant.

6.3. Shareholder monitoring

The third alternative explanation runs through shareholder monitoring. Ahmed et al. (2020) show that a larger tick size improves shareholder monitoring, as reflected in higher financial reporting quality as measured by the magnitude of discretionary accruals (*AbsDACC*).[27] Arguably, better shareholder monitoring could increase investment−q sensitivity by enabling managers to make investment choices that are more consistent with growth opportunities instead of with a desire to extract private benefits (Foucault and Frésard, 2012). To rule out this shareholder-monitoring channel, we add controls for both shareholder monitoring and its interactions with Q and CF to regression (1). Building on the findings of Ahmed et al. (2020), we use *AbsDACC* as the proxy for shareholder monitoring. We calculate *AbsDACC* in two ways: one based on the Dechow and Dichev (2002) model modified by McNichols (2002) and the other based on the Jones (1991) model modified by Dechow et al. (1995). A higher value of *AbsDACC* indicates weaker shareholder monitoring. In Panel C of Table 7 we report the results of regression (1) after controlling for *AbsDACC* and relevant interaction terms. $TREAT \times POST \times Q$ remains significantly positive, suggesting that the effect of tick size on investment−q sensitivity is not driven by better shareholder monitoring documented in Ahmed et al. (2020). We also find a significantly negative coefficient on $AbsDACC \times CF$ and a significantly positive coefficient on $AbsDACC \times Q$ for *AbsDACC* based on the modified Dechow and

[26] Hoberg and Maksimovic (2015) construct *FINCONS* from mandatory disclosures in Management Discussion and Analysis (MD&A) sections of Form 10-Ks, and *FINCONS* is based on management teams' summaries of their firms' ability to obtain financing for planned investments. *FINCONS* fits our purpose nicely, as Hoberg and Maksimovic (2015) show that firms with high *FINCONS* curtail investments to a greater extent than those with low *FINCONS* when exposed to negative unexpected shocks.

[27] To be sure, evidence regarding the effects of tick size on shareholder monitoring during TSP is mixed. Li and Xia (2021) conclude that a larger tick size harms shareholder monitoring, as reflected in larger magnitudes of real earnings management.

Dichev model, suggesting that managers rely to a greater (lesser) extent on the price (non-price) measure of growth opportunities when financial reporting quality is lower.

7. Conclusion

In this study we document a real effect of market microstructure through managerial learning: an exogenous increase in tick size leads to higher investment−q sensitivity in the controlled experiment of the TSP. Consistent with the interpretation that RPE and managerial learning increase with the tick size, we find that changes in managerial beliefs, as reflected in adjustments of forecasted annual capex, also respond more strongly to market reactions to capex forecasts as the tick size increases. Furthermore, we find a portfolio of evidence that is consistent with a learning-based mechanism through which tick size affects investment−q sensitivity: a larger tick size reduces AT, thereby encouraging FIA. Increased FIA generates additional information that is new to managers and consequently enhances managerial learning from stock prices. While each individual result may be interpreted differently, it is difficult for an alternative mechanism to explain all the evidence we present. Nevertheless, we acknowledge that our results based on small- and mid-cap firms included in the TSP may not be generalizable to large firms.

Our results have a direct policy implication. While it is widely known that a reduced tick size increases overall stock liquidity (Bessembinder, 2003; SEC, 2012; Yao and Ye, 2018) and FPE measured in certain ways (Chordia et al., 2008; Albuquerque et al., 2020), we show that it can at the same time reduce RPE and managerial learning from stock prices. As a result, regulatory changes in tick size introduce a trade-off between the two essential functions of secondary stock markets: liquidity and price discovery for real corporate decisions. This trade-off provides new insights into the complexity of the real effects of secondary stock markets.

Data availability

Data will be made available on request.

Appendix. Variable Definitions

Variable	Definition
INV	Investment is defined as capital expenditures (Compustat *capx*) plus R&D (Compust *xrd*) scaled by lagged total assets (Compust *at*) (%).
Q	Tobin's q is defined as the market value of equity (Compustat $prcc\_f \times csho$) plus the book value of assets (Compust *at*) minus the book value of equity (Compustat *ceq*) scaled by the book value of assets.
CF	Cash flow is defined as net income before extraordinary items (Compustat *ib*) plus depreciation and amortization expenses (Compustat *dp*) plus R&D expenses (Compust *xrd*) scaled by lagged assets.
INVAST	The inverse of the book value of assets in $billions.
ADJ_CAPEX	Adjustment of forecasted capex is defined as the percentage difference between capital expenditures made by a firm in a given year and the amount forecasted by the firm for the same year (scaled by the latter). For range forecasts, we follow Jayaraman and Wu (2020) in defining *ADJ_CAPEX* as the difference between annual capex and the endpoints of the range, such that upward (downward) adjustments are defined as annual capex minus the upper (lower) end of the range scaled by the forecast.
CAR	Market reactions to management capex forecasts are defined as cumulative abnormal returns (i.e., firm-level returns minus S&P500 index returns) over the 5 days surrounding a management capex forecast date (i.e., days [-2, 2] relative to the forecast date).
SIZE	Firm size is defined as the market value of equity at the end of the most recent quarter (closing stock price times shares outstanding) preceding a management capex forecast.
PRC	Share price at the end of the most recent quarter before the management capex forecast.
LAG_CAPEX	Capex in the most recent year (in US$ millions) before the management capex forecast date.
SURP	Earnings surprises are defined as seasonal changes in earnings-per-share for the most recent quarter before a management capex forecast.
EA_DUM	An indicator variable that equals one if a management capex forecast is accompanied by earnings announcements and zero otherwise.
CTT	The daily cancel-to-trade ratio is defined as the total number of canceled orders divided by the total number of trades. The annual cancel-to-trade ratio is defined as the average of the daily ratio. These data are collected from the SEC Market Information Data Analytics System (MIDAS) website https://www.sec.gov/marketstructure/downloads.html.
OLR	The daily odd-lot ratio is defined as the number of odd-lot trades (i.e., trades of less than 100 shares) divided by the total number of trades. The annual odd-lot ratio is defined as the average of the daily ratio. These data are collected from the SEC MIDAS website.
TRADESIZE	Daily average trade size is defined as total trading volume in shares divided by the total number of trades. The annual average trade size is defined as the average of the daily average trade size. These data are collected from the SEC MIDAS website.
ESV	EDGAR search volume is defined as average daily non-robotic EDGAR downloads of corporate filings over three-day windows around quarterly earnings announcements during a firm-year. We thank James Ryan for sharing the data at http://www.jamesryans.com.
CYCLICALITY	A firm's macroeconomic exposure to Gross Domestic Product (GDP) is defined as the R^2 from the firm-level estimation of the following model over the prior 12 quarters: $EARN_{i,q} = \alpha_0 + \alpha_1 GDP_{i,q} + \varepsilon_{i,q}$, where *EARN* is defined as income before

(*continued*)

Variable	Definition
	extraordinary items (Compustat *ibq*) and *GDP* is the quarterly nominal GDP. GDP data are made available by the Bureau of Economic Analysis (http://www.bea.gov/national/index.htm#gdp).
ENERGY	A firm's macroeconomic exposure to energy prices is defined as the R^2 from the firm-level estimation of the following model over the prior 12 quarters: $EARN_{i,q} = \alpha_0 + \alpha_1 Energy_{i,q} + \varepsilon_{i,q}$, where *EARN* is defined as income before extraordinary items (Compustat *ibq*) and *Energy* is the quarterly nominal energy price. Quarterly energy price is constructed as the quarterly mean of the monthly commodity fuel (energy) index, which includes crude oil (petroleum), natural gas, and coal price indices. These data are obtained from the International Monetary Fund (http://www.imf.org/external/np/res/commod/index.asp).
$1 - R^2$	Return non-synchronicity is defined as one minus the R^2 from a firm-specific regression of daily stock returns on value-weighted market returns for a year.
VAR_RATIO	The daily variance ratio is defined as the ratio of five times the intraday variance of 1-min mid-quote returns to the intraday variance of 5-min mid-quote returns. The annual variance ratio is defined as the average of the daily variance ratio.
FINCONS	Financial constraint is defined as 10-K text-based financial constraint scores developed by Hoberg and Maksimovic (2015).
AbsDACC	The magnitude of discretionary accruals is the absolute value of residuals from one of the following two accrual models: (a) $ACC_{i,t} = \delta_0 + \delta_1 \cdot (\Delta SALE_{i,t} - \Delta RECT_{i,t}) + \delta_2 \cdot PPE_{i,t} + \varepsilon_{i,t}$ (b) $ACC_{i,t} = \delta_0 + \delta_1 \cdot OCF_{i,t-1} + \delta_2 \cdot OCF_{i,t} + \delta_3 \cdot OCF_{i,t+1} + \delta_4 \cdot \Delta SALE_{i,t} + \delta_5 \cdot PPE_{i,t} + \varepsilon_{i,t}$ *ACC* is operating accruals (the sum of Compustat *recch*, *invch*, *apch*, *apalch*, *aoloch*, and *dpc*, multiplied by −1) deflated by average total assets (Compustat *at*). *ΔSALE* is change in sales (Compustat *sale*) deflated by average total assets. *ΔRECT* is change in accounts receivable (Compustat *rect*) deflated by average total assets. *PPE* is property, plant, and equipment (Compustat *ppent*) deflated by average total assets. *OCF* is operating cash flows (Compustat *oancf*) deflated by average total assets. Residuals are obtained from estimating regressions (a) and (b) by two-digit SIC industry-years with at least 15 observations. We label *AbsDACC* generated by model (a) as $AbsDACC_{MJ}$ and that generated by model (b) as $AbsDACC_{MDD}$.

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