Algorithmic trading and corporate investments

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Abstract

Using the Tick Size Pilot experiment as an exogenous shock to algorithmic trading (AT), we document that a reduction in AT has a negative causal effect on corporate investments. This result reflects lower speed and the extent to which stock prices capture signals about the value of investments. Consistently, we show that slower price response to a firm's disclosure of investment signals leads to stock underpricing, which promotes fewer investments. The effect we document is not explained by changes in stock liquidity, institutional ownership, firm monitoring, financial constraints, or in the quality of the firm's information environment.

JEL: D53; G12; G14; M41

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1. Introduction

Theoretical models, e.g., Fishman and Hagerty (1989) and Dow and Gorton (1997), predict that managerial incentives to spend resources on investments decrease when the stock price does not fully and quickly capture the expected benefits of investments, such as their impact on earnings growth and returns, i.e., when price discovery is slow.[1] We propose that algorithmic traders (ATs) increase price discovery and reduce underreaction to investment signals and underpricing, which promotes more investments.[2] ATs, defined as investors who use automated systems to execute low-latency trading strategies, increase price discovery through their trades on public signals and supplying liquidity to non-ATs, such as hedge funds (Chordia and Miao, 2020, Chakrabarty, Moulton, and Wang 2021, Rindi and Werner, 2019, Albuquerque, Song, and Yao, 2020, Zhang 2010). ATs have a material impact on price discovery as in recent years their trades have 'accounted for more than 50 per cent of the reported trading volume in U.S. stock markets', Lee and Watts (2021, p.375).

The price discovery channel we study differs from the effect that ATs have on price informativeness and managerial learning. Weller (2018) and Lee and Watts (2021) document that ATs screening of informed order flow deters information acquisition by fundamental investors, by transferring prospective rents away from information acquirers', which results in less informative prices. Less informative prices reveal less useful information to managers (Chen,

[1] Dow and Gorton (1997) model recognizes that managers have a discretion in making investments and are compensated based on price performance thus if prices do not capture benefits of investments, managers expected compensation reduces. Fishman and Hagerty (1989, p. 634) highlight that managers would not pursue activities that do not contribute to the increase in share value and that '[I]t is the presence of the information in the market, and the efficient pricing of shares that is beneficial.' Managers care about stock price performance because share price targets are a frequent performance measure in compensation contracts (Ittner, Larcker, and Rajan 1997; Indjejikian and Nanda 2002; Core, Guay, and Verrecchia 2003), and the share price performance bears on managers' compensation, e.g., through stock options, and career outcomes (Chang, Dasgupta and Hilary 2010). Bond, Edmans and Goldstein (2012, p. 5) argue that decision makers 'care about market prices because they are party to contracts that are contingent on market prices. This is most relevant for firm managers, whose compensation is tied to the firm's share price. Then, the manager's incentives to take real actions will depend on the extent to which these actions will be reflected in the stock price.'

[2] Past research documents undervaluation of high investment stocks. Lev and Sougiannis (1996) and Chan, Lakonishok and Sougiannis (2001) document that R&D spending predicts future stock returns. Deng, Lev and Narin (1999) find that current period patent count and citations, readily available public metrics of corporate innovation, predict future abnormal returns. Gu (2005, p. 385) reports that analysts and investors 'do not fully incorporate the implication of enhanced innovation capabilities for future earnings into stock prices and earnings forecasts. This bias is significantly associated with future abnormal stock returns.'

Goldstein and Jian 2007; Bond et al. 2012). Consistently, Ye, Zheng, and Zhu (2022) document that a reduction in algorithmic trading (AT) associates with an increase in a firm's investment sensitivity to stock prices as managers glean new information from prices to guide their investment decisions. As managerial learning reduces investment risk, it should promote more and higher quality investments through a reduction in investment risk, the option value of delaying an investment, and better project screening (Bernanke, 1983, Craine 1989, Ingersoll and Ross 1992, Weeds 2002). Thus, by reducing stock prices informativeness and managerial learning from stock prices, ATs should promote less investments, which contrasts the positive effect ATs can have on investments through the price discovery channel.[3]

The impact of AT on investment is further obfuscated by their effect on stock liquidity. ATs increase stock liquidity (Hendershott, Jones, and Menkveld, 2011, Hasbrouck and Saar, 2013) and Fang, Tian, and Tice (2014) find that an increase in liquidity causes a reduction in future investments and innovation as it promotes ownership by non-dedicated institutions who pressure managers to boost current profits, leading to investment cuts, or risk the exit of these investors. Further, stock liquid can also lower takeover costs, in turn motivating managers to reduce investment spending to improve firm short-term performance and reduce takeover pressure (Edmans 2009; Fang et al. 2014; Stein 1988; Shleifer and Summers 1988). Given the complex and opposing economic forces through which AT can affect investments, we examine this question empirically.

To establish causality between algorithmic trading and corporate investments, we take advantage of the exogenous shock to AT related to the regulatory Tick Size Pilot (TSP) program. In October 2016, the SEC started a two-year experimental program to examine the impact an increase in tick size will have on market quality and liquidity provision of small-capitalization stocks (market capitalization of $3 billion or less). SEC *randomly* selected 1,200 treatment firms where the

[3] Ye et al. (2022) document that investment sensitivity to stock prices increases as algorithmic trading reduces, but they do not examine whether AT affect the quantity and quality of investments and if there is a countervailing effect ATs have on investments through the price discovery channel.

tick size increased from \$0.01 to \$0.05, and a sample of 1,400 securities that continued trading with a tick size of \$0.01. The pilot ran for two years after which treatment stocks reverted to the original \$0.01 tick size. A consequence of a larger tick size was (i) a lower frequency with which quotes need to be updated, eroding the speed advantage of algorithmic trades over staled quotation (Foucault, Roell, and Sandas 2003), and (ii) a higher cost ATs faced when stepping in front of other limit orders, which reduced their incentives to trade in affected stocks. Lee and Watts (2021) show a significant reduction in AT in treated, but not in control stocks, after the start of TSP. Consistent with lower AT reducing price discovery, Chakrabarty, Cox and Upson (2021, p. 3) report 'that the relative price discovery of tick-constrained [treated] firms decreases significantly' compared to control stocks. The TSP program has the classic characteristics of a laboratory-style *randomized* natural experiment that allows us to causally link changes in AT, as a result of the TSP program, to corporate investments using the difference-in-differences research design.[4] To align the length of the pre-treatment period with the treatment period, we set the months from October 2014 to September 2016 as the pre-treatment period and October 2016 to September 2018 as the treatment period.

Following a well-established literature (Schmookler 1962, 1966; Sokoloff 1988; Jaffe and Trajtenberg 2002; Hall, Jaffe and Trajtenberg 2005; Moser and Voena 2012; Kogan, Papanikolaou, Seru and Stoffman 2017; Moser 2016), we investigate the impact AT has on both ex-ante and ex-post measures of corporate investments. The ex-ante (input) measures capture resources spend on investments and include R&D spending, capital expenditures, and percentage change in book value of total assets (Baysinger, Kosnik and Turk 1991; Hill and Snell 1989; Scherer 1984; Barker and

[4] We confirm earlier evidence on a statistically and economically significant reduction in AT after the start of TSP for treated compared to controls stocks in our sample of firms that engaged in innovation activity at any point over the sample period. We use six proxies for the trading activity of ATs: the odd lot ratio, which captures the fraction of trading volume associated with abnormally small trades that are more likely AT driven (O'Hara, Yao, and Ye, 2014), two trade-to-order ratios that are inversely related to the significant number of electronic order submissions ATs place as part of their 'slice and dice' algorithms (Hendershott, Jones, and Menkveld 2011), two cancel-to-trade ratios that are associated with the increased number of order cancellations by ATs stemming from their nearly instantaneous update of quotes (Hasbrouck and Saar, 2013), and the average trade size that is inversely related to AT activity as ATs split larger orders into smaller ones (Conrad, Wahal, and Xiang, 2015; O'Hara et al. 2014).

Mueller 2002). The limitation of the input investment measures is that we cannot ascertain the quantity or quality of investment output, thus, we complement them with ex-post (output) investment measures that include the quantity, quality and the private economic value of patents (Trajtenberg 1990; De Rassenfosse and Jaffe, 2018; Kogan et al. 2017). We measure characteristics of patents at the patent grant application date, which previous research argues is close to the time the underlying research took place (Trajtenberg, Jaffe and Henderson 1997; Hall, Jaffe, and Trajtenberg 2001).

We document a negative causal relation between a reduction in AT and investments using both the input and output measures of investments. The effect is economically significant — to illustrate, treated firms have on average 4.9% less R&D spending, compared to control firms, after the start of TSP and 5.3% less patent applications. These effects are material considering that the intensity of AT for treated firms reduces by between 37.9% and 8.9%, depending on a measure, thus a complete termination of AT activity would reduce treated firms' R&D spending by between 12.9% and 55.1% and patents by between 14% and 59.6%. For other investment measures, we document a 1.3% reduction in CAPEX spending (a 27.8% reduction compared to the sample mean) and 0.8% lower quarterly percentage change in the book value of total assets (a 23.7% reduction compared to the sample mean). The effect becomes significant in the latter half of the TSP period, consistent with managers needing time to observe changes in AT and understand the implications lower AT has on price discovery and to adjust firm investment levels accordingly.[5]

To support the argument that the AT effect on investment is channeled through price discovery, we examine the speed of price reactions to the U.S. Patent and Trademark Office disclosure of patent grant. Relative to control stocks and after the start of TSP, treated firms have 13.3% slower price discovery of patent disclosures around patent grant announcements. Further, we confirm that a reduction in AT leads to 0.9% underpricing of treated firms relative to control

[5] The economic effect in the second half of the TSP period is on average twice the magnitude compared to the effect in the first half.

stocks after the start of TSP (from the patent grant announcement date to approximately 60 days after). Annualized, this translates into 21.7% lower return for treated firms compared to control stocks disclosing patent grants – such lower returns can make managers reconsider spending resources on new investments.[6]

Next, we contrast the negative effect that lower AT has on investments channeled through price discovery with the potentially positive effect channeled through managerial learning (Ye et al., 2022). First, we document no significant changes in treated firms' value after the start of TSP, measured as in Ye et al. (2022) by Tobin's Q, that could explain their lower investment rates compared to control firms.[7] Second, increased managerial learning should result in managers selecting better quality investments and avoiding value-reducing projects resulting in higher operating performance. However, we find a *reduction* in treated firm's financial performance measured by return on assets relative to control stocks. Third, we find a significant reduction in the quality, originality and economic value of patents treated firms apply for during the TSP period. The economics magnitudes are again significant: treated firms' patents have on average 50.4% fewer citations compared to control stocks' patents after the start of TSP and using Kogan et al. (2017) measures of economic value of patents, we find that, in nominal terms, the average dollar value of a patent reduces by $0.494m for treated firms relative to control firms after the start of TSP.[8] These results are inconsistent with managers trading off better quality projects for a lower number of projects. Overall, the results support our inference that AT reduction has a net detrimental effect on treated firms' investments due to slower price discovery.

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[6] We calculate this number as abnormal return of −0.9% over a 60-day period × average of 4.025 patents for treated firms × 360/60.

[7] Ye et al. (2022) report an increased sensitivity of investments to Tobin's Q thus a reduction in Tobin's Q could explain lower investment among treated firms.

[8] The measure of economic value of patents in Kogan et al. (2017) looks at the stock market reactions to patent grants and is based on the intuition that stock prices are forward-looking and provide an estimate of the private value to the patent holder that is based on ex ante information. Kogan et al. (2017) report the measure is positively related to the scientific value of patents, growth, reallocation, and creative destruction. As TSP stocks are small size firms, less than $3billion in market capitalizations, such reduction in patent values are material for treated firms.

Finally, we address possible alternative explanations. An increase in tick size lowers stock liquidity that could affect investments, e.g., through narrowing of or changes in the composition of shareholder base.[9] To distinguish the effect of AT on investments from the liquidity effect of changes in tick size in treated firms, we perform three tests. First, we examine changes in total institutional ownership and in ownership by transient and by dedicated investors. We do not find significant evidence of changes in total institutional holdings or in the share of transient investors' holdings who could pressure managers to abandon investments to boost short-term performance (Cremers, Pareek, and Sautner 2020). Dedicated ownership tends to increase for the treated firms, which should have a positive effect on investments (Bushee 1998, Aghion, Van Reenen and Zingales 2013).[10] Thus, changes in ownership composition do not explain our results. Second, the result we find is not stronger for financially constrained treated firms, which would be most affected by a lower ability to raise financing, due to lower stock liquidity. This result suggests the financial constraints channel is unlikely to explain our results.[11] Third, to speak directly to the AT vs. tick size channels, we show that our results are present only for treated stocks that experienced a reduction in AT, but not for treated firms that despite a decrease in the tick size (and the resulting lower liquidity) did not experience a reduction in AT. Finally, relevant for the liquidity channel, Fang et al. (2014) document that lower stock liquidity, measured by higher spreads, *increases* innovation through changes in investor composition and takeover pressure, thus lower liquidity of treated firms should have a positive effect on investments, which further excludes the liquidity channel affecting our conclusions.

We also address whether the results could capture an increase in analyst coverage (external monitoring), which could pressure managers to meet short-term earnings expectations and reduce

[9] Studies document that TSP treated firms experienced an increase in quoted and effective spreads and a reduction in trading volume (Rindi and Werner 2019; Albuquerque, Song and Yao 2017; Chung, Lee and Rösch 2020; Lee and Watts 2021, Hope and Liu 2022).

[10] Borochin and Yang (2017) document that dedicated investors have informational advantage and their trades decrease future firm misvaluation relative to fundamentals, while transient investors have the opposite effect.

[11] Boehmer, Fong and Wu (2019) report that less AT promotes more seasoned equity offerings, consistent with lower cost of external financing. Their results suggest treated firms should not face higher cost of raising external capital during TSP that would constrain their investments.

investments as a result (He and Tian 2013). We find no evidence of (i) changes in analyst coverage between the treated and control firms nor (ii) changes in analyst forecast dispersion measured before earnings announcements that would suggest changes in the quality of the firm's information environment, which could explain changes in investments (Biddle, Hilary and Verdi 2009). Further, we show that the lower treated firms' investment rates are not explained by improved reporting quality (Ahmed, Li and Xu 2020) nor by managerial myopic underinvestment to boost short-term profits.[12]

To close the loop, cross-sectional tests show that the positive effect of AT on investments is stronger for stocks with a higher proportion of the CEO's stock-based compensation in total compensation. This result is consistent with efficient pricing that reduces the likelihood of stock undervaluation being more important when a larger share of managerial compensation depends on the stock price performance (Fishman and Hagerty 1989). Further, the relation between AT and investments is weaker for less opaque firms, as measured by lower accruals and higher financial reporting quality proxies. High quality accounting numbers increase the relative usefulness of accounting information compared to stock prices for assessing managerial effort resulting in lower sensitivity of compensation to price changes (Kang and Liu 2008, Garvey and Swan 2002).

The study contributes to the emerging literature on the real effects AT has on capital markets. The evidence suggests ATs have *real* impact on corporate investments through their effect on stock price discovery. This result has important policy implications as regulators debate how to regulate AT and the risk it poses to capital markets.[13] The study also complements the research

[12] Myopic underinvestment presumes that AT reduction in treated firms associates with amplified capital market pressures to boost reported earnings, which seems unlikely. Deteriorating financial performance of treated firms is also inconsistent with myopic reduction in investment spending to boost profits (Kraft, Vashishtha and Venkatachalam 2017).

[13] Securities and Exchange Commission's report 'Staff Report on Algorithmic Trading in U.S. Capital Markets' highlights that ATs pose significant capital market risks as they 'exacerbate periods of unusual market stress or volatility.', SEC (2020). The report also acknowledges the need for 'continued vigilance in monitoring these advances in technology and trading, and updating of systems and expertise will be necessary in order to help ensure that our capital markets remain fair, deep, and liquid.'

focused on the impact ATs have on liquidity, price discovery and informativeness.[14] Further, the research contributes novel evidence to the literature on the links between the key actors in financial markets and corporate investments. He and Tian (2013) show that financial analysts exert pressure on managers to meet short-term goals and as a result, managers spend less on research and development. Institutional investors (Aghion, et al. 2013), foreign institutions (Luong, Moshirian, Nguyen, Tian and Zhang 2017), and hedge funds (Brav, Jiang, Ma, and Tian 2018) have a positive effect on investments due to their expertise in improving investment efficiency and their monitoring role. He and Tian (2019) document that short-sellers play a disciplinary role affecting the quality and value of patents. Our study shows that ATs, who account for a significant portion of daily trading volume, significantly affect corporate investments and innovation.

2 Literature review

2.1 Algorithmic trading and investments

In the last decade, algorithmic trading has attracted significant attention from academics, regulators, market operators (e.g., the listing exchanges), practitioners, and the public.[15] The literature documents that the automation and the speed advantage of ATs trading strategies improves price discovery through liquidity demand and liquidity supply functions (Brogaard, Hendershott, and Riordan 2019).[16] AT facilitates faster and more complete impounding of information that is in the public domain into stock prices helping to eliminate price drifts, return autocorrelations and to reduce short-term volatility and arbitrage opportunities.[17] Bhattacharya,

[14] For this research, see Hendershott, et al. (2011), Hasbrouck and Saar (2013), Chordia and Miao (2020), Chakrabarty, Moulton and Wang (2020), Bhattacharya et al. (2020), Hu, Pan and Wang (2017), Weller (2018), Lee and Watts (2020), Boehmer, Fong and Wu (2021), and Ye et al. (2022).

[15] The book Flash Boys by Michael Lewis (2014) became the #1 best seller by arguing that algorithmic trading firms use their speed advantage to make a profit at the expense of ordinary investors. AT advocates responded arguing that the book is a 'work of fiction'. This controversy resulted in significant publicity and numerous studies by academics, in addition to political and investment-side pressure on regulators.

[16] ATs trade frequently during the day and act strategically with respect to trading information from other investors, public news, and order flow, profiting by either providing or taking liquidity and by taking advantage of even the smallest trading opportunities. ATs end up the trading day with zero or very low stock inventory.

[17] See Hendershott et al. (2011), Chordia, Roll and Subrahmanyam (2011), Hasbrouck and Saar (2013), Hagstromer and Norden (2013), Chaboud, Benjamin, Hjalmarsson and Vega (2014), Conrad et al. (2015)

Chakrabarty and Wang (2020) and Chordia and Miao (2020) document stronger market reactions to earnings announcements for high AT firms, and Chakrabarty et al. (2021) report that AT facilitates price efficiency during low attention periods.[18] Rogers, Skinner and Zechman (2017) and Hu, Pan and Wang (2017) report significant improvement in price efficiency to EDGAR filings and Michigan Index of Consumer Sentiment announcements for high AT stocks.

We expect that the positive effect AT has on price efficiency facilitates quick and more complete impounding of public investment signals into stock prices promoting fairer pricing and a reduction in undervaluation of high investment stocks (Gu 2005; Deng et al., 1999; Lev and Sougiannis 1996; Chan et al., 2001), which in turn increases managers' incentives to invest. Managers care about quick and efficient impounding of investment news into stock prices, e.g., about the impact investments will have on future earnings, because the stock price performance affects managers' career prospects (Chang, Dasgupta and Hilary 2010) and managerial contracts are typically tied to the stock price performance to reduce agency risk (Ittner et al. 1997; Indjejikian and Nanda 2002; Core et al. 2003; Aghion et al. 2013). Therefore, a more efficient pricing, through AT, provides the necessary incentive for corporate managers to exert costly effort to improve the firm's fundamental value through investments and innovation, key drivers of corporate growth (Caballero and Jaffe 1993; Klette and Kortum 2004; Lentz and Mortensen 2008; Garcia-Macia, Hsieh and Klenow 2019).[19]

2.2 Price informativeness and investments

AT promoted price efficiency comes at the cost of lower price *informativeness*, which captures the amount of discoverable information that can be reflected in stocks prices. Korajczyk and Murphy (2019) document that ATs can identify and almost concurrently trade in the same direction—and

[18] The literature considers price efficiency on public signals to reflect the speed of price discovery (Weller 2018; Bhattacharya et al. 2020; Chordia and Miao 2020).
[19] Though risky, investments are a key driver of corporate growth and is estimated to account for 50% of U.S. GDP growth (He and Tian, 2018).

at the expense—of informed institutions, reducing the latter's incentive to acquire costly private information. Consistently, Weller (2018) and Lee and Watts (2021) argue that AT discourages fundamental investors from acquiring costly private information before earnings announcements. Building on this insight, Ye et al. (2022, p. 1) document that a reduction in AT promotes higher sensitivity of investments to stock prices, 'suggesting that managers glean more new information from stock prices to guide their investment decisions', which they argue reflects that a reduction in AT encourages more fundamental information acquisition.[20] Lower investment uncertainty should promote more investments through a reduction in projects' discount rate as investment risk reduces, in the option value of delaying investments, and improve average quality of projects (Ingersoll and Ross 1992; Weeds 2002; Bond et al. 2012). However, it is unclear if and to what extent this negative effect ATs have on investments will be offset by the positive effect on investments mediated through price discovery. This tension motivates our empirical analysis of this research question.

3. Research methods: The Tick Size Pilot program

To examine the causal effect AT has on corporate investments, we use the Tick Size Pilot Program, a randomized controlled experiment that intended to examine the effect of the tick size increase on market making and price discovery of small capitalization securities. All eligible stocks included in the program have a market capitalization of less than $3 billion, an average closing price of at least $2, and an average trading volume of 1 million shares or less. The program introduced a widening of quoting and trading increments from $0.01 to $0.05 for 1,200 randomly selected securities, while 1,400 control securities continued to be traded in the normal quote of $0.01. The pilot was phased in during October 2016, lasted two years, and with its completion in October 2018, all treated stocks returned to their original trading tick size. We exploit the increase in the

[20] Earlier studies investigating managerial learning from stock prices include Chen et al. (2007), Betton, Eckbo, Thompson, and Thorburn (2014), Fresard (2010), Bond, et al. (2012), Hsu, Tian and Xu (2014), and Li, Moshirian, Tian and Zhang (2016).

tick size within the pilot program and use a difference-in-differences research design to understand how an exogenous reduction in AT, thus lower stock price efficiency, affects quantity and quality of corporate investments.

3.1 Measures of AT activity in a stock

ATs are characterized by a high daily trading volume and low latency of order submissions and cancellations. As in Weller (2018) and Lee and Watts (2021), we use the SEC Market Information Data Analytics System (MIDAS) data to construct six daily proxies that capture these characteristics. The odd lot volume ratio, *odd_lot,* is calculated as the total odd lot trade volume divided by total trade volume. The cancel-to-trade ratio, *cancel_ord* (*cancel_ord2*), is the count of all cancelled orders divided by the count of all trades based on displayed orders (total number of trades). A higher odd lot and cancel-to-trade ratio is associated with greater algorithmic trading activity. The trade-to-order ratio, *trade_vol* (*trade_vol2*) is calculated as the total trade volume based on displayed orders (total trade volume) divided by the total order volume. *Trade_size* is the average trade size defined as total trade volume times 1000 and scaled by total trades. A higher trade-to-order ratio and trade size is associated with less algorithmic trading activity. All six proxies are calculated as averages for each quarter of the two-year pre-TSP and the post-TSP period.[21]

3.2 Investment measures

Following extant literature (Hall et al. 2001; Hirshleifer, Low, and Teoh 2012; Atanassov 2013; Seru 2014; Sunder, Sunder and Zhang 2017), we construct three measures to capture the ex-ante (input) investment measures. The first measure is the quarterly research and development spending

[21] Lee and Watts (2021, p.383) highlight that '[I]n contrast to TAQ data, which only provide information on the national best bid offer (NBBO), MIDAS incorporates quote and cancellation information from the entire order book' and '[A]s discussed in Weller (2018), MIDAS data allow researchers to construct vastly improved AT proxies. For instance, some earlier AT studies used the NASDAQ AT proprietary dataset (e.g., Brogaard, Hendershott, and Riordan 2017; O'Hara, Yao, and Ye 2014; Carrion 2013), which covers a short sample period, 2008–2009, and includes only around 120 stocks. Other studies used TAQ data, which only include the NBBO, thus omitting the rest of the order book where AT activity may be taking place. Further, TAQ data traditionally ignored odd lot trades, where a large amount of AT activity is known to occur (O'Hara et al. 2014).'

scaled by the lagged book value of total assets for the quarter, *R&D*.[22] The second measure is the quarterly capital expenditure scaled by the lagged total quarterly book value of total assets, *CAPEX*.[23] The third measure is the quarterly percentage change in book value of total assets between consecutive quarters, ΔTA. Although these measures do not capture the success of the investment nor its quality, they reflect the intensity with which firms pursue investments (Hausman et al. 1984; Becker-Blease 2011).

To capture the quantity and quality of investment outcomes, we use several ex-post (output) investment measures. We use the total number of patent grant applications filed in a quarter that are eventually granted, *#patents*, to capture a firm's innovation quantity.[24] As in Griliches, Pakes and Hall (1987) and Sunder et al. (2017), we use the patent *application date* to capture the timing of innovation as it more closely aligns with the time of actual innovation than the patent grant date. In further tests, we also create an industry-adjusted measure of innovation similar to Ciftci, Lev and Radhakrishnan (2011), *adj #patents*, to capture relative innovation by a firm compared to the industry average.

To capture the patents' quality and their technological and economic importance, we count the total number of citations and their economic value. *#citations* is the number of citations made to the granted patent as of December 31st 2019. Roach and Cohen (2013, p. 504) argue that 'patent citations are the most widely employed measure of knowledge flows in the economics, management, and policy literatures.' A patent that receives more citations is more likely to include

[22] Some studies scale R&D expenses by revenue (e.g., Dechow and Sloan 1991; Chambers, Jennings and Thompson 2002; Ciftci and Cready 2011). The idea is that (i) R&D funding comes primarily from revenue making it a better denominator than assets, (ii) SFAS No.86 requires capitalization of certain software development costs, an exception to SFAS No.2 that requires immediate expensing of R&D, thus in the high R&D software industry (Mohd, 2005), R&D is part of both the numerator and denominator reducing comparability across industries, and (iii) that book values of assets can be distorted, e.g., mature firms' assets tend to be understated compared to younger firms due to using historical costs on the balance sheet and adjusting for depreciation (thus firms with similar market capitalization and R&D spending may have significantly different ratios of R&D when scaled by assets). Our results are similar using quarterly revenue in the denominator.

[23] We take the Compustat Quarterly year-to-date amount of net capital expenditure for the first fiscal quarter. Because the value is reported as a cumulative over the fiscal year, for fiscal quarters two to four we calculate CAPEX as changes in year-to-date capital expenditures between the current and previous fiscal quarter.

[24] The U.S. Patent and Trademark Office does not disclose information on unsuccessful patent applications. The rate of granted to applied patents is estimated to be between 97% (Quillen and Webster 2001) and 75% in Lemley and Sampat (2008).

technology that is valuable for subsequent innovation advances. Thus, forward citations capture the scientific value of the patent (Trajtenberg et al. 1997; Hall et al. 2001). Following Hall et al. (2001), we also measure patents' originality, *Originality*, which captures how many previous patents an invention draws on to produce a novel idea. More backward citations indicate lower originality as the patent is more closely related to previous innovations.

To speak to the economic value of patents, we use the Kogan et al. (2017) measure of the average stock market response to news about patents granted to a firm in a quarter-year. Kogan et al. (2017, p.669) argue the measure 'contains considerable information about [patent-promoted] firm growth in addition to what is contained in patent citations.' We measure the dollar value of granted patents both in inflation-adjusted values, *$rValue*, and in nominal terms, *$nValue*. We measure patent values at the grant date for two reasons. Frist, Kogan et al. (2017, 682) report that 'USPTO does not publish applications at the time they are filed' and since 2000, patent applications are published 18 months after the filing date and their disclosure associate with very weak price reactions. In contrast patent grant disclosure dates associate with strong significant price reactions 'suggesting that the information content around the application publication date may be small', Kogan et al. (2017, 681). Second, patent grants follow typically around 2 years after the patent applications (Hegde and Luo 2018), thus we observe price reactions at the time of TSP but to research itself unaffected by TSP. Our use of these alternative measures of patent value also addresses the concern that patent citations may not adequately measure knowledge flows (Agrawal and Henderson 2002; Jaffe et al. 2002). The number and quality of patents measure innovation output conditional on the firm's decision to protect the innovation through a patent and on the successful outcome of the patent application. Griliches (1990) and Sunder et al. (2017) highlight that despite this limitation, there is no other widely available measure to better capture firms' technological advances, which explains the popularity of the patent measure in research.

3.4 Regression model

To speak to the causality of the relation between AT activity and corporate investments, we employ a difference-in-differences research design using the randomized experiment of the Tick Size Pilot, and estimate the average treatment effect on corporate investments in treated firms using the following model:

$$investment_{i,t} = \gamma_0 + \gamma_1 Post_t + \gamma_2 Treatment_i + \gamma_3 Post_t \times Treatment_i + Controls_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $investment_{i,t}$ is the logarithm of one plus the measures of firm's R&D, CAPEX or patents in quarter *t*. We use unlogged values of percentage change in total assets and industry-adjusted patents as the values can also be negative. $Post_t$ is an indicator variable that takes the value of one for each quarter of the TSP period from October 2016 to September 2018, and zero for the period from October 2014 to September 2016. $Treatment_{i,t}$ equals one if a firm *i* belongs in the treatment group that experienced an increase in tick size, and zero otherwise. The main variable of interest that captures the incremental effect of the exogenous reduction in AT activity on a treatment firm's investment activities is captured by the interaction term, $\gamma_3 Post_t \times Treatment_i$. To the extent that AT activity enhances the efficiency of stock prices in capturing investments, the decrease in AT in treated firms during the TSP period should reduce corporate investments, and thus γ_3 should be negative. On the other hand, lower AT activity in treated firms may increase information acquisition by fundamental investors increasing stock price informativeness. Higher stock price informativeness means managers are better able to learn from stock prices leading to positive γ_3.

Lee and Watts (2021, p.379) highlight that a key advantage of the TSP is that it allows a researcher 'to estimate treatment effects with relatively few concerns for selection issues that would otherwise exist absent a randomized control sample' and that including controls can lead to a 'bad controls' problem (e.g., Angrist and Pischke 2009), if, for example, the controls are correlated with the tick size treatment.[25] These concerns motivated Lee and Watts (2021) to present results without controls, and as robustness, results with four controls variable (firm size, book-to-market, ROA and asset growth). However, to build confidence in our results, we include several firm-level control variables in the regression model. We control for firm size, growth opportunities and profitability using the natural logarithm of total assets (*Firm size*), the book-to-market ratio (*B/M*), and return on assets (*ROA*). To account for the effect of capital structure, we also include the leverage ratio (*Leverage*) and use internally generated cash to capture cash liquidity (*Cash/Assets*). We also control for institutional ownership using the percentage of institutional holdings (*Institutional ownership*). Control variables are measured for each quarter. All models include industry and quarter fixed effects, while standard errors are clustered at industry and quarter. Variables definitions are in Appendix A. To minimize the effect of extreme observations, we winsorize all continuous variables at the top and bottom 1% of each variable's distribution.

4. Data

The list of securities included in the TSP is obtained from the FINRA website. Following Weller (2018) and Rindi and Werner (2019), we exclude preferred stocks, stocks dropped due to mergers, delistings or with prices below $1, or stocks that changed TSP group during our sample period, which leaves 1,970 firms (987 treated and 983 control firms). We construct our AT activity proxies using daily order book information across all major U.S. stock exchanges from MIDAS. We obtain R&D, CAPEX and quarterly book value of total assets from Compustat and patent-level data from the U.S. Patent and Trademark Office (USPTO) database, which we match to the TSP sample.[26]

[25] Lee and Watts (2021, p.379) highlight that 'while controlling for liquidity or institutional ownership might seem sensible, these variables themselves can be affected by the tick size treatment (e.g., Rindi and Werner 2019; Albuquerque et al. 2020)' and that 'the securities in this pilot study are smaller firms by design, and data availability can be an issue when a large set of control variables is added.' They show that differences between key firm characteristics, such as market capitalization of treatment and control firms before the start of the program are not statistically significant. Albuquerque et al. (2020) in their Table 2 find no significant differences in returns, size, market-to-book ratio and various liquidity measures between treatment and control stocks before TSP.

[26] See Graham, Hancock, Marco and Myers (2013) and Graham, Marco and Myers (2018) for a description of the U.S. Patent and Trademark Office data.

Similar to Kogan et al. (2017) and Ye et al. (2022), for our main tests, we only keep firms with at least one non-missing R&D and one patent observation at any point over the period October 2014 to September 2018, which covers our pre- and TSP period. We focus on firms with R&D activity and patents as Hausman, Hall, and Griliches (1984) caution against using samples with excessive firm-years with zero patent counts as they can produce spurious correlations. [27] Further, we want results to be comparable between ex-ante and ex-post measures of investments. However, robustness tests show our conclusions are unchanged when we assign zero to firms with no R&D or patent information. We use CRSP and Compustat to calculate fundamental ratios for control variables and collect institutional ownership data from 13F filings. The final sample includes 3,954 firm-quarter-years (1,980 treated firm-quarter-years and 1,974 control firm-quarter-years), which is comparable to 5,544 observations in Ye et al. (2022).[28]

5. Results

In Panel A of Table 1, we present descriptive statistics for our investment measures. The mean R&D spending is 3.2% of assets, CAPEX spending 4.1% and the percentage change in book value of assets is 3.5%. During our period, sample firms obtained on average 3.552 patents per year-quarter (−0.014 industry-adjusted patents) with an average of 5.076 citations. The mean nominal (real) value of patents is $8.177 million ($3.364 million). Given that our sample comprises of smaller firms, it is not surprising that our proxies for corporate investments are smaller, yet comparable, to those reported in related research. For example, Shroff (2017) report mean (median) R&D of 0.061 (0.033) and CAPEX of 0.066 (0.042) for all Compustat firms between 1991 and 2007. Kim, Park and Song (2019) report an average number of patents of 5.447 per year for their sample of firms with non-missing patent information over 1980–2004.

[27] Assuming zero for a firm that would never engage in a patent development can produce spurious associations between patent counts and predictors of innovation (Hausman et al., 1984).
[28] The main reason for our slightly lower sample size compared to Ye et al. (20220 is that we require patent data.

In panel B of Table 1, we present descriptive statistics for the control variables used in the analyses. Our sample firms have an average market value of $1,155 million, which reflects that the SEC only considered firms with market capitalization of less than $3 billion for the TSP experiment. Consistent with the TSP firms being earlier in the firm's life cycle, they tend to have low profitability, cash holdings and leverage, but high growth potential. The average institutional ownership in our sample is 70.8%.

Appendix B reports descriptive statistics for the AT measures, which are comparable with previous research. We also document that there are no significant differences in AT for treated compared to control stocks before the start of TSP and a significant reduction thereafter across all measures similar to the finding in Cox, Van Ness, and Van Ness (2019), Chung, Lee and Rösch (2020) and Lee and Watts (2021). To illustrate, treated firms exhibit a reduction in the two cancel to trade ratios of 31.1% and 37.9% in the post-TSP period and an increase in trade size of 8.9% consistent with a significant decrease in AT activity relative to control firms after the start of the TSP program.

[Table 1]

In Panel A (Panel B) of Table 2, we examine whether there are significant differences in the mean values of the investment (control) variables between our treatment and control samples in the pre-TSP period. We do not find any significant differences in the pre-treatment means of the two groups, a result that is consistent with the random allocation of stocks to treated and control groups of the pilot program.

Panel C evaluates the presence of pre-existing trends following the approach from Donelson, McInnis and Mergenthaler (2016) and Ahmed et al. (2020). Specifically, we include pre-TSP period indicators in Eq. (1) and their interactions with the treatment firm indicator. This approach allows control and treated firms to have different pre-treatment trends in investments. Specifically, *Pre_Sept2015* is an indicator variable for the pre-treatment period between March 2015 and September 2015. *Pre_March2016* is an indicator for the pre-treatment period between October

2015 and March 2016, and *Pre_Sept2016* for the pre-treatment period between April 2016 and September 2016. The intercept captures the pre-TSP period between October 2014 (i.e., the start of our sample period) and February 2015. The regression result shows that none of the interaction terms between pre-TSP period indicators and the treatment dummy are significant, which suggests no significant differential trend for treated firms before TSP.[29] This result is consistent with the parallel trend assumption holding in the data and further supports the supposition that the random assignment of the TSP program did not result in selectivity bias on firm investment activities.[30]

[Table 2]

5.1 Regression results for the relation between AT and investments

Panel A of Table 3 examines the effect of TSP on investments. Regression results show a significant reduction in R&D spending for treated firms relative to controls after the start of TSP. The economic effect is significant showing a 4.9% reduction in 1+R&D spending (considering that the intensity of AT for treated firms reported in Appendix B reduces by between 37.9% and 8.9%, depending on a AT measure, the associated reduction in treated firms' R&D spending is between 12.9% and 55.1%).[31] We find similar evidence of a reduction in treated firms investments after the start of TPS when we examine capital spending and changes in book value of assets. Specifically, we document a 1.3% reduction in 1+CAPEX spending (a 27.8% reduction compared to the sample mean in Table 1) and 0.8% lower quarterly percentage change in total assets (a 23.7% reduction compared to the sample mean).

[29] Including pre-treatment period indicators changes the interpretation of the coefficient on the interaction Post×Treatment in Table 4, which now captures the differential effect relative to the pre-TSP period between October 2014 and February 2015 captured by the intercept. The true 'difference-in-differences' comparison as specified in Eq. (1) is presented in the next section.

[30] The evidence that innovation levels are similar between treated and control firms also reduces the likelihood that our results capture a correction in previous excess investments of treated but not control firms. This case would require non-random assignment between treated and control firms on innovation, which the TSP natural experiment avoids.

[31] We calculate this value by dividing the coefficient on *Post×Treated* by the average range reduction in AT activity in treated stocks, i.e., $\frac{4.9\%}{8.9\%}$ and $\frac{4.9\%}{37.9\%}$.

The input investment measures do not distinguish if lower investments reflect a reduction in pre-treatment overinvestment, suboptimal investment (underinvestment) or a trade-off between lower quantity but higher quality of investments. To help us distinguish these channels, we examine changes in patents applications, an important output of investment. The last columns of Panel A document that the decreased AT activity in treated compared to control firms following the introduction of the TSP program resulted in a significant decrease in the number of patent applications. The economic magnitude of the effect is around 5.3%, which is comparable to the effect on R&D spending. Lower treated firms' patent counts may reflect a reduction in patentable research and a delay in patent grant application. We cannot distinguish these two channels as we do not observe when a company is ready to file a patent application. However, both a reduction in patentable research and delays in patent applications are consistent with lower benefits that treated firms expect from patent disclosure, such as their impact on the stock price.[32]

Because investment activities vary significantly between industries, we also examine the industry-adjusted number of patents. Specifically, each year-quarter we calculated the mean patent count for the Fama-French industry the firm belongs to (including firms not in the TSP sample), which we then subtract from the firm-year patent count. We then use the (unlogged) industry-adjusted patent count as the dependent variable in Eq. (1). We continue to find a significant negative coefficient on the interaction term *Post×Treatment.* Overall, we find consistent evidence that a reduction in AT leads to a reduction in the level of corporate investments.[33]

[Table 3]

5.2 Price discovery vs. managerial learning

[32] Delays in patent application increase the risk a competing patent on a similar idea may emerge thus increase the risk of losing the benefits from the patent, which incentivizes managers to quickly apply for a patent (Griliches et al. 1987; Sunder et al. 2017).

[33] A large proportion of Compustat firms have missing values for R&D and patents. Koh and Reeb (2015) report that more than half of NYSE firms have missing R&D expenditures. Large-sample studies document that between 84% (Atanassov, Nanda, and Seru 2007) and 73% (Tian and Wang 2014) of Compustat firms have missing patent data between 1974–2006. We also expect to see a significant proportion of missing patent data in our sample that includes small firms. Appendix C repeats the main regression assuming zero for missing R&D and patent data and our conclusions are unchanged.

Ye et al. (2022) document that a reduction in AT promotes 'Increased fundamental information acquisition [that] generates incremental information about growth opportunities, macroeconomic factors, and industry factors', which in turn increases managerial learning from stock prices and in turn investment sensitivity to stock prices. Managerial learning reduces investment uncertainty promoting higher investment spending (Bond et al. 2012; Goldstein and Yang 2019; Goldstein et al. 2022).[34] To understand the countervailing effect of increased managerial learning on treated firms investment rates, we use Eq. (1) from Ye et al. (2022) which is augmented with the normalized stock price or Tobin's Q, calculated as the market value of equity at quarter end plus the quarterly book value of total assets minus the quarterly book value of equity scaled by the quarterly book value of total assets, *Q*. We then interact Tobin's Q with *Post*, *Treatment* and their interaction and include them in the regression model jointly with firm-fixed and year effects.[35]

Panel B of Table 3 reports regression results for the model augmented with Tobin's Q interaction terms. Ye et al. (2022) report a positive coefficient on the triple interaction term $Post \times Treatment \times Q$ when regressed on R&D spending, consistent with increased managerial learning, a result we confirm. We find broadly similar result for other investment measures. This evidence, jointly with *a potential* result that treated firms experienced a *reduction* in Tobin's Q after the start of TSP, could explain lower investment rates in treated firms that we observe. To test this prediction, the bottom rows of Panel B report mean values of Tobin's Q before and after the start of TSP for treated and control firms. We find no significant differences in Tobin's Q between the two groups before treatment, consistent with the random allocation of stocks between treated and control groups. Further, the difference in Tobin's Q after the treatment is also similar between

[34] Lower investment uncertainty (i) reduces investment risk and the discount rate increasing the pool of projects with positive net present value and (ii) reduces the option value of delaying the investment (Yang, Burns and Backhouse, 2004)

[35] Because our sample period is short — two years before and two years of the TSP period, firm-fixed effects largely control for (i) managerial characteristics and (ii) the characteristics of managerial contracts that could affect innovation.

treated and control stocks. Thus, the learning channel cannot explain why treated firms reduce their investment spending after TSP compared to control stocks.

5.3 Future operating performance and managerial learning

To further understand if managerial learning can explain our result, we examine future operating performance. Managerial learning should help managers select more profitable projects and avoid pursuing negative NPV projects with both channels resulting in higher future operating performance. Panel C of Table 3 reports results for Eq. (1) where we use future quarterly average ROA and cash/assets measured over six quarters relative to the current year-quarter.[36] Treated firms have lower future ROA and generate less cash, a result consistent with treated firms rejecting positive NPV projects that would have associated with better operating performance in the future, not with managerial learning explaining our result.

The evidence that treated firms have poor financial performance in the future relative to control firms also helps to rule out that the investment decline for treated firms that we observe reflects *myopic underinvestment* by treated firms' managers to temporarily boost corporate performance (we do not see a reason why a reduction in AT should associate with amplified capital market pressures to boost reported earnings leading to myopic underinvestment). Further, it excludes the possibility our results capture *pre-treatment overinvestment* where both treated and control firms pursue some negative NPV projects. Reducing overinvestment should result in a comparatively higher operating performance for treated firms compared to control firms after the start of TSP.

[36] We look six quarters ahead because (i) we do not expect benefits of innovation to have instantaneous impact on financial performance and (ii) the period is short enough to give us confidence that changes in financial performance are linked to changes in firm's investments.

5.4 Price discovery around patent grants announcements

Our argument on the positive relation between AT and investments is based on the premise that AT increases price discovery and reduces underreaction to public signals about corporate investments. Our next test validates this proposition for public announcements of patent grants by the U.S. Patent Office. We focus on patent grants as their public announcements are not confounded by associated releases of other financial information, which happens at quarterly and annual earnings announcements when firms report R&D spending jointly with other financial information in 10Q and 10K filings. Further, patent grants signal a value-enhancing investment outcome as the Patent Office determined the innovation offers incremental and unique value that must be protected by a patent.[37] Consistently, previous research documents strong positive price reaction to patent grants, see Pakes (1985), Hall et al. (2005), Nicholas (2008) and Kogan et al. (2071). In contrast, R&D, CAPEX and changes in book value of assets reveal only the investment cost, which makes it harder for investors to assess how the spending will affect future cash flows and firm value, thus the direction and magnitude of price reactions. Lower precision of such disclosures makes assessing price discovery around such events more challenging. For example, Doukas and Switzer (1992) report that disclosures of an increase in R&D expenditure associates with positive (negative) price reactions in high (low) market concentration industries. Consistent with investors facing difficulties in interpreting R&D signals, Deng et al. (1999) and Gu (2005) document significant investor underreaction to R&D disclosures. Investors face lower difficulties in interpreting patent disclosures as these reflect an outcome of successful investment expected to generate positive future cash flows (Kogan et al., 2017) and patent grants include information on the potential uses and benefits of patents (Trajtenberg 1990; De Rassenfosse and Jaffe, 2018; Stoffman, Woeppel and Yavuz 2022).

[37] To be patentable, the invention must be statutory, novel, useful, and nonobvious with usefulness 'refers to the condition that the subject matter has a useful purpose.' See https://www.uspto.gov/patents/basics/general-information-patents.

Kogan et al. (2017, p.673) describe that '[T]he USPTO issues patents on Tuesdays, unless there is a federal holiday. The USPTO's publication, Official Gazette, also published every Tuesday, lists patents that are issued that day along with the details of the patent.' To speak about the speed of price discovery, in the spirit of Weller (2018), we create a ratio of the price reaction on the patent grant announcement day (abnormal return, AR (0)) to the total signal content measured in a three-day window centered on the patent grant disclosure day, $\frac{AR(0)}{CAR(-1,1)}$. Higher values of the ratio suggest that most of the signal content impounds on the announcement day. The ratio is not dependent on the economic value of the patent thus removing the need to control for the quality/value of patents between treated and control firms. The normal return benchmark we use to calculate abnormal returns around the patent grant announcement is the Carhart (1997) four-factor model estimated over 100 days before the patent grant date.

Table 4 documents that price discovery happens more outside the announcement day for treated firms relative to controls after TSP.[38] This result is consistent with lower AT associating with less efficient impounding of public innovation signals into stock prices. As the mean value of the normalized price reaction, $\frac{AR(0)}{CAR(-1,1)}$, is 0.64, there is a 13.3% reduction in the speed at which investors react to treated firms' patent grants announcements, a significant effect.[39]

[Table 4]

To understand if price inefficiency, i.e., underreaction, persists after the patent grant announcement, we also examine post-grant date abnormal returns over various windows. As Table 4 shows, we continue to find a negative coefficient on the interaction term *Post*×*Treatment* from one to 60 days after the grant date. This result is consistent with underpricing of treated firms

[38] The conclusions are similar when we measure the total signal content over the period from the announcement day to five days after the announcement.

[39] In untabulated results, we also examined other investments disclosures events such as management CAPEX guidance. We identify 769 instances of CAPEX guidance but in all cases, the CAPEX forecast was bundled with an EPS forecast. This made it challenging to identify the information content of the CAPEX forecast. However, using those guidance release days, we continue to find significantly slower speed of price discovery in the TSP period.

relative to controls for about two months after the grant date.[40] The positive coefficient on *Post×Treatment* in the window from 61 to 100 days after the patent grant date suggests the initial underreaction for treated stocks is reversed over this window. Starting from day 101 after the announcement, we find no evidence of abnormal return performance. To put these numbers into perspective, a 0.009 lower price reaction over a 60-day window multiplied by the average 4.025 patents for treated firms from Table 2 generates 21.7% lower annualized return for treated firms compared to control stocks. Such lower returns can make managers reconsider the value of spending resources to purse new investments. Jointly, Table 4 results are consistent with lower efficiency with which prices impound patent information and temporary undervaluation of treated firms after TSP compared to control stocks.

5.5 Quality and economic value of innovation

Ye et al. (2022) document increased managerial learning, which should help managers select higher quality projects that are more valuable to the firm. Though we do not find an improvement in future operating performance, investments can generate cashflows over several years, which may not be captured by the financial ratios we use. To provide further comparative evidence on the effect price discovery compared to managerial learning from stock prices have on investment rates, we examine (i) the scientific significance of patents captured by the number of citations (Harhoff, Narin, Scherer and Vopel 1999) and originality (Hall et al. 2001) and (ii) economics value of patents. This test helps us to differentiate whether managers trade-off a lower number of patent applications for a relatively higher quality of patents, consistent with managerial learning, or whether both the count and quality of innovation are reduced by lower AT activity.

[40] Our results are consistent with Chordia and Miao (2020), who report that more intensive AT reduces the post-earnings announcement drift.

The first columns of Table 5 document that the number of citations decreases for treated firms following the start of TSP.[41] The economic effect is significant with citations reducing by 50.4% relative to the average reduction in AT , $\left(i.e., \frac{11.8\%}{1/2(8.9\%+37.9\%)}\right)$. We reach a similar conclusion when we examine the average originality of patents. After the start of TSP, new patents draw more strongly on previous inventions, which suggests lower uniqueness of newly developed patents. Jointly, the evidence suggests the scientific significance of patents decreases for treated firms.

[Table 5]

Next, we use the real and nominal measures of private economic value of patents from Kogan et al. (2017) as dependent variables in Eq. (1). We document a significant reduction in the economic value of patents for treated firms relative to controls stocks after the start of TSP. In nominal terms, the average dollar value of a patent reduces by $0.494m for treated firms relative to control firms after the start of TSP. As the TSP experiment included only small firms, this is a substantial reduction in patent's economic value. Jointly, Table 5 results suggest that the scientific and economic value of patents reduce as AT activity decreases.[42] Overall, we believe a reduction in treated firms' investment rates cannot be explained by managerial learning and is consistent with slower and less complete impounding of investment signals into stock prices resulting in temporary undervaluation of treated firms.

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[41] We collect patent data in 2021, which alleviates the concern that the average two-year lag between a patent's application date and the grant date leads to patents data under review missing from the dataset (Hall et al. 2001). There is also a concern that citations accumulate over long period of time and more recent patents will, by construction, have fewer citations. Our difference in differences design adjusts for this effect as control firms would suffer from a similar bias.

[42] In untabulated results, we find that our conclusions from Table 5 are unchanged when we scale raw citation counts and the real and nominal measures of private economic value by the number of patents.

6. Additional tests and alternative explanations

This section first examines the speed with which treated firms adjust investments in response a reduction in AT. Next, we address the concern the results capture a reduction in stock liquidity of treated firms. These tests address alternative explanations based on changes in treated firms' ownership structure, external monitoring and quality of the information environment. Finally, we report that financial constraints do not explain our findings.

6.1 The speed with which treated firms react to TSP

We recognize that managers need time to understand the implications lower AT has on price efficiency and to adjust firm investment levels accordingly. Though Ye et al. (2022) find that managerial learning happens quickly, already in year one of the TSP, and increases in magnitude over time, we expect a gradual change in treated firms' investment patters. For this test, we split the TSP period into the early and later subperiods. *Post_Sept2017* is an indicator variable for the early part of the TSP period that is between October 2016 and September 2017. *Post_ Sept2018* captures the period between October 2017 and the end of the TSP program in September 2018. We then interact the subperiod indicators with the treatment dummy, which compares the investment activities of treated firms with that of control firms in each subperiod.

Table 6 reports regression results when we include the subperiod indicators and their interactions in Eq. (1). The coefficients on the interaction term between the treatment dummy and the indicator for the early months of the TSP period, *Post_Sept2017×Treatm*ent, are generally negative but insignificant for the investment measures. The coefficients on *Post_Sept2018×Treatment* are significant, which suggests that the effect we document becomes significant in the later period of the TSP. The result is consistent with a gradual change to treated firm's investment strategies as managers recognize delayed impact on stock prices from disclosure of investment spending and patents. The magnitudes of the coefficients in the latter TSP period are on average higher compared to the full sample results reported in Table 3 suggesting the full-sample magnitudes may be understated.

[Table 6]

6.2 The effect of changes in AT vs. in stock liquidity on investments

The result that a reduction in AT affects investments could be confounded by the effect of a higher tick size, which increases trading costs in treated firms. Thus, it is plausible that it is treated firms' lower liquidity that reduces investments. Fang et al. (2014) document that lower stock liquidity promotes more investments by reducing the risk of hostile takeovers and ownership by non-dedicated investors who pressure managers to reduce investment spending to boost short-term operating performance. Thus, if our results captured the liquidity channel, we should observe an *increase* in investments in treated firms. However, we recognize that stock liquidity may affect investments through other channels than identified in Fang et al. (2014), for example, lower liquidity in treated firms may discourage investment by monitoring institutional investors and it is lower monitoring that reduces incentives to invest. Thus, we examine whether it is lower liquidity or lower AT that explains reduced investments in treated firms.

As a first test, to distinguish between the liquidity and AT channels, we identify the direction of the change in AT for treated firms after the start of the pilot program, which we then interact with the interaction term *Post×Treatment*. This approach splits the interaction term into two variables: *Post×Treatment×decrease in AT* and *Post×Treatment×zero or increase in AT*, where variables *decrease in AT* and *zero or increase in AT* are indicator variables for a directional change in AT in the treatment vs. pre-TSP period and are equal to zero in the pre-treatment period. To capture directional changes in AT, we use the odd lot ratio which has a positive association with AT. Further, we create an *AT factor* based on the principal component analysis of the six AT measures to identify an average increase or reduction in AT in the treatment compared to the pre-treatment period. The weights in the AT factor are −0.208 for ln *odd_lot*, −0.286 for ln *cancel_ord*, −0.280 for ln *cancel_ord2*, 0.197 for ln *trade_vol*, 0.203 for ln *trade_vol2* and 0.171 for ln *trade_size*.

We multiply the *AT factor* by −1 so that higher values of the measure reflect higher intensity of AT.

Table 7 confirms that the reduction in investments comes from treated firms that also experience a reduction in AT. The coefficients on *Post×Treatment×decrease in AT* are significantly negative for the odd lot ratio and the AT factor measures of AT. The insignificant coefficient on *Post×zero or increase in AT* is consistent with Eaton, Irvine and Liu (2021) and Dass, Nanda, and Xiao (2017) that liquidity has no association with innovation as measured by patents.[43] Thus, the liquidity channel cannot explain our results, but we continue to find support for the AT channel. In Appendix D, we perform further tests that rely on cross-sectional identification and report lower patent counts for treated firms that experienced a more significant reduction in AT. Thus, keeping the tick size effect (i.e., the cost of trading) constant, we show the effect varies with the magnitude of AT, which further supports the AT channel. Further, we show our evidence is absent in a placebo test when we assign as pre-treatment the period from January 2012 to September 2014 and the pseudo-treatment period from October 2014 to December 2016. Thus, absent the effect on TSP on AT, there is no evidence of differences in investment rates between treated and control firms.

[Table 7]

6.3 Changes in institutional ownership

Previous research has documented a positive relation between institutional ownership and corporate investments (Kochhar and David 1996; Aghion et al. 2013). Thus, it is possible that the decreased levels of investments we document for the treated firms in the TSP period may in fact be the result of a confounding decrease in their institutional ownership and not the result of AT

[43] Fang et al. (2014) argue their result on a negative effect liquidity has on innovation captures higher risk of hostile takeovers and of exit by institutional investors dissatisfied with poor firm performance. However, Eaton et al. (2021, p.836) argue that '[T]he importance of the former reason [higher risk of hostile takeovers] is debatable due to the greatly decreased frequency of hostile takeovers since the late 1980s', further, they find that by using a price impact measure to capture institutional trading costs, there is no evidence of a relation between liquidity and innovation. Dass et al. (2017), using more recent patent data, find that liquidity has no impact on innovation.

reduction. We believe this channel is unlikely to explain our findings as we control for institutional holdings in all regressions. Nevertheless, to ensure that our results are not confounded by changes in institutional ownership, Table 8 examines whether treated firms exhibit relatively lower levels of institutional ownership in the TSP period.

[Table 8]

The evidence presented in the first column of Table 7 suggests that treated firms do not exhibit changes in their overall level of institutional ownership between the pre- and TSP periods and relative to control stocks. Under the premise that the positive effect of institutional investors on investments should be mostly related to increases in ownership by institutions with long investment horizons, as investment benefits take long time to materialize, we classify institutional investors based on their investment type using the classification from Bushee (1998). We find no evidence of changes in transient ownership and evidence of an increase in dedicated ownership for treated firms relative to controls after TSP. As dedicated ownership associates with an increase in investments (Aghion et al. 2013), it cannot explain why investments reduce for treated firms after the start of TSP.

6.4 Changes in reporting quality and in firm monitoring

Our results could capture changes in firm's reporting and consequently in firm monitoring that could affect investments. Ahmed et al. (2020, p.869) argue that a larger tick size 'increases the scrutiny of managers' financial reporting choices and reduces their incentives to engage in misreporting. They report 'a significant decrease in the magnitude of discretionary accruals, a significant reduction in the likelihood of just meeting or beating analysts' forecasts, and a marginally significant decrease in restatements for the treated firms in the pilot program.' Biddle and Hilary (2006, p.963) report that higher accounting quality promotes more investments 'by reducing information asymmetry between managers and outside suppliers of capital.' Park (2018, p.874) also reports a positive relation between financial reporting quality and corporate investments as it 'helps investment decision makers identify value-enhancing opportunities with fewer errors' and promotes internal collaboration. Wang, Zhai, Sun, and Colombage (2020) document a positive relation between earnings quality and earnings persistence and R&D activity. Thus, the increase in reporting quality and in monitoring for treated stocks should work against our result. The monitoring explanation is also inconsistent with our evidence of reduced quality and value of innovation, and lower future operating performance.

6.4.1 Substitution between stock prices and accounting information in managerial monitoring

If stock prices do not capture managerial effort in creating shareholder value, e.g., through investments, the firm's compensation committee and investors will put more weight on accounting information, such as earnings performance, to judge managerial performance (Hölmstrom 1979; Banker and Datar 1989; Milgrom and Roberts 1992; Feltham and Xie 1994; Yermack 1995). Thus, lower monitoring usefulness of stock prices should have a lesser effect on investments for firms with higher earnings quality as monitoring through financial statements can substitute reduced stock price monitoring. Consistently, Appendix E results confirm a weaker link between AT and patent application counts when accounting numbers provide more precise signals of managerial effort in creating shareholder value.

6.4.2 Changes in analyst monitoring

Treated firms could experience an increase in analyst coverage, thus pressure to deliver better short-term earnings even at a cost of lower investment. He and Tian (2013, p.856) report that 'firms covered by a larger number of analysts generate fewer patents and patents with lower impact', however, using a more recent patent data, Dass et al. (2017) show no association between analyst coverage and patent counts. To further examine the link between the quality of the firm's information environment and investments, we also look at potential changes in analyst coverage for treated firms. Table 9 reports Eq.(1) results where the dependent variable is the number of analysts covering the stock. We find no evidence of changes in analyst coverage for treated firms compared to controls stocks in our sample. Further, we look at analyst forecast dispersion, which is a common measure of information environment quality (Lang and Lundholm 1996; Barron, Byard and Kim 2002). We calculate forecast dispersion based on the analyst's last EPS forecast issued before quarterly earnings announcements, which we then use as a dependent variable in Eq.(1). The last columns of Table 9 show no evidence of change in forecast dispersion. Jointly, the test results make it unlikely that changes in the firm's information environment explain our results.

[Table 9]

6.4.3 Voluntary disclosure and additional controls

Hope and Liu (2022, p. 6) report that lower liquidity of TSP stocks reduces treated firms' frequency of management earnings guidance, but they 'do not find evidence that algorithmic trading or fundamental information acquisition explain [their] results.' When we control for earnings guidance in our regressions (result untabulated), the magnitude of the coefficient on *Post*×*Treatment* is actually slightly higher (coefficient = −0.057, p-value = 0.015). Coupled with the evidence that lower voluntary disclosure promotes more investments (Chen, Huang, Huang and Wang 2021), we believe it is unlikely that our evidence on lower investments is because of reduced voluntary disclosures in treated firms.[44]

Finally, we also run Eq. (1) when we control for earnings quality, voluntary disclosure, analyst coverage, analyst forecast dispersion, CEO total compensation and CEO gender and find that our main result remains significant despite the sample size reducing by half (results untabulated). However, we are careful to draw conclusions from the regression with too many

[44] Hope and Liu (2022) argue that lower liquidity in treated firms reduces incentives to trade in a stock thus managerial incentives to provide voluntary disclosure. Their evidence suggests that increasing investment disclosure may not counter the negative effect on investments stemming from lower AT in treated firms when investors' incentives to trade are low. Thus, managers may not have viable investment disclosure strategies to mitigate the negative effect that a reduction in AT has on innovation.

controls as Lee and Watts (2020, p.379) caution that '[A] key advantage of the Tick Size Pilot setting is that it allows us to estimate treatment effects with relatively few concerns for selection issues or omitted variable bias that would otherwise exist. In our randomized setting, over-usage of control variables may in fact introduce a "bad controls" problem, resulting in less efficient estimators and potential bias in estimates (e.g., Angrist and Pischke 2009).'

6.5 Investments and financial constraints

TSP can affect treated firms' ability to raise financing for new projects, e.g., because treated firms' stock liquidity becomes lower, which can increase cost of project financing, particularly for financially constrained firms. Though we control for firm's financial constraints through the Cash/Assets ratio, to speak more directly to this alternative explanation, we interact Cash/Assets with the indicators *Post*, *Treatment* and *Post*×*Treatment* from Eq. (1). If the effect is channelled via financial constraints, the triple interaction term should be positive. In untabulated results, we find that the interaction terms are insignificant and our main conclusions remain unchanged. Thus, it is unlikely that our results reflect a shock to financially constrained firms that, in response, reduce their investments.

6.6 CEO stock compensation

Managers will care more about stock prices reflecting their effort related to investments if their compensation is more closely tied to the stock price performance (Lewellen, Loderer, and Martin 1987; Smith and Watts 1992; Gaver and Gaver 1993; and Bushman, Indjejikian, and Smith 1996). Thus, the effect of AT on investments should be more pronounced when a larger portion of managerial compensation is stock based. Following previous studies, e.g., Cheng (2004), we measure CEO's fraction of share-price dependent compensation as the ratio of the sum of stock awards and stock options and restricted stock holdings and grants to total compensation, *% stock compensation*, which we then interact with the indicators for treatment, the TSP period, and their interaction. Table 10 reports a negative coefficient on the triple interaction term *Post×Treatment×% stock compensation* in predicting R&D and patent applications, which is consistent with the effect of ATs on investments being incrementally more important when a larger share of CEO's compensation is stock based.[45]

[Table 10]

7. Conclusions

We use the Tick Size Pilot natural experiment to examine the causal impact of algorithmic trading on investments. We document an economically significant relation between a reduction in AT in treated firms and investments. We argue that the result reflects that lower AT in treated firms reduces the efficiency with which prices reflect patent information leading to temporary stock undervaluation, which reduces managerial incentives to spend resources on investments.

Our study identifies an important channel through which market mechanisms, here the stock price efficiency promoted by AT, affect corporate investments. Previous research that established a positive relation between stock returns and investments builds on the efficient market hypothesis to assume prices efficiently capture the expected benefits of investments and more innovative firms are rewarded with higher returns (e.g., Pakes 1985; Griliches, Hall and Pakes 1991; Hall, et al., 2005). We showcase that a reduction in price efficiency, due to a reduction in AT, has a negative impact on investments. Our evidence is consistent with managers rationally reducing investments if they believe investments' benefits will not be quickly and fully reflected in the stock price. In this way, the findings also add to our understanding of the factors affecting managers' investment decision. Finally, the study responds to the regulatory call for more research on capital market consequences of AT. The evidence suggests that regulators should consider the impact regulatory constraints on AT can affect firm innovative behavior.

[45] In untabulated results, we find no significant differences in the mean percentage CEO stock compensation between control and treated stocks before and during TSP.

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Appendix A. Definitions of variables used in the study

Variable name	Variable description
Panel A: Dependent and main independent variables	
R&D	The ratio of research and development expenditures for the previous quarter scaled by lagged book value of total assets for the quarter.
CAPEX	The ratio of quarterly capital expenditures for the previous quarter scaled by the lagged book value of total assets. We take the Compustat year-to-date amount of net capital expenditure for the first fiscal quarter. Because Compustat reports the cumulative value over the fiscal year, CAPEX for fiscal quarters two to four is calculated as changes in the current and previous quarter year-to-date capital expenditure.
ΔTA	Percentage quarterly change in book value of total assets between consecutive quarters calculated for each firm-year-quarter.
#patents	The total number of patents a company applied for in a quarter that were ultimately granted.
#citations	Total number of citations the granted patent made counted up till December 31st, 2019.
Industry-adjusted #patents	The number of firm patents less the mean patent count for the Fama-French industry the firm belongs to calculated for each year-quarter.
$nValue	Kogan et al. (2017) value of innovation in millions of nominal dollars calculated for each firm-year-quarter.
$rValue	Kogan et al. (2017) value of innovation in millions of dollars deflated to 1982 using the CPI calculated for each firm-year-quarter.
Originality	Originality of patents. The measure is defined as the sum of backward citations a patent makes scaled by the maximum sum of backward citations made for all patents in the firm's two-digit SIC industry in the previous year. We then take 1 − the average value of the measure across all patents a firm applied in quarter t.
Treatment	An indicator variable for a firm in the treatment group that experienced an increase in tick size.
Post	An indicator variable for the post-treatment period that is between October 2016 and September 2018.
decrease in AT	An indicator variable for a decrease in algorithmic trading.
zero or increase in AT	An indicator variable for a no change or an increase in algorithmic trading.
Post_Sept2017	An indicator variable for the early part of the post-treatment period that is between October 2016 and September 2017.
Post_ Sept2018	An indicator variable for the middle part of the post-treatment period that is between October 2017 and September 2018.
Post_Sept2018	An indicator variable for the late part of the post-treatment period that is between January 2018 and September 2018.
Pre_Sept2015	An indicator variable for the pre-treatment period that is between March 2015 and September 2015.
Pre_March2016	An indicator variable for the pre-treatment period that is between April 2015 and March 2016.
Pre_Sept2016	An indicator variable for the pre-treatment period that is between April 2016 and September 2016.
Panel B: AT measures	
odd_lot	Quarterly average odd lo to volume ratio defined as total odd lot volume to total trade volume, calculated per firm
cancel_ord	Quarterly average cancelled to trades ratio, defined as the ratio of total cancel orders to the total number of displayed orders, calculated per firm
cancel_ord2	Quarterly average cancelled order to the total number of trades defined as the total number of cancelled orders to total number of trades, calculated per firm
trade_vol	Quarterly average total trading volume ratio calculated as the total displayed trading volume to the order volume, calculated per firm

Continued on next page

Appendix A, *continued*

Variable name	Variable description
trade_vol2	Quarterly average total trading volume ratio per displayed order defined as the total trading volume divided by total number of trades, calculated per firm
trade_size	Quarterly average trade size defined as total trade volume times 1000 and scaled by total trades, calculated per firm
Panel C: Controls and other measures	
Firm size	Firm size calculated as the log of total assets for the most recent fiscal quarter.
ROA	Return on assets calculated as the ratio of net income over total assets for the most recent fiscal quarter.
Leverage	Leverage calculated as the ratio of long-term debt over total assets for the most recent fiscal year.
Cash/Assets	Firm liquidity calculated as the sum of income before extraordinary items and depreciation and amortization scaled by total assets calculated for the most recent fiscal year.
B/M	The book-to-market ratio calculated as the ratio of common equity scaled by total market capitalization for the most recent fiscal quarter.
Q	Tobin's Q defined as the market value of equity plus the book value of assets minus the book value of equity scaled by book assets.
Institutional ownership	Percentage institutional ownership in a stock.
Transient	Transient institutional ownership using the classification from Bushee (1998).
Dedicated	Dedicated institutional ownership using the classification from Bushee (1998).
% stock compensation	The ratio of stock-based to total compensation. Stock-based compensation is the sum of value of stock awards, restricted stock holdings, grant date fair value of options granted, and restricted stock grant. total compensation equals to salary + bonus + other annual + restricted stock grants + LTIP payouts + all other + value of option grants.
Number of analysts	The number of analysts who issued at least one EPS forecasts for the firms in the previous quarter.
Dispersion	The dispersion in the analyst EPS forecasts issued before firm's quarterly earnings announcements. We keep only the latest EPS forecast issued for a firm.
AR(0)/CAR(-1,1)	The ratio of the patent grant announcement date price reaction to the cumulative abnormal return measured from one day before to one day after the announcement.
Quarter effect	Quarter effects
Industry effect	Industry effects based on Fama-French industry definitions.

Appendix B. Confirming significant reduction in AT in the sample of treated firms

This section first presents descriptive statistics for the AT measures and then confirms a significant reduction in AT for treated compared to control stocks after the start of TSP. Panel A of Table A1 presents descriptive statistics for the six AT measures. The AT measures exhibit comparable values to those in previous research, alleviating the concern that the distribution of AT measures may be affected by a non-random sample selection process. Specifically, the mean (median) value of the average trade size in Lee and Watts (2021) is 95.09 (85.51) and similar to our sample mean (median) of 97.986 (89.191). Similarly, the mean (median) value of the odd lot ratio in Lee and Watts (2021) is 0.192 (0.163) that is close to the respective value of 0.166 (0.159) for our sample. Lee and Watts (2021) report a mean value of 0.0359 (28.33) for the trade to order (cancel to trade) ratio that falls between our two measures of trade to order (cancel to trade) 0.033 and 0.040 (26.358 and 35.589). The correlations between the six AT proxies presented in Panel B are significant and comparable to earlier research (e.g., Lee and Watts 2021). Finally, Panel C reports pre-TSP means for the AT measures split between treatment and control stocks and their difference. Consistent with earlier studies (e.g., Chakrabarty et al. 2021), there are no significant differences in the pre-treatment intensity of AT between the two groups.

Changes in AT for treated stocks after the start of TSP

Because our sample does not include all firms in the original TSP, we first examine whether the documented reduction in AT activity following the TSP is present for the treatment relative to control firms in our sample. For this analysis, we use the difference-in-differences panel regression framework similar to that depicted in Eq. (1) by regressing each of the six AT measures on *Post*, *Treatment* and their interaction. Table A2 results indicate a significant reduction in AT activity for treated relative to control firms after the introduction of the program as evidenced by significant coefficients on the interaction term *Post* × *Treatment*. The reduction in AT activity is economically significant.

Table A1. Descriptive statistics for AT measures

	Mean	Median	Std Dev	Lower Quartile	Upper Quartile
Panel A: Descriptive statistics for AT measures					
odd lot	0.166	0.159	0.080	0.110	0.210
trade_vol	0.033	0.031	0.017	0.020	0.043
trade_vol2	0.040	0.038	0.020	0.026	0.052
cancel_ord	35.589	24.219	45.625	16.908	37.371
cancel_ord2	26.358	20.353	25.430	14.494	29.618
trade size	97.986	89.191	35.814	77.435	108.150

	odd lot	trade_vol	trade_vol2	cancel_ord	cancel_ord2
Panel B: Pearson correlations between AT measures					
trade_vol	−0.492				
	0.000				
trade_vol2	−0.472	0.976			
	0.000	0.000			
cancel_ord	0.165	−0.416	−0.365		
	0.000	0.000	0.000		
cancel_ord2	0.124	−0.468	−0.429	0.927	
	0.000	0.000	0.000	0.000	
trade size	−0.734	0.438	0.464	0.070	0.093
	0.000	0.000	0.000	0.000	0.000

	Treatment	Control	Difference	p-value
Panel C: Pre-treatments means for the AT measures				
odd lot	0.150	0.146	0.004	0.476
trade_vol	0.028	0.029	−0.001	0.410
trade_vol2	0.034	0.036	−0.002	0.209
cancel_ord	45.421	44.035	1.386	0.709
cancel_ord2	33.214	31.291	1.923	0.316
trade size	100.879	103.693	−2.814	0.320

The table reports descriptive statistics for the algorithmic trading measures (Panel A), their Pearson correlations (Panel B) and pre-TSP means split between treatment and control stocks (Panel C). The sample includes 3,954 firm-quarters for firms with at least one patent at any point over the period October 2014 to September 2018, which covers the pre- and TSP period. *odd_lot* is the quarterly average odd lot volume ratio defined as total odd lot volume to total trade volume. *trade_vol* is the quarterly average total trading volume ratio calculated as the total displayed trading volume to the order volume. *trade_vol2* is the quarterly average total trading volume ratio per displayed order defined as the total trading volume divided by total number of trades. *cancel_ord* is the quarterly average cancelled to trades ratio, defined as the ratio of total cancel orders to the total number of displayed orders. *cancel_ord2* is the quarterly average cancelled order to the total number of trades defined as the total number of cancelled orders to total number of trades. *trade_size* is the quarterly average trade size defined as total trade volume times 1000 and scaled by total trades.

Table A2. Changes in AT measures for the sample of treated and control stocks

	Y = odd_lot		Y = cancel_ord		Y = cancel_ord2		Y = trade_vol		Y = trade_vol2		Y = trade size	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Predicted sign on Post×Treatment	−		−		−		+		+		+	
Intercept	−2.651	0.000	4.218	0.000	3.790	0.000	−3.384	0.000	−3.019	0.000	5.158	0.000
Post	0.277	0.000	−0.303	0.000	−0.302	0.000	0.272	0.000	0.256	0.000	−0.127	0.000
Treatment	−0.004	0.866	0.023	0.235	0.024	0.162	0.000	0.997	−0.008	0.699	−0.003	0.809
Post×Treatment	−0.137	0.000	−0.379	0.000	−0.311	0.000	0.270	0.000	0.212	0.000	0.089	0.000
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
Quarter effects	Yes		Yes		Yes		Yes		Yes		Yes	
Industry effects	Yes		Yes		Yes		Yes		Yes		Yes	
N	3954		3954		3954		3954		3954		3954	
R^2	33.03%		30.09%		30.37%		23.26%		23.89%		45.01%	

The table reports the difference-in-differences regressions results where the dependent variables are the measures of algorithmic trading. *Treatment* is an indicator variable for a firm in the treatment group that experienced an increase in tick size. *Post* is an indicator variable for the post-treatment period that is between October 2016 and September 2018. p-values are based on standard errors clustered at the industry and quarter level.

Appendix C. Further tests using the full sample of TSP firms and assuming zero for missing R&D and patent data

To build confidence in our conclusion, we repeat the analysis in Table 3 assuming zero for missing R&D and patent data. For this analysis, we augment Eq. (1) with an indicator for missing patent observations, *Missing_Patent_D*. The sample size increases to 23,035 observations and the coefficient on the interaction term *Post*×*Treatment* remains significantly negative. Table A3 results show that assuming missing values reflect no investment activity produces similar conclusion to our main tests.

Table A3. Assuming zero for missing R&D and patent data

	R&D		#patents	
	Coeff	p	Coeff	p
Intercept	0.205	0.071	−0.033	0.487
Post	0.000	0.937	0.026	0.265
Treatment	−0.005	0.447	0.027	0.692
Post×Treatment	−0.004	0.067	−0.037	0.095
Missing_Inv_D	−0.045	0.004	−0.438	0.091
Controls	Yes		Yes	
Quarter effects	Yes		Yes	
Industry effects	Yes		Yes	
Firm effects	No		No	
N	23035		23035	
R^2	48.46%		9.51%	

The table reports results for Eq. (1) when we use a sample of all TSP stocks and assume zero if the firm did not report any R&D or patents in either pre- or the TSP period. *Missing_Inv_D* is an indicator variable for missing R&D or patent data. The dependent variable is log (1+R&D) and log (1+number of patents).

Appendix D. Intensity of AT and placebo tests

This section shows that our conclusion on a positive relation between AT and investments vary cross-sectionally with the intensity of AT. We base this test on the fact that the SEC split stocks in the treatment group into subcategories based on the intensity of trading restrictions. Stocks with the smallest trading restrictions are quoted in \$0.05 increments but can trade at the \$0.01 tick size. Stocks with the strictest trading restrictions are quoted and traded at \$0.05 increments and subject to a 'trade-at' requirement. The trade-at requirement prohibits a trading venue from meeting an incoming order without displaying the National Best Bid and Offer. This discourages trades channelled to dark and alternative venues. Rindi and Werner (2017) and Comerton-Forde, Gregoire and Zhong (2019) highlight that ATs are disincentivized to trade in stocks where orders have to be executed at 'trade-at' rule. We expect higher trading restrictions to lead to a larger reduction in AT and consequently a more significant impact on investments. For this test, we create an indicator variable *TR_Intensity*, which captures treatment stocks with the strictest trading restrictions, i.e., stocks quoted and traded at \$0.05 increments and subject to a 'trade-at' requirement, that we interact with *Treatment* and *Post*×*Treatment* indicators.

In Panel A of Table A4, we first test that indeed treated stocks quoted and traded at \$0.05 increments and subject to a 'trade-at' requirement experience an incremental reduction in AT. For this test, we use the AT factor, the principal component analysis AT measure, as the dependent variable in Eq. (1).[46] The first columns confirm an incremental reduction in AT for treated stocks subject to the strictest trading restrictions. Next, we show that these treated firms also experience an incremental negative effect on R&D and patent applications. We focus on R&D and patents as the most commonly used measures of investment input and output but the results are similar for

[46] We perform this test because it is not obvious that treated stocks with most strict trading restrictions will experience an incremental reduction in AT. For example, Lee and Watts (2021, p.373) highlight that '[P]rior studies (e.g., Rindi and Werner 2019; Chung, Lee, and Rösch 2020), as well as our own analyses, find that the effect on liquidity is economically similar across the three groups of treated firms', which is why they 'combine these three subgroups and refer to them collectively as the "treated firms"'. Lee and Watts (2021) do not test if TSP had a differential effect on the intensity of AT across stocks subject to varying level of trading restrictions.

CAPEX and changes in assets. This evidence is consistent with innovation reducing in the intensity of AT in treated firms.

To build confidence the effect we document is due to changes in AT prompted by the SEC Tick Size Pilot program, we also run a placebo test where we select the same treatment and control stocks and define the pre-treatment period from January 2012 to September 2014 and the pseudo-treatment period from October 2014 to December 2016, *Placebo_post*. We then run equation (1) with either the AT factor or the number of patents as the dependent variable. Panel B, Table A4 regression results show no significant differences in the intensity of AT for the treated firms compared to controls for the placebo period nor significant differences in innovation between the two groups. These results suggest that there are no changes in the intensity of AT and investments between treated and control firms absent the TSP program.

Table A4. Intensity of AT and placebo effects

	Y=AT factor		Y=#patents	
	Coeff	p	Coeff	p
Panel A: Intensity of AT				
Intercept	8.314	0.006	−0.156	0.033
Post	−2.149	0.000	−0.062	0.001
Treatment	0.066	0.933	0.034	0.129
Post×Treatment	−3.773	0.000	−0.035	0.099
Treatment×AT factor	1.975	0.126	−0.022	0.502
Post×Treatment×AT factor	−3.342	0.010	−0.054	0.057
Controls	Yes		Yes	
Quarter effects	Yes		Yes	
Industry effects	Yes		Yes	
N	3954		3954	
R^2	11.06%		10.26%	

	Y=AT factor		Y=#patents	
	Coeff	p	Coeff	p
Panel B: Placebo effect				
Intercept	−0.230	0.928	0.768	0.000
Post	0.228	0.840	−0.048	0.234
Treatment	2.055	0.342	0.063	0.146
Post×Treatment	−2.183	0.296	0.009	0.635
Controls	Yes		Yes	
Quarter effects	Yes		Yes	
Industry effects	Yes		Yes	
N	4768		4768	
R^2	6.71%		15.81%	

Panel A reports regression results for Eq. (1) where we include a dummy variable for the intensity of trading restrictions among treated firms, *TR_Intensity*, which captures treatment stocks with the strictest trading restrictions, i.e., stocks quoted and traded at $0.05 increments and subject to a 'trade-at' requirement. *AT factor* measures the intensity of AT and is an index measure based on the six AT measures. We use the *AT factor* as the dependent variable in Eq. (1) and report regression results in column 'Y=AT factor'. The other dependent variable is log (1+number of patents). Panel B reports regression results for Eq. (1) when we define the pre-treatment period from January 2012 to September 2014 and the pseudo-treatment period from October 2014 to December 2016, *Placebo_post*. p-values are based on standard errors clustered at the industry and quarter level.

Appendix E. The effect of AT on investments in high accounting quality firms

This section examines the link between AT and investments for firms with higher reporting quality where accounting information can provide a relatively reliable signal of managerial performance compared to the changes in the stock price. Following the literature, we use total accruals as a measure of earnings quality (Dechow, Ge and Schrand 2010), which is defined as the assets-scaled difference between net income before extraordinary items and cash flow from operating activities, *Accruals*. We multiply accruals by −1 so that higher values capture higher earnings quality, *Low accruals*. We then interact *Low accruals* with the indicators for *Post*, *Treatment* and their interaction. Table A5 documents that the coefficient on the triple interaction term *Post*×*Treatment*×*Low accruals* is positive, consistent with a weaker link between AT and patent applications when accounting numbers provide more precise signals of managerial effort in creating shareholder value.

Accruals remain a contentious measure of earnings quality (DeFond 2010), which is why we also use a composite measure of high reporting quality, *Composite high EQ measure*, based on a principal component analysis of audit fees (weight 0.596), a dummy variable for restatement (weight −0.14), accruals (weight −0.595) and an indicator for whether the auditor is PCAOB registrant (weight 0.026). Table A5 results confirm incrementally weaker effect on patent applications for treated firms relative to control stocks after the start of TSP when a firm has high reporting quality. This result is consistent with financial information substituting less efficient prices in monitoring managerial effort related to investments.

The disciplining role of stock prices: Probability of forced CEO turnover

Less efficient prices should play a lower disciplining role thus should less influence CEO career outcomes. We test this prediction by estimating the sensitivity of forced managerial turnover next quarter to past stock return performance (Hayes, Lemmon and Qiu 2012) using the data on forced turnover from Peters and Wagner (2014). To capture the return performance, we calculate cumulative abnormal returns measured over 180 days before quarter-end and use the S&P500 index as the normal return benchmark. To make the interpretation easier, we multiple cumulative abnormal returns by −1 so that higher values capture more negative return performance. The last columns of Table A5 confirm that CEO turnover in treated firms is less sensitive to poor return performance after the start of TSP, consistent with a lower impact stock price performance has on managerial career outcomes.[47]

Table A5. The effect of patents in high accounting quality firms and probability of forced turnover

	X=Low accruals		X= Composite high EQ measure		Probability of forced turnover X=−1×abnormal returns	
	Coefficient	p-value	Coefficient	p-value	p-value	p-value
Intercept	1.013	0.000	1.037			0.000
Post×X	0.056	0.681	−0.275	0.117	0.337	0.483
Treatment×X	−0.422	0.091	−0.952	0.165	0.138	0.028
Post×Treatment×X	0.204	0.033	0.760	−0.235	0.023	0.018
X	−0.014	0.944	0.324	−0.218	0.106	0.449
Uninteracted Post and Treatment	Yes		Yes		Yes	
Controls	Yes		Yes		Yes	
Quarter effects	Yes		Yes		Yes	
Industry effects	Yes		Yes		Yes	
N	3954		3836		3942	
R^2	17.15%		16.98%		14.44%	

The table presents abbreviated results for Eq. (1) augmented with interaction terms capturing high earnings quality measured by accruals and by a composite earnings quality measure. *Low accruals* are firm total accruals multiplied by −1 so that higher values indicate higher earnings quality. Total accruals are calculated as net income before extraordinary activities less net cash flow from operating activities and then scaled by total assets. *Composite high EQ measure* is an index measure of high earnings quality based on a principal component analysis of audit fees (weight 0.596), a dummy variable for restatement (weight −0.14), accruals (weight −0.595) and an indicator for whether the auditor is PCAOB registrant (weight 0.026). Column 'Probability of forced turnover' reports regression results for a model predicting the likelihood of a forced CEO turnover next quarter as a function of cumulative abnormal returns measured over 180 days before the quarter-end where the normal return benchmark is the S&P500 index. We multiple the cumulative abnormal returns by −1 so that higher values capture more negative return performance. p-values are based on standard errors clustered at the industry and quarter level.

[47] The fraction of the sample with forced CEO turnover is only 2%, which is why we also used Execucomp to calculate instances of managerial turnover, which identified 9.8% of observations with CEO changes. Our conclusions are the same for this sample though it also includes voluntary CEO departures.

Table 1. Descriptive statistics for investment regression variables

	Mean	Median	Std Dev	Lower Quartile	Upper Quartile
Panel A: Dependent variables					
R&D	0.032	0.018	0.041	0.001	0.046
CAPEX	0.041	0.029	0.036	0.014	0.055
ΔTA	0.035	0.003	0.195	-0.037	0.037
#patents	3.552	2.000	4.964	1.000	4.000
#citations	5.076	1.000	13.242	0.000	3.000
Industry-adjusted #patents	−0.014	−1.244	4.703	−2.231	0.425
$nValue	8.177	5.939	8.671	2.939	10.827
$rValue	3.364	2.441	3.525	1.217	4.485
Originality	0.822	0.979	0.555	0.911	0.994
Panel B: Controls					
MV	1155.800	835.800	1160.700	292.300	1679.800
ROA	−0.024	0.003	0.076	−0.042	0.017
Leverage	0.433	0.412	0.272	0.208	0.580
Cash	−0.015	0.012	0.076	−0.032	0.026
B/M	0.416	0.358	0.364	0.206	0.570
IO	0.708	0.782	0.286	0.559	0.921

The table reports descriptive statistics for the main variables used in the study. Panel A reports the measures of investment. *R&D* is quarterly research and development expenditure scaled by quarterly total assets, *CAPEX* is annual capital expenditures scaled by annual total sales, and ΔTA is the percentage quarterly change in total assets between consecutive quarters. *#patents* is the total number of patents a company applied for in a quarter that were ultimately granted. *#citations* is the total number of citations the granted patent made counted till December 31st, 2019. *Industry-adjusted #patents* is the number of firm patents less the mean patent count for the Fama-French industry the firm belongs to (including firms not in the TSP sample) calculated for each year-quarter. *$nValue* is the Kogan et al. (2017) value of innovation in millions of nominal dollars calculated for each firm-year-quarter. *$rValue* is the Kogan et al. (2017) value of innovation in millions of dollars deflated to 1982 using the CPI calculated for each firm-year-quarter. *Originality* captures how many previous patents an invention draws on to produce a novel idea. Panel B reports descriptives statistics for control variables that we define in Appendix A.

Table 2. Pre-treatment means for the variables and test of parallel trend

	Treatment	Controls	Difference	t-test	p-value
Panel A: Pre-treatment means for dependent variables					
R&D	0.030	0.035	−0.006	−1.410	0.158
CAPEX	0.039	0.045	−0.006	0.890	0.376
ΔTA	0.030	0.035	−0.005	0.600	0.551
#patents	4.025	3.497	0.528	0.900	0.391
#citations	6.683	6.766	−0.083	−0.580	0.575
Industry-adjusted #patents	0.096	−0.123	0.219	−1.060	0.288
$nValue	6.228	6.512	−0.284	1.140	0.255
$rValue	2.617	2.702	−0.085	0.470	0.638
Originality	0.815	0.830	−0.016	−0.380	0.704
Panel B: Pre-treatment means for control variables					
MV	951.500	961.200	−9.700	−0.140	0.893
ROA	−0.016	−0.031	0.015	0.300	0.772
Leverage	0.437	0.406	0.031	1.420	0.189
Cash	−0.006	−0.022	0.016	0.310	0.764
B/M	0.457	0.421	0.036	0.880	0.402
IO	0.706	0.676	0.030	0.910	0.384

	R&D		CAPEX		ΔTA		#Patents	
	Coeff	p	Coeff	p	Coeff	p	Coeff	p
Panel C: Test of parallel trends								
Intercept	0.472	0.002	0.019	0.492	−0.011	0.571	0.943	0.000
Pre_Sept2015×Treatment	0.018	0.751	−0.017	0.550	−0.017	0.132	−0.004	0.940
Pre_March2016×Treatment	0.029	0.501	−0.036	0.120	0.011	0.268	−0.044	0.552
Pre_Sept2016×Treatment	−0.018	0.738	−0.030	0.190	0.017	0.240	−0.045	0.275
Pre_Sept2015	0.006	0.870	0.014	0.122	0.002	0.671	0.023	0.728
Pre_March2016	0.020	0.391	0.032	0.137	−0.014	0.468	0.024	0.720
Pre_Sept2016	0.074	0.169	0.024	0.308	−0.018	0.125	0.069	0.238
Post×Treatment	−0.051	0.067	−0.038	0.002	−0.005	0.089	−0.084	0.094
Post	0.052	0.092	0.019	0.492	0.006	0.361	−0.086	0.128
Treatment	0.029	0.034	−0.017	0.550	0.002	0.814	0.086	0.162
Quarter effects	Yes		Yes		Yes		Yes	
Industry effects	Yes		Yes		Yes		Yes	
N	3954		3954		3954		3954	
R^2	43.34%		13.13%		4.81%		12.01%	

Panel A presents pre-treatment means for the dependent variables separately for the treatment and control firms. We also report the difference in means and the corresponding t-test and p-value. Panel B reports means for the control variables and their difference between treated and control stocks. Panel C tests the parallel trend assumption that there is no difference in investment levels between treated and control firms before TSP. *Pre_Sept2015* is an indicator variable for the pre-treatment period that is between March 2015 and September 2015. *Pre_March2016* is an indicator variable for the pre-treatment period that is between October 2015 and March 2016. *Pre_Sept2016* is an indicator variable for the pre-treatment period that is between April 2016 and September 2016. The dependent variables are ex-ante measures of investments: log 1+ R&D spending, log 1+capital expenditures and percentage change in quarterly total assets, and ex-post measures of investment captured by the log 1+number of patent a firm applied for in a quarter. p-values are based on standard errors clustered at the industry and quarter level.

Table 3. The relation between AT and investments

	R&D		CAPEX		ΔTA		#patents		adj #patents	
	Coeff	p	Coeff	p	Coeff	p	Coeff	p	Coeff	p
Panel A: Main analysis										
Intercept	0.578	0.083	0.037	0.470	−0.018	0.238	0.966	0.000	−0.558	0.028
Post	0.011	0.675	−0.012	0.323	0.013	0.008	−0.132	0.001	−0.163	0.206
Treatment	0.027	0.600	0.003	0.813	0.005	0.072	0.060	0.142	0.241	0.178
Post×Treatment	−0.049	0.011	−0.013	0.057	−0.008	0.074	−0.053	0.004	−0.439	0.022
Controls	Yes		Yes		Yes		Yes		Yes	
Quarter effects	Yes		Yes		Yes		Yes		Yes	
Industry effects	Yes		Yes		Yes		Yes		Yes	
N	3954		3954		3954		3954		3954	
R^2	42.27%		29.52%		4.46%		12.34%		4.18%	

Panel B: The effect of managerial learning from stock prices (Ye et al., 2022)

	R&D		CAPEX		ΔTA		#patents	
	Coeff	p	Coeff	p	Coeff	p	Coeff	p
Post×Treatment	−0.124	0.014	−0.044	0.097	−0.061	0.083	−0.157	0.000
Post×Q	−0.008	0.425	0.005	0.372	0.021	0.006	−0.042	0.000
Treatment×Q	0.015	0.536	0.016	0.174	−0.004	0.756	0.011	0.552
Post×Treatment×Q	0.067	0.000	0.021	0.092	−0.029	0.223	0.020	0.093
Q	0.030	0.073	0.017	0.051	0.013	0.152	0.009	0.464
Controls	Yes		Yes		Yes		Yes	
Quarter effects	Yes		Yes		Yes		Yes	
Firm effects	Yes		Yes		Yes		Yes	
N	3499		3499		3499		3499	
R2	85.13%		85.54%		48.22%		69.04%	

	Treatment	Controls	Difference	t-test	p-value
Pre-treatment means in Q	2.262	2.604	-0.342	-1.350	0.209
TSP-treatment means in Q	2.612	2.814	-0.201	-1.360	0.207

Panel C: Future financial performance and analyst CAPEX forecasts

	Future ROA		Future Cash/Assets		Analyst ΔCAPEX forecasts	
	Coeff	p	Coeff	p	Coeff	p
Intercept	−0.044	0.000	−0.030	0.000	1.243	0.136
Post	0.004	0.108	0.006	0.137	0.386	0.016
Treatment	0.001	0.411	0.005	0.115	0.194	0.034
Post×Treatment	−0.005	0.099	−0.009	0.033	−0.300	0.039
Controls	Yes		Yes		Yes	
Quarter effects	Yes		Yes		Yes	
Industry effects	Yes		Yes		Yes	
N	3499		3499		3499	
R2	61.4%		63.0%		5.74%	

Panel A reports Eq. (1) difference-in-differences regression results where the dependent variables are ex-ante measures of investments: log 1+ R&D spending, log 1+capital expenditures and percentage change in quarterly total assets, and ex-post measures of investment captured by the log 1+number of patent a firm applied for in a quarter. Panel B reports regression results for Eq. (1) augmented with Tobin's Q and its interactions and firm-fixed effects as in Ye et al. (2022). The bottom rows test for differences in mean Tobin's Q between treated and control firms before and during TSP. Panel D uses future quarterly mean ROA, *Future ROA*, and mean cash/assets, *Future Cash/Assets*, measured over six quarters relative to the current year-quarter as the dependent variables in Eq. (1). p-values are based on standard errors clustered at the industry and quarter level.

Table 4. Price discovery at the patent grant date

	$\frac{AR(0)}{CAR(-1,1)}$		CAR(1,60)		CAR(61,100)		CAR(101,140)	
	Coeff	p	Coeff	p	Coeff	p	Coeff	p
Intercept	0.566	0.000	−0.004	0.647	0.051	0.211	0.023	0.557
Post	0.084	0.096	0.005	0.146	−0.011	0.333	−0.011	0.294
Treatment	0.071	0.153	−0.001	0.677	−0.011	0.041	−0.011	0.220
Post×Treatment	−0.086	0.048	−0.009	0.063	0.020	0.075	0.017	0.304
Controls	Yes		Yes		Yes		Yes	
Quarter effects	Yes		Yes		Yes		Yes	
Industry effects	Yes		Yes		Yes		Yes	
N	9565		9565		9565		9565	
R^2	0.14%		0.27%		2.06%		1.26%	

Column $\frac{AR(0)}{CAR(-1,1)}$ reports results for Eq. (1) where the dependent variable is the ratio of the patent grant announcement date price reaction standardized by the total signal value measured in a three-day window around the patent grant announcement. Column CAR(1,60) reports results for Eq. (1) where the dependent variable is the cumulative abnormal return (CAR) from day 1 to day 60 after the patent grant date. Column CAR(61,100) reports results for Eq. (1) where the dependent variable is CAR measured over 61 to 100 days after the patent grant. Column CAR (101,140) reports results for Eq. (1) where the dependent variable is CAR measured over 101 to 140 days after the patent grant. We use the Carhart (1997) four-factor model as the normal return benchmark. p-values are based on standard errors clustered at the industry and quarter level.

Table 5. Number of citations and KSPP innovation value measure

	#citations		Originality		KSPP real		KSPP nominal	
	Coeff	p	Coeff	p	Coeff	p	Coeff	p
Intercept	1.098	0.000	0.721	0.000	−0.872	0.084	−2.431	0.058
Post	−0.488	0.000	−0.001	0.831	0.068	0.747	0.443	0.381
Treatment	0.113	0.041	−0.001	0.874	−0.044	0.594	−0.099	0.622
Post×Treatment	−0.118	0.034	−0.013	0.088	−0.196	0.028	−0.494	0.028
Controls	Yes		Yes		Yes		Yes	
Quarter effects	Yes		Yes		Yes		Yes	
Industry effects	Yes		Yes		Yes		Yes	
N	3954		3954		2737		10291	
R^2	9.36%		12.32%		11.59%		2.16%	

The table reports regression results for Eq.(1) where the dependent variable is the log 1+number of citations, the measure of patents' average originality, and the Kogan et al. (2017) measures of the private economic value of patents calculated in real and nominal terms. p-values are based on standard errors clustered at the industry and quarter level.

Table 6. The speed with which firms react to TSP

	R&D		CAPEX		ΔTA		#patents	
	Coeff	p	Coeff	p	Coeff	p	Coeff	p
Intercept	0.493	0.073	0.017	0.666	−0.014	0.471	−0.200	0.416
Post_Sept2017× Treatment	−0.037	0.172	−0.016	0.301	0.007	0.221	−0.039	0.161
Post_Sept2018× Treatment	−0.051	0.001	−0.022	0.002	−0.006	0.038	−0.097	0.034
Post_Sept2017	0.050	0.168	−0.004	0.413	0.003	0.606	−0.040	0.108
Post_Sept2018	0.019	0.626	−0.001	0.965	0.015	0.154	−0.107	0.118
Treatment	0.041	0.401	0.008	0.613	−0.014	0.471	0.033	0.550
Controls	Yes		Yes		Yes		Yes	
Quarter effects	Yes		Yes		Yes		Yes	
Industry effects	Yes		Yes		Yes		Yes	
N	3954		3954		3954		3954	
R^2	44.69%		13.74		9.04%		10.20%	

The table reports Eq. (1) results where we split the TSP period into subperiods. *Post_Sept2017* is an indicator variable for the early part of the post-treatment period that is between October 2016 and end of September 2017. *Post_ Sept2018* captures the period between October 2017 and the end of the TSP program at the end of September 2018. p-values are based on standard errors clustered at the industry and quarter level.

Table 7. Addressing the liquidity channel as an alternative explanation for the results

	R&D				#patents			
	AT = odd_lot		AT = AT factor		AT = odd_lot		AT = AT factor	
	Coeff	p	Coeff	p	Coeff	p	Coeff	p
Intercept	0.505	0.001	0.496	0.000	0.961	0.000	0.978	0.000
Post	0.003	0.871	0.003	0.865	−0.131	0.000	−0.131	0.000
Treatment	0.023	0.439	0.022	0.468	0.061	0.010	0.060	0.010
Post×Treatment×decrease in AT	−0.050	0.051	−0.051	0.059	−0.122	0.000	−0.127	0.000
Post×Treatment×zero or increase in AT	−0.002	0.958	0.002	0.970	−0.025	0.364	−0.034	0.175
Controls	Yes		Yes		Yes		Yes	
Quarter effects	Yes		Yes		Yes		Yes	
Industry effects	Yes		Yes		Yes		Yes	
N	3954		3954		3954		3954	
R^2	44.67%		44.68%		12.44%		12.55%	

The table reports regression results for Eq.(1) where we identify the direction of change in AT for treated firms. *decrease in AT* is an indicator variable for a reduction in AT. *zero or increase in AT* is an indicator variable for a zero or increase in AT. The dependent variable is log of 1 + R&D or number of patents. To capture AT, we use the odd lot and the AT factor measures. p-values are based on standard errors clustered at the industry and quarter level.

Table 8. Tick Size Pilot and institutional ownership

	Y=Institutional ownership		Y=Transient		Y=Dedicated	
	Coeff	p	Coeff	p	Coeff	p
Intercept	0.526	0.000	0.270	0.000	0.057	0.000
Post	0.022	0.041	0.006	0.681	−0.022	0.000
Treatment	0.026	0.028	−0.008	0.269	−0.027	0.005
Post×Treatment	0.000	0.993	−0.011	0.204	0.021	0.015
Controls	Yes		Yes		Yes	
Quarter effects	Yes		Yes		Yes	
Industry effects	Yes		Yes		Yes	
N	3815		3815		3815	
R^2	6.98%		6.32%		7.87%	

The table reports regression results for Eq.(1) where the dependent variable is the percentage institutional ownership and the ownership by transient and dedicated investors as a fraction of total institutional ownership. p-values are based on standard errors clustered at the industry and quarter level.

Table 9. Analyst coverage and forecast dispersion

	Y=Number of analysts		Y=Dispersion	
	Coeff	p	Coeff	p
Intercept	2.326	0.000	0.250	0.156
Post	−0.126	0.537	0.164	0.454
Treatment	−0.277	0.178	−0.044	0.362
Post×Treatment	−0.273	0.245	−0.184	0.408
Controls	Yes		Yes	
Quarter effects	Yes		Yes	
Industry effects	Yes		Yes	
N	3746		3556	
R^2	26.00%		3.63%	

The table reports Eq.(1) regression results where the dependent variable is either the number of analysts covering a stock or analyst forecast dispersion measured before quarterly earnings announcements. p-values are based on standard errors clustered at the industry and quarter level.

Table 10. The effect of managerial stock compensation

	R&D		#patents	
	Coefficient	p-value	Coefficient	p-value
Intercept	0.670	0.000	1.296	0.000
Post×% stock compensation	0.026	0.134	0.018	0.618
Treatment×% stock compensation	0.029	0.066	0.084	0.041
Post×Treatment×% stock compensation	−0.035	0.082	−0.096	0.054
X	−0.021	0.139	−0.024	0.477
Uninteracted dummies	Yes		Yes	
Controls	Yes		Yes	
Quarter effects	Yes		Yes	
Industry effects	Yes		Yes	
N	2166		2166	
R^2	12.00%		11.69%	

The table presents abbreviated results for Eq. (1) where the dependent variable is log of 1 + R&D or number of patents and the equation is augmented with interaction terms capturing the intensity of managerial stock compensation. *% stock compensation* is the ratio of stock-based to total compensation. p-values are based on standard errors clustered at the industry and quarter level.