# Does Algorithmic Trading Affect Analyst Research Production?

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**Abstract**

We document a causal negative relationship between algorithmic trading (AT) and analyst research production, as captured by a decreased frequency of earnings forecasts and stock recommendations and lower analyst coverage. This is consistent with AT increasing the speed of price discovery, reducing the profitability of trades on analyst research by non-algorithmic traders and, consequently, their demand for analyst investment advice. Supporting evidence shows that the effect of AT on analyst research production is stronger for stock recommendations, which institutions follow primarily for investment decisions, and for forecasts issued before earnings announcements when analysts' information discovery dominates the information interpretation role. We also find a negative relationship between AT and investment-focused institutional investors such as transient and non-monitoring investors. Our analysis demonstrates that AT can have long-lasting consequences on capital markets, beyond microstructure effects, through its negative effect on firm's information environment.

JEL: D53; G12; G14; M41

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# 1. Introduction

This study examines the impact that algorithmic traders (ATs) have on analyst research production.[1] We focus on ATs as they (i) account for around 50% of daily trading volume starting in 2009 (Lee and Watts, 2020) and (ii) base their trades primarily on technical and order-flow analysis rather than fundamental analysis, thus are not analysts' clientele.[2] One mechanism through which ATs can influence analyst research production is via a reduction in institutional investors' demand for analyst investment advice. In particular, we propose that in stocks with strong algorithmic trading (AT), the profitability of institutional investors' trades decreases, which in turn reduces their demand for analyst research for investment decisions.

Our prediction builds on prior research that shows that ATs dissuade non-ATs' private information acquisition by screening order flow and pre-empting private information driven trades (Stiglitz 2014; Han, Khapko and Kyle 2014, Korajczyk and Murphy 2019).[3] Consistently, Weller (2018) and Lee and Watts (2020) find that AT before earnings announcements decreases *price informativeness*, i.e. the extent to which prices reflect all available information, because investors abstain from acquiring private information they cannot profitably trade on. Brogaard, Hendershott and Riordan (2014, p. 32) argue that ATs' orders surrounding corporate events 'impose significant adverse selection on longer-term investors', which reduce the benefits of private information

[1] We follow Weller (2018) and Lee and Watts (2020) and define algorithmic trading as any computer-assisted low-latency trading activity, such as that of high frequency traders (see also Brogaard, Hendershott and Riordan 2014; Biais and Foucault 2014; Hendershott and Riordan 2013).
[2] ATs look for trade signals based on searches for public news, technical analysis, and order flow analysis. The Tabb Group report documents a sharp increase in the fraction of daily trading volume that originates with ATs from 30% in 2006 to 60% in 2009 and averaging at around 55% till 2017 (https://www.ft.com/content/d81f96ea-d43c-11e7-a303-9060cb1e5f44). JPMorgan estimates that 'fundamental discretionary traders' who base their trades on fundamental analysis account for only 10% of daily trading (https://www.cnbc.com/2017/06/13/death-of-the-human-investor-just-10-percent-of-trading-is-regular-stock-picking-jpmorgan-estimates.html).
[3] Securities and Exchange Commission Concept Release on Equity Market Structure, U.S. Securities and Exchange Commission (2010) describes rules governing order anticipation strategies, front- and back-running, which attempt to trade ahead of large and informed trades.

acquisition. Though ATs reduce price informativeness, their ultra-fast trading, through both AT liquidity demand as well as liquidity supply functions (Brogaard, Hendershott, and Riordan, 2019), improve *price efficiency*—the speed with which prices reflect new information that enters the public domain. Bhattacharya, Chakrabarty, and Wang (2020) and Chordia and Miao (2020) report a significant speed increase in price discovery *after* quarterly earnings announcements.[4] The much faster price discovery of ATs should result in prices that quickly impound a significant portion of new information, such as that contained in analyst reports. This in turn reduces the expected profitability of non-ATs' trades on analyst research and, therefore, non-ATs' demand for analyst investment advice, whether publicly or privately disseminated. A consequence is decreased analyst coverage due to lower research fee and 'soft dollar' potential (Irvine 2000, 2004; Conrad, Johnson and Wahal 2001).

However, the predicted negative relationship between analyst research production and AT, may be offset by the positive effect of AT on stock liquidity (Hendershott, Jones and Menkveld 2011; Hasbrouck and Saar 2013) and institutions' preference to invest in more liquid stocks (Gompers and Metrick 2001, Dahlquist and Robertsson 2001, McCahery, Sautner and Starks 2016). This reduction in the cost of trading can be attractive for institutions trading for non-information reasons - e.g., for liquidity reasons, hedging risk (rebalancing) purposes, tax-minimization, or even for window dressing (Chakravarty and Ray 2020)-. Although portfolio choices based on liquidity should not directly affect demand for analyst research as they are not information-based, they are expected to do so indirectly, through the need of institutions to satisfy

[4] Consistent with AT promoting price efficiency, Frino, Prodromou, Wang, Westerholm and Zheng (2017) document that algorithmic trades in the 90 seconds after earnings announcements incorporate most of the signals' value into stock prices. Rogers, Skinner and Zechman (2017) find that information in Edgar filings is impounded into stock prices at the time the filings are made available to ATs using the SEC public dissemination system, seconds before they are posted on the EDGAR website.

a "prudent person" standard that is often met by the use of analyst reports. O'Brien and Bhushan (1990) explain that "[I]nstitutions require information, both as a basis for investment decisions and to satisfy standards of fiduciary responsibility". Thus, higher AT may be associated with higher institutional ownership that is not driven by pure or immediate investment considerations, increasing in turn demand for analyst research.

The above discussion suggests that the effect of ATs on analyst research production is not a priori clear. Given the important role of financial analysts as information intermediaries in capital markets we examine this question empirically. We use the Securities and Exchange Commission's Market Information Data Analytics System (MIDAS) to identify AT trades over the period 2012–2019. 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 an increased number of order cancellations by ATs stemming from their nearly instantaneously 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). We measure analyst research activity by the number of quarterly earnings forecasts and stock recommendations (Ivković and Jegadeesh 2004; Chen et al. 2010; Livnat and Zhang 2012), and in further analysis, by the number of analysts covering a stock.

We document a significant negative effect AT has on analyst research production and the economic magnitude is material—depending on the AT measure, stocks in the top quartile of algorithmic trading have on average between 10.7% to 19.9% fewer forecasts and stock recommendations compared to stocks in the bottom quartile. We recognize that this evidence can reflect either a reduction in the frequency of reports, or termination of analyst coverage. The latter effect is arguably a stronger signal of less favorable conditions for analyst research, because termination implies losing the cost of analyst 'investment' in learning about the firm and building a relation with the managerial team, which is higher than the cost of reducing report frequency.[5] To distinguish changes in the frequency of reports from analyst coverage decisions, we examine the two effects separately. We document that for stocks with high AT, analysts reduce both measures of research production. Importantly, we also find that the reduction in the frequency of reports is present when we condition on analysts' maintaining coverage of the stock.

Next, we report evidence supporting the two premises that underlie the negative relation between AT and analyst research production. First, that the fast and automated trades of ATs increase the speed of price discovery, which in turn erodes non-ATs' profitability of trades on analyst research as their orders' execution prices already impound a significant portion of the information signal. Second, given fewer opportunities for profitable trades, holdings by trade-oriented investors are reduced, which in turn lowers the demand for analyst investment advice.

To provide support for the first premise, we examine the speed of price adjustment to analyst research announcements conditional on the trading activity of ATs. For this test, we calculate the speed with which prices impound the analyst reports' content. We find that the speed of price discovery to analyst reports increases in AT, which in turn should associate with lower profitability of non-ATs trades. To further validate the prediction that the profitability of non-ATs' trades on analyst research decreases for high AT stocks, we follow Baruch, Panayides, and Venkataraman (2017) and measure the speed of price discovery using intraday prices from the TAQ database and the unbiasness regression methodology. The intuition for this test is that faster

[5] Previous research suggests analyst incur significant cost to learn about the firm and build relations with the managerial team (Ertimur, Mayew and Stubben 2011; Irvine 2003; Branson, Guffey and Pagach 1998).

price discovery more quickly aligns prices after the analyst report announcement with the equilibrium stock price reflecting all price-relevant information in the report (which we assume to be the price at the end of day one after the announcement).[6] We document that for low AT stocks, it takes at least 30 minutes longer for prices to impound the analyst report information with the same efficiency as for high AT stocks, for which price efficiency is reached almost immediately. This result is consistent with faster price discovery and less opportunities for non-AT traders to profitably trade on information in analyst reports, which reduces the investment value of and consequently the associated demand for analyst research.

Next, we test the second premise that underlies the negative relation between AT and analyst research production, namely that AT is associated with lower institutional demand for analyst investment advice. We examine this conjecture in three ways. First, we argue that the decrease in demand for analyst research should be mostly related to demand from institutions which rely on generating profits from active stock trading. In contrast institutions with long investment horizons, whose portfolio profitability stems mainly from price appreciation over longer periods, or from passively tracking market indices should not be deterred from holding stocks with high AT activity. Our results provide support for this conjecture. Specifically, we document that the relative ownership of both transient (Bushee 1998) and non-monitoring institutions (Chen, Harford and Li 2007) is negatively related to AT activity, consistent with trade-oriented institutional investors reducing their holdings in stocks which do not provide opportunities for profitable short-term trading.

Second, we examine the impact of AT separately for analyst stock recommendations, which reflect investment advice, and earnings forecasts, which also play an external corporate governance

[6] The test focuses on analyst stock recommendations issued at least one hour before the market close and without accompanying earnings forecasts to avoid confounding effects.

role.[7] Given that investors' demand for earnings forecasts is not only affected by trading incentives, the negative relation between AT and analyst research production should be stronger (weaker) for stock recommendations (earnings forecasts). We find that the reduction in the number of stock recommendations is greater than the reduction in the number of analyst earnings forecasts. This result is consistent with a stronger negative effect AT has on demand for analyst research that is more likely used for investment decisions.

Third, we posit that the adverse effect of AT on analyst research should be more evident when analysts fulfill their information discovery role (Dempsey 1989; Shores 1990), which is the basis for analyst investment advice (Ivković and Jegadeesh 2004; Asquith et al. 2005), than their information intermediation role (Francis et al. 2002; Frankel et al. 2006).[8] We follow Chen, Cheng and Lo (2010) and examine the impact ATs have on analyst research production before earnings announcements, a period when analysts engage mainly in private information discovery, compared to the post-earnings announcement period, when analysts play mainly an interpretative role. We find that ATs reduce analyst research production both before and after earnings announcements, however, the effect is almost two times stronger before earnings announcements.

To address endogeneity and speak to the causality of the negative relation between ATs and analyst research production, we employ three tests. First, we run the analysis controlling for firm-fixed effects to capture time-invariant firm characteristics that could correlate with AT and analyst

[7] Earnings forecasts provide a yardstick against which investors assess quarterly earnings (Brown and Caylor 2005) and managerial performance (Matsunaga and Park 2001; Carter, Ittner and Zechman 2009). Several studies show that failing to meet analyst earnings benchmarks is associated with negative price reactions (e.g., Bartov, Givoly and Hayn 2002) and other outcomes such as increased cost of debt (Jiang 2008).

[8] We do not preclude that analysis of public information can form a basis for a profitable investment advice, e.g., in instances when the market fails to fully incorporate public news. However, previous research ascribes value of analyst investment advice mainly to analyst private information discovery (Dempsey 1989; Shores 1990; Womack 1996; Loh and Stulz 2011).

research activity.[9] Second, we use instrumental variables regression methodology using as instrument the Investors Exchange (IEX) speed bump implementation at the end of August 2016, a delay mechanism that slows quotes and trades by about 350 microseconds. Chakrabarty et al. (2020) show that the IEX introduction of a speed bump affected market quality across other exchanges by documenting significant price changes. As a result, we expect the IEX speed bump to decrease ATs activity across all stocks, but it should not affect analyst research production, thus the instrument meets the relevance and exclusion conditions for our sample. Instrumental variables analysis supports our main conclusions.[10]

Third, we take advantage of the natural experiment related to the Tick Size Pilot (TSP), a two-year experimental program that the SEC adopted to examine the impact of tick size increases on liquidity provision and market quality of small-capitalization stocks (market capitalization of $3 billion or less). Firms in the program were randomly assigned to treated and control groups. For the sample of treated firms, the tick size increased from $0.01 to $0.05 during the two-year duration of the program. One important consequence of the larger tick size was the exogenous decrease in AT for treated firms which when combined with the program's relatively short duration allows us to causally link changes in algorithmic trades to analyst research activity. We document that lower AT activity in treated stocks is related to an increase in the number of EPS forecasts and stock recommendations issued for treated firms relative to control firms. The effect of lower AT activity on analyst research production is economically significant: using interquartile values for the six AT measures, an average percentage interquartile reduction in the AT measures for treated firms associates with a 18.9% increase in the number of analyst earnings forecasts and stock

[9] Instead of firm-fixed effects, we also run regressions in changes, which factor out time-invariant characteristics that could correlate with both analyst research production and AT. Results from this analysis support our main conclusions.
[10]Our conclusions are unchanged when we use lagged stock price as an instrument for AT (Weller 2018).

recommendations. We conclude that ATs have a sizable, causal, negative effect on analyst research production.[11]

Our study makes contributions to two streams of literature. First, we contribute to the analyst literature that examines the factors affecting analyst research activity. Related research has documented that analysts tend to follow firms with better prospects (Das, Guo, and Zhang 2006), enhanced disclosure (Lang and Lundholm 1996), better corporate governance (Lang, Lins, and Miller 2004), reduced return volatility (O'Brien and Bhushan 1990), high institutional ownership (Bhushan 1989; Boone and White 2015; Brown, Call, Clement and Sharp 2015), and more complex annual reports (Lehavy, Li and Merkley 2011). Our finding on a negative relation between AT and analyst research production adds to this literature and is particularly important given the benefits that accrue to firms from analyst following including an increase in firm value (Lang, Lins, and Miller 2003), higher stock liquidity (Irvine 2003), market efficiency (Ayers and Freeman 2003), investor recognition (Li and You 2015) and decreases in default risk (Cheng and Subramanyam 2008).

Second, our study contributes novel insights to the literature that examines the market impact of ATs. Related research provides conflicting results on the effect of ATs in capital markets. On one hand, the academic literature has identified that ATs improve liquidity, price discovery (Hendershott, Jones and Menkveld 2011; Hasbrouck and Saar 2013; Chordia and Miao 2020) and price efficiency (Chakrabarty, Moulton and Wang 2020; Bhattacharya, et al 2020; Hu, Pan and Wang 2017). On the other hand, more recent work shows a negative effect on price informativeness (Weller 2018; Lee and Watts 2020). We contribute to this debate by documenting a negative effect of ATs on analyst research production. Our evidence is consistent with the

[11] In sensitivity tests, we also show that our results are not due to potential changes in disclosures of firms with high AT activity or changes in these stock's liquidity.

theoretical model of Baldauf and Mollner (2020, p. 1497): '[I]ntuitively, [ATs'] order anticipation reduces the amount of rent that informed traders can extract by trading on a piece of information, thereby weakening the incentive to obtain such information. Less fundamental research is then conducted so that markets provide less information about the fundamental value of the security, potentially generating further (unmodeled) distortions in the wider economy.' We document one such distortion, namely changes in analyst research activity as a result of AT. Relatedly, we identify analyst research activity as an important channel that can explain the recent findings in Weller (2018) and Lee and Watts (2020) that AT decreases price informativeness before earnings announcements. Specifically, our evidence shows that the effect of AT on analyst research is stronger in the period before earnings consistent with the evidence in both papers that information is reduced in the same period.

Third, prior research focused on the daily and (more often) intraday impact that AT has on stock liquidity and price efficiency with no clear guidance on whether these ultra-short impacts have longer-lasting consequences beyond microstructure effects. Stiglitz (2014, p. 9) argues that '…real decisions, e.g., about how much to invest in a steel mill, are clearly unlikely to be affected by [these] variations in prices within a nanosecond. In that sense, they [ATs] are fundamentally irrelevant for real resource allocations.' We document that ATs can have real impacts on capital markets through their negative effect on analyst research production. Our evidence should be important to regulators who are still striving to assess the overall impact of ATs on capital markets and echoes their concerns that ATs reduce price informativeness by discouraging outside information production.[12]

[12] See SEC's "Staff Report on Algorithmic Trading in U.S. Capital Markets" to the Congress, https://www.sec.gov/files/Algo_Trading_Report_2020.pdf

## 2. Research design

ATs are characterized by high daily trading volume and low latency of order submissions and cancellations. They 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. Though ATs trade multiple times during the day, they end up with very low inventory at the end of the day. As in Weller (2018) and Lee and Watts (2020), we use six daily proxies that capture these characteristics. The first three are the total volume executed in quantities smaller than 100 shares divided by total trading volume (*odd_lot*), and the number of cancelled orders divided by either the number of trades based on displayed orders or the total number of trades (*cancel_ord and cancel_ord2*). Higher values of *odd_lot*, *cancel_ord* and *cancel_ord2* indicate higher trading activity of ATs. The additional three measures that capture AT trading activity are the total trading volume based on displayed orders (*trade_vol*) and the total trading volume (*trade_vol2*) divided by the total order volume. Based on the assumption that ATs tend to trade in smaller orders, we also compute the average order size by dividing the number of shares traded by the total number of trades (*trade_size*). Higher values of *trade_vol*, *trade_vol2* and *trade_size* indicate less algorithmic trading. We aggregate all six daily proxies to quarterly averages for our analyses. Results are presented for all six measures since Lee and Watts (2020, p. 21) observe that 'there is substantial individual variation across the proxies, suggesting each may capture a slightly different aspect of, or strategy within, algorithmic trading'.[13] To reduce

[13] As highlighted in Weller (2018) and Lee and Watts (2020), the AT proxies constructed using MIDAS data have several advantages compared to other approaches. First, compared to TAQ data, MIDAS data incorporate quote and cancellation information from the entire order book and odd lot trades, where significant AT activity takes place (O'Hara et al. 2014). Thus, the precision of the measures is superior compared to comparative measures based on TAQ data. Further, MIDAS covers all US exchanges whereas some studies used proprietary dataset from NASDAQ that covered only 120 stocks over a two-year period 2008-2009 (Brogaard, Hendershott, and Riordan 2017; O'Hara et al. 2014; Carrion 2013).

dimensionality of the data while also minimizing information loss, we also use principal component analysis to create an index measure from the six AT measures, *AT factor*. The weights are −0.145 for ln *odd_lot*, −0.228 for ln *cancel_ord*, −0.228 for ln *cancel_ord2*, 0.250 for ln *trade_vol*, 0.240 for ln *trade_vol2* and 0.138 for ln *trade_size.* We multiply the AT factor by −1 so that higher values of the *AT factor* reflect higher intensity of AT. Appendix A details how we construct the measures of algorithmic trading and other variables used in the study.

We measure analyst research production in three ways. First, we count the total number of quarterly earnings forecasts and the number of stock recommendations issued by analysts in a firm-quarter, *#EPS and stock recommendations*. Second, we look at the number of analysts covering a firm in a quarter, *#analysts.* Third, in additional tests, we separately count the number of quarterly EPS forecasts, *#EPS*, and stock recommendations, *#stock recommendations*, for each firm-quarter. The basic regression model relating the measures of analyst research production to proxies for the trading activity of ATs is

$$\ln\left(\#EPS\ and\ stock\ recommendations\right)_{i,q,t} = \varphi_0 + \varphi_1 AT_{i,q,t} + Controls_{i,q,t} + Year_t + Quarter_q + Industry_i + e_{i,q,t} \tag{1}$$

where AT is one of the six ATs trading activity proxies. The set of *Controls* includes institutional ownership, firm size, the book-to-market ratio, and proxies for firm profitability, leverage, cash position and sales growth (McNichols and O'Brien 1997; Bhushan 1989; Rajan and Servaes 1997; Barth et al. 2001; Bradley et al. 2003). The model also includes quarter and year fixed effects to capture within fiscal year and across-time variation in research production, as well as industry fixed effects to capture cross-sectional variation in analyst research activities across industries. All continuous variables are winsorized at the 1% level to mitigate the impact of outliers and standard errors are clustered at year-quarter.

## 3. Data

We collect analyst quarterly EPS forecasts and analyst stock recommendations from I/B/E/S. Compustat is our source of quarterly accounting information and CRSP of market data. For the construction of the AT activity proxies, we rely on the SEC Market Information Data Analytics System (MIDAS) which is comprised of order level daily summary information of market activity across all major U.S. stock exchanges. This data is available from 2012 to 2019 producing a sample of 57,078 firm-quarter-year observations.

Table 1 reports descriptive statistics for the number of EPS forecasts and stock recommendations for our sample (Panel A), the AT measures (Panel B), and the control variables from equation (1) (Panel C). The average number of EPS forecasts and stock recommendations issued for a firm in a quarter is 50.879 with an average of 8.769 unique analysts. Our descriptives are comparable with earlier research. Weller (2018), for example, who also uses MIDAS data, reports an average number of 5.53 analysts issuing EPS forecasts at earnings announcements, which is comparable to our value when considering that our measure includes all analysts that issued at least one EPS forecast or a stock recommendation in a firm-quarter. The mean values of AT measures are also comparable with those in Weller (2018). For example, the mean log trade size in Weller (2018) is 4.71 (Table 1) and 4.52 in our sample. Panel D reports Pearson correlations between AT proxies, which conform to the expected signs.

[Table 1]

## 4. Main results

This section first presents regression results documenting a negative association between AT and analyst research production. We next present additional analyses that validate the underlying premises of the documented relation.

### 4.1. The relation between AT and analyst research production

Panel A of Table 2 reports regression results for equation (1). We find a negative association between AT proxies and the number of analyst EPS and stock recommendations with the signs of coefficients conforming to the predictions. The effect ATs have on analyst research is economically significant: depending on the measure, stocks in the top quartile of AT measures have on average between 10.7% and 19.9% fewer forecasts compared to stocks in the bottom quartile.[14] This evidence suggests that the presence of ATs in a broad cross-section of stocks has a significant negative impact on analyst research production. Appendix B shows the results are robust to alternative treatments for standard errors including firm, firm-quarter, firm-year and industry-quarter clustering.

A reduction in analyst research activity can reflect a reduction in both the frequency of analyst output and in analyst coverage. Reduced analyst coverage is a stronger indication of less favorable conditions for analyst research as the cost of dropping coverage is higher compared to reducing report frequency (Irvine 2003; Branson, Guffey and Pagach 1998). Results presented in Panel B of Table 2 indicate a significant reduction in the number of analysts covering stocks as AT increases further supporting the negative relation between AT and analyst research production. To ensure that the decrease in analyst production is not a mechanical result stemming from the decrease in analyst following, Panel C reports equation (1) results conditional on analyst maintaining coverage of the stock across consecutive quarters. We continue to find a significant decrease in the frequency of analyst forecasts and stock recommendations in the presence of higher AT activity, suggesting that the AT is related to both lower report frequency and lower analyst coverage.

[14] The absolute economic effects for individual measures are 15.9% for *odd_lot*, 19.1% for *cancel_ord,* 19.99% for *cancel_ord2*, 16.4% for *trade_vol*, 15.1% for *trade_vol2* and 10.7% for *trade_size*.

[Table 2]

**4.2 ATs and the speed of adjustment to analyst reports**

Our first set of validation analyses provides support to the premise that ATs' low latency trades lead to faster impounding of the analyst report's information into stock prices, so that non-ATs' order execution prices already reflect most of the new information revealed in the report. To test for the speed of price adjustment to new information revealed through analyst research, we follow Weller's (2018) methodology and calculate the normalized price reaction to an analyst earnings forecast or stock recommendation issued for firm *i* on day *d*:

$$Jump_{i,d} = \frac{AR_{id}(0)}{CAR_{id}(-21,2)}. \tag{2}$$

*Jump* captures the speed with which prices impound the report information content relative to the total signal value of the report. Higher values of the ratio are suggestive of fewer opportunities for non-ATs to profitably trade on the analyst report's information signal on the report announcement day.[15] Following Weller (2018), we retain events with material information, i.e., those that satisfy $\left|CAR_{it}^{(T-21,T+2)}\right| > \sqrt{24}\hat{\sigma}_{it}$, where $\hat{\sigma}_{it}$ is the daily return volatility from $T$ - $42$ to $T$ - $22$ days before an analyst report. Our conclusions remain the same when we include all analyst reports. We then use *Jump* as the dependent variable in equation (1) and expect a speedier price discovery in high AT stocks. We also augment equation (1) with the absolute magnitudes of earnings forecasts and

[15] Similarly to Weller (2018), we measure the total value of the signal in the denominator in the period -21 to 2 to account for informed trading prior to the release of the analyst report (Irvine, Lipson and Puckett 2007) and delayed investor reaction (Elgers, Lo and Pfeiffer 2001). We normalize abnormal returns around the report announcement by the total value of the signal (i) to account for the differences in magnitudes of the announcement signal across analyst-firm-days, e.g. differences in the magnitude of the revision in analyst forecasts and in the content of the report, and (ii) to account for the variation in expected abnormal returns across stocks and over time; for example, smaller stocks have on average stronger price reaction to new information because of their lower quality information environment where information is scarce (Bhattacharya et al. 2020).

stock recommendations revisions to control for the magnitude of the surprise conveyed in the analyst report which will affect the overall market reaction.[16]

Table 3 results are consistent with our expectation that the information content of analyst reports is impounded faster in high AT stocks with significant coefficients on five out of the seven AT measures, including the AT factor, and with the correct sign. The evidence in Table 3 is consistent with fewer opportunities for non-ATs to profitably trade on analyst reports in a fast price discovery environment (Weller 2018).[17]

[Table 3]

The second test we use to capture the effect of AT on the profitability of trades by non-ATs around analyst report announcements looks at the speed of price discovery using intraday prices from the TAQ database and unbiasness regressions (Baruch, et al. 2017). Specifically, we regress the return from the time of the stock recommendation announcement to the end of the following day, $ret_{[0,+1]}$, on the return from the time of the recommendation announcement to the end of time $T$, $ret_{[0,T]}$. For $T$, we use overlapping intervals increasing by 10 minutes,

$$ret_{[0,+1]} = \alpha + \beta ret_{[0,T]} + \varepsilon_i. \tag{3}$$

We then separately run a cross-sectional regression for each time period $T$, starting with $T$=10 minutes, and estimate the slope $\beta$. Barclay and Hendershott (2003) interpret the $\beta$ slope as a signal-to-noise ratio. If price discovery is faster, we expect $\beta$ to move closer to one earlier in time as the stock price reflects the recommendation information price with increasing precision. Intuitively, if the stock recommendation information is fully impounded into stock prices within the first 10

[16] Our results remain unchanged when we adjust the *Jump* measure for analyst reports issued after trading hours. For these reports, we assign the announcement day the next trading day.
[17] The conclusions are the same when we use Weller's (2018) jump measure where the numerator is CAR(-1,2) and when we exclude a six-day window centred on the quarterly earnings announcements.

minutes of the report release, then β will be one in the interval T≥10 minutes as price movements after the first 10 minutes are random absent other news. For this test, we select the sample of stock recommendation revisions for stocks in the top and bottom deciles of the AT factor. We also remove recommendation revisions issued jointly with earnings forecast revisions to limit the influence of information content in EPS forecasts. [18]

[Figure 1]

Figure 1 presents the estimated β slope for high and low AT stocks. The β estimate approaches one faster as we increase *T* for the high AT firms and is always closer to one than the slope for the low AT firms. Put differently, it takes at least 30 minutes longer for the price of low AT firms to impound the analyst report information with the same efficiency as in the 10-minute period for the high AT firms, for which price efficiency is reached almost immediately. In untabulated results, we find that the half-hour average β estimate for the low AT firms is statistically smaller (at the 5% level) than for the high AT firms for *T* in the intervals [+10, +20, +30]. The same holds but is marginally significant (at the 10% level) for *T* in the intervals [+160,+170,+180]. Overall, the findings indicate that the speed of price discovery, and hence price efficiency, is lower for low AT firms, which suggests greater trade profitability opportunities for non-AT investors.

### 4.3 ATs and institutional investor demand for analyst investment advice

In this section we provide evidence in support of the premise that AT is associated with lower institutional demand for analyst investment advice.

[18] Because our focus is on the speed of price discovery, we also exclude illiquid firms from the analysis (based on quoted spreads).

*4.3.1. The effect of AT on Institutional ownership*

In our first analysis, we relate AT to the stock holdings of institutions that actively engage in stock trading. We argue that the increased speed of price discovery associated with AT and the resulting erosion of trade profitability for non-ATs will deter institutions with short-term investment horizons from trading in these stocks. Thus, the ownership of short-term institutions in stocks with high AT activity will be reduced. We define short-term institutions as transient institutions based on the measure in Bushee (1998) but for robustness we also report results based on the measure of non-monitoring institutions as in Chen, Harford and Li (2007). Based on the expectation that the decreased profitability of trades will not have a similar impact on the holdings of institutions with long-term investment horizons, as their portfolio choices are less affected by short-term trading profits and more by long-term capital appreciation, and investors whose portfolios mimic an index (Bushee 1998), we divide short-term ownership by the total institutional holdings (i.e., holdings of transient and long-term investors, and quasi-indexers). We expect that the *relative* ownership of trading-intensive institutions will be negatively associated with our measures of AT.

We obtain transient institutional ownership data from Brian Bushee's Institutional Investor Classification website.[19] In the first seven columns of Table 4, we relate the relative ownership by transient institutions, to our six measures of AT and the AT factor. For robustness, (and in sake of brevity), the last column of the table reports regression results associating the AT factor to short-term institutional ownership based on the relative ownership of non-monitoring institutions.[20] Results in Table 4 indicate that higher algorithmic trading activity is negatively associated with the relative ownership of institutions with short trading horizons, as expected. This result is significant

[19] https://accounting-faculty.wharton.upenn.edu/bushee/

[20] Monitoring institutional ownership is based on ownership concentration, independence, and long-term investment style. Relative non-monitoring institutional ownership equals 1 minus the ownership by monitoring institutions divided by total ownership.

and in the right direction for all models presented in Table 4.[21] We conclude that trade-oriented institutional investors reduce their holdings in stocks that do not provide opportunities for profitable short-term trading, a result consistent with reduced demand for analyst investment advice for these stocks.

[Table 4]

*4.3.2 The differential effect of AT on EPS forecasts and stock recommendations*

To provide further support to the premise that AT reduces demand for analyst investment advice, we next examine whether the presence of ATs is more negatively associated with the generation of stock recommendations than of earnings forecasts. We base this analysis on the evidence that analyst earnings forecasts are useful both as investment signals (Livnat and Mendenhall 2006, Loh and Mian 2006) and as a monitoring mechanism for managerial performance (Brown and Caylor 2005; Matsunaga and Park 2001). Stock recommendations are mainly investment signals (Mikhail et al. 2004; Li 2005). Thus, if lower investment demand drives the negative relation between AT activity and analyst research production, the supply of stock recommendations should be more affected than the supply of earnings forecasts.

Panel A of Table 5 reports equation (1) results when we separately regress the number of earnings forecasts and the number of stock recommendations on our AT proxies. Our sample for this test includes 56,891 firm-quarter-years with EPS forecasts and 35,455 firm-quarter-years with stock recommendations. Because the frequency of EPS forecasts is significantly higher than that of stock recommendations, we report standardized coefficients where all variables are standardized to a mean of zero and unit standard deviation. Panel B of the same table presents t-tests for the difference in the coefficients between the two regressions for each AT measure. The evidence

[21] Our conclusion is the same when we use unscaled holdings of institutions with short trading horizons.

suggests that both earnings forecasts and analyst recommendations are negatively related to AT activity. However, we document a stronger impact of algorithmic trades on the supply of stock recommendations than of earnings forecasts for most regressions, consistent with the lower demand for analyst investment advice.

[Table 5]

*4.3.3. Analyst dissemination vs. information discovery roles*

Analyst reports reflect both their private information about a stock and their interpretation of public news. The former captures the important role analysts play in uncovering information not yet reflected in stock prices, which is the basis for their investment advice; the latter captures analysts' role in analyzing and repackaging complex public information (Chen, Cheng and Lo 2010; Lang and Lundholm 1996; Ivković and Jegadeesh 2004). The negative relation between ATs and analyst research production is based on the premise that the reduced trade profitability for non-ATs decreases demand for analyst investment advice. Thus, the presence of ATs should primarily reduce demand for analyst reports which convey information used for investment purposes, a prediction we test next.

We follow Chen et al. (2010) and examine the impact ATs have on analyst research production before earnings announcements, which is more likely to reflect their private information discovery, compared to after earnings announcements. Analyst reports after earnings announcements play mainly an interpretative role and facilitate the analysis and dissemination of public news. We expect AT to have a larger impact on analyst research production before than after earnings announcement. For this test, we focus on analyst research production in a 60-day window centered on the earnings announcement day. We augment equation (1) with an indicator variable *Before EA* which identifies analyst reports issued in a 30-day period before quarterly earnings announcements, and interact it with the measures of AT. To avoid contaminating the results with analyst revisions at earnings announcements, we remove the six-day window centered on the earnings announcements.

Table 6 presents the results of this analysis. The positive coefficient on the indicator *Before EA* in all seven models suggests that analysts are incrementally more active before than after earnings announcement, consistent with increased investor demand for analyst private information about upcoming announcement of corporate results (Chen et al. 2010). Interestingly, and consistent with our expectation, ATs have a significantly stronger negative impact on analyst research production before earnings announcements a result that holds in 5 out of the seven models presented, including for the AT factor. This result is consistent with analysts reducing their costly private information acquisition in the presence of ATs, providing further support to the conclusion that ATs decrease the demand for analyst research.

[Table 6]

## 5. Robustness tests

This section presents additional tests that help us address and preclude alternative explanations for our results.

### 5.1 Tests addressing endogeneity

To address endogeneity and speak to the causal relation between AT and analyst research, we first present regression with firm-fixed effects, then instrumental variables results, and finally evidence from a quasi-natural experiment related to the Tick Size Pilot program.

#### *5.1.1 Firm-fixed effects*

Panel A of Table 7 repeats equation (1) when we include firm-fixed effects to control for time-invariant firm characteristics that could correlate with the AT and analyst research activities. All coefficients remain significant and with the correct sign, which supports our main conclusions.

### *5.1.2 Instrumental variable analysis*

Next, we implement a two-stage least squares regression analysis using two different instruments. First, we use the adoption of speed bumps as an instrument. Speed bumps slow down trading, eliminating the speed advantage of ATs. Following Chakrabarty, Huang, and Jain (2020), we focus on the Investors Exchange (IEX) implementation of a speed bump in late August 2016.[22] The delay mechanisms—a 38-mile optical fiber coil that sits in front of its matching engine—slows quotes and trades by about 350 microseconds. By slowing down order entry, proprietary data and outbound routing, the exchange gives slower traders an additional 350 microseconds to trade before faster traders (ATs) detect their order flow (Aoyagi, 2019). Since IEX is a registered exchange, following Reg NMS, all orders have to be routed to IEX when, at any instance, it has the national best bid/offer (NBBO) quotes. As a result, we expect the IEX speed bump to decrease ATs activity across all stocks, but it should not affect analyst research production, thus the instrument meets the relevance and exclusions conditions for our sample. We define the instrument, *Post Speed Bump*, to take a value one for the four-quarter period after the implementation date of the IEX speed bump, and zero for the four quarters before the implementation date. This creates a balanced sample with the same pre and post periods ending in the 4$^{th}$ quarter of 2018. We augment equation (1) with a first stage for the proxies for the trading activity of ATs. The two-stage model has the form,

[22] IEX was introduced in the market as a dark pool on October 25, 2013 and only entered the lit market competition after it gained stock exchange status, on June 17, 2016. It started trading stocks as a lit market in late August 2016.

$$AT_{i,q,t} = a_0 + a_1 Post\ Speed\ Bump_{q,t} + Controls_{i,q,t} + Quarter_q + Industry_i + \delta_{i,q,t}$$

and

$$\ln(\#EPS\ and\ stock\ recommendations)_{i,q,t} = \varphi_0 + \varphi_1 \widehat{AT}_{i,q,t} + Controls_{i,q,t} + Year_t + Quarter_q + Industry_i + e_{i,q,t} \quad (4)$$

Panel B of Table 7 reports the second stage results, which continue to support a negative relation between AT proxies and analyst research production.[23] Thus, instrumental variables analysis supports our main conclusions.

Second, following Weller (2018) we use the log of the average stock price as an instrument for algorithmic trading activity. Weller (2018) argues that 'variation in lagged stock prices should relate little to the incentives of market participants to acquire information or to the amount of information available to acquire', however, algorithmic trading should comprise 'a greater share of trading in stocks with higher prices all else equal'. Because analysts' incentives are similar to investors, we expect that the share price level does not affect analyst incentives to acquire information or the availability of information, which would mediate through a variation in analyst research production. Thus, the lagged price meets the exclusion and relevance conditions. We augment equation (1) with a first stage for the proxies for the trading activity of ATs and the two-stage model has the form

$$AT_{i,q,t} = a_0 + a_1 Lagged\ Log\ Price_{i,q,t} + Controls_{i,q,t} + Year_t + Quarter_q + Industry_i + \delta_{i,q,t} \quad (5)$$

and

[23] Appendix C reports first stage regression results showing on average a negative effect speed bumps have on the trading activity of ATs, consistent with Chakrabarty et al. (2020).

$$\ln\left(\#EPS\ and\ stock\ recommendations\right)_{i,q,t} = \varphi_0 + \varphi_1\widehat{AT}_{i,q,t} + Controls_{i,q,t} + Year_t + Quarter_q + Industry_i + e_{i,q,t}$$

Panel C of Table 7 reports second stage regression results using the natural logarithm of the average stock price for the quarter before analyst report announcement as an instrument and we find a consistent negative relation between AT and analyst research production.

[Table 7]

*5.1.3 Tick size pilot results*

Next, we use the natural experiment related to the implementation of the Tick Size Pilot program to examine the causal link between AT activity and analyst research production. In May 2015, the SEC approved a randomized experiment where a select group of small capitalization firms would be traded at the higher tick size of $0.05 compared to the normal quote of $0.01. The goal of the program was to understand the impact that the widening of the quoting and trading increment and lower trading activity of ATs would have on market making and price discovery (Chung, Lee, and Rösch 2020). For the experiment, the SEC selected securities with a market capitalization of less than $3 billion, average closing price of at least $2, and an average trading volume of up to one million shares measured in a two-week assignment period. A random sampling process was used to select 1,200 stocks into the treatment group and 1,400 stocks into the control group. Companies could not opt in or out of their allocated group. The program started on October 3, 2016 and was phased in gradually during the course of the month. The end date for the program was October 18, 2018 when treated firms returned to their original trading tick size.[24] Lee and Watts (2020) document a significant reduction in AT activity in the treated stocks of around 10.68% relative to

[24] For further description of the TSP, see Rindi and Werner (2019), Albuquerque et al. (2020), Chung, Lee, and Rösch (2020), and Lee and Watts (2020) and SEC Plan to Implement the TSP (https://www.sec.gov/divisions/marketreg/tick-size-pilot-plan-final.pdf).

controls stocks. Because of the random firm assignment to treated and controls stocks, the experiment is exogenous to the analyst coverage decisions, which helps us causally link changes in AT trading intensity to analyst research production.

We thus use the Tick Size Pilot randomized experiment to causally link AT activity and analyst research production. Specifically, we use the standard difference-in-differences research design to estimate the average treatment effect for analyst research activity in treated firms:

$$\begin{aligned}\ln(\#EPS\ and\ stock\ recommendations)_{i,q,t} \\ = \gamma_0 + \gamma_1 Post_{q,t} + \gamma_2 Treatment_{i,q,t} + \gamma_3 Post_{q,t} \times Treatment_{i,q,t} \\ + Controls_{i,q,t} + \varepsilon_{i,q,t}\end{aligned} \quad (6)$$

where *Post* equals one for all quarters *q* in year *t* in the post-TSP period of October 2016 to September 2018, and zero otherwise. The pre-treatment period is from October 2014 to September 2016. *Treatment* is an indicator variable that takes the value one if firm *i* belongs in the treatment group that experienced an increase in tick size, and zero otherwise. The incremental effect of the program on analyst research activity is captured by the third term, *Post* × *Treatment.*[25] If lower AT activity promotes more demand for analyst research, $\gamma_3$ should be positive. We start with a sample of 1,970 firms (987 treated and 983 control firms) from Rui, Song and Yao (2020).[26] Limiting the sample to the two years before to two years after the TSP and additional data requirements reduce the sample to 10,273 firm-quarter-years with 584 treated and 573 control stocks. Appendix D reports descriptive statistics for the number of EPS forecasts and stock recommendations for the

[25] There is a concern that the experiment may be affected by liquidity spillover from treated to control stocks as TSP can reduce trades in a broad group of small stocks (Rindi and Werner 2019; Lin, 2019; Lee and Watts 2020). The effect of this spillover would be to reduce the economic magnitude of the TSP effect as treated and control firms remain similar after the treatment. Lee and Watts (2020) report evidence on economically small spillover effects from treated to control stocks.

[26] The list of firms in the treatment and control groups are from the FINRA website. As in prior studies (e.g., Weller 2018; Rindi and Werner 2019) we omit securities that are not common equity (e.g., preferred stocks) or are dropped from the pilot study, due to mergers, delistings, or prices below $1.

TSP sample (Panel A), the AT measures (Panel B) and the control variables (Panel C). Descriptive statistics for the AT measures are comparable with previous research using TSP, for example, the mean average trade size in Lee and Watts (2020) is 95.09 which is similar to our sample's mean of 87.795.

Next, we examine if changes in AT activity affected analyst research production among treated stocks. Panel A of Table 8 reports pre-treatment means for the *#EPS and stock recommendations* for treated and control stocks. We do not find a significant difference between the means of the two groups, which is consistent with the random allocation of stocks to treated and control groups of the pilot program. This result is consistent with the parallel trend assumption and jointly with the evidence from Appendix D, that the distribution of AT measures is similar between treatment and control firms before TSP, confirms that random TSP program assignment did not produce selectivity on analyst coverage.

[Table 8]

Panel B reports equation (6) regression results. We follow Lee and Watts (2020) and report results of equation (6) with and without controls. The coefficients on *Post* × *Treatment* is positive, in all models indicating that analysts increase their research production for treated firms relative to firms in the control group following the decrease in AT trading after the introduction of TSP. The positive effect on analyst research production among treated firms is particularly notable considering the large negative coefficient on *Post*, which suggests that control firms experienced, on average, a significant reduction in analyst research activity in the post-TSP period. This result is consistent with a gradual decline in analyst coverage among U.S. stocks, in particular for smaller firms.[27]

The economic magnitude of the effect related to the reduction in AT activity for treated stocks is significant: we find that compared to control stocks, treated firms have on average 4.1% more quarterly earnings forecasts and stock recommendations after the start of the pilot program. Jointly with Appendix D evidence suggesting a reduction in AT activity of between 6.3% to 37.2% for treated firms after the start of TSP, the result suggests a material effect AT trading reduction has on analyst research production—a quick calculation using quartile values for the six AT measures from Panel B of Appendix D shows that an average percentage interquartile reduction in AT measures would associate with a 18.9% increase in the number of analyst earnings forecasts and stock recommendations.[28] In untabulated results, we find similar magnitudes of estimates using a negative binomial model.

The last columns of Panel B augment equation (6) with the magnitudes of changes in the AT factor between the pre-TSP and the TSP period, split by the direction of the change. $-\Delta$*AT factor* measures the reduction in AT factor from before to the TSP period. $+\Delta$*AT factor* measures the increase in AT factor from the pre-TSP to TSP period. We then interact the measures of directional change in AT factor with the *Post* indicator. We expect that it is the reduction in AT for treated stocks that associates with an increase in analyst research production as captured by the interaction *Post*×*Treatment*. The significant and positive coefficient on *Post*×$-\Delta$*AT factor* confirms that the increase in analyst research production is driven by treated stocks that experienced a reduction in AT activity. The insignificant coefficient on *Post*×$+\Delta$*AT factor* suggests

[27] WRDS release notes show a significant drop in the number of unique I/B/E/S analysts from 2,749 in August 2009 to 1,567 in May 2018. The decline in analyst headcount over time has also been reported in Fang, Hope, Huang and Moldovan (2020). It is also consistent with spillover effects from treated to control stocks.

[28] We calculate this number as $\frac{4.1\%}{1/2(6.3\%+37.2\%)} *$ (average percentage interquartile reduction in AT measures).

that there are few cases where AT increased for treated stocks. Panel C of Table 8 shows that results are not affected if analyst research production is proxied by analyst following (column '#analysts following a firm') or when the pre and post-TSP samples are constrained to include the same firm-analyst pairs in both periods (column 'Constant sample of analyst-firms'). [29]

Further, to build confidence in our Table 8 evidence, we 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. We then run equation (6) for this sample and find insignificant coefficients on the interaction term (see Appendix E). Thus, the results in Table 8 are absent outside the TSP program and the placebo test evidence is consistent with TSP assignment into treated and controls firms not selecting stocks on analyst coverage.[30]

Finally, in untabulated results, we confirm our main sample results on (i) lower price reactions to analyst report announcements for the treated stocks after the start of TSP program compared to control firms, consistent with higher expected non-AT profitability of trades on analyst research for treated firms, (ii) slower price discovery on the information in analyst reports in the post-TSP period; it takes at least 30 minutes longer for prices to impound the analyst report information in the post-TSP period with the same efficiency as in the 10-minute period before the TSP, (iii) an incremental increase in ownership by investment focused institutional investors in treated stocks , (iv) incrementally higher increase in the production of stock recommendations than EPS forecasts, consistent with higher investment demand for analyst research, and (v) more intense

[29] The results in Table 8 may be confounded by a reduction in liquidity for treated firms, e.g., Lee and Watts (2020) note a reduction in trading volume around earnings announcements for treated firms during the pilot. However, lower liquidity should *reduce* analyst research production in treated stocks as expected research fee and soft dollars potential reduces (Roulstone 2003). Thus, the effect would be the opposite to what we find.

[30] To exclude the effect the TSP had on treated firms reporting quality (Ahmed, Li and Xu 2020), we re-did Table 8 analysis keeping only the first three quarters before and after the start of the TSP and the results (untabulated) are unchanged.

research production before earnings announcement, consistent with increased demand for new information. These additional tests provide further support to the negative relation between AT and analyst research production and suggest that our comparable tests for the main sample are not affected by endogeneity. Our results help explain the evidence in Chung et al. (2020) and Lee and Watts (2020) on an improvement in price efficiency for treated stocks as at least some of the private information discovery is channeled through analyst reports.[31]

### 5.2 Additional robustness analyses

Table 9 presents additional robustness tests when we introduce sample and model modifications. First, we exclude analyst reports issued in a 6-day window centered on the earnings announcement day to reduce the likelihood that our main results are driven by changes in corporate disclosures (Griffin, 2003). Results are presented in column 'Exclude EA' and for brevity, only for the AT factor. We continue to find that the coefficient on the AT factor is negative and significant alleviating concerns that our results are confounded by changes in the informativeness of corporate communication.

To build confidence that our results do not capture a negative association between AT and reporting quality (Ahmed et al. 2020), we include in equation (1) several controls for earnings quality. We follow Ahmed et al. (2020) and calculate two measures of discretionary accruals in a quarter adjusted for non-linear growth in return on assets, market-to-book ratio and sales growth (Collins, Pungalliya and Vijh 2017). Specifically, *ADA DD*, is the absolute value of residuals from the NcNichols (2002) modified Dechow and Dichev (2002) model adjusted for non-linear growth (Kothari, Leone and Wasley 2005) and controls from Collins et al. (2017), with change in working

[31] In contrast to our results, Chen, Huffman, Narayanamoorthy and Zhang (2021) report a decline in analyst coverage for treated stocks in the first eight months of the Tick Size Pilot program. We address their evidence in Appendix F.

capital accruals as the dependent variable. *ADA MJ* is the absolute value of residuals from the modified Jones model adjusted for non-linear growth and including control variables from Collins et al. (2017), with change in working capital accruals as the dependent variable. We also create a measure of earnings smoothing, *Smooth*, which is the ratio of the standard deviation of net income to the standard deviation of cash flow from operations, calculated using firm data for the eight prior quarters. The three columns labelled 'Earnings quality measures' in Table 9 document that, consistent with Lobo, Song and Stanford (2012), analyst research production increases when earnings quality reduces. Lobo et al. (2012, p. 497) argue this result is 'consistent with the services of financial analysts becoming more valuable and in greater demand as accruals provide weaker signals about future cash flows.' Importantly, our main conclusion on the negative association between AT and analyst research production is unchanged when we control for firm's earnings quality.

Lastly, to ensure that our results do not capture any spurious effects, we augment equation (1) to include the quarterly mean of daily quoted spreads, *Spread* which is shown to affect analysts coverage (Roulstone 2003). Column 'Liquidity effect' in Table 9 shows that, as expected, higher spreads are associated with decreased analyst research production. Importantly, the coefficient on AT factor remains negative and significant and very close in magnitude to Table 2 estimates (0.138 vs. 0.139). Finally, in untabulated results, we also find that using lagged values of AT measures in equation (1) yields same conclusions.

## 6. Conclusions

The Financial Times 2018 report highlights that AT accounts for over 55% of daily training volume in U.S. equities since 2009 (Meyer, Bullock and Rennison 2018). Though several papers examine how AT affects price efficiency, price discovery and stock liquidity (e.g., Hendershott et al. 2011; Hu et al. 2017; Weller 2018; Bhattacharya et al. 2020; Brogaard et al. 2019; Korajczyk and Murphy 2019; Chakrabarty et al. 2020; Lee and Watts 2020), there is scarce research on other channels through which AT affects capital markets. We contribute to this debate by documenting a negative and casual impact ATs have on analyst supply of earnings forecasts and stock recommendations. This result is consistent with lower profitability on non-ATs' trades on analyst research, resulting in lower demand for analyst investment advice. We validate these results by showing that AT is associated with reduced trade profitability around analyst reports and by showing that the demand for analyst research for investment advice is lower in the presence of high AT. Importantly, our conclusions are robust to a number of sensitivity analyses including corrections for endogeneity.

Our results are relevant for brokerage houses in appreciating how the evolution in stock trading from manual execution to automated and ultra-fast trades affects demand for analyst research. The evidence is also important to firm managements as AT affects the quality of firm information environment. Finally, our results should be relevant to regulators as they strive to assess the overall impact of ATs on stock markets. Our evidence speaks to their concerns that ATs can reduce price informativeness by discouraging outside information production.

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## Appendix A. Variables definitions

| Variable name | Variables description | Source |
|---|---|---|
| **Panel A: Dependent and independent variables** | | |
| #EPS and stock recommendations | The total number of quarterly earnings forecasts and stock recommendations for a firm-quarter | I/B/E/S |
| #EPS | The total number of quarterly EPS forecasts for a firm-quarter | I/B/E/S |
| #stock recommendations | The total number of stock recommendations for a firm-quarter | I/B/E/S |
| #analysts | The number of analysts covering a stock | I/B/E/S |
| 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. | |
| **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 | MIDAS |
| 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 | MIDAS |
| 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 | MIDAS |
| trade_vol | Quarterly average total trading volume ratio calculated as the total displayed trading volume to the order volume, calculated per firm | MIDAS |
| 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 | MIDAS |
| trade_size | Quarterly average trade size defined as total trade volume times 1000 and scaled by total trades, calculated per firm | MIDAS |
| AT factor | A principal component from analyzing the six AT measures. The weights are -0.145 for ln *odd_lot*, -0.228 for ln *cancel_ord*, -0.228 for ln *cancel_ord2*, 0.250 for ln *trade_vol*, 0.240 for ln *trade_vol2* and 0.138 for ln *trade_size*. We multiply *AT factor* by -1 so that higher values of the AT factor reflect higher intensity of AT. | |
| **Panel C: Controls** | | |
| Firm size | Firm size calculated as the log of total assets for the most recent fiscal quarter. | FUND_QTRUS |
| ROA | Return on assets calculated as the ratio of net income over total assets for the most recent fiscal quarter. | FUND_QTRUS |
| Leverage | Leverage calculated as the ratio of long-term debt over total assets for the most recent fiscal year. | FUND_QTRUS |
| 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. | FUND_QTRUS |
| Book-to-market | The book-to-market ratio calculated as the ratio of common equity scaled by total market capitalization for the most recent fiscal quarter. | FUND_QTRUS |
| Sales growth | Growth in sales calculated as the percentage changes in revenue between two consecutive quarters. | FUND_QTRUS |
| Institutional ownership | Percentage institutional ownership in a stock. | S34TM1 |

*Continued on next page*

Appendix A, *continued*

| Variable name | Variables description | Source |
|---|---|---|
| Quarter effects | Fiscal quarter fixed-effects. | |
| Year effects | Year fixed-effects based on the calendar year of the report issue date. | |
| Firm effects | Firm-fixed effects. | |
| Industry effects | Industry-fixed effects based on the company's SIC code. | |
| **Panel D: Other variables** | | |
| Transient IO Ratio | The percentage of institutional ownership by transient institutional investors, scaled by total institutional ownership. We use Bushee's (1998) method to classify transient investors as short-term, and dedicated and quasi-indexer investors as long-term investors. | S34TM1 |
| Non-Monitor IO Ratio | The percentage of institutional ownership by non-monitoring institutions, scaled by total institutional ownership. Monitoring institutions are characterized jointly by high concentration, independence, and long-term investment style suited to monitoring activities. We follow Ferreira and Matos (2008) to classify institutional investors into blockholders if they hold more than 5% of the firm's market capitalization. We use Bushee's (1998) method to classify dedicated and quasi-indexer investors as long-term investors. We use CDA/Spectrum institutional classification and consider investors in group 3 and 4 as independent investors. | S34TM1 |
| Jump | The ratio of abnormal returns on the analyst report announcement day relative to the total variation before, on and after the report announcement. Following Weller (2018), we retain events with material information, i.e. those that satisfy $\left\|CAR_{it}^{(T-21,T+2)}\right\|>\sqrt{24}\hat{\sigma}_{it}$. | CRSP |
| ADA MJ | The absolute value of residuals from the modified Jones model adjusted for non-linear growth in return on assets, the market-to-book ratio and sales growth, and including control variables from Collins et al. (2017), with change in working capital accruals as the dependent variable | FUND_QTRUS |
| ADA DD | The absolute value of residuals from the McNichols (2002) modified Dechow and Dichev (2002) model adjusted for non-linear growth in return on assets, the market-to-book ratio and sales growth, (Kothari et al., 2005) and controls from Collins et al. (2017), with change in working capital accruals as the dependent variable | FUND_QTRUS |
| Smooth | The ratio of firm-quarter standard deviation of net income to the firm-quarter standard deviation of cash flow from operations, calculated using data for eight prior quarters. | FUND_QTRUS |
| Spread | The quarterly mean of daily quoted spreads. | CRSP |
| Speed bump | An indicator variable equal to 1 for the four quarters after the introduction of the IEX speed bump (Q4 2016 to Q3 2017), and 0 in the four quarters before (Q4 2015 to Q3 2016). | |
| ln price | The natural logarithm of the average stock price for the quarter before analyst report announcement.. | CRSP |
| -ΔAT factor | A measure of the reduction in AT factor from before to the TSP period. | MIDAS |
| +ΔAT factor | A measure of the increase in AT factor from the pre-TSP to TSP period. | MIDAS |

## Appendix B. Alternative treatment of standard errors

The table reports equation (1) regression results for various treatments of standard errors. We report results for firm-clustered standard errors (Panel A), firm-year clustering (Panel B), firm-quarter clustering (Panel C) and industry-quarter clustered standard errors (Panel D). Coefficient estimates are shown in the first row and their p-values in the second.

| | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor |
|---|---|---|---|---|---|---|---|
| Predicted sign for ln X | – | – | – | + | + | + | – |
| **Panel A: Firm-level clustering** | | | | | | | |
| ln X | −0.205 | −0.289 | −0.309 | 0.245 | 0.242 | 0.327 | 0.139 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **Panel B: Firm-year clustering** | | | | | | | |
| ln X | −0.205 | −0.289 | −0.309 | 0.245 | 0.242 | 0.327 | 0.139 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **Panel C: Firm-quarter clustering** | | | | | | | |
| ln X | −0.205 | −0.289 | −0.309 | 0.245 | 0.242 | 0.327 | 0.139 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| **Panel D: Industry and quarter** | | | | | | | |
| ln X | −0.205 | −0.289 | −0.309 | 0.245 | 0.242 | 0.327 | 0.139 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 57078 | 57078 | 57078 | 57078 | 57078 | 57078 | 57078 |

## Appendix C. First-stage regression results

In Panel A, we report the first-stage regression of equation (4), where the instrument is an indicator variable equal to one for the four quarters after the introduction of the IEX speed bump (Q4 2016 to Q3 2017), and 0 in the four quarters before (Q4 2015 to Q3 2016). Panel B presents first stage results for equation (5), where we use lagged log stock price as the instrument. Lagged log stock price is calculated as the natural logarithm of the average stock price for the quarter before analyst report announcement. Coefficient estimates are shown in the first row and their p-values in the second.

**Panel A: Instrumental variables regressions: speed bump**

| X= | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor |
|---|---|---|---|---|---|---|---|
| Predicted sign for ln X | − | − | − | + | + | + | + |
| ln X | 0.124 | −0.329 | −0.318 | 0.328 | 0.307 | −0.046 | 0.550 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 14847 | 14847 | 14847 | 14847 | 14847 | 14847 | 14847 |
| Adj $R^2$ | 16.69% | 23.64% | 24.07% | 20.49% | 21.35% | 20.40% | 18.57% |

**Panel B: Instrumental variables regressions: lagged stock price**

| X= | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor |
|---|---|---|---|---|---|---|---|
| Predicted sign for ln X | − | − | − | + | + | + | |
| ln X | −0.380 | −0.298 | −0.306 | 0.089 | 0.391 | 0.295 | −0.955 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 56571 | 56571 | 56571 | 56571 | 56571 | 56571 | 56571 |
| Adj $R^2$ | 40.41% | 35.95% | 74.70% | 74.66% | 50.20% | 44.22% | 48.92% |

## Appendix D. The effect Tick Size Pilot program has on ATs trading

The table A reports descriptive statistics for the number of analyst EPS and stock recommendations issued in a quarter (Panel A), six AT proxies (Panel B) and quarterly fundamentals (Panel C) for the sample of treated and control stocks over the period October 3, 2014 to October 2, 2018. Panel D reports pre-treatment means for the six AT measures between treated and control stocks, their difference and the relevant t-test with Newey-West standard errors. Panel E documents difference-in-differences regression results where the dependent variables are the six AT measures. *Treatment* indicates firms that experienced an increase in tick size. *Post* indicates the post-treatment period that is between October 31, 2016 and October 18, 2018. AT and control variables definitions are in Appendix A. Coefficient estimates are shown in the first row and their p-values in the second.

| | Mean | Median | Std Dev | Q1 | Q3 |
|---|---|---|---|---|---|
| **Panel A: Analyst research activity proxies** | | | | | |
| #EPS and stock recommendations | 27.681 | 26.000 | 12.168 | 18.000 | 37.000 |
| #unique analysts | 5.258 | 5.000 | 2.322 | 4.000 | 7.000 |
| **Panel B: AT measures** | | | | | |
| odd_lot | 0.185 | 0.183 | 0.072 | 0.133 | 0.232 |
| cancel_ord | 30.889 | 24.931 | 21.112 | 17.571 | 37.086 |
| cancel_ord2 | 24.392 | 21.076 | 13.526 | 15.227 | 29.588 |
| trade_vol | 0.030 | 0.028 | 0.014 | 0.019 | 0.040 |
| trade_vol2 | 0.036 | 0.034 | 0.016 | 0.024 | 0.047 |
| trade_size | 87.795 | 83.166 | 23.783 | 72.825 | 96.631 |
| **Panel C: Control variables** | | | | | |
| ln Assets | 6.696 | 6.703 | 1.321 | 5.787 | 7.639 |
| ROA | −0.002 | 0.005 | 0.039 | −0.002 | 0.015 |
| Leverage | 0.556 | 0.549 | 0.254 | 0.363 | 0.762 |
| Cash/Assets | 0.007 | 0.014 | 0.039 | 0.003 | 0.026 |
| Book-to-market | 0.500 | 0.456 | 0.329 | 0.263 | 0.680 |
| Sales growth | 0.037 | 0.023 | 0.184 | −0.032 | 0.085 |

| | Correlation with ATs trading | Treated firms | Control firms | Difference | t-test |
|---|---|---|---|---|---|
| **Panel D: Pre-treatment means** | | | | | |
| ln odd_lot | + | −1.903 | −1.882 | 0.021 | −1.14 |
| ln cancel_ord | + | 3.518 | 3.509 | −0.010 | 0.43 |
| ln cancel_ord2 | + | 3.306 | 3.300 | −0.007 | 0.34 |
| ln trade_vol | – | −3.824 | −3.830 | −0.006 | 0.24 |
| ln trade_vol2 | – | −3.595 | −3.602 | −0.007 | 0.31 |
| ln trade_size | – | 4.504 | 4.494 | −0.010 | 1.13 |

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| | ln odd lot | ln cancel_ord | ln cancel_ord2 | ln trade_vol | ln trade_vol2 | ln trade size |
| **Panel E: Difference in differences tests** | | | | | | |
| Pred sign for Post×Treatment | – | – | – | + | + | + |
| Post×Treatment | −0.100 | −0.372 | −0.279 | 0.262 | 0.185 | 0.063 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Post | 0.258 | −0.284 | −0.305 | 0.261 | 0.257 | −0.119 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Treatment | −0.033 | 0.003 | 0.000 | 0.016 | 0.017 | 0.017 |
| | 0.000 | 0.776 | 0.979 | 0.218 | 0.155 | 0.000 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter effects | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 10273 | 10273 | 10273 | 10273 | 10273 | 10273 |
| Adj R2 | 27.71% | 30.54% | 31.03% | 25.39% | 24.12% | 32.46% |

## Appendix E. Placebo test

The table reports equation (6) results where we assign pre-treatment period as from January 2012 till September 2014 and the pseudo-treatment period from October 2014 to December 2016. Post_p equals one for the pseudo-treatment period and zero otherwise. Coefficient estimates are shown in the first row and their p-values in the second.

| | Model 1 | Model 2 |
|---|---|---|
| | Est/p | Est/p |
| Post_p × Treatment | 0.017 | 0.001 |
| | 0.364 | 0.950 |
| Post_p | 0.031 | -0.028 |
| | 0.457 | 0.544 |
| Treatment | 0.007 | 0.006 |
| | 0.687 | 0.723 |
| Controls | No | Yes |
| N | 15630 | 15630 |
| Adj R2 | 0.06% | 27.67% |

## Appendix F. Addressing the evidence in Chen, Huffman, Narayanamoorthy and Zhang (2021)

Chen et al. (2021) document that analyst coverage and the number of quarterly EPS forecasts declined for TSP-treated stocks, a result counter to our findings. We identify three reasons for this discrepancy. First, Chen et al. (2021) focus on analyst coverage and EPS forecasts issued *prior to* earnings announcements. However, previous research documents that analyst revise their quarterly EPS forecasts more frequently after annual and interim earnings announcements (Stickel 1989, Altinkilic and Hansen, 2009). Thus, Chen et al. (2021) remove a significant proportion of analyst forecasts from their analysis. Further, Chen et al. (2021) focus on forecasts in a *90-day* period before quarterly earnings announcements, which removes a large proportion of forecasts analysts issue early in the fiscal year (Yeung, 2009). To illustrate, all forecasts for quarters 2 to 4 issued after prior fiscal year will be removed. Also, Chen et al. (2021) only examine the first eight months after the start of TSP thus capture only a third of the TSP period. Chen et al. (2021) sample selection criteria result in a truncated sample that is over 31% smaller than ours (7,036 observation in Chen et al., 2021 vs. 10,273 in our Table 8 with the mean number of analysts of 3.87 in Chen et al., 2021 vs. 5.258 in our sample). The sample bias in Chen et al. (2021) likely results in a violation of the parallel trend assumption (their Table 1 reports significant differences in analyst coverage before the start of the TSP) and can explain some puzzling findings, e.g. they find that analyst coverage is higher for loss firms, with higher volatility and poorer returns, which is counter to a well-documented analyst preference to follow firms with less volatile fundamentals (e.g., Bhushan 1989, Lang and Lundholm, 1996, Mola, Rau and Khorana, 2013). In untabulated results, we replicated as closely as possible the sample selection choices from Chen et al. (2021) and confirm a reduction in coverage for this subsample. We believe that avoiding sample selection bias, jointly with the large sample evidence on a negative relation between AT and analyst research production, builds confidence in our TSP results on an increase in analyst research production for treated firms.

Second, Chen et al. (2021) results can be due to including control variables that are affected by the TSP program, which leads to biased coefficients on the interaction term *Post*×*Treatment* and spurious conclusions (Lee and Watts 2020). Specifically, there could be a mechanical correlation between the interaction term *Post*×*Treatment* and a measure of treated firms' idiosyncratic volatility that can produce spurious results in Chen et al. (2021). Lower AT in treated stocks associates with less price discovery and less market-wide information being reflected in stock prices (see Table 8, Lee and Watts, 2020), which should associate with higher idiosyncratic volatility (see Table 8 in Chung et al. 2020). Counter to prior research, e.g., Table 6 in O'Brien and Bhushan (1990), Chen et al. (2021) report that idiosyncratic volatility is a strong positive predictor of higher coverage in treated firms, but we suspect this result captures higher coverage of treated firms that experience an increase in idiosyncratic volatility due to lower AT. Including idiosyncratic volatility in the model, which is affected by the TSP event, the negative coefficient on *Post*×*Treatment* in their Table 2 captures lower analyst coverage of firms with low idiosyncratic volatility that tend to associate with high AT, which is consistent with our results that high AT reduces analyst research production. Chen et al. (2021) do not report regression results without controls, as recommended by Lee and Watts (2020), thus we cannot directly comment on this prediction based on their results.

Finally, we find that ATs have a stronger impact on analyst stock recommendations than EPS forecasts as the former is a direct trade advice. Thus, our study is better able to identify how ATs affect analyst investment-focused research production.

## Table 1. Descriptive statistics

The table reports descriptive statistics for the number of analyst EPS and stock recommendations issued in a quarter (Panel A), six AT proxies (Panel B) and quarterly fundamentals (Panel C) for all stocks over the period 2012-2019. Measures for AT activity and control variables are defined in Appendix A. Panel D reports Pearson correlations between the number of EPS and stock recommendations and AT proxies.

| | Mean | Median | Std Dev | Q1 | Q3 |
|---|---|---|---|---|---|
| **Panel A: Dependent variables (N=57,078)** | | | | | |
| #EPS and stock recommendations | 50.879 | 36.000 | 46.858 | 17.000 | 70.000 |
| #unique analysts | 8.769 | 7.000 | 6.601 | 4.000 | 12.000 |
| **Panel B: AT measures** | | | | | |
| odd_lot | 0.165 | 0.153 | 0.084 | 0.100 | 0.217 |
| cancel_ord | 30.608 | 24.354 | 22.034 | 17.823 | 34.789 |
| cancel_ord2 | 24.357 | 20.692 | 14.457 | 15.257 | 28.466 |
| trade_vol | 0.030 | 0.028 | 0.014 | 0.020 | 0.039 |
| trade_vol2 | 0.037 | 0.034 | 0.016 | 0.024 | 0.046 |
| trade_size | 96.646 | 89.837 | 36.202 | 76.423 | 105.943 |
| AT factor | 0.000 | -0.012 | 1.000 | -0.623 | 0.642 |
| **Panel C: Controls** | | | | | |
| ln Assets | 7.342 | 7.336 | 1.720 | 6.119 | 8.515 |
| ROA | 0.002 | 0.007 | 0.037 | 0.000 | 0.018 |
| Leverage | 0.572 | 0.575 | 0.246 | 0.389 | 0.757 |
| Cash/Assets | 0.011 | 0.016 | 0.037 | 0.003 | 0.028 |
| Book-to-market | 0.481 | 0.415 | 0.355 | 0.226 | 0.676 |
| Sales growth | 0.031 | 0.018 | 0.180 | −0.037 | 0.081 |
| Institutional ownership | 0.737 | 0.792 | 0.236 | 0.607 | 0.914 |

**Panel D: Correlations between HFT measures (N=57,078)**

| | Correlation between intensity of AT and AT measure | ln odd_lot | ln cancel_ord | ln cancel_ord2 | ln trade_vol | ln trade_vol2 | ln trade_size |
|---|---|---|---|---|---|---|---|
| ln odd_lot | + | 1.000 | | | | | |
| | | 0.000 | | | | | |
| ln cancel_ord | + | 0.253 | 1.000 | | | | |
| | | 0.000 | 0.000 | | | | |
| ln cancel_ord2 | + | 0.191 | 0.973 | 1.000 | | | |
| | | 0.000 | 0.000 | 0.000 | | | |
| ln trade_vol | − | −0.392 | −0.759 | −0.766 | 1.000 | | |
| | | 0.000 | 0.000 | 0.000 | 0.000 | | |
| ln trade_vol2 | − | −0.321 | −0.693 | −0.740 | 0.978 | 1.000 | |
| | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | |
| ln trade_size | − | −0.927 | −0.147 | −0.109 | 0.410 | 0.369 | 1.000 |
| | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| AT factor ln | + | 0.549 | 0.863 | 0.862 | −0.946 | −0.909 | −0.522 |
| | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

## Table 2. Algorithmic trading and analyst research production

The table reports results for equation (1) where the dependent variable is either the number of EPS and stock recommendations issued for a firm in a quarter (Panel A), the unique number of analysts issuing either EPS forecasts or stock recommendations for a firm in a quarter (Panel B) or the number of EPS forecasts and stock recommendations for analysts who follow the stock in the current and previous quarter (Panel C). Coefficient estimates are shown in the first row and their p-values in the second.

**Panel A: Analyst research production**

| | Y = ln(#EPS and stock recommendations) | | | | | | |
|---|---|---|---|---|---|---|---|
| X= | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor |
| Predicted sign for ln | − | − | − | + | + | + | − |
| ln X | −0.205 | −0.289 | −0.309 | 0.245 | 0.242 | 0.327 | −0.139 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 57078 | 57078 | 57078 | 57078 | 57078 | 57078 | 57078 |
| Adj $R^2$ | 49.92% | 50.53% | 50.40% | 49.98% | 49.85% | 49.57% | 50.46% |

**Panel B: Analyst coverage**

| | Y = ln(# of analysts) | | | | | | |
|---|---|---|---|---|---|---|---|
| X= | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor |
| Predicted sign for ln | − | − | − | + | + | + | − |
| ln X | −0.204 | −0.214 | −0.226 | 0.213 | 0.210 | 0.372 | −0.118 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 57078 | 57078 | 57078 | 57078 | 57078 | 57078 | 57078 |
| Adj $R^2$ | 57.70% | 57.47% | 57.24% | 57.25% | 57.03% | 57.31% | 57.94% |

**Panel C: Forecasts for analysts who maintain coverage in the current and next quarter**

| | Y = ln(#EPS and stock recommendations) | | | | | | |
|---|---|---|---|---|---|---|---|
| X= | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor |
| Predicted sign for ln X | − | − | − | + | + | + | − |
| ln X | −0.238 | −0.283 | −0.301 | 0.262 | 0.255 | 0.379 | −0.149 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 22674 | 22674 | 22674 | 22674 | 22674 | 22674 | 22674 |
| Adj $R^2$ | 49.95% | 50.39% | 50.18% | 49.94% | 49.74% | 49.56% | 50.45% |

## Table 3. The profitability of trades on analyst reports and AT activity around analyst report announcements

The table reports results from equation (1) where the dependent is the ratio of abnormal returns on the analyst report announcement day relative to the total variation before, on and after the report announcement $Jump_{i,d} = \frac{AR_{id}(0)}{CAR_{id}(-21,2)}$. Regressions control for the absolute magnitude of earnings forecasts and recommendations revisions and include controls from equation (1). Coefficient estimates are shown in the first row and their p-values in the second.

| X= | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor |
|---|---|---|---|---|---|---|---|
| Predicted sign for ln X | + | + | + | − | − | − | + |
| ln X | 0.012 | 0.045 | 0.054 | −0.036 | −0.044 | −0.031 | 0.018 |
| | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| \|ΔEPS\| and \|Δrecommendation\| | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1141573 | 1141573 | 1141573 | 1141573 | 1141573 | 1141573 | 1141573 |
| Adj $R^2$ | 3.0% | 3.1% | 3.2% | 3.1% | 3.1% | 3.0% | 3.1% |

## Table 4. Holdings of trade-focused institutional investors

Column ‘Transient IO’ reports regression results where the dependent variable in equation (1) is the ratio of transient institutional ownership scaled by total institutional ownership. Column ‘Non-monitor IO’ reports regression results where the dependent variable in equation (1) is the ratio of non-monitoring institutional ownership scaled by total institutional ownership. Coefficient estimates are shown in the first row and their p-values in the second.

| | Transient IO | | | | | | | Non-monitoring IO |
|---|---|---|---|---|---|---|---|---|
| X= | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor | AT factor |
| Predicted sign for ln X | − | − | − | + | + | + | − | − |
| ln X | −0.047 | −0.051 | −0.055 | 0.043 | 0.042 | 0.073 | −0.026 | −0.001 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.043 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 57078 | 57078 | 57078 | 57078 | 57078 | 57078 | 57078 | 57078 |
| Adj $R^2$ | 29.57% | 29.41% | 29.22% | 28.46% | 28.21% | 28.48% | 29.56% | 9.38% |

## Table 5. The differential effect on EPS forecasts and stock recommendations

Panel A reports results for equation (1) where the dependent variable is the log of one plus the number of earnings forecasts (column EPS) or log one plus the number of stock recommendations (column REC). Regression coefficients are standardized to enable their comparison across the two models. Coefficient estimates are shown in the first row and their p-values in the second.

**Panel A: The effect on EPS vs. stock recommendations**

| **Y=** | EPS | REC | EPS | REC | EPS | REC | EPS | REC | EPS | REC | EPS | REC | EPS | REC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| X= | odd_lot | | cancel_ord | | cancel_ord2 | | trade_vol | | trade_vol2 | | trade_size | | AT factor | |
| Predicted sign for ln X | − | − | − | − | − | − | + | + | + | + | + | + | − | − |
| ln X | −0.129 | −0.181 | −0.144 | −0.163 | −0.142 | −0.164 | 0.113 | 0.142 | 0.110 | 0.144 | 0.113 | 0.186 | −0.133 | −0.167 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 56891 | 35455 | 56891 | 35455 | 56891 | 35455 | 56891 | 35455 | 56891 | 35455 | 56891 | 35455 | 56891 | 35455 |
| Adj $R^2$ | 49.00% | 17.50% | 49.30% | 16.80% | 49.20% | 16.80% | 48.80% | 16.70% | 48.70% | 16.80% | 48.60% | 17.30% | 51.10% | 18.70% |

**Panel B: t-test for the difference in coefficients on ln X between #EPS and #REC models**

| | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor |
|---|---|---|---|---|---|---|---|
| Predicted sign | + | + | + | − | − | − | + |
| Difference | 0.052 | 0.018 | 0.023 | −0.029 | −0.035 | −0.074 | 0.033 |
| t-stat | 5.045 | 1.383 | 1.738 | −2.378 | −2.788 | −5.679 | 2.989 |
| p-value | 0.000 | 0.167 | 0.082 | 0.017 | 0.005 | 0.000 | 0.003 |

## Table 6. Analysts' information discovery role

The table reports results from equation (1) where the dependent variable is the number of EPS and stock recommendations issued in a 60-day period around a quarterly earnings announcement. 'Before EA' augments equation (1) with an indicator variable for whether an EPS forecast or a stock recommendation was issued in a 30-day period before a quarterly earnings announcement, *Before EA*. EPS and stock recommendations issued 3 days around quarterly earnings announcements are excluded from the analysis. Coefficient estimates are shown in the first row and their p-values in the second.

| X= | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor |
|---|---|---|---|---|---|---|---|
| Predicted sign for ln X×Before EA | − | − | − | + | + | + | − |
| ln X×Before EA | −0.100 | −0.187 | −0.137 | 0.005 | −0.046 | 0.140 | −0.042 |
| | 0.004 | 0.000 | 0.003 | 0.884 | 0.238 | 0.026 | 0.004 |
| ln X | −0.038 | −0.048 | −0.096 | 0.162 | 0.207 | 0.140 | −0.055 |
| | 0.116 | 0.070 | 0.003 | 0.000 | 0.000 | 0.003 | 0.000 |
| Before EA | 0.534 | 1.339 | 1.161 | 0.773 | 0.599 | 0.105 | 0.753 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.700 | 0.000 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 52632 | 52632 | 52632 | 52632 | 52632 | 52632 | 52632 |
| Adj $R^2$ | 32.4% | 32.8% | 32.7% | 32.6% | 32.6% | 32.4% | 32.8% |

## Table 7. Addressing Endogeneity: Firm-fixed effects and instrumental variables regressions

Panel A reports results for equation (1) with firm-fixed effects. Panel B presents second stage results of an instrumental variable regression on the association between the number of EPS and stock recommendations and the AT measures (equation 4). The instrument is an indicator variable equal to one for the four quarters after the introduction of the IEX speed bump (Q4 2016 to Q3 2017), and 0 in the four quarters before (Q4 2015 to Q3 2016). Panel C presents second stage results for instrumental variables regression when we use stock price as the instrument calculated as the natural logarithm of the average stock price for the quarter before analyst report announcement (equation 5). Coefficient estimates are shown in the first row and their p-values in the second.

**Panel A: Firm-fixed effects**

| X= | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor |
|---|---|---|---|---|---|---|---|
| Predicted sign for ln X | – | – | – | + | + | + | – |
| ln X | −0.378 | −0.150 | −0.133 | 0.174 | 0.153 | 0.787 | −0.105 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 57078 | 57078 | 57078 | 57078 | 57078 | 57078 | 57078 |
| Adj $R^2$ | 89.21% | 89.07% | 89.06% | 89.08% | 89.06% | 89.21% | 89.12% |

**Panel B: Instrumental variables regressions: Speed bumps**

| X= | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor |
|---|---|---|---|---|---|---|---|
| ln X | −0.919 | −1.616 | −1.982 | 1.690 | 2.030 | 1.983 | −0.598 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 14847 | 14847 | 14847 | 14847 | 14847 | 14847 | 14847 |
| Adj $R^2$ | 37.93% | 34.14% | 32.33% | 32.41% | 29.73% | 35.93% | 37.93% |

**Panel C: Instrumental variables regressions: lagged stock price**

| X= | odd_lot | cancel_ord | cancel_ord2 | trade_vol | trade_vol2 | trade_size | AT factor |
|---|---|---|---|---|---|---|---|
| ln X | −0.572 | −0.129 | −0.172 | 0.133 | 0.170 | 0.166 | −0.053 |
| | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Quarter Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 56571 | 56571 | 56571 | 56571 | 56571 | 56571 | 56571 |
| Adj $R^2$ | 51.95% | 52.04% | 52.07% | 51.99% | 52.01% | 51.90% | 52.03% |

## Table 8. Addressing endogeneity: The Tick Size Pilot program

Panel A reports the mean number of EPS forecasts and stock recommendations for treated and control stocks before the start of TSP program. Panel B and C report results for equation (6) that examines changes in analyst research production after the start of the Tick Size Pilot program. The dependent variable in Panel B is the log number of analyst EPS forecasts and stock recommendations issued in a firm-quarter. −ΔAT factor measures the reduction in AT factor from before to the TSP period. +ΔAT factor measures the increase in AT factor from the pre-TSP to TSP period. Panel C reports results using the number of analysts covering a stock as the dependent variable and for a constant sample of analyst-firms. Column *#analysts following a firm* reports results where the dependent variable is the log number of analysts covering a firm. Columns *Constant sample of analyst-firms* documents results for a sample of analysts who maintain coverage in treated and control stocks after the start of the TSP. *Treatment* indicates firms that experienced an increase in tick size. *Post* indicates the post-treatment period that is between October 2016 and September 2018. Controls are the control variables from equation (1). Coefficient estimates are shown in the first row and their p-values in the second.

| | Treated firms | Control firms | Difference | t-test |
|---|---|---|---|---|
| **Panel A: Pre-treatment means** | | | | |
| #EPS and stock recommendations | 28.752 | 29.267 | -0.514 | 1.45 |

| | Pred sign | Base regression | Base regression with controls | Direction of change in AT factor |
|---|---|---|---|---|
| **Panel B: Difference-in-differences regression results** | | | | |
| Post × Treatment | + | 0.052 | 0.041 | |
| | | 0.002 | 0.012 | |
| Post | ? | −0.122 | −0.148 | −0.137 |
| | | 0.013 | 0.010 | 0.020 |
| Treatment | ? | −0.022 | −0.022 | |
| | | 0.043 | 0.051 | |
| Post ×−ΔAT factor | + | | | 0.037 |
| | | | | 0.015 |
| Post ×+ΔAT factor | − | | | 0.014 |
| | | | | 0.562 |
| −ΔAT factor | + | | | −0.007 |
| | | | | 0.398 |
| +ΔAT factor | − | | | −0.036 |
| | | | | 0.079 |
| Controls | | No | Yes | Yes |
| Quarter effects | | No | Yes | Yes |
| N | | 10273 | 10273 | 9644 |
| Adj $R^2$ | | 1.12% | 9.22% | 8.13% |

| | Pred sign | #analysts following a firm | | Constant sample of analyst-firms | |
|---|---|---|---|---|---|
| **Panel C: Difference-in-differences regression results: further tests** | | | | | |
| Post × Treatment | + | 0.036 | 0.023 | 0.034 | 0.026 |
| | | 0.004 | 0.056 | 0.005 | 0.025 |
| Post | ? | −0.015 | −0.050 | −0.053 | −0.076 |
| | | 0.710 | 0.120 | 0.283 | 0.192 |
| Treatment | ? | −0.026 | −0.024 | −0.032 | −0.032 |
| | | 0.006 | 0.008 | 0.001 | 0.000 |
| Controls | | No | Yes | No | Yes |
| Quarter effects | | No | Yes | No | Yes |
| N | | 10273 | 10273 | 9877 | 9877 |
| Adj $R^2$ | | 0.04% | 13.74% | 0.20% | 7.54% |

## Table 9. Sensitivity tests

Column 'Exclude EA' reports equation (1) results excluding EPS forecasts and recommendations issued three days before and three days after earnings announcements. Column 'Earnings quality measures' reports equation (1) results augmented with measures of firm's earnings quality. *ADA MJ* is the absolute value of residuals from the modified Jones model adjusted for non-linear performance and growth and including control variables from Collins et al. (2017), with change in working capital accruals as the dependent variable. *ADA DD*, is the absolute value of residuals from the McNichols (2002) modified Dechow and Dichev (2002) model adjusted for non-linear earnings growth (Kothari et al., 2005) and controls from Collins et al. (2017), with change in working capital accruals as the dependent variable. *Smooth* is the ratio of firm-quarter standard deviation of net income to the firm-quarter standard deviation of cash flow from operations, calculated using data for eight prior quarters. Column 'Liquidity' reports results for equation (1) augmented with the quarterly mean of daily quoted spreads. Coefficient estimates are shown in the first row and their p-values in the second.

| | | Exclude EA | Earnings quality measures | | | Liquidity effect |
|---|---|---|---|---|---|---|
| | Pred. sign | Est/p | Est/p | Est/p | Est/p | Est/p |
| AT factor | − | −0.139 | −0.170 | −0.181 | −0.139 | −0.138 |
| | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| ADA MJ | ? | | 0.199 | | | |
| | | | 0.000 | | | |
| ADA DD | ? | | | 0.200 | | |
| | | | | 0.000 | | |
| Smooth | ? | | | | 0.000 | |
| | | | | | 0.303 | |
| Spread | − | | | | | −15.812 |
| | | | | | | 0.000 |
| Controls/Quarter/Year/ Industry effects | | Yes | Yes | Yes | Yes | Yes |
| N | | 57075 | 32530 | 31358 | 56929 | 56617 |
| Adj $R^2$ | | 50.30% | 50.40% | 51.30% | 50.50% | 50.50% |

**Figure 1. The intraday speed of price discovery to stock recommendation revisions**

The figure plots the speed of price discovery after analyst recommendation revisions for low and high AT firms. For each 10 minute time period, in the intervals [0,+3 hours], we regress the analyst daily announcement return, $ret_{[0,+1]}$, on returns from minute 0 to the end of time period $T$ ($\mathrm{ret}_{[0,T]}$). We then run the unbiasness regressions cross-sectionally and estimate the beta coefficient for each $T$. Beta coefficient of one (shown here with the horizonal line) is consistent with the stock recommendation information content fully impounded in the stock price.