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ALGORITHMIC TRADING AND INVESTMENT-TO-PRICE SENSITIVITY

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Abstract. Does the increased prevalence of algorithmic trading (AT) produce real economic effects? We find that AT contributes to managerial learning by fostering the production of new information and thereby increases firms' investment-to-price sensitivity. We link AT's impact on the investment-to-price sensitivity to the revelatory price efficiency — extent to which stock prices reveal information for real efficiency. AT-driven investment-to-price sensitivity helps managers make better investment decisions, leading to improved firm performance. While in aggregate AT contributes positively to managerial learning, we also show that there is a subset of AT strategies, namely opportunistic AT that is harmful to managerial learning.

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1. Introduction

Dramatic improvements in technology (e.g., high-speed computers and real-time data feeds) and regulatory environment (e.g., Regulation National Market System in the U.S.) have led to the proliferation of automated trading with a considerably high trading speed in financial markets. Does the proliferation of algorithmic trading (AT) produce real effects on the economy? Given the extensive literature on the effects of AT on market quality, it is surprising that we know little about the real economic effects of AT.[1] In this paper, we address this question by exploring whether AT enables firm managers to obtain more informative feedback from the financial markets and use it in their investment decisions.

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[1] AT (also known as automated trading or algo-trading) uses a computer program that follows an algorithm to place and manage orders and trades. We take a broader definition of automated trading and define AT based on all participants who use algorithms to submit and cancel orders including high-frequency trading (HFT) which is a subset of AT with a considerably higher trading speed. Throughout this paper, the acronym AT is used interchangeably to refer to algorithmic trading and algorithmic traders.

Specifically, we investigate the empirical relationship between AT and the sensitivity of corporate investment to stock prices (investment-to-price sensitivity).

Establishing the relationship between AT and the investment-to-price sensitivity is important for various reasons. First, the theory dating back to Hayek (1945) suggests one of the main roles of financial markets is that stock prices aggregate information of many different market participants who do not have direct channels for communication with the firm outside the trading process (e.g., Dow and Gorton 1997; Subrahmanyam and Titman 1999). Thus, stock prices complement the information of managers and guide them in making corporate investment decisions. Our research sheds light on the extent to which AT improves or distorts the informational role of financial markets.

Second, the previous studies of AT mainly focus on the impact of AT on different aspects of market quality, and in particular, liquidity and price discovery.[2] However, an AT-sourced liquidity or price discovery does not necessarily imply changes in managers' investment decisions since market quality in sub-second intervals may not be too important in making corporate investment decisions (e.g., Cochrane 2013). The real economic effects of AT depend on the extent to which stock prices reveal information for real efficiency, not on the overall impact of AT on price discovery. Due to the importance of such a distinction, Bond et al. (2012) distinguish between two notions of price efficiency: (i) the forecasting price efficiency (FPE) as the extent to which the price of a given security accurately predicts the future value of that security and (ii) the revelatory price efficiency (RPE) as the extent to which prices reveal information necessary for decision makers. While the previous studies of AT mainly focus on the role of AT in driving the FPE, the innovation in this paper is to show the impact of AT on the RPE. As Foucault et al. (2017, p. 1090) state, "little is known about the social value of accelerating by a few milliseconds the speed at which prices converge to efficient levels or at which arbitrageurs respond to price pressures".

Third, many modern financial market participants employ algorithms to make certain trading decisions and submit and manage orders. ATs drive most of the trading in financial markets; for instance, HFT represents about 50% of US equities trading volume.[3] Therefore, AT is at the very core of market design issues to promote market liquidity and attract trading volume. For example, Budish et al. (2015) view the high-frequency trading arms race as a symptom of flawed market design and propose to use frequent batch auctions instead of the continuous limit order book to reduce the socially wasteful arms

[2] See, for example, Brogaard et al. (2014), Foucault et al. (2016), Foucault et al. (2017), Weller (2018), Brogaard et al. (2019), and Yang and Zhu (2020).

[3] See, for example, https://www.ft.com/content/d81f96ea-d43c-11e7-a303-9060cb1e5f44.

race between ATs/HFTs. Understanding the real economic effects of AT would help policymakers and market organizers to design trading rules that optimally balance the costs and benefits of AT.

Finally, it is not only the trading in the financial markets has become super-fast due to the dominance of ATs/HFTs, but also the speed of the real economy has accelerated in recent years. Perhaps this was no more evident than during the Covid-19 pandemic when policymakers and practitioners demanded high-frequency economic data to better predict the economic indicators and understand how we respond to changing consumer and corporate behavior.[4] Firm managers face challenges to determine the timeliness, riskiness, and valuation of their investment decisions. Not only do executives need to forecast future economic opportunities, but also, they must spend resources to find out how the economy is doing now. While information acquisition of real-time economic data is costlier than usual for firm managers, they significantly benefit from high-frequency information processing ability of financial market participants.

Motivated by these issues, the paper contributes to the debate on the real economic implications of AT. Specifically, we test the effects of AT on the investment-to-price sensitivity of firms using a large sample of US-listed stocks during 1996-2019. We use a normalized measure of electronic message traffic (quote-to-trade ratio, QT) as a proxy for AT and capital expenditures, including and excluding research and development expenses and change in total assets as measures of firms' investment. We find that the amount of AT activities in stocks significantly increases the investment-to-price sensitivity of firms. Financial markets process available information of market participants and reflect in stock prices, and naturally, managers have incentives to learn from stock prices (e.g., Dow and Gorton 1997; Subrahmanyam and Titman 1999; Foucault and Gehrig 2008). Our results suggest that AT enhances managers' learning experience by fostering the production of new information.

We start our analysis with the empirical relationship between AT and the investment-to-price sensitivity in the ordinary least squares (OLS) setting. We find that, on average, AT increases the effect of one standard deviation shock on the stock price on the next year's capital expenditures (CAPEX) by 50%, capital expenditures including research and development expenses (CAPEXRND) by 22%, and change in total assets (CHGASSET) by 40%. That means managers are more likely to use stock prices to guide their investment

[4] For example, the FED chairman, Mr. Jerome Powell stated during the press-conference following the July 2020 Federal Open Market Committee (FOMC) meeting that: "We monitor quite a lot of what we think of as sort of nonstandard, high-frequency data. That's become a very important thing, even more important than usual in the work that we do… We're watching this high-frequency data… I think all we can say today is that there's evidence in the high-frequency data, the surveys, and, you know, you're tracking — you get pictures of spending" (retrieved from https://www.federalreserve.gov/mediacenter/files/FOMCpresconf20200729.pdf)

decisions when AT is more widespread in their stocks. The economic magnitudes of these effects are substantial and highlight the important economic effects of AT on corporate investment decisions.

It is certainly possible that the relationship between AT and investment-to-price sensitivity is not causal. For example, Biais and Foucault (2014) argue that ATs are inherently attracted to liquid stocks. This implies that ATs tend to trade the stocks of the firms with greater investment-to-price sensitivity and benefit from their price informativeness, raising a reverse causality concern. In addition, there may be omitted variables that simultaneously affect the trading/order book activity and firms' investment decisions. To rule out these endogeneity concerns, we use the introduction of NYSE Autoquote as an exogenous event in the difference-in-differences setting, where we compare the change in the investment-to-price sensitivity of the NYSE-listed stocks (treatment group) to that of the NASDAQ-listed stocks (control group). Next, we employ the two-stage instrumental variable framework that exploits three instruments: (i) the staggered implementation of autoquoting for the NYSE stocks, (ii) lagged QT and (iii) average QT by stock i's size quartile group.[5] Our findings confirm the baseline OLS results and allow us to establish a causal relationship between AT and the investment-to-price sensitivity.

We link the positive association between AT and the investment-to-price sensitivity to the contribution of AT to the RPE in three different ways. First, we investigate the impact of AT on managers' earnings forecast accuracy. Management earnings forecasts are a key voluntary disclosure mechanism through which firm managers provide earnings guidance to financial markets. Based on the information received from the market, firm managers update their earnings forecasts throughout the year. Conceptually, the idea is that ATs have a greater capacity for quickly processing various pieces of fundamental information and incorporating them into stock prices. Therefore, we hypothesize that if AT contributes to the RPE by revealing new information that is unknown to managers, then AT should also improve managers' earnings forecast accuracy. Consistently, we find that an average level of AT increases the effect of one standard deviation shock on the stock price on managers' forecast accuracy by about 18%.

Second, we investigate the impact of AT on the information acquisition of market participants as measured by the number of non-robot downloads of financial reporting data of firms from the SEC's EDGAR server. The idea is that ATs also indirectly contribute to the RPE by impacting how other market participants acquire information. Although financial data of firms in EDGAR is not new to managers, information acquisition of market participants is likely to increase RPE as investors usually combine their private information with the information posted by firms to make their trading decisions (e.g., Edmans

[5] We also use the two-stage Heckman estimation approach to test for selection bias in how ATs trade across stocks and report the results in the Internet Appendix. The results confirm our main findings.

et al. 2015). Consistently, we find a positive association between AT and the number of non-robot downloads of financial data from the SEC EDGAR database, suggesting that AT encourages overall information acquisition in the market.

Third, we analyze which stock characteristics influence the magnitude of the impact of AT on the investment-to-price sensitivity. We focus on five variables that theoretically have clear predictions about the association between AT and RPE. We find that the impact of AT on the investment-to-price sensitivity is stronger when firms' stocks have (i) high institutional holdings, (ii) high private information as measured by Brogaard et al. (2022), (iii) low relative spread, (iv) high trading volume, and (v) more positive information as measured by the amount of earnings surprise. That means the effects of AT on the investment-to-price sensitivity is stronger when stock prices are more informative, more liquid and reflect more positive information. While a stronger AT and investment-to-price sensitivity association for informative and liquid stocks is intuitive, the intuition for positive information is that managerial learning disincentivizes informed traders to trade on negative information as it increases the stock price, resulting in less profitability for trading on negative information (e.g., Goldstein and Guembel 2008, Edmans et al. 2015). These results show that the impact of AT on the investment-to-price sensitivity is higher when AT is more likely to contribute to RPE and hence, provide further support to the association between AT and RPE.

We extend the baseline tests in various directions. First, we divide stocks into quintiles based on the amount of AT activities and test the variation in the effects of different levels of AT on the investment-to-price sensitivity. We find that the association between AT and the investment-to-price sensitivity is strong and persistent across all quintiles. This implies that our main results are not only driven by firms whose shares are more actively traded by ATs but rather capture the pervasive effects of AT on the investment-to-price sensitivity. Second, we control for several additional factors to explore alternative explanations for our main finding. We find that the association between AT and the investment-to-price sensitivity remains positive and significant after controlling for (i) managers' existing information, (ii) analyst coverage, and (iii) firms' capital constraints. Third, we construct additional AT measures by using the Securities and Exchange Commission's (SEC) Market Information Data Analytics System (MIDAS) data and present that the results are robust to various measures of AT.

Fourth, we separately measure the level of opportunistic AT for a random sample of 120 stocks during 1996-2019 in the spirit of Budish et al. (2015) as the number of latency arbitrage opportunities that ATs can exploit in high frequency for each stock separately for each year. We then investigate the impact of opportunistic AT on the investment-to-price sensitivity. We find that while in aggregate AT contributes positively to the investment-to-price sensitivity of firms, opportunistic ATs weaken the investment-to-price sensitivity by exploiting profitable latency arbitrage opportunities. This reconciles our results with the literature focusing on negative impacts of AT on the acquisition of new information and price discovery (e.g., Dugast and Foucault 2018; Weller 2018).

Lastly, we investigate the association between AT and firms' ex-post performance as measured by return on assets and sales growth. We find that the amount of AT activities in stocks and the resulting increase in the investment-to-price sensitivity significantly improve firms' future operating performance. In terms of economic magnitude, a median level increase in AT increases the next year's return on assets by 2.75% and sales growth by 26%. This suggests that as the information content of stock prices and managers' investment-to-price sensitivity increases due to AT, managers are better equipped with decision-relevant information, resulting in better investment decisions and superior firm performance.

1.1. Related literature. The paper contributes to different strands of literature. First, it contributes to the ongoing debate about the real economic consequences of ATs. On the one hand, Budish et al. (2015), Biais and Foucault (2014), and Biais et al. (2015) focus on the socially wasteful arms race between ATs/HFTs (see also Aquilina et al. 2022). On the other hand, Jovanovic and Menkveld (2016) argue that ATs face lower adverse selection costs due to their ability to quickly update quotes and thereby improve gains from trade through their greater willingness to provide liquidity. Our paper contributes to this debate by providing evidence on the impact of AT on firm's investment decisions and the resulting firm performance.

Second, the paper contributes to the literature on the impact of AT on market quality. The evidence on this has so far been inconsistent. On the one hand, AT increases liquidity through processing public information quickly, decreasing spread, and trading against transitory prices pressures. Foucault and Gehrig (2008) and Fang et al. (2009) show that higher liquidity and/or lower trading costs increase informed traders' incentive to obtain private information and thus, improve the informativeness of stock prices. Given that ATs' participation in the market increases liquidity, it is plausible that AT also leads to greater price informativeness. Consistent with this, Brogaard et al. (2019) show that efficient price discovery occurs predominantly through HFTs-initiated limit orders.

On the other hand, while ATs incorporate existing information into prices, due to their opportunistic such as back-running and order anticipation strategies, they may also discourage the acquisition of new information and worsen price discovery (e.g., Weller 2018). That is, back-running strategies may erode rents to information acquirers and reduce incentives to search for new information (e.g., Yang and Zhu 2020). For example, Ye et al. (2022) find that a larger tick size increases the investment-to-price sensitivity by reducing

AT and encouraging fundamental information acquisition. Furthermore, arbitrage strategies employed by ATs may deteriorate price discovery by increasing the transaction costs (e.g., Foucault et al. 2016; Foucault et al. 2017).

Our paper contributes to these papers in three important ways. First, the literature generally focuses on the effects of AT on market quality with no distinction between FPE and RPE. By contrast, our results are along the direction of the real economic consequences of AT — the impact of AT on the RPE. Second, we complement and also reconcile the abovementioned studies by showing that the association between AT strategies and the RPE is not uniform, but depends on the trading strategies employed by ATs. While being consistent with the literature focusing on negative externalities of AT (e.g., Weller 2018, Yang and Zhu 2020, Ye et al. 2022) that ATs weaken the investment-to-price sensitivity by exploiting opportunistic strategies, we find that in aggregate AT improves RPE, increases the investment-to-price sensitivity and leads to superior firm performance. Third, the literature generally investigates AT's effects at seconds and milliseconds frequencies (see Menkveld 2016 for a detailed survey). By contrast, due to its impact on corporate investment, operating performance, and, more generally, resource allocation, our results emphasize the importance of AT for long-term investors. In that, the closest papers to ours are Chakrabarty et al. (2015) and Chordia and Miao (2020) that provide some evidence for long-term implications of AT by focusing on the price informativeness around earning announcements.

We also contribute to the literature that analyzes how stock prices affect firms' investment decisions (e.g., Barro 1990; Morck et al. 1990). The paper is related to the growing empirical studies of managerial learning channel: the role of private information in stock prices (e.g., Chen et al. 2007), cross-listing in multiple exchanges (e.g., Foucault and Frésard 2012), the informativeness of peers' stock prices (e.g., Foucault and Fresard 2014; Dessaint et al. 2019), firms' capital constraints (e.g., Baker et al. 2003) in driving the investment-to-price sensitivity of firms. We contribute to these studies by showing that AT produces new information to managers and increases the efficiency of managers' learning process, resulting in superior firm performance.

The paper is structured as follows. Section 2 describes the sample selection, measures, and descriptive statistics. In Section 3, we present the main findings — the impact of AT on the investment-to-price sensitivity of firms — and link our findings to the association between AT and RPE by investigating the impact of AT on managers' forecast accuracy, information acquisition of market participants, and cross-sectional analysis. In Section 4, we present the extensions and robustness checks, where we investigate the investment-to-price sensitivity by AT quintiles, control for additional factors, rely on alternative measures of AT, separate opportunistic AT strategies, and examine the impact of AT on firm's operating performance. Section 5 concludes. All other tests mentioned but not reported in the paper are relegated to the Internet Appendix.

2. Data and descriptive statistics

2.1. Sample selection. We compile data from multiple sources. We obtain intraday data on trades and quotes, aggregated at an hourly frequency, from Refinitiv Tick History (RTH) and yearly financial statement data from Compustat. The data on daily stock prices, bid and ask quotes, trading volume, and shares outstanding are from the Center for Research in Security Prices (CRSP). We use RTH to compute the measure of algorithmic trading for all ordinary common shares in CRSP and Compustat that trade on the New York Stock Exchange, the American Stock Exchange, and Nasdaq for the period of 1996-2019. We use Compustat variables to capture firms' investment and performance measures along with other control variables such as firms' cash flow and total assets.

From Compustat, we collect firms' market value of equity, total assets, capital expenditures, research and development (R&D) expenses, sales, cash flows, and additional variables that serve as proxies for firm profitability and financial policy for the period of 1996– 2019. We follow Foucault and Frésard (2012) and exclude financial firms (SIC codes between 6000 and 6999) and international affairs and non-operating establishments (SIC codes 9000– 9999) as these industries' financial statement numbers are dependent on statutory capital requirements. We also exclude firms with missing information on total assets, equity, and capital expenditures, as well as firms with less than 3 years of observations and firms with market values less than $10 million.

For the models that we use Compustat and RTH data in the baseline analysis, our final sample includes 51,581 firm-year observations and 5,195 unique firms during 1996-2019. We complement our main datasets with the institutional ownership data obtained from Refinitiv, "Company Issued Guidance" (CIG) data from Refinitiv, EDGAR downloads from the SEC, insider trading activities from Thomson Financial's TFN database, and the number of analysts following the stock from I/B/E/S to run additional tests.

2.2. AT measures. To investigate the impact of AT on the investment-to-price sensitivity, one needs to directly observe whether a particular order is generated and submitted by computer algorithms. This data is not generally available, and therefore, researchers employ various proxies for AT. We follow Hendershott et al. (2011) and Malceniece et al. (2019) and use the ratio of number of quote messages to number of trades, $QT_{i,t}$, as the main proxy for AT.[6] The intuition of this measure is that the majority of message activity is

[6] The number of quote messages is the sum of best bid and best ask updates during the hourly interval, where an update is a change to the price or quantity at either the best bid or offer. The quote messages capture all order submissions, amendments, and cancellations, at or within the best prevailing quotes (e.g., Hendershott et al. 2011; Malceniece et al. 2019).

generated by ATs. Thus, the number of quote messages increases with the amount of AT activities in stocks. However, using the number of quotes alone would pick up the effects of trading volume, and hence, we normalize the number of quotes with the number of trades for each day and then calculate yearly averages.

In the robustness tests, we construct three more AT measures capturing different aspects of AT strategies. The first measure is the cancel-to-trade ratio, $CT_{i,t}$, computed as the number of all cancel messages (full or partial) divided by the number of trades obtained from the SEC's MIDAS data. Hasbrouck and Saar (2013) show that most of the messages submitted by ATs are cancelled. A higher $CT_{i,t}$ is thus associated with more AT. The second AT measure is the odd-lot rate, $OddLot_{i,t}$, or the number of odd-lot trade messages (trades with less than 100 shares) divided by the number of all trade messages obtained from the SEC's MIDAS data. Given that ATs split their parent orders into smaller child orders to reduce the price impact of their trades, it is expected that $OddLot_{i,t}$ increases with AT (e.g., O'Hara et al. 2014; Weller 2018). Lastly, to capture the opportunistic AT strategies, we use the first-level quote data from Refinitiv and identify the total number of latency arbitrage opportunities ($LAO_{i,t}$) associated with the correlation breakdown at high frequency similar to Budish et al. (2015). Given the massive size of the quote data, we construct this measure for a random sample of 120 firms.[7]

2.3. Investment measures. We use three different investment measures. The first measure is $CAPEX_{i,t+1}$, measured as the capital expenditure for year $t+1$ divided by the total asset for year t. The second measure is $CAPEXRND_{i,t+1}$ computed as the sum of capital expenditures including research and development expenses for year $t+1$ divided by the total asset for year t. The last measure is $CHGASSET_{i,t+1}$, calculated as the percentage change in book value of assets from year t to $t+1$. These measures capture various aspects of firms' investment activities. While $CAPEX_{i,t+1}$ and $CAPEXRND_{i,t+1}$ include firms' ongoing investments, $CHGASSET_{i,t+1}$ captures firms' acquisition and divestiture activities.

2.4. Performance measures. We employ two operating performance measures: return on assets ($ROA_{i,t+1}$) and sales growth ($SG_{i,t+1}$). $ROA_{i,t+1}$ is computed as the earnings before interest, taxes, depreciation, and amortization ($EBITDA$) in year $t+1$ divided by total assets in the same year. $SG_{i,t+1}$ is the percentage change in total revenue from year t to $t+1$. To take into account that the investment decision usually takes time to materialize into performance, we also calculate the average annual values of ROA and SG over the next three years and include the results in the Internet Appendix.

[7] To make our sample selection random and consistent with the literature, we use the same 120 firms that have been included in the widely-accepted NASDAQ HFT dataset (e.g., Brogaard et al. 2014).

2.5. Other variables. We employ several other variables in our analysis. The normalized stock price (Tobin's Q) for firm i in year t, $Q_{i,t}$, is computed as the market value of equity plus the book value of assets minus the book value of equity, scaled by the book value of assets.[8] We follow Foucault and Frésard (2012) and include the cash flow scaled by the book value of assets for firm i at time t ($CF_{i,t}$) and the natural logarithm of total assets ($\ln(Asset_{i,t})$) for firm i at time t in our regressions to control for the effects of cash flow and firm size. $CF_{i,t}$ is the sum of net income before extraordinary items, depreciation and amortization expenses, and R&D expenses for year t, scaled by total assets in year $t-1$.

In addition, we include institutional holdings ($INS_{i,t}$) and institutional traders' horizon ($INSTR_{i,t}$) for firm i in year t to control for the real effects of institutional investors for reasons unrelated to managerial learning (e.g., Derrien et al. 2013). $INS_{i,t}$ is computed as the fraction of institutional holdings to total shares outstanding for firm i in year t. $INSTR_{i,t}$ is the weighted average of the quarterly churn rates of institutional investors. Following Gaspar et al. (2005), we calculate the quarterly churn rate for each institutional investor as the absolute change in the dollar value of the investor's position from last quarter, scaled by the average dollar value of the investor's position in that quarter. Thus, $INSTR_{i,t}$ shows how frequently institutional investors rotate stock positions in their portfolio and higher $INSTR_{i,t}$ implies shorter investment horizon.

To investigate whether AT contributes to the RPE, we compute managers' earnings forecast accuracy ($\Delta Accuracy_{i,t}$) from the "Company Issued Guidance" (CIG) database maintained by Refinitiv and the number of non-robot viewership data ($EDGAR_{i,t}$) from the SEC's EDGAR server. Managers' earnings forecast accuracy for firm i in year t is computed following Zuo (2016) as the difference in the errors of two subsequent forecasts scaled by the stock price before the first forecast. The number of non-robot viewership data ($EDGAR_{i,t}$) for firm i in year t is identified following Drake et al. (2015) and Ryans (2017) by removing downloads by computer programs (or robots) from the log files. We do this filtering by using a classification algorithm proposed in Ryans (2017).[9]

We conduct cross-sectional analysis based on five stock characteristics. Our stock characteristics are institutional holdings ($INS_{i,t}$), the private information measure of Brogaard et al. (2022) ($PrivateInfo_{i,t}$), relative spread ($Spread_{i,t}$), trading volume ($Volume_{i,t}$), and the amount of earning surprise ($ESP_{i,t}$). As defined above, $INS_{i,t}$ is the fraction of institutional holdings. $PrivateInfo_{i,t}$ is computed using a vector autoregression model

[8] We calculate the book value of equity as the book value of the stockholder's equity (Compustat item SEQ) plus balance sheet deferred taxes and investment tax credit (Compustat item $TXDITC$) minus the book value of preferred stocks. The book value of preferred stocks is the first non-missing value of redemption (Compustat item $PSTKRV$), liquidation (Compustat item $PSTKL$), or par value (Compustat item $PSTK$) in that order (e.g., Fama and French 1993).

[9] An IP address is considered to be a robot if the address (i) downloads more than 25 items in a single minute, (ii) downloads more than 3 different companies' items in a single minute, and (iii) downloads more than 500 items in a single day. See Ryans (2017) for more details.

(VAR) to decompose a return variance into four components (market-wide information, private firm-specific information, public firm-specific information, and noise).[10] $Spread_{i,t}$ and $Volume_{i,t}$ are liquidity measures. $Spread_{i,t}$ is the yearly average of the differences between monthly ask and bid quotes divided by the midquote. $Volume_{i,t}$ is the total number of shares traded for firm i's stock in year t. $ESP_{i,t}$ is defined as the percentage difference between actual and average analyst forecast earnings per share for firm i and year t.

In the robustness tests, we include additional controls for the informational and capital environment of firms. We use the ratio of insider dollar volume to the total dollar volume ($Insider_{i,t}$) and the abnormal stock return around the earnings announcement dates ($RES_{i,t}$) for a given firm-year to capture the managerial information. $RES_{i,t}$ is computed as the yearly average of the absolute market-adjusted returns over four quarterly earnings announcements periods (day - 1 to day 1). Additionally, we control for the average number of analysts issuing earnings forecasts ($Analyst_{i,t}$), and firms' capital constraints measured by the four-variable version of the Kaplan-Zingales index ($KZ_{i,t}$) as constructed by Baker et al. (2003).[11] Table 1 provides the definitions of all variables, computation methods, and data sources.

[Table 1 here]

2.6. Summary statistics. Table 2 provides the summary statistics of all main (Panel A) and supplementary variables (Panel B). Our main sample (at the intersection of Compustat and RTH) consists of 5,195 unique firms and 51,581 firm-year observations. We have eleven other subsamples for extensions and robustness tests. The number of observations of each variable is provided in Table 2.

In our full sample, the mean of $QT_{i,t}$, is 11.17, indicating that, on average, 1 out of 11 quotes is executed. The average Tobin's Q is 1.95. The average $CAPEX_{i,t}$ and $CAPEXRND_{i,t}$ are 5.92% and 11.02%, respectively, suggesting that, on average, firms roughly spend 5.9% of their total assets on capital expenditure and 5.1% on research and development projects. The mean of $CHGASSET_{i,t}$ is 12.94%, indicating, on average, firms' total assets increase by about 13% during the sample period. In terms of firms'

[10] To construct $PrivateInfo_{i,t}$, we first estimate the responses of stock returns to three shocks, namely market returns, firm-specific order flow, and other idiosyncratic shocks captured in the stock-return residual in the VAR setting. The market return is the average value of all stocks' returns and firm-specific order flow is the signed dollar trading volume computed as the product of price, volume, and the sign of stock's daily return. $PrivateInfo_{i,t}$ is the product of the firm-specific order flow innovation in the structural VAR and the long-run effect of a unit shock on the firm-specific order flow, inferred from the cumulative impulse response function. See Brogaard et al. (2022) for more details.

[11] The Kaplan-Zingales index is computed as a weighted sum of cash flow ($Cash_{i,t}$), cash dividend ($DIV_{i,t}$), and cash balances ($C_{i,t}$) all scaled by lagged assets, and the leverage ratio ($LEV_{i,t}$). We use the following Compustat items to calculate the Kaplan-Zingales index: $Cash_{i,t} = CH/AT$, $DIV_{i,t} = (DVP + DVC)/AT$, $C_{i,t}= CHE/AT$, and $LEV_{i,t} = (DLTT + DLC)/(DLTT + DLC + SEQ)$.

operating performance, an average firm has 9.1% return on assets and 5.6% annual sales growth. The average $INS_{i,t}$ is 0.56, suggesting that, on average, about 56% of shares are owned by institutional traders. The medians and standard deviations of the main and supplementary variables are also reported in Table 2.

[Table 2 here]

3. Main tests

3.1. AT and investment-to-price sensitivity.

3.1.1. *Ordinary least squares* (*OLS*). To measure the impact of AT on the investment-to-price sensitivity, we estimate various specifications of the standard investment equation (e.g., Baker et al. 2003; Chen et al. 2007; Foucault and Frésard 2012):

$$\begin{aligned} I_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Q_{i,t} + \beta_2 QT_{i,t} + \beta_3 Q_{i,t} QT_{i,t} + \delta_1 CF_{i,t} + \delta_2 \ln(Asset_{i,t}) \\ + \delta_3 INS_{i,t} + \delta_4 INSTR_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where $I_{i,t+1}$ is the investment of firm i in year $t+1$ proxied by $CAPEX_{i,t+1}$, $CAPEXRND_{i,t+1}$ and $CHGASSET_{i,t+1}$ in different versions of the model. α_i and γ_t are firm and time fixed effects, $Q_{i,t}$ is the firm's normalized stock price, $QT_{i,t}$ is the measure of AT, $CF_{i,t}$ is the firm's cash flow, $\ln(Asset_{i,t})$ is the natural logarithm of the firm's total assets, $INS_{i,t}$ is institutional holdings, and $INSTR_{i,t}$ is the institutional investors' horizon. All these variables are defined in Table 1.

According to Equation (1), the overall (marginal) effect of AT ($QT_{i,t}$) in stock *i* on the firm *i*'s investment activities is given by $\frac{\partial I_{i,t+1}}{\partial QT_{i,t}} = \beta_2 + \beta_3 Q_{i,t}$. Our primary focus of interest in Equation (1), however, is the investment-to-price sensitivity with and without AT, the difference of which captures the impact of AT on the investment-to-price sensitivity. The investment-to-price sensitivity without AT (i.e., $QT_{i,t} = 0$) is given by $\frac{\partial I_{i,t+1}}{\partial Q_{i,t}} = \beta_1$, whereas the investment-to-price sensitivity with AT is given by $\frac{\partial I_{i,t+1}}{\partial Q_{i,t}} = \beta_1 + \beta_3 QT_{i,t}$. The coefficient β_3, therefore, measures the extent to which the association between investment $I_{i,t+1}$ and price $Q_{i,t}$ differs due to AT. If firm managers learn more information from observing their stock price when AT is more widespread in their stocks and use this information to make investment decisions, we expect this coefficient to be positive and significant.

Table 3 reports the findings for the model in Equation (1) with $CAPEX_{i,t+1}$, $CAPEXRND_{i,t+1}$, and $CHGASSET_{i,t+1}$ as an investment measure to examine the association between AT and the investment-to-price sensitivity. Standard errors are double clustered by firm and year as defined in Petersen (2009) and all regressions are estimated with de-meaned variables to account for firm and year fixed effects in this and all subsequent models. First, in line with the prior literature, all three measures of investment

($I_{i,t+1}$) are positively and significantly (at 1 percent level) associated with $Q_{i,t}$. The classical explanation for this relationship given by Tobin (1969) and Von Furstenberg (1977) is that stock prices reflect the marginal product of capital. Alternatively, the association may arise simply because high stock prices may induce financially constrained firms to issue shares and undertake new investments with the proceeds (e.g., Baker et al. 2003), or stock prices may allow firm managers to learn new information from stock prices (e.g., Chen et al. 2007).

Our main goal is to examine whether AT enhances this learning process by conveying more information that is new to managers, estimated as the coefficient of the interaction term, (β_3) in Equation (1). The results show that, for all investment measures, the coefficient of the interaction term between $Q_{i,t}$ and $QT_{i,t}$ are positive and statistically significant at 1 percent level with t-statistics of 11.20 for $CAPEX_{i,t+1}$, 7.19 for $CAPEXRND_{i,t+1}$, and 13.37 for $CHGASSET_{i,t+1}$. Thus, the investment-to-price sensitivity is higher for firms whose shares are more actively traded by ATs.

[Table 3 here]

To put the economic significance into perspective, we consider a one standard deviation shock on $Q_{i,t}$ (1.43). This shock, on average, is associated with an increment of 1.256% ($\beta_1 \cdot StdDev(Q) = 0.878 \cdot 1.43$) in $CAPEX_{i,t+1}$ without AT. However, an average level of AT increases this impact to 1.878% ($\beta_1 \cdot StdDev(Q) + \beta_3 \cdot StdDev(Q) \cdot Average(QT) = 0.878 \cdot 1.43 + 0.039 \cdot 1.43 \cdot 11.17$) increasing the previous increment by about 50%. That is, an average level of AT increases the impact of one standard deviation price shock on $CAPEX_{i,t+1}$ by 50%. The economic magnitude of the impact of the average level of AT on one standard deviation price shock is 22% for $CAPEXRND_{i,t+1}$ and 40% for $CHGASSET_{i,t+1}$.[12] These are indeed substantial economic effects and explicitly show the importance of AT for investment decisions. These results suggest managers are more likely to use stock prices to guide their investment decisions when AT is more widespread in their stocks.

3.1.2. *Difference-in-differences* (DID). We have now established that there is a positive association between AT and the investment-to-price sensitivity. It is, however, not sufficient to regress investment on stock price and the interaction of stock price with AT and other controls to establish a causal link between AT and the investment-to-price sensitivity. There

[12] An alternative way to interpret the economic impact of AT on the investment-to-price sensitivity is to see how one standard deviation shock on AT impacts the average investment-to-price sensitivity. The average CAPEX-to-price sensitivity is $\beta_1 \cdot Average(Q) = 0.878 \cdot 1.95 = 1.71\%$ and one standard deviation shock on AT increases that to $\beta_1 \cdot Average(Q) + \beta_3 \cdot Average(Q) \cdot StdDev(QT) = 0.878 \cdot 1.95 + 0.039 \cdot 1.95 \cdot 13.58 = 2.74\%$. That means one standard deviation shock on AT increases the average CAPEX-to-price sensitivity by about 60%. Similarly, one standard deviation shock on AT increases CAPEXRND-to-price sensitivity by about 27% and CHGASSET-to-price sensitivity by about 49%.

are two main challenges to establishing such a causal link. First, ATs are more active in the most liquid stocks implying that ATs could choose to trade stocks of the firms that have the higher investment-to-price sensitivity due to their stocks' greater price informativeness (e.g., Biais and Foucault 2014). While we use the first lag of independent variables in Equation (1), this could still raise a concern of reverse causality (e.g., Bond et al. 2012). Second, there may be variables that simultaneously affect the trading/order book activity (AT proxies are generally computed by using trading and order book data) and firms' investment decisions. It is not possible to control all these variables, and hence, we may have an omitted variable issue.[13]

To alleviate endogeneity concerns and establish stronger causality between AT and firms' investment decisions, we first employ difference-in-differences estimation method. We use the introduction of NYSE Autoquote in 2003 as an exogenous event to identify the causal effect of AT on the investment-to-price sensitivity by comparing the NYSE-listed stocks as the treatment group to the NASDAQ-listed stocks as the control group. As discussed in Hendershott et al. (2011) and Chordia and Miao (2020), Autoquote was an important innovation that allowed ATs to continuously monitor the market and automatically update their quotes. Thus, it provides an immediate feedback about the potential impacts of AT trades on investment. Specifically, we estimate the following model:

$$\begin{aligned} I_{i,t+1} = \alpha_i &+ \beta_1 Q_{i,t} + \beta_2 Event_{i,t} + \beta_3 Treatment_{i,t} + \beta_4 Event_{i,t} Treatment_{i,t} \\ &+ \beta_5 Q_{i,t} Event_{i,t} + \beta_6 Q_{i,t} Treatment_{i,t} + \beta_7 Q_{i,t} Event_{i,t} Treatment_{i,t} \\ &+ \delta_1 CF_{i,t} + \delta_2 \ln(Asset_{i,t}) + \delta_3 INS_{i,t} + \delta_4 INSTR_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where $Event_{i,t}$ is a dummy variable that is set to zero before the Autoquote introduction and one afterward. We use 24 months window period in this model and drop the Autoquote launch year (2003) from the sample. Hence, $Event_{i,t}$ is set to zero in 2001 and 2002 and set to one in 2004 and 2005. $Treatment_{i,t}$ is a dummy variable that is set to one for the NYSE-listed firms and zero for the NASDAQ-listed firms. We do not have time fixed effects in this model because there is no time variation in $Event_{i,t}$. The other variables are the same as defined in Table 1.

We present the estimation results in Table 4. The triple interaction term, $Q_{i,t} Event_{i,t} Treatment_{i,t}$, is our main variable of interest as its coefficient captures the effect of AT on the investment-to-price sensitivity. The association between AT and the investment-price-sensitivity after the introduction of Autoquote is positive for all three investment measures and statistically significant for $CAPEX_{i,t+1}$ and $CAPEXRND_{i,t+1}$. The coefficients of the triple interaction term for $CAPEX_{i,t+1}$ and $CAPEXRND_{i,t+1}$ are

[13] In Section 4.2, we control more directly for additional factors that could explain the association between AT and the investment-to-price sensitivity.

0.448 and 1.356 with t-statistics of 2.88 and 4.79, respectively. Consistent with the OLS estimation, these results suggest that the introduction of Autoquote in the NYSE led the investment-to-price sensitivity of the NYSE-listed firms to increase in comparison to the NASDAQ-listed firms.

[Table 4 here]

3.1.3. *Two-stage least squares (2SLS).* To address the potential concerns about the assumptions of the DID model, we further use a two-stage least-squares (2SLS) instrumental variable (IV) approach to mitigate endogeneity concerns. For example, the NASDAQ introduced its dual listing in 2004, implying that the parallel trend assumption of DID may not hold (e.g., Erhard and Sloan 2020). In addition, we cannot include time fixed effects in the DiD model as the $Event_{i,t}$ variable does not have time variation. To address such concerns, we use several instrumental variables in the 2SLS setting.

First, we use the introduction of the Autoquote system as an instrument by also taking advantage of its staggered implementation. In this model, we follow Hendershott et al. (2011) and restrict the sample to the NYSE-listed stocks only. The NYSE-listed stocks have been included in the Autoquote system from January 29, 2003 to May 27, 2003. To capture the staggered implementation of the Autoquote, we first build a daily panel data from 1 January, 2001 to 31 December, 2005. In the first stage, we regress our daily QT measure on the $Autoquote$ dummy that is set to zero before the introduction of NYSE Autoquote and one afterward along with control variables that capture the main market quality dynamics of the trading process. In the second stage, we follow Malceniece et al. (2019) and use the yearly averages of daily fitted values of QT in the baseline investment-to-price sensitivity model. To be consistent with the literature, we also use the yearly averages of the daily control variables from the first-stage model in the second-stage estimation.

Our sample period with the Autoquote instrument is smaller than the full sample, spanning from 2001 to 2005. To capture the whole sample period, we use additional instruments. First, following Sarkar and Schwartz (2009) and Foley and Putnins (2016), we use the first lag of $QT_{i,t}$ ($QT_{i,t-1}$) as an instrument. Second, we use the average level of AT in all other stocks in the corresponding market capitalization quartile ($AveQT_{i,t}$) as an intrument (e.g., Hasbrouck and Saar 2013, Comerton-Forde and Putnins 2015). We also include both $QT_{i,t-1}$ and $AveQT_{i,t}$ as instruments in a separate specification. While the last two instruments are widely used in the market microstructure literature, we add a caveat that they are not as strong as the Autoquote instrument to satisfy the exclusion restriction required for a causal interpretation. Hence, our subsequent analysis rely more on the 2SLS model with the Autoquote instrument along with the OLS model. We estimate four different versions of the following model:

$$I_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Q_{i,t} + \beta_2 \widehat{QT}_{i,t} + \beta_3 Q_{i,t}\widehat{QT}_{i,t} + Controls + \varepsilon_{i,t}, \tag{3}$$

where $\widehat{QT}_{i,t}$ is the fitted values of $QT_{i,t}$ obtained from the first-stage model with different instruments. The control variables are the firm's cash flow $(CF_{i,t})$, the natural logarithm of the firm's total assets $(\ln(Asset_{i,t}))$, the fraction of institutional holdings to total shares outstanding $(INS_{i,t})$, and institutional investors' turnover $(INSTR_{i,t})$ in all versions of the 2SLS model. We additionally include the first lag values of inverse price, trading volume, relative spread, natural logarithm of market value, and the absolute value of price changes in the Autoquote model to control for the market quality dynamics as the first stage of the Autoquote model is at the daily frequency.

[Table 5 here]

We report the findings of the second-stage of all four versions of the 2SLS model when the investment is measured as $CAPEX_{i,t+1}$ in Table 5 and report the results of the first-stage of the models as well as the results of $CAPEXRND_{i,t+1}$ and $CHGASSET_{i,t+1}$ in the Internet Appendix. In all specifications, we find that the association between $CAPEX$ and the interaction of Q and QT is positive and statistically significant. Importantly, we obtain statistically significant association between AT and the investment-to-price sensitivity with the Autoquote instrument even with a small sample size. Overall, the coefficient estimates range between 0.007 to 0.048 and t-statistics vary between 2.04 and 10.89 in the 2SLS framework. These results are consistent with the results of the OLS and DiD approaches and suggest that there is a strong and persistent causal link between AT and the investment-to-price sensitivity.

3.2. AT and revelatory price efficiency. Our analysis with various empirical specifications reveals that AT positively impacts the investment-to-price sensitivity of firms, and thereby contributes to managerial learning from stock prices. Intuitively, managerial learning from stock prices should only occur if managers learn new information from stock prices, the concept known as *'revelatory price efficiency'* (RPE) in the literature (e.g., Bond et al. 2012, Foucault and Frésard 2012). Thus, managerial learning increases by the level of RPE in prices (e.g., Edmans et al. 2017). The desideratum for the impact of AT on RPE is not that firm managers are less informed though, but only that ATs incorporate or encourage the incorporation of some incremental information that is useful to firm managers.[14]

[14] Theoretically, firm managers could be the most informed agents about their firms, but there are still aspects of potential investment opportunities that they can learn from financial market participants. This is because although an individual trader may be less informed than the firm manager, the market aggregates the information of many traders who collectively may be more informed (see, for example, Grossman 1976;

To investigate the impact of AT on RPE, we adopt three approaches. First, we investigate the impact of AT on managers' earnings forecast accuracy. Second, we investigate the impact of AT on information acquisition as measured by the number of non-robot downloads of financial reporting data of firms from the SEC's EDGAR server. We argue that the impact of AT on both of these variables are conceptually related to the RPE. Third, we follow Bond et al. (2012) and Foucault and Frésard (2012) and conduct cross-sectional analysis based on stock characteristics with theoretically clear predictions about the impact of AT on the investment-to-price sensitivity through managerial learning. The intuition of the cross-sectional analysis is that the impact of AT on the investment-to-price sensitivity is expected to be stronger for firms where learning is more valuable, helping to further address endogeneity concerns (e.g., Bond et al. 2012).

3.2.1. *Managers' forecast accuracy.* Management earnings forecasts are a key voluntary disclosure mechanism through which firm managers provide guidance to financial markets and markets significantly react to such disclosures (e.g., Beyer et al. 2010; Zuo 2016). Therefore, managers also revise annual earnings forecasts based on the information received from the market. We hypothesize that if AT increases RPE by revealing *new* information that is unknown to managers, then AT should also improve managers' earnings forecast accuracy. Following Zuo (2016), we compute the change in the manager's forecast accuracy for firm i in year t ($\Delta Accuracy_{i,t}$) as the difference in the errors of two subsequent forecasts of the manager scaled by the stock price just before the first forecast.

To investigate the effects of AT on managers' forecast accuracy, we regress the yearly average of $\Delta Accuracy_{i,t}$ on the absolute return for firm i in year t ($|Return_{i,t}|$ computed as the absolute percentage return over the period between managers' initial and updated forecast dates), the yearly AT proxy, and their interaction as

$$\begin{aligned}\Delta Accuracy_{i,t} = \alpha_i + \gamma_t + \beta_1 |Return_{i,t}| + \beta_2 QT_{i,t-1} + \beta_3 \Delta |Return_{i,t}| QT_{i,t-1} \\ + Controls + \varepsilon_{i,t},\end{aligned} \tag{4}$$

where $Controls$ are the fraction of institutional holdings to total shares outstanding ($INS_{i,t}$), the institutional investors' turnover ($INSTR_{i,t}$), book-to-market ratio ($BMT_{i,t}$), total assets ($TA_{i,t}$), and trading volume ($Volume_{i,t}$). We expect a positive sign for the coefficient of the interaction term between $|Return_{i,t}|$ and $QT_{i,t-1}$, indicating the impact of price changes on the accuracy of managerial earnings forecasts is more pronounced for stocks with higher AT activities.

[Table 6 here]

Hellwig 1980). Additionally, investment decisions depend not only on internal information of the firm that the firm manager are generally more informed, but also on external information such as the state of the economy, the position of competitors and so on (see Bond et al. 2012 for more discussion).

We report the results in Table 6, where in the first column, we exclude $QT_{i,t-1}$ and $|Return_{i,t}|QT_{i,t-1}$ from the above model, whereas in the second column, we include them. Consistent with Zuo (2016), the first column shows a positive and statistically significant association between $\Delta Accuracy_{i,t}$ and $|Return_{i,t}|$, suggesting that managers learn from changes in stock prices. Importantly, we find that the interaction term, $|Return_{i,t}|QT_{i,t-1}$, is positive (the coefficient estimate is 0.005) and statistically significant (t-statistic is 1.72) at 10%. Note that we have a small sample size with 1,540 observations for this analysis because (i) managers' earnings forecast data is not available before 2003, and (ii) the computation of the dependent variable ($\Delta Accuracy_{i,t}$) requires having forecast revisions, and therefore, we drop companies that post one and no forecast as this is a voluntary disclosure and not all firms post forecasts.

To calculate the economic significance of AT on managerial forecast accuracy, we consider one standard deviation shock on $|Return_{i,t}|$ (2.83). This shock, on average, is associated with an increment of 0.906% ($\beta_1 \cdot StdDev(|Return_{i,t}|) = 0.320 \cdot 2.83$) in $\Delta Accuracy_{i,t}$ without AT. However, an average level of AT increases this impact to 1.071% ($\beta_1 \cdot StdDev(|Return_{i,t}|) + \beta_3 \cdot StdDev(|Return_{i,t}| \cdot Average(QT) = 0.320 \cdot 2.83 + 0.005 \cdot 2.83 \cdot 11.17$) increasing the previous increment by about 18%. That is, an average level of AT increases the impact of one standard deviation price shock on managers' forecast accuracy by 18%. We interpret this result as evidence that ATs provide *new* information that is unknown to firm managers and contribute to managerial learning.

3.2.2. *Information acquisition.* Information acquisition and dissemination drive asset price movements and thereby allow firm managers to learn from prices.[15] The proliferation of the use of algorithms in trading impacts the speed at which traders can acquire and incorporate value-relevant information into prices. As such, ATs in modern financial markets should play a first order role in managerial learning. The role of ATs on managerial learning is, however, not limited to how quickly they can parse through various pieces of information and incorporate that into asset prices, but also on how they impact information acquisition of other market participants. On the one hand, Menkveld (2016) argues that replacing market makers in canonical market microstructure models (e.g., Glosten and Milgrom 1985) would result in less adverse-selection cost and tighter bid-ask spread and encourage other market participants to acquire information. On the other hand, Weller (2018) argues that AT may impede the acquisition of new information by other market participants and result in lower information content in prices.

[15] How market participants acquire information and incorporate that into asset prices is among the most fundamental questions in finance. There is a large body of theoretical literature on information acquisition (e.g., Grossman and Stiglitz 1980, Diamond and Verrecchia 1981, Hellwig 1980, Admati 1985, Veldkamp 2006) and the resulting equilibrium in financial and information markets.

To investigate the impact of AT on information acquisition, we take advantage of a dataset containing investors' access of regulatory filings of financial reporting data of firms through the Securities and Exchange Commission (SEC)'s EDGAR (Electronic Data Gathering, Analysis, and Retrieval) system. The EDGAR system is the main source of firms' regulatory filings and the SEC maintains log files of all activities performed by users on EDGAR.[16] Following Lee et al. (2015) and Ryans (2017), we first eliminate the requests made by computer programs or automated webcrawlers (i.e., robots) and only use non-robot EDGAR downloads.[17] From the data, we are able to directly observe investors' information acquisition activity for a broad cross-section of firms over a sample period of 2003-2017.

We are interested in the impact of AT on the consumption of financial information by other (non-robot) market participants. The idea is that while the information in EDGAR is not new to managers, as discussed in Edmans et al. (2015), information acquisition of market participants is likely increase RPE by improving the feedback effect from these market participants to managers. This is because these investors usually combine their own private information with the information posted by companies to make their trading decisions. Thus, AT encouraging information acquisition of market participants allows firm managers to extract new information from stock prices.

To examine whether the amount of AT activities in stocks increases the information acquisition of market participants as proxied by the number of non-robot EDGAR downloads, we regress $EDGAR_{i,t}$ on $QT_{i,t}$ as

$$EDGAR_{i,t+1} = \alpha_i + \gamma_t + \beta_1 QT_{i,t} + Controls + \varepsilon_{i,t}, \tag{5}$$

where we control for other variables that can impact information acquisition in markets. We use inverse price ($InverseP_{i,t}$), relative spread ($Spread_{i,t}$), natural logarithm of market value ($\ln(MV_{i,t})$), trading volume ($Volume_{i,t}$), absolute value of price changes ($\Delta Price_{i,t}$), institutional holdings ($INS_{i,t}$), and institutional investors' horizon ($INSTR_{i,t}$) as control variables. All these variables are defined in Table 1.

[Table 7 here]

We report the findings in Table 7, where the first column shows the findings for raw values of $QT_{i,t}$ and the second column shows for the predicted values of $QT_{i,t}$ using

[16] The raw data is available for download at https://www.sec.gov/data/edgar-log-file-data-set.html and the processed data is available at http://www.jamesryans.com.

[17] We use three different filtering algorithms proposed by Drake et al. (2015), Loughran and McDonald (2017) and Ryans (2017). The results are virtually the same with all three approaches. For brevity, we only report the results with Ryans (2017) and report the other two in the Internet Appendix. For more details on various classifications of robot and non-robot downloads procedure and an evaluation of their accuracy, see Ryans (2017).

$Autoquote_{i,t}$ as an instrument. The effect of AT on non-robot EDGAR downloads are positive and statistically significant in both models, suggesting that ATs increase information acquisition of market participants. The magnitude of the impact is economically meaningful. An average level of $QT_{i,t}$ (11.17) increases $EDGAR_{i,t}$ by about 5.1% ($\beta_1 \cdot Average(QT_{i,t})/Average(EDGAR_{i,t}) = 11.17 \cdot 0.003/0.66$). Thus, ATs not only directly contribute to managerial learning by incorporating new information into stock prices, but also indirectly contribute to managerial learning by encouraging the overall information acquisition in the market.

3.2.3. *Cross-sectional analysis.* We now analyze which stock characteristics influence the magnitude of the impact of AT on the investment-to-price sensitivity. We do this analysis by allocating stocks to high (above 75th percentile) group each year according to five stock characteristics:[18] (i) the fraction of institutional holdings to total shares outstanding ($INS_{i,t}$), (ii) the variance of stock returns driven by private information ($PrivateInfo_{i,t}$), (iii) relative spread ($Spread_{i,t}$), (iv) trading volume ($Volume_{i,t}$), and (v) the amount of earnings surprise ($ESP_{i,t}$). These variables are defined in Section 2.5 and Table 1. We focus on these stock characteristics as theoretically they have clear predictions about how AT should impact the investment-to-price sensitivity through the managerial learning and the level of RPE in prices.

First, following Foucault and Frésard (2012), we conduct cross-sectional analysis with the fraction of institutional holdings to total shares outstanding ($INS_{i,t}$) as institutional investors are generally considered as informed investors that have positive impact on RPE. Second, we use the variance of returns driven by private information ($PrivateInfo_{i,t}$) based on Brogaard et al. (2022). We prefer this measure over standard private information measures because it excludes noise and a significant proportion of news already known by managers and arguably is more related to RPE. Thus, we expect that the impact of AT on the investment-to-price sensitivity to increase with both measures.

Next, we include stocks' liquidity as measured by relative spread and trading volume in the cross-sectional analysis for two reasons. First, stocks with higher liquidity have relatively greater price informativeness (e.g., Foucault and Gehrig 2008; Fang et al. 2009). Second, ATs are more active in liquid stocks and therefore, the contribution of AT to price informativeness is expected to be higher in these stocks. Hence, we expect the impact of AT on the investment-to-price sensitivity to be greater when liquidity is higher (i.e., trading volume is higher and spread is lower).

[18] We repeat the same analysis by using median values as a cut-off to allocate stocks to high and low groups and obtain consistent results.

Lastly, we conduct cross-sectional analysis based on the difference between the actual and the average earnings per share forecast by analysts, i.e., the amount of earnings surprise ($ESP_{i,t}$). The cross-sectional analysis with $ESP_{i,t}$ aims to capture the asymmetry in the learning about positive and negative information from stock prices. Such asymmetry should conceptually arise because it should take more time for prices to reflect negative information compared to positive information due to the feedback from financial markets. The intuition is that managerial learning disincentivizes informed traders to trade on negative information because managerial learning (even with bad news) increases the stock price, resulting in less profitability for trading on negative information (e.g., Edmans et al. 2015). Thus, we expect the impact of AT-driven investment-to-price sensitivity to be higher for firms with positive news than the firms with negative news.

To conduct the cross-sectional analysis, we create a dummy variable D_h that is equal to one if the firm's stock is in the high group according to each stock characteristic. We then re-estimate Equation (1) by including D_h, $Q_{i,t}D_h$, $QT_{i,t}D_h$, and $QT_{i,t}Q_{i,t}D_h$ as

$$\begin{aligned} I_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Q_{i,t} + \beta_2 QT_{i,t} + \beta_3 D_h + \beta_4 Q_{i,t} QT_{i,t} + \beta_5 Q_{i,t} D_h + \beta_6 QT_{i,t} D_h \\ + \beta_7 Q_{i,t} QT_{i,t} D_h + Controls + \varepsilon_{i,t}, \end{aligned} \tag{6}$$

where the coefficient of interest is β_7, showing the difference in the impact of AT on the investment-to-price sensitivity in the high group compared to the low group. A positive (resp. negative) β_7 implies the positive impact of AT on the investment-to-price sensitivity is higher in the high (resp. low) group. The results for $CAPEX_{i,t+1}$ are reported in Table 8.[19]

[Table 8 here]

In all specifications, AT is positively and statistically significantly related to the investment-to-price sensitivity. This implies that AT positively impacts the investment-to-price sensitivity of firms irrespective of their group. In addition, the coefficient of the triple interaction (β_7) is positive and statistically significant for $INS_{i,t}$, $PrivateInfo_{i,t}$, $Volume_{i,t}$, and $ESP_{i,t}$ and negative and statistically significant for $Spread_{i,t}$. That is, the impact of AT on the investment-to-price sensitivity is higher for firms (i) whose shares are more traded by institutional and informed investors, (ii) with more liquid shares, and (iii) with more positive information. These results are also economically significant. For instance, for the average level of $QT_{i,t}$, the difference in the impact of one standard deviation price shock on $CAPEX_{i,t+1}$ between the high and low institutional trading group is 0.43% ($\beta_7 \cdot Average(QT) \cdot StdDev(Q)$), constituting 7.3% of the average $CAPEX_{i,t+1}$. The

[19] We conduct the same analysis for $CAPEXRND_{i,t+1}$ and $CHGASSET_{i,t+1}$ and obtain qualitatively consistent results, albeit with lower statistical significance in some cases. These results are reported in the Internet Appendix.

respective economic magnitudes are 6.8% for $PrivateInfo_{i,t}$, -5.1% for $Spread_{i,t}$, 15.1% for $Volume_{i,t}$, and 6.5% for $ESP_{i,t}$. These results provide further support for the argument that AT fosters the production of information that is new to managers and have positive impact on RPE and managerial learning.

4. Extensions and robustness tests

In this section, we extend the baseline tests in various directions. First, we examine whether AT's effect on the investment-to-price sensitivity is pervasive across stocks with various levels of AT activities. Second, we control for the factors that could explain the positive impact of AT on the investment-to-price sensitivity. Third, we employ alternative measures of AT to check the robustness of our baseline results. Fourth, we differentiate between two main AT strategies, namely market-making and opportunistic strategies, to examine their respective impacts on the investment-to-price sensitivity. Lastly, we study the impact of AT-driven investment-to-price sensitivity on firm's future operating performance.

4.1. Investment-to-price sensitivity by AT quintiles. To document a potential variation in the impact of AT on the investment-to-price sensitivity across different levels of AT, we divide stocks into quintiles (quintile 1 for stocks with low AT activities and quintile 5 for stocks with high AT activities). Our aim is to test the pervasiveness of AT's effect on the investment-to-price sensitivity across various AT quintiles. This is an important analysis because the association between AT and the investment-to-price sensitivity may be driven by a few firms with higher AT activities in their shares. To investigate such a variation across different AT levels, we estimate the following model:

$$I_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Q_{i,t} + \sum_{n=2}^{n=5} \beta_n QT_n + \sum_{n=2}^{n=5} \gamma_n Q_{i,t} QT_n + Controls + \varepsilon_{i,t}, \tag{7}$$

where QT_n is the dummy variable that is equal to one if the stock is in the *n*th quintile. The coefficients of interest in Equation (7) are the interaction coefficients of stock price $Q_{i,t}$ and AT quintile dummies QT_n ($\gamma_2 - \gamma_5$). Table 9 reports the results. We find that the association between AT and the investment- to-price sensitivity is positive and statistically significant (at 1 percent level) across all AT quintiles. This suggests that AT contributes to managerial learning in even stocks with relatively fewer AT activities and hence, the impact of AT on the investment-to-price sensitivity is pervasive across stocks with different levels of AT activities.

[Table 9 here]

4.2. Controlling for additional factors. In this sub-section, we provide additional robustness tests to further strengthen the finding that AT contributes to managerial learning and rule out alternative channels. Specifically, we extend the baseline model in Equation (1) by controlling for additional factors that may affect the association between AT and the investment-to-price sensitivity. First, we control for the managerial information as measured by the insiders' trading activities and the return around earnings' announcements. The intuition is that if AT does not contribute to the production of new information and only improve information content of prices by incorporating existing information that firm managers already know about, then the positive association between AT and the investment-to-price sensitivity should disappear after controlling for the managerial information.

We obtain the insiders' trading activities from the Thomson Financial's TFN database. The vast literature on insider trading activities shows that it is profitable for managers to trade based on their information as their information reveals private information that is not known by other market participants (e.g., Meulbroek 1992; Seyhun 1992). We measure insiders' trading activities with insider volume rate computed as the insider transactions' dollar volume divided by the total dollar volume of all transactions for firm i in year t ($Insider_{i,t}$). We also use the return around earnings' announcements ($RES_{i,t}$) computed as the yearly average of the absolute market-adjusted stock returns over the four quarterly earnings announcements periods (day-1 to day 1) for stock i in year t. The idea is that firm managers know the accounting numbers before they are released to investors and thus, the absolute abnormal (market-adjusted) return around an earnings announcement is a proxy for the managerial information that was not impounded entirely into stock prices before the announcement (e.g., Frésard 2012). Table 10 reports the results after controlling for $Insider_{i,t}$ in column (i) and $RES_{i,t}$ in column (ii). The coefficients of the interaction term ($Q_{i,t}QT_{i,t}$) are positive and statistically significant (t-statistics are 8.62 and 10.30) in both models.

[Table 10 here]

Next, we control for the analyst coverage. We measure the analyst coverage of a given firm by the annual average of the monthly number of earnings per share forecasts for the next fiscal year of the firm from the I/B/E/S database. Analyst coverage is one of the important sources of information for firm managers. Therefore, when there is more coverage by analysts, managers may have less incentive to learn from stock prices, impacting the association between AT and the investment-to-price sensitivity. To test this, we extend the model by adding analyst coverage ($Analyst_{i,t}$) and the interaction of Tobin's Q and analyst coverage ($Q_{i,t}Analyst_{i,t}$) as additional control variables and report the results in column (iii) of Table 10. We find that the relationship between AT and the investment-to-price sensitivity ($Q_{i,t}QT_{i,t}$) is positive and significant even after controlling for the analyst coverage, indicating that AT-driven price informativeness is an important source of new information to firm managers.

Lastly, we control for the level of financial constraints of firms. It is well-documented that firms with highly liquid stocks have lower expected returns (e.g., Amihud and Mendelson 1986; Amihud 2002; Acharya and Pedersen 2005). Butler et al. (2005) find that firms with higher stock market liquidity incur less cost of raising external capital. Given that ATs are one of the main determinants of stock market liquidity (e.g., Hendershott et al. 2011; Menkveld 2013), it is plausible that AT reduces the cost of capital. Consistently, Rosu et al. (2021) find that a large quote-to-trade ratio ($QT_{i,t}$) is associated with low expected returns.

A lower cost of capital implies easier access to external equity finance, leading the firms with a lower cost of capital to be more equity dependent. Along this line, Baker et al. (2003) provide evidence that the investment-to-price sensitivity is higher for firms with greater equity dependence. The cost of capital channel is one of the well-established channels that financial markets can affect investment decisions (e.g., Fischer and Merton 1984; Morck et al. 1990; Stein 1996). The positive association between AT and the investment-to-price sensitivity could then be explained by the extent to which AT impacts the cost of capital or capital constraints of firms. If this mechanism explains our findings, the relation between AT and the investment-to-price sensitivity should then disappear in the framework controlling for capital constraints.

We control for capital constraints of firms by including a four-variable version of the Kaplan-Zingales measure ($KZ_{i,t}$) constructed by Baker et al. (2003). $KZ_{i,t}$ is a weighted sum of cash flow, cash dividend, cash balances (all scaled by lagged assets), and the leverage ratio (see Table 1 for the computation of $KZ_{i,t}$). As reported in column (iv) of Table 10, the coefficient of the $KZ_{i,t}$ is negative and significant, implying that more capital-constrained firms have a lower level of investment. The coefficient of the interaction between $Q_{i,t}$ and $KZ_{i,t}$ is positive and significant, suggesting that firms with more capital constraints have higher investment-to-price sensitivity as reported in Baker et al. (2003). More importantly, the association between AT and the investment-to-price sensitivity remains positive and significant even after controlling for capital constraints, ruling out the possibility that firms' capital constraints are the main driver of our results. These results confirm and strengthen our main findings in Section 3.

4.3. Alternative measures of AT. Throughout the analysis, we have used the quote-to-trade ratio ($QT_{i,t}$) as our main AT measure. While $QT_{i,t}$ is one of the common AT proxies used in the literature, we employ two additional AT measures from the SEC's MIDAS database for robustness: (i) the cancel-to-trade ratio ($CT_{i,t}$) and (ii) the odd-lot ratio ($OR_{i,t}$).

The cancel-to-trade ratio for a given firm-year is computed as the number of all cancellation messages (full or partial) divided by the number of all trade messages. The odd lot ratio for a given firm-year is computed as the number of odd-lot trade messages (i.e., trade messages that executed smaller than 100 shares) divided by the number of all trade messages.

The intuition of the cancel-to-trade ratio is similar to the intuition of the quote-to-trade ratio. ATs continuously submit and cancel limit orders to monitor the conditions of limit-order book (e.g., Hasbrouck and Saar 2013). Therefore, the increased level of cancel-to-trade ratio in a particular stock is associated with the increased level of AT activities in that stock. Another trading strategy of ATs is slicing large parent orders into smaller child orders, reducing the price impact of a given order. We, therefore, use the odd-lot ratio as an additional measure of the level of AT activities (e.g., O'Hara et al. 2014).

[Table 11 here]

Tables 11 reports the relationship between the new measures of AT and the investment-to-price sensitivity, where for brevity we only report $CAPEX_{i,t+1}$ as the investment measure and report $CAPEXRND_{i,t+1}$ and $CHGASSET_{i,t+1}$ in the Internet Appendix. In line with our main findings, the impact of AT on the investment-to-price sensitivity is positive and statistically significant for both measures of AT with a slight decrease in t-statistics. The lowered statistical significance is expected because of the smaller MIDAS sample size of 10,665 firm-year observations covering a shorter period of 2012-2019.

4.4. Opportunistic AT strategies. Our results suggest that, in aggregate, AT incorporates new information into stock prices and encourages information acquisition, resulting in increased stock price informativeness and managerial learning from stock prices. However, there are various AT strategies that can be harmful for stock price informativeness. For example, Dugast and Foucault (2018) provide a theoretical argument on how the reduction of the cost of information that are often associated with the technological improvements in information acquisition can reduce the stock price informativeness due to the low precision signals crowding out the high precision signals. Similarly, Weller (2018) provides evidence that AT can impede the acquisition of new information and thereby worsen stock price informativeness.

To reconcile our results with that of the literature focusing on the negative aspects of AT strategies, we differentiate between the market-making (liquidity-supplying) and opportunistic (liquidity-demanding) AT strategies and examine their impacts on the investment-to-price sensitivity. On the one hand, liquidity-supplying strategies used by market-maker ATs can increase liquidity and reduce the cost of information acquisition and improve stock price informativeness (e.g., Hendershott et al. 2011; Menkveld 2013;

Brogaard et al. 2019). On the other hand, order anticipation strategies (such as back-running and latency arbitrage) used by opportunistic ATs can discourage the acquisition of new information by eroding rents to information acquirers and deteriorate stock price informativeness (e.g., Budish et al. 2015; Weller 2018; Yang and Zhu 2020). We argue that the difference in the results can be attributed to the various AT strategies, and in what follows, we provide evidence in this direction.

To capture the opportunistic AT activities, we focus on the latency arbitrage opportunities that ATs can exploit. Latency arbitrage opportunities are mechanical arbitrage opportunities associated with the correlation breakdown at high frequency available to the fastest traders. Our argument is that if indeed opportunistic ATs discourage the amount of new information acquisition, AT should then reduce the investment-to-price sensitivity of firms when large number of latency arbitrage opportunities are available for opportunistic ATs to exploit.

We measure the number of latency arbitrage opportunities in the spirit of Budish et al. (2015) as the number of "stale" quotes. Budish et al. (2015) identify stale quotes using the jump size in mid-price. Specifically, the quote at time $z-1$ is considered as stale if the absolute value of mid-price changes from time $z-1$ to z exceeds half-spread. The intuition is that such stale quotes can be exploited ("sniped") by opportunistic ATs before being cancelled. Using this intuition more conservatively, we measure the jump size based on the difference between the mid-price at time z and the ask and bid quotes at time $z-1$. Formally, if $MidPrice_z > Ask_{z-1} + TickSize$, where $TickSize = 0.01$ USD then there is a profitable latency arbitrage opportunity and an opportunistic AT can submit a limit buy order at $Ask_{z-1} + Tick\,Size$ to exploit this opportunity at time z. Similarly, if $MidPrice_z < Bid_{z-1} - TickSize$, then an opportunistic AT can submit a limit sell order at $Bid_{z-1} - Tick\,Size$ to exploit this opportunity at time z.

The main challenge of computing a latency arbitrage opportunity is that it requires ultra high-frequency data. For this, we obtain the first-level of quote data from Refinitiv. Our measure of the latency arbitrage opportunities ($LAO_{i,t}$) is the total number of first-level quotes satisfying the above criteria for each firm i and year t. Given the massive size of this data, we use only 120 firms in this test. Consistent with the main analysis, our sample period is from 1996 to 2019. To make our sample selection random and consistent with the literature, we use the same 120 firms that have been included in the widely-accepted NASDAQ HFT dataset (e.g., Brogaard et al. 2014). To differentiate the effects of the market-maker and opportunistic ATs on the investment-to-price sensitivity, we re-estimate the baseline model in Equation (1) with $LAO_{i,t}$:

$$\begin{aligned} I_{i,t+1} = {} & \alpha_i + \gamma_t + \beta_1 Q_{i,t} + \beta_2 QT_{i,t} + \beta_3 Q_{i,t} QT_{i,t} + \beta_4 LAO_{i,t} + \beta_5 Q_{i,t} LAO_{i,t} \\ & + \beta_6 QT_{i,t} LAO_{i,t} + \beta_7 Q_{i,t} QT_{i,t} LAO_{i,t} + Controls + \varepsilon_{i,t}. \end{aligned} \tag{8}$$

Three points stand out from the results reported in Table 12. First, consistent with our main findings, the coefficient of $Q_{i,t}QT_{i,t}$, showing the aggregate impact of AT on the investment-to-price sensitivity is positive for all three investment investment measures and statistically significant for $CAPEX_{i,t+1}$ and $CHGASSET_{i,t+1}$ even after controlling for $LAO_{i,t}$. Second, the interaction between $Q_{i,t}$ and $LAO_{i,t}$ is negative for all three measures of investment and statistically significant for $CAPEX_{i,t+1}$ and $CAPEXRND_{i,t+1}$, suggesting that the investment-to-price sensitivity is lower when there are large number of profitable latency arbitrage opportunities. While this result is consistent with our expectation, it is not enough to make a conclusive statement about the role of opportunistic ATs as $LAO_{i,t}$ captures the latency arbitrage opportunities and does not necessarily mean that ATs actually exploit them. Third, the coefficient of the triple interaction term, $Q_{i,t}QT_{i,t}LAO_{i,t}$, is negative and statistically significant for $CAPEX_{i,t+1}$ and $CAPEXRND_{i,t+1}$, implying that the opportunistic ATs in fact weaken the aggregate association between AT and the investment-to-price sensitivity by exploiting profitable latency arbitrage opportunities. These findings are consistent with that of Weller (2018) and Ye et al. (2022) who show that the ATs that incorporate information into stock prices at the expense of new information acquisition reduce RPE and deteriorate managerial learning.

[Table 12 here]

These results confirm our main findings and show that, in aggregate, the positive impact of liquidity-supplying strategies of AT on the RPE and managerial learning dominates the potentially negative AT strategies. We find that the positive AT strategies on the investment-to-price sensitivity is persistent even with small sample of 120 randomly selected firms. It is also clear from this analysis that various strategies used by ATs can in fact impact stock price informativeness differently and juxtaposition of such strategies is important to understand the broader role of AT.

4.5. AT and operating performance. The practical implication of our main results so far is that AT helps managers make better-informed and more efficient investment decisions and hence, increases managers' ability to identify projects with positive net present values. In this sub-section, we test this hypothesis by examining the effects of the AT-driven investment-to-price sensitivity on firms' future operating performance. To directly examine this hypothesis, we need the interaction coefficient (β_3) in Equation (1) for each firm-year and then relate it to a firm's future operating performance. Estimating β_3 for each firm-year is not empirically feasible. We, therefore, proceed with two alternative approaches: (i) a ranking approach and (ii) a portfolio approach.

In the ranking approach, we follow Chen et al. (2007) and construct a new variable, $Ranking_{i,t}$, representing the percentile of the amount of AT activities of stock i in year t.

We then estimate:

$$OP_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Ranking_{i,t} + \beta_2 Q_{i,t} + Controls + \varepsilon_{i,t}, \tag{9}$$

where $OP_{i,t+1}$ is the operating performance of firm i in year $t+1$, $Ranking_{i,t} \in (0,\ 100)$ represents the percentile of the degree of AT for firm i in year t. We employ two performance measures: (i) one-year ahead return on assets ($ROA_{z,t+1}$) and (ii) one-year ahead sales growth ($SG_{z,t+1}$). We also use the average of the three-year ahead values of these performance measures ($ROA_{z,t+3}$ and $SG_{z,t+3}$) and report the results of these tests in the Internet Appendix. The control variables are $CF_{i,t}$, $\ln(Asset_{z,t})$, $INS_{i,t}$, $INSTR_{i,t}$, and the lagged value of the respective operating performance to control for the persistence in the operating performance of firms. All these variables including the control variables are defined in Table 1.

Table 13 reports the results. In columns (i) and (ii), $Ranking_{i,t}$ is determined based on the actual $QT_{i,t}$ in the full sample and in columns (iii) and (iv), $Ranking_{i,t}$ is determined based on the predicted $QT_{i,t}$ ($\widehat{QT}_{i,t}$) in the autoquote sample using autoquote as an instrument. The associations between $Ranking_{i,t}$ and $OP_{i,t+1}$ are positive and statistically significant across all specifications. The coefficient of $Ranking_{i,t}$ is 0.005 with a t-statistic of 2.38 when the performance measure is $ROA_{i,t+1}$ and 0.029 with a t-statistic of 5.80 when the performance measure is $SG_{i,t+1}$. These results are economically significant. A median level increase in $QT_{i,t}$ increases $ROA_{i,t+1}$ by 2.75% and $SG_{i,t+1}$ by 25.85%.[20] Thus, AT-driven investment-to-price sensitivity positively impacts firms' future operating performance. Consistent with our main findings, these results suggest that AT contributes to managerial learning and helps them make better investment decisions.

[Table 13 here]

In the portfolio approach, we first split our sample into deciles each year based on the interaction variable ($Q_{i,t}QT_{i,t}$) and run year-by-year investment regressions for each portfolio to obtain the interaction coefficient for each of the 10 portfolios each year (denoted as $\beta_{z,t}$). Effectively, $\beta_{z,t}$, captures AT-driven investment-to-price sensitivity for portfolio z in year t. Then, we estimate the following regression:

$$OP_{z,t+1} = \alpha_z + \gamma_t + \beta_1 \beta_{z,t} + \beta_2 Q_{z,t} + Controls + \varepsilon_{z,t}, \tag{10}$$

where $OP_{z,t+1}$ is the operating performance of portfolio z in year $t+1$ and $\beta_{z,t}$ is the AT-driven CAPEX-to-price sensitivity of portfolio z in year t, and $Q_{z,t}$ is the average Tobin's

[20] We calculate the economic impact of the median level increase in the amount of AT ($QT_{i,t}$) on return on assets ($ROA_{i,t+1}$) as $\beta_1 Median(Ranking)/Average(ROA) = 0.005 \cdot 50/9.09 = 2.75\%$. The calculation follows similarly for the sales growth ($SG_{i,t+1}$).

Q for portfolio z in year t. The control variables are the average cash flow $(CF_{z,t})$, the average logarithm of the total assets $(\ln(Asset_{z,t}))$, the average fraction of institutional holdings to total shares outstanding $(INS_{z,t})$, the average turnover of institutional investors $(INSTR_{z,t})$, and the lagged dependent variable $(OP_{z,t})$ for portfolio z in year t. α_z and γ_t are portfolio and time fixed effects. The coefficient of interest in Equation (10) is β_1, showing the impact of the AT-driven investment-to-price sensitivity on the future operating performance of portfolios.

Table 14 reports the impact of the AT-driven CAPEX-to-price sensitivity $(\beta_{z,t})$ on the future operating performance of firms. The impact of $\beta_{z,t}$ is positive for both measures of operating performance and statistically significant (at 1 percent level) for $ROA_{z,t+1}$. We also report the average of the three-year ahead values of the operating performance and the results for CAPEXRND- and CHGASSET-to-price sensitivity in the Internet Appendix. We find a positive association between the AT-driven investment-to-price sensitivity and future operating performance of firms across all specifications, though the results of CHGASSET-to-price sensitivity is not statistically significant. The lowered significance is expected because we only have 240 portfolio-year observations (10 portfolios for 24 years) in the final sample. Overall, these results are in line with the ranking approach and provide additional support to our hypothesis that AT helps managers make better-informed investment decisions and improves firms' future operating performance.

[Table 14 here]

4.6. Additional tests. We perform a series of additional tests to check the robustness of our results and report the results in the Internet Appendix. These tests include (i) further controls such as the interaction of $Q_{i,t}$ and two measures of institutional trading $(INS_{i,t}$ and $INSTR_{i,t})$, (ii) further estimation approaches such as the Heckman (1979) selection and Fama-Macbeth approach, and (iii) further measures such as Peters and Taylor (2017) $Q_{i,t}$ instead of original Tobin's $Q_{i,t}$ to account for intangible capital and the average of the next three years operating performance measures. In all these tests, the results are generally consistent with our main findings.

5. Conclusion

The real economic consequences of AT is an open question that lends itself to an ongoing discussion. To contribute to this discussion, we provide evidence that the increased level of AT activities in firms' stocks is positively related to the investment-to-price sensitivity of firms. We obtain this result using various estimation procedures, namely OLS, difference-in-differences and 2SLS with different instrumental variables. We link our findings to the impact of AT on the revelatory price efficiency (RPE) by showing that (i) there is a positive association between AT and managers' forecast accuracy, (ii) there is a positive association between AT and non-robot downloads of financial reporting data from the SEC's EDGAR database and (iii) the impact of AT on the investment-to-price sensitivity is stronger for stocks with higher institutional ownership, higher private information, more liquid, and more positive information.

Extending the baseline analysis, we show that the positive impact of AT on the investment-to-price sensitivity holds in even stocks with relatively fewer AT activities. We rule out alternative explanations such as other information sources and firms' capital constraints as the main drivers of our results. We also document that while, in aggregate, AT is positively associated with the investment-to-price sensitivity, opportunistic ATs that exploit profitable latency arbitrage opportunities weaken the investment-to-price sensitivity. Lastly, we show that AT-driven investment-to-price sensitivity leads to superior firm performance, suggesting that AT helps managers to make better investment decisions. These results are robust to various measures of investment, operating performance, algorithmic trading, and normalized stock price.

Our findings highlight that the role of AT is not limited to market quality only in high frequency but also has broader implications for long-term investors. From these findings, it might be tempting to conclude that the investment behavior of firms with more AT activities must necessarily be more efficient than the firms with fewer AT activities, and so, AT should be encouraged in financial markets. Multiple caveats apply before one jumps into this sort of definitive welfare conclusions. First, while AT may be welfare-improving in the dimension of the investment-to-price sensitivity and firm performance, it may well be welfare-destroying in another dimension. Our results only shed light on the impact of AT on the investment-to-price sensitivity and operating performance of firms. Second, while our results show that, all else equal, AT enhances managers' learning from stock prices, this may not be enough to justify the huge infrastructure costs spent by ATs. Lastly, while our results suggest the *overall* positive impact of AT on managerial learning, various opportunistic AT strategies may adversely impact the managerial learning from stock prices. We provide suggestive evidence for one of these cases.

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Table 1

Definitions of variables

This table reports the notation, description, and source of variables. The units of the variables are in parentheses following the variable names. Panel A reports the main model variables and Panel B reports the supplementary variables.

Panel A: Main model variables		
Variable	**Description**	**Data source**
$CAPEX_{i,t}$ (%)	Capital expenditure for firm i in year t is computed as capital expenditures in year t scaled by total assets in year $t-1$.	Compustat
$CAPEXRND_{i,t}$ (%)	Capital expenditure plus research and development expenditure (R&D) for firm i in year t is computed as capital expenditures plus R&D in year t scaled by total assets in year $t-1$.	Compustat
$CHGASSET_{i,t}$ (%)	Change in total assets for firm i in year t is computed as the percentage change in book value of assets from year $t-1$ to year t.	Compustat
$ROA_{i,t}$ (%)	Return on assets for firm i in year t is computed as earnings before interest, tax, depreciation, and amortization $(EBITDA_{i,t})$ in year t divided by total assets in year t.	Compustat
$SG_{i,t}$ (%)	Sales growth for firm i in year t is computed as the percentage change in total revenue from year $t-1$ to year t.	Compustat
$QT_{i,t}$	Algorithmic trading measure for firm i in year t is computed as the number of quote messages divided by the number of transactions.	Refinitiv
$Q_{i,t}$	The normalized stock price for firm i and year t is computed as the market value of the equity plus the book value of assets minus the book value of equity, scaled by the book value of assets.	Compustat
$CF_{i,t}$ (%)	Cash flow for firm i in year t is computed as the sum of net income before extraordinary items, depreciation and amortization expenses, and R&D expenses for year t, scaled by total assets in year $t-1$.	Compustat
$\ln(Asset_{i,t})$	Natural logarithm of the total assets in dollars for firm i in year t.	Compustat
$INS_{i,t}$ (%)	Institutional holdings measure for firm i in year t is computed as the fraction of institutional holdings to total shares outstanding.	Refinitiv
$INSTR_{i,t}$	Institutional traders' horizon measure for firm i in year t is computed as the weighted average of the quarterly churn rates of institutional investors. The churn rate for each institutional investor r and quarter q is computed following Gaspar et al. (2005) as: $CR_{r,q} = \frac{\sum_{j\in Q} \lvert N_{j,r,q}P_{j,q} - N_{j,r,q-1}P_{j,q-1} - N_{j,r,q-1}\Delta P_{j,q}\rvert}{\sum_{j\in Q} \frac{N_{j,r,q}P_{j,q} + N_{j,r,q-1}P_{j,q-1}}{2}}$, where j is a company index and Q is the set of companies held by an institutional investor, $N_{j,r,q}$ is the number of shares of company j held by institutional investor r at quarter q, and $P_{j,q}$ is the price of share of company j for quarter q.	Refinitiv
$\Delta Accuracy_{i,t}$ (%)	Manager's forecast accuracy for firm i in year t is computed following Zuo (2016): $\Delta Accuracy_{i,t} = -100 \cdot \frac{(\lvert MF_{i,t}^{d_2} - AEarning_{i,t}\rvert - \lvert MF_{i,t}^{d_1} - AEarning_{i,t}\rvert)}{P_i^{d_1-2}}$, where $MF_{i,t}^{d_2}$ is the earnings forecast released by firm i on date d_2, $MF_{i,t}^{d_1}$ is the most recent earnings forecast (for the same earning) released by firm i prior to $MF_{i,t}^{d_2}$, $AEarning_{i,t}$ is the actual earnings for year t announced by firm i, and $P_i^{d_1-2}$ is the stock price two days before the issuance of $MF_{i,t}^{d_1}$.	Refinitiv
$EDGAR_{i,t}$ (00,000)	The number of non-robot EDGAR filings downloads for firm i in year t. Following Ryans (2017), IP addresses are considered as robot if they (i) download more than 25 items in a single minute, (ii) download more than 3 different companies' items in a single minute, and (iii) download more than 500 items in a single day.	SEC

Panel B: Supplementary variables		
Variable	**Description**	**Data source**
$ESP_{i,t}$ (%)	The amount of earning surprise measure for firm i in year t is computed as the percentage difference between the actual and forecast earnings per share. Forecast earnings per share is the average earnings forecast of analysts.	I/B/E/S
$PrivateInfo_{i,t}$	The private firm-specific information for firm i in year t is computed using a vector autoregression model following Brogaard et al. (2022), where the responses of stock returns to three shocks (market returns, firm-specific order flow, and other idiosyncratic shocks captured in the stock-return residual) are estimated. $PrivateInfo_{i,t}$ is then computed as the product of the firm-specific order flow innovation and the long-run effect of a unit shock on the firm-specific order flow, inferred from the cumulative impulse response function.	CRSP
$Insider_{i,t}$ (%)	Insider volume rate for stock i in year t is computed as the ratio of insider dollar volume to the total dollar volume of all transactions for stock i in year t.	TFN/CRSP
$RES_{i,t}$ (%)	Return around earnings announcements for stock i in year t is computed as the yearly average of the absolute market-adjusted return over the four quarterly earnings announcements periods (day-1 to day 1) for stock i in year t.	TFN/CRSP
$Analyst_{i,t}$	Annual average of monthly number of analysts issuing EPS forecasts for the next year of firm i in year t.	I/B/E/S
$KZ_{i,t}$	Kaplan-Zingales metric for firm i in year t is computed as the weighted sum of cash flow ($CF_{i,t}$), cash dividend ($DIV_{i,t}$), and cash balances ($C_{i,t}$) all scaled by lagged assets, and the leverage ratio following Baker et al. (2003) as: $KZ_{i,t} = -1.002CF_{i,t} - 39.368DIV_{i,t} - 1.315C_{i,t} + 3.139LEV_{i,t}$	Compustat
$CT_{i,t}$	Cancel to trade ratio for firm i in year t is computed as the number of all cancellation messages (full or partial) divided by the number of trade messages for firm i's stock in year t.	MIDAS
$OddLot_{i,t}$ (%)	Odd lot ratio for firm i in year t is computed as the number of odd lot trade (trades with less than 100 shares) messages divided by the number of all trade messages for firm i's stock in year t.	MIDAS
$LAO_{i,t}$ (00,000)	Latency arbitrage opportunities for firm i in year t is the total number of "stale" quotes (first-level quote updates with mid-price jump) as in Budish et al. (2015). The ask (resp. bid) quote at time $z-1$ is stale $MidPrice_z > Ask_{z-1} + TickSize$ (resp. $MidPrice_z < Bid_{z-1} - TickSize$), where $TickSize = 0.01$ USD.	Refinitiv
$\lvert Return_{i,t}\rvert$ (%)	Absolute value of return for firm i in year t is computed as the percentage return over the period between managers' initial and updated forecast dates.	CRSP
$InverseP_{i,t}$ (1/$)	Inverse price for firm i in year t is computed as the yearly average of monthly inverse price (1/price) for firm i in year t.	CRSP
$Spread_{i,t}$ (%)	Relative spread for firm i in year t is the yearly average of the monthly relative spread for firm i in year t. Monthly relative spread is computed as the difference between closing ask and bid prices for each month divided by the midpoint of closing ask and bid prices.	CRSP
$\ln(MV_{i,t})$	Natural logarithm of the market value for firm i in year t.	CRSP
$Volume_{i,t}$ (000,000)	The total volume of shares traded for firm i in year t.	CRSP
$TA_{i,t}$ (000,000)	Total asset for firm i in year t.	CRSP
$BTM_{i,t}$	Book-to-market ratio firm i in year t.	CRSP

Table 2
Summary statistics
This table reports the summary statistics (mean, median, and standard deviation) of main and supplementary model variables across all firms/stocks. Panel A reports the summary statistics for the main model variables and Panel B reports the supplementary variables. For the definitions and calculations of variables refer to Table 1. The units of variables are in parentheses following the variable names in the first column and the number of firm-year observations for each variable is in the last column.

Panel A: Main model variables				
	Mean	Median	Std. dev.	N
$CAPEX_{i,t}$ (%)	5.92	3.72	6.75	51,581
$CAPEXRND_{i,t}$ (%)	11.02	7.43	11.56	51,581
$CHGASSET_{i,t}$ (%)	12.94	5.40	36.50	51,581
$ROA_{i,t}$ (%)	9.09	11.15	14.88	51,581
$SG_{i,t}$ (%)	5.61	4.95	21.30	51,581
$Q_{i,t}$	1.95	1.48	1.43	51,581
$QT_{i,t}$	11.17	6.84	13.58	51,581
$CF_{i,t}$ (%)	9.71	10.07	12.50	51,581
$\ln(Asset)_{i,t}$	6.42	6.28	2.00	51,581
$INS_{i,t}$ (%)	0.56	0.59	1.23	51,581
$INSTR_{i,t}$	0.26	0.24	0.12	51,581
$\Delta Accuracy_{i,t}$ (%)	4.37	0.00	12.31	1,540
$EDGAR_{i,t}$ (00,000)	0.66	0.33	1.62	30,605
Panel B: Supplementary variables				
$ESP_{i,t}$ (%)	-3.43	0.33	97.57	40,689
$PrivateInfo_{i,t}$	0.01	0.00	0.01	31,126
$Insider_{i,t}$ (%)	6.41	0.20	671.63	40,299
$RES_{i,t}$ (%)	6.20	5.16	4.37	38,135
$Analyst_{i,t}$	7.93	5.58	7.07	39,842
$KZ_{i,t}$	-0.19	0.05	5.01	45,239
$CT_{i,t}$	37.97	26.73	30.69	10,665
$OddLot_{i,t}$ (%)	35.38	34.71	13.41	10,665
$LAO_{i,t}$ (00,000)	0.15	0.06	0.41	1,450
$\lvert Return_{i,t} \rvert$ (%)	2.47	1.48	2.83	1,540
$InverseP_{i,t}$ (1/$)	0.15	0.06	0.34	30,605
$Spread_{i,t}$ (%)	0.69	0.20	1.25	30,605
$\ln(MV_{i,t})$	13.32	13.25	1.97	30,605
$Volume_{i,t}$ (000,000)	1.21	0.27	3.81	30,605
$TA_{i,t}$ (000,000)	12.73	4.36	20.17	1,540
$BTM_{i,t}$	0.47	0.39	0.33	1,540

Table 3
AT and investment-to-price sensitivity: OLS

This table reports the results for the estimation of the impact of AT on the investment-to-price sensitivity using the following ordinary least squares (OLS) model:

$$I_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Q_{i,t} + \beta_2 QT_{i,t} + \beta_3 Q_{i,t} QT_{i,t} + \delta_1 CF_{i,t} + \delta_2 \ln(Asset_{i,t}) + \delta_3 INS_{i,t} + \delta_4 INSTR_{i,t} + \varepsilon_{i,t}$$

where $I_{i,t+1}$ is the investment of firm i in year $t+1$. In columns (i), (ii), and (iii) investment is respectively defined as the capital expenditures divided by lagged total assets ($CAPEX_{i,t+1}$), the capital expenditures plus R&D expenses divided by lagged total assets ($CAPEXRND_{i,t+1}$), and the annual change in total assets divided by lagged total assets ($CHGASSET_{i,t+1}$). Across all specifications, $Q_{i,t}$ is the firm's normalized stock price (Tobin's Q), $QT_{i,t}$ is the yearly AT proxy, $CF_{i,t}$ is the firm's cash flow, $\ln(Asset_{i,t})$ is the natural logarithm of the firm's total assets, $INS_{i,t}$ is the fraction of institutional holdings to total shares outstanding, $INSTR_{i,t}$ is institutional investors' turnover. All versions of models include both firm and year fixed effects (α_i and γ_t, respectively). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and year. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively. For the detailed definitions of variables refer to Table 1.

	$CAPEX_{i,t+1}$	$CAPEXRND_{i,t+1}$	$CHGASSET_{i,t+1}$
$Q_{i,t}$	0.878*** (31.84)	1.848*** (36.59)	9.940*** (37.87)
$QT_{i,t}$	-0.057*** (-10.90)	-0.037*** (-4.78)	-0.384*** (-9.92)
$\mathbf{Q_{i,t}QT_{i,t}}$	**0.039*** (11.20)**	**0.037*** (7.19)**	**0.359*** (13.37)**
$CF_{i,t}$	0.040*** (16.37)	0.034*** (7.21)	0.099*** (4.26)
$\ln(Asset_{i,t})$	-1.250*** (-30.04)	-3.035*** (-43.02)	-15.826*** (-44.90)
$INS_{i,t}$	0.014 (1.02)	-0.001 (-0.03)	0.187 (0.97)
$INSTR_{i,t}$	-0.954*** (-5.28)	-0.921*** (-3.42)	-1.632 (-1.28)
N obs.	51,581	51,581	51,581
R^2	9%	16%	18%

Table 4

AT and investment-to-price sensitivity: DiD

This table reports the results for the estimation of the impact of AT on the investment-to-price sensitivity using the following differences-in-difference (DiD) model:

$$I_{i,t+1} = \alpha_i + \beta_1 Q_{i,t} + \beta_2 Event_{i,t} + \beta_3 Treatment_{i,t} + \beta_4 Event_{i,t} Treatment_{i,t} + \beta_5 Q_{i,t} Event_{i,t} + \beta_6 Q_{i,t} Treatment_{i,t} + \beta_7 Q_{i,t} Event_{i,t} Treatment_{i,t} + \delta_1 CF_{i,t} + \delta_2 \ln(Asset_{i,t}) + \delta_3 INS_{i,t} + \delta_4 INSTR_{i,t} + \varepsilon_{i,t}$$

where $I_{i,t+1}$ is the investment of firm i in year $t+1$. In columns (i), (ii), and (iii) investment is respectively defined as the capital expenditures divided by lagged total assets ($CAPEX_{i,t+1}$), the capital expenditures plus R&D expenses divided by lagged total assets ($CAPEXRND_{i,t+1}$), and the annual change in total assets divided by lagged total assets ($CHGASSET_{i,t+1}$). Across all specifications, $Q_{i,t}$ is the firm's normalized stock price (Tobin's Q), $Event_{i,t}$ is a dummy variable set to zero before the autoquote introduction and one afterward, $Treatment_{i,t}$ is a dummy variable set to one for NYSE-listed firms and zero for Nasdaq-listed firms, $CF_{i,t}$ is the firm's cash flow, $\ln(Asset_{i,t})$ is the natural logarithm of the firm's total assets, $INS_{i,t}$ is the fraction of institutional holdings to total shares outstanding, $INSTR_{i,t}$ is institutional investors' turnover. All versions of models include firm fixed effect (α_i). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and year. The sample includes NYSE- and Nasdaq-listed stocks only and the sample period is from 2001 to 2005. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively. For the detailed definitions of variables refer to Table 1.

	$CAPEX_{i,t+1}$	$CAPEXRND_{i,t+1}$	$CHGASSET_{i,t+1}$
$Q_{i,t}$	0.798***	1.999***	8.494***
	(12.65)	(13.93)	(11.92)
$Event_{i,t}$	0.555***	1.853***	4.889***
	(2.84)	(4.99)	(2.62)
$Treatment_{i,t}$	1.469	11.215**	134.234*
	(0.97)	(2.29)	(1.75)
$Event_{i,t}Treatment_{i,t}$	-0.453	-1.614***	-2.343
	(-1.46)	(-3.13)	(-0.94)
$Q_{i,t}Event_{i,t}$	-0.246***	-0.747**	-1.300
	(-3.20)	(4.24)	(-1.47)
$Q_{i,t}Treatment_{i,t}$	0.852**	-0.353	-0.090
	(4.45)	(-1.23)	(-0.06)
$\mathbf{Q_{i,t}Event_{i,t}Treatment_{i,t}}$	**0.448*** **	**1.356*** **	**1.956**
	(2.88)	**(4.79)**	**(1.51)**
$CF_{i,t}$	0.039***	0.057***	0.277***
	(8.10)	(5.74)	(5.37)
$\ln(Asset_{i,t})$	-0.960***	-3.263***	-18.623***
	(-9.16)	(-16.38)	(-17.94)
$INS_{i,t}$	3.883***	3.175***	22.781***
	(7.08)	(3.44)	(4.83)
$INSTR_{i,t}$	0.448	0.545	0.640
	(0.91)	(0.69)	(0.18)
N obs.	8,515	8,515	8,515
R^2	11%	18%	19%

Table 5
AT and investment-to-price sensitivity: 2SLS IV

This table reports the results for the estimation of the impact of AT on the investment-to-price sensitivity using the following two-stage instrumental variable approach (2SLS IV) model:

$$I_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Q_{i,t} + \beta_2 \widehat{QT}_{i,t} + \beta_3 Q_{i,t}\widehat{QT}_{i,t} + Controls + \varepsilon_{i,t}$$

where $I_{i,t+1}$ is the investment of firm i in year $t+1$ defined as the capital expenditures divided by lagged total assets $CAPEX_{i,t+1}$, $Q_{i,t}$ is the firm's normalized stock price, and $\widehat{QT}_{i,t}$ is the predicted value of AT proxy using different instrumental variables in the first stage. In Model 1, $\widehat{QT}_{i,t}$ is the yearly average of the predicted daily AT proxy $QT_{i,d}$ using the model $QT_{i,d} = \alpha_i + \gamma_d + \beta_1 Autoquote_{i,d} + Controls^* + \varepsilon_{i,d}$, where α_i is firm and γ_d is day fixed effects, $Autoquote_{i,d}$ is a dummy variable set to zero before the autoquote introduction and one afterward, and $Controls^*$ are the first lag values of inverse price, trading volume, relative spread, natural logarithm of market value, and the absolute value of price changes. In Model 2, we predict the yearly AT proxy $\widehat{QT}_{i,t}$ using the average QT by stock i's size quartile group $(AvgQT_{i,t})$ as an instrumental variable. In Model 3, we predict the yearly AT proxy $\widehat{QT}_{i,t}$ using the lagged QT $(QT_{i,t-1})$ as an instrumental variable. In Model 4, the instrumental variables are $AvgQT_{i,t}$ and $QT_{i,t-1}$. Across all specifications, we include the firm's cash flow $(CF_{i,t})$, the natural logarithm of the firm's total assets $(\ln(Asset_{i,t}))$, the fraction of institutional holdings to total shares outstanding $(INS_{i,t})$, and institutional investors' turnover $(INSTR_{i,t})$ as control variables. All models include both firm and year fixed effects (α_i and γ_t, respectively). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and year. In Model 1, the sample includes NYSE-listed stocks only and the sample period is from 2001 to 2005. In Models 2, 3 and 4, we use the full sample (1996-2019). *, **, and *** denote the significance at 10%, 5%, and 1%, respectively. For the detailed definitions of variables refer to Table 1.

	Model 1 $Autoquote_{i,d}$	Model 2 $AvgQT_{i,t}$	Model 3 $QT_{i,t-1}$	Model 4 $AvgQT_{i,t}$ and $QT_{i,t-1}$
$Q_{i,t}$	1.020*** (7.28)	0.624*** (15.77)	1.064*** (32.49)	0.822*** (27.90)
$\widehat{QT}_{i,t}$	-0.116*** (-4.59)	-0.146*** (-13.91)	-0.053*** (-9.08)	-0.061*** (-9.43)
$\mathbf{Q_{i,t}\widehat{QT}_{i,t}}$	**0.007**** **(2.04)**	**0.048***** **(9.74)**	**0.033***** **(10.89)**	**0.032***** **(9.84)**
Controls	Yes	Yes	Yes	Yes
N obs.	4,669	58,907	45,114	45,114
R^2	13%	10%	9%	9%

Table 6
Revelatory Price Efficiency: AT and manager's forecast accuracy
This table reports the results for the estimation of the impact of AT on managers' forecast accuracy using the following model:

$$\Delta Accuracy_{i,t} = \alpha_i + \gamma_t + \beta_1 |Return_{i,t}| + \beta_2 QT_{i,t-1} + \beta_3 \Delta |Return_{i,t}| QT_{i,t-1} + Controls + \varepsilon_{i,t}$$

where $\Delta Accuracy_{i,t}$ is the manager's forecast accuracy of firm i in year t, $|Return_{i,t}|$ is the absolute value of return of firm i's stock in year t (computed as the percentage return over the period between managers' initial and updated forecast dates), $QT_{i,t-1}$ is the yearly AT proxy, and $Controls$ are the fraction of institutional holdings to total shares outstanding ($INS_{i,t}$), the institutional investors' turnover ($INSTR_{i,t}$), book-to-market ratio ($BMT_{i,t}$), total asset ($TA_{i,t}$), and volume ($Volume_{i,t}$). In column (i), we exclude $QT_{i,t-1}$ and $|Return_{i,t}|QT_{i,t-1}$ from the above model, whereas in column (ii) we include them. All versions of models include both firm and year fixed effects (α_i and γ_t, respectively. The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and year. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively. For the detailed definitions of variables refer to Table 1.

	(i)	(ii)
$\mathbf{\|Return_{i,t}\|}$	**0.356*** (3.07)**	**0.320** (2.75)**
$QT_{i,t-1}$		-0.120* (-1.85)
$\mathbf{\|Return_{i,t}\| QT_{i,t-1}}$		**0.005* (1.72)**
$INS_{i,t}$	0.802 (0.22)	0.893 (0.24)
$INSTR_{i,t}$	-3.093 (-0.70)	-3.102 (-0.71)
$BMT_{i,t}$	5.228*** (2.92)	5.413*** (3.01)
$TA_{i,t}$	-0.118*** (-3.59)	-0.112*** (-3.39)
$Volume_{i,t}$	2.355 (1.29)	2.230 (1.22)
N obs.	1,540	1,540
R^2	2.5%	2.8%

Table 7

Revelatory Price Efficiency: AT and non-robot EDGAR downloads

This table reports the results for the estimation of the impact of AT on the non-Robot EDGAR downloads using the following model:

$$EDGAR_{i,t+1} = \alpha_i + \gamma_t + \beta_1 QT_{i,t} + Controls + \varepsilon_{i,t}$$

where $EDGAR_{i,t+1}$ is the non-robot EDGAR downloads, $QT_{i,t}$ is the yearly AT proxy, and $Controls$ are the inverse price ($InverseP_{i,t}$), the relative spread ($Spread_{i,t}$), the natural logarithm of market value ($\ln(MV_{i,t})$), the trading volume ($Volume_{i,t}$), the absolute value of price changes ($\Delta Price_{i,t}$), the fraction of institutional holdings to total shares outstanding ($INS_{i,t}$), and the institutional investors' turnover ($INSTR_{i,t}$). The number of non-robot EDGAR downloads is measured using Ryans (2017). In column (i), AT is measured using $QT_{i,t}$ based on the full sample period (1996-2019) and in column (ii), AT is measured using the predicted values of $QT_{i,t}(\widehat{QT}_{i,t})$ by the Autoquote instrument (as defined in Table 5) based on the truncated sample period (2001-2005). All versions of models include both firm and year fixed effects (α_i and γ_t, respectively). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and year. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively. For the detailed definitions of variables refer to Table 1.

	(i) Full sample $QT_{i,t}$	(ii) Autoquote sample $\widehat{QT}_{i,t}$
$\mathbf{QT_{i,t}}$	**0.003*** (10.63)**	**0.006*** (5.60)**
$InverseP_{i,t}$	0.130** (2.49)	0.003 (0.08)
$Spread_{i,t}$	0.018*** (2.61)	0.005 (1.16)
$\ln(MV)_{i,t}$	0.207*** (8.80)	0.042** (2.21)
$Volume_{i,t}$	0.041*** (3.14)	0.013 (0.64)
$\Delta Price_{i,t}$	0.194** (2.20)	0.023* (1.61)
$INS_{i,t}$	-0.004 (-1.15)	-0.007 (-0.36)
$INSTR_{i,t}$	0.146*** (3.53)	-0.163*** (-4.96)
N obs.	30,605	3,250
R^2	4%	1.9%

Table 8

Revelatory Price Efficiency: Cross-sectional analysis

This table presents the results for the estimation of the cross-sectional impact of AT on the investment-to-price sensitivity using the following model:

$$I_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Q_{i,t} + \beta_2 QT_{i,t} + \beta_3 D_h + \beta_4 Q_{i,t} QT_{i,t} + \beta_5 Q_{i,t} D_h + \beta_6 QT_{i,t} D_h + \beta_7 Q_{i,t} QT_{i,t} D_h + Controls + \varepsilon_{i,t},$$

$I_{i,t+1}$ is the investment of firm i in year $t+1$ defined as the capital expenditures divided by lagged total assets $CAPEX_{i,t+1}$, $Q_{i,t}$ is the firm's normalized stock price, $QT_{i,t}$ is the yearly AT proxy, and D_h is a dummy variable that is equal to one if the value of a given measure is above the 75th percentile of that measure across all other stocks each year. In columns (i) to (v), D_h is respectively determined based on the fraction of institutional holdings to total shares outstanding ($INS_{i,t}$), the variance of returns driven by private information ($PrivateInfo_{i,t}$), relative spread ($Spread_{i,t}$), trading volume ($Volume_{i,t}$), and the amount of earning surprises ($ESP_{i,t}$). Controls are $CF_{i,t}$, $\ln(Asset_{i,t})$, $INS_{i,t}$ (excluded in column (ii)) and $INSTR_{i,t}$. All models include both firm and year fixed effects (α_i and γ_t, respectively). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and year. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively. For the detailed definitions of variables refer to Table 1.

	(i) $D_h = INS_{i,t}$	(ii) $D_h = PrivateInfo_{i,t}$	(iii) $D_h = Spread_{i,t}$	(iv) $D_h = Volume_{i,t}$	(v) $D_h = ESP_{i,t}$
$Q_{i,t}$	0.887*** (26.82)	0.848*** (21.43)	0.770*** (25.78)	0.835*** (23.98)	0.853*** (27.61)
$QT_{i,t}$	-0.054*** (-9.76)	-0.045*** (-5.95)	-0.059*** (-7.69)	-0.044*** (-7.63)	-0.065*** (-8.87)
D_h	0.602*** (3.67)	-0.099 (-0.70)	-1.443** (-9.84)	1.014** (5.78)	-0.265** (-2.08)
$QT_{i,t}Q_{i,t}$	0.037*** (10.02)	0.027*** (5.32)	0.037*** (7.96)	0.030*** (7.79)	0.044*** (9.82)
$Q_{i,t}D_h$	-0.076 (-1.54)	-0.004 (-0.07)	0.018 (0.26)	-0.085* (-1.65)	0.052 (1.12)
$QT_{i,t}D_h$	-0.069*** (-3.18)	-0.024* (-1.79)	0.039*** (3.56)	-0.135*** (-4.88)	-0.034** (-2.43)
$\mathbf{QT_{i,t}Q_{i,t}D_h}$	**0.027** (2.40)**	**0.025*** (2.71)**	**-0.019** (-2.53)**	**0.056*** (4.05)**	**0.024*** (2.70)**
$Controls$	Yes	Yes	Yes	Yes	Yes
N obs.	51,581	31,126	46,136	46,136	40,450
R^2	10%	10%	9.7%	9.4%	10%

Table 9
Investment-to-price sensitivity by AT quintiles
This table presents the impact of AT on the investment-to-price sensitivity by AT quintiles using the following regression:

$$I_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Q_{i,t} + \sum_{n=2}^{n=5} \beta_n QT_n + \sum_{n=2}^{n=5} \gamma_n Q_{i,t} QT_n + Controls + \varepsilon_{i,t}$$

where $I_{i,t+1}$ is investment of firm i in year $t+1$. In columns (i), (ii), and (iii) investment is respectively defined as the capital expenditures divided by lagged total assets ($CAPEX_{i,t+1}$), the capital expenditures plus R&D expenses divided by lagged total assets ($CAPEXRND_{i,t+1}$), and the annual change in total assets divided by lagged total assets ($CHGASSET_{i,t+1}$). Each firm-year observation is assigned into quintiles by the average $QT_{i,t}$ with the lowest value in quintile 1 and the highest value in quintile 5. Across all specifications, QT_n is the dummy variable that is equal to one if the stock is in the n^{th} quintile group. We omit QT_1 to handle the dummy variable trap. $Controls$ are the firm's cash flow ($CF_{i,t}$), the natural logarithm of the firm's total assets ($\ln(Asset_{i,t})$), the fraction of institutional holdings to total shares outstanding ($INS_{i,t}$), and institutional investors' turnover ($INSTR_{i,t}$). All models include both firm and year fixed effects (α_i and γ_t, respectively). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and year. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively. For the detailed definitions of variables refer to Table 1.

	(i) $CAPEX_{i,t+1}$	(ii) $CAPEXRND_{i,t+1}$	(iii) $CHGASSET_{i,t+1}$
$Q_{i,t}$	0.776*** (24.30)	1.769*** (29.84)	9.457*** (30.82)
QT_2	-0.957*** (-6.05)	-0.824*** (-3.16)	-7.405*** (-5.42)
QT_3	-1.607*** (-9.41)	-0.946*** (-3.52)	-6.765*** (-5.07)
QT_4	-1.821*** (-10.44)	-1.354*** (-5.11)	-8.858*** (-6.61)
QT_5	-1.606*** (-8.37)	-1.145*** (-4.08)	-6.814*** (-4.83)
$\mathbf{Q_{i,t}QT_2}$	**0.495*** (6.94)**	**0.478*** (3.79)**	**4.082*** (5.82)**
$\mathbf{Q_{i,t}QT_3}$	**0.866*** (10.51)**	**0.574*** (4.30)**	**4.222*** (6.34)**
$\mathbf{Q_{i,t}QT_4}$	**0.952*** (11.24)**	**0.846*** (6.39)**	**6.021*** (8.89)**
$\mathbf{Q_{i,t}QT_5}$	**0.775*** (7.61)**	**0.602*** (4.13)**	**4.303*** (5.74)**
$Controls$	Yes	Yes	Yes
N obs.	51,581	51,581	51,581
R^2	10%	16%	18%

Table 10

AT and investment-to-price sensitivity: Additional controls

This table reports the results for the estimation of the impact of AT on the investment-to-price sensitivity using the following ordinary least squares (OLS) model:

$$I_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Q_{i,t} + \beta_2 QT_{i,t} + \beta_3 Q_{i,t} QT_{i,t} + \delta_1 CF_{i,t} + \delta_2 \ln(Asset_{i,t}) + \delta_3 INS_{i,t} + \delta_4 INSTR_{i,t} + \delta_5 Control_{i,t} + \delta_6 Q_{i,t} Control_{i,t} + \varepsilon_{i,t}$$

where $I_{i,t+1}$ is the investment of firm i in year $t+1$ defined as the capital expenditures divided by lagged total assets $CAPEX_{i,t+1}$, $Q_{i,t}$ is the firm's normalized stock price, and $QT_{i,t}$ is the yearly AT proxy. The other explanatory variables are the firm's cash flow ($CF_{i,t}$), the natural logarithm of the firm's total assets ($\ln(Asset_{i,t})$), the fraction of institutional holdings to total shares outstanding ($INS_{i,t}$), institutional investors' turnover ($INSTR_{i,t}$), and $Control_{i,t}$ and $Q_{i,t}Control_{i,t}$. From column (i) to (iv), $Control_{i,t}$ is respectively given by $Insider_{i,t}$ (insider volume rate), $RES_{i,t}$ (return around earnings announcements), $Analyst_{i,t}$ (analysts' coverage), and $KZ_{i,t}$ (Kaplan-Zingales metric). All versions of models include both firm and year fixed effects (α_i and γ_t, respectively). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and year. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively. For the detailed definitions of variables refer to Table 1.

	(i) $Insider_{i,t}$	(ii) $RES_{i,t}$	(iii) $Analyst_{i,t}$	(iv) $KZ_{i,t}$
$Q_{i,t}$	0.826*** (27.71)	0.852*** (20.86)	0.844*** (20.35)	0.874*** (29.99)
$QT_{i,t}$	-0.047*** (-7.98)	-0.056*** (-9.81)	-0.057*** (-8.58)	-0.058*** (-10.35)
$\mathbf{Q_{i,t}QT_{i,t}}$	**0.033*** (8.62)**	**0.038*** (10.30)**	**0.038*** (9.15)**	**0.040*** (10.89)**
$CF_{i,t}$	0.038** (14.00)	0.038*** (14.01)	0.041*** (15.32)	0.036*** (13.46)
$\ln(Asset_{i,t})$	-1.191*** (-25.96)	-1.194*** (-24.24)	-1.204*** (-24.70)	-1.237*** (-27.37)
$INS_{i,t}$	0.009 (0.96)	0.008 (0.98)	0.012 (1.00)	0.009 (0.94)
$INSTR_{i,t}$	-0.708*** (-3.50)	-1.065*** (-5.01)	-0.775*** (-3.55)	-1.016*** (-5.22)
$Control_{i,t}$	-0.000 (-0.24)	-0.011 (-0.98)	0.020* (1.92)	-0.066*** (-5.98)
$Q_{i,t}Control_{i,t}$	0.000 (0.21)	0.000 (0.01)	-0.001 (-0.34)	0.010*** (4.68)
N obs.	40,299	38,135	39,842	45,239
R^2	9%	9%	10%	10%

Table 11

AT and investment-to-price sensitivity: MIDAS

This table presents the results for the estimation of the impact of AT on the investment-to-price sensitivity using the following model:

$$I_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Q_{i,t} + \beta_2 MIDASAT_{i,t} + \beta_3 Q_{i,t} MIDASAT_{i,t} + Controls + \varepsilon_{i,t}$$

where $I_{i,t+1}$ is the investment of firm i in year $t+1$ defined as the capital expenditures divided by lagged total assets $CAPEX_{i,t+1}$, $Q_{i,t}$ is the firm's normalized stock price, $MIDASAT_{i,t}$ is the yearly AT proxy obtained from the SEC's MIDAS data. In column (i), $MIDASAT_{i,t}$ is the cancel-to-trade ratio ($CT_{i,t}$) and in column (ii), it is the odd-lot trade rate ($OddLot_{i,t}$). $Controls$ are the firm's cash flow ($CF_{i,t}$), the natural logarithm of the firm's total assets ($\ln(Asset_{i,t})$), the fraction of institutional holdings to total shares outstanding ($INS_{i,t}$), and institutional investors' turnover ($INSTR_{i,t}$). All versions of models include both firm and year fixed effects (α_i and γ_t, respectively). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and year. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively. For the detailed definitions of variables refer to Table 1.

	(i) $MIDASAT_{i,t} = CT_{i,t}$	(ii) $MIDASAT_{i,t} = OddLot_{i,t}$
$Q_{i,t}$	0.420*** (6.50)	0.407*** (5.14)
$MIDASAT_{i,t}$	-0.008** (-2.14)	0.019*** (2.80)
$\mathbf{Q_{i,t}MIDASAT_{i,t}}$	**0.008*** (3.57)**	**0.005** (2.13)**
$CF_{i,t}$	0.033*** (7.87)	0.033*** (7.90)
$\ln(Asset_{i,t})$	-1.081*** (-9.03)	-1.240*** (-10.28)
$INS_{i,t}$	0.234 (0.81)	0.199 (0.72)
$INSTR_{i,t}$	-0.511** (-2.01)	-0.567** (-2.22)
N obs.	10,665	10,665
R^2	6%	6%

Table 12
AT and investment-to-price sensitivity: Latency arbitrage

This table reports the results for the estimation of the impact of AT on the investment-to-price sensitivity using the following ordinary least squares (OLS) model:

$$I_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Q_{i,t} + \beta_2 QT_{i,t} + \beta_3 Q_{i,t} QT_{i,t} + \beta_4 LAO_{i,t} + \beta_5 Q_{i,t} LAO_{i,t} + \beta_6 QT_{i,t} LAO_{i,t} + \beta_7 Q_{i,t} QT_{i,t} LAO_{i,t} + Controls + \varepsilon_{i,t}$$

where $I_{i,t+1}$ is the investment of firm i in year $t+1$, $Q_{i,t}$ is the firm's normalized stock price, $QT_{i,t}$ is the yearly AT proxy, and $LAO_{i,t}$ is the number of latency arbitrage opportunities for stock i in year t. In columns (i), (ii), and (iii) investment is respectively defined as the capital expenditures divided by lagged total assets ($CAPEX_{i,t+1}$), the capital expenditures plus R&D expenses divided by lagged total assets ($CAPEXRND_{i,t+1}$), and the annual change in total assets divided by lagged total assets ($CHGASSET_{i,t+1}$). $Controls$ are the firm's cash flow ($CF_{i,t}$), the natural logarithm of the firm's total assets ($\ln(Asset_{i,t})$), the fraction of institutional holdings to total shares outstanding ($INS_{i,t}$), and institutional investors' turnover ($INSTR_{i,t}$). All models include both firm and year fixed effects (α_i and γ_t, respectively). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and year. *, **, and *** denote the significance at 10%, 5%, and 1%, respectively. For the detailed definitions of variables refer to Table 1.

	$CAPEX_{i,t+1}$	$CAPEXRND_{i,t+1}$	$CHGASSET_{i,t+1}$
$Q_{i,t}$	0.868*** (6.77)	1.722*** (8.15)	5.834*** (6.35)
$QT_{i,t}$	-0.121*** (-4.00)	-0.055 (-1.37)	-0.842*** (-3.12)
$\mathbf{Q_{i,t}QT_{i,t}}$	**0.075*** (4.23)**	**0.030 (1.20)**	**0.553*** (3.41)**
$LAO_{i,t}$	2.536*** (3.69)	3.344*** (2.82)	9.971* (1.77)
$\mathbf{Q_{i,t}LAO_{i,t}}$	**-0.389** (-2.56)**	**-0.628*** (-2.05)**	**-1.183 (-0.80)**
$QT_{i,t}LAO_{i,t}$	0.139** (0.98)	0.262 (1.29)	0.059 (0.05)
$\mathbf{Q_{i,t}QT_{i,t}LAO_{i,t}}$	**-0.110** (-2.06)**	**-0.158** (-2.10)**	**-0.270 (-0.67)**
$CF_{i,t}$	0.038*** (2.10)	0.079** (2.50)	0.336*** (2.96)
$\ln(Asset_{i,t})$	-0.865*** (-3.10)	-2.864*** (-6.96)	-13.543*** (-5.45)
$INS_{i,t}$	-0.069 (-0.11)	2.058 (1.60)	9.718* (1.78)
$INSTR_{i,t}$	-0.056 (-0.06)	-2.778 (-1.61)	-5.481 (-0.56)
N obs.	1,468	1,468	1,468
R^2	18%	27%	20%

Table 13
AT and operating performance: Ranking approach
This table presents the results for the estimation of the impact of AT on the firms' future operating performance using the following model:

$$OP_{i,t+1} = \alpha_i + \gamma_t + \beta_1 Ranking_{i,t} + \beta_2 Q_{i,t} + Controls + \varepsilon_{i,t}$$

where $OP_{i,t+1}$ is the performance of firm i in year $t+1$, $Ranking_{i,t} \in (0,\ 100)$ represents the percentile of the degree of AT for firm i in year t, and $Q_{i,t}$ is the firm's normalized stock price (Tobin's Q). In columns (i) and (ii), $Ranking_{i,t}$ is determined based on the actual $QT_{i,t}$ in the full sample (1996-2019) and in columns (iii) and (iv), $Ranking_{i,t}$ is determined based on the predicted $QT_{i,t}$ ($\widehat{QT}_{i,t}$) in the autoquote sample using autoquote as an instrument (2001-2005). Across all specifications, $Controls$ are $CF_{i,t}$, $\ln(Asset_{i,t})$, $INS_{i,t}$, $INSTR_{i,t}$ and the lagged value of the respective operating performance ($OP_{i,t}$). All versions of models include both firm and year fixed effects (α_i and γ_t, respectively). The standard errors used to compute the t-statistics (in brackets) are double clustered by firm and year. *, **, and *** denote significance at 10%, 5%, and 1%, respectively. For the detailed definitions of variables refer to Table 1.

	Full sample		Autoquote sample	
	(i)	(ii)	(iii)	(iv)
	$ROA_{i,t+1}$	$SG_{i,t+1}$	$ROA_{i,t+1}$	$SG_{i,t+1}$
$\mathbf{Ranking_{i,t}}$	**0.005****	**0.029*****	**0.057*****	**0.213*****
	(2.38)	**(5.80)**	**(3.28)**	**(4.37)**
$Q_{i,t}$	0.946***	2.801***	1.314***	1.886***
	(15.61)	(25.19)	(5.43)	(5.03)
$CF_{i,t}$	-0.015*	-0.069***	-0.024	-0.181**
	(-1.67)	(-4.99)	(-0.90)	(-4.09)
$\ln(Asset_{i,t})$	-0.818***	-4.367***	-0.522***	-1.559**
	(-10.54)	(-24.64)	(-2.73)	(-2.41)
$INS_{i,t}$	0.004	0.257***	0.236	6.847***
	(0.77)	(4.40)	(0.31)	(3.35)
$INSTR_{i,t}$	0.521	-0.926	0.732	1.166
	(1.48)	(-1.09)	(0.76)	(0.43)
$ROA_{i,t}$	0.455***	-	0.492***	-
	(39.32)		(12.59)	
$SG_{i,t}$	-	0.025**	-	0.010
		(2.49)		(0.53)
N obs.	51,581	51,581	4,669	4,669
R^2	9%	16%	30%	2%

Table 14

AT and operating performance: Portfolio approach

This table presents the results for the estimation of the impact of AT-driven investment-to-price sensitivity on the portfolio's future operating performance using the following model:

$$OP_{z,t+1} = \alpha_z + \gamma_t + \beta_1\beta_{z,t} + \beta_2 Q_{z,t} + Controls + \varepsilon_{z,t}$$

where $OP_{z,t+1}$ is the performance of portfolio z in year $t+1$ and $\beta_{z,t}$ is the AT-driven CAPEX-to-price sensitivity of portfolio z at time t, and $Q_{z,t}$ is the average Tobin's Q for portfolio z in year t. To obtain $\beta_{z,t}$ for each portfolio-year, we first split the sample into deciles each year based on the interaction variable, $Q_{i,t}QT_{i,t}$. We then run year-by-year investment regressions for each portfolio to obtain the interaction coefficient for each of the 10 portfolios each year. In columns (i), performance is defined as one year ahead return on assets ($ROA_{i,+1}$) and in columns (ii), performance is defined as one year ahead sales growth ($SG_{i,t+1}$). Across all specifications, $Controls$ are the average cash flow ($CF_{z,t}$), the average logarithm of the total assets ($\ln(Asset_{z,t})$), the average fraction of institutional holdings to total shares outstanding ($INS_{z,t}$), the average turnover of institutional investors ($INSTR_{z,t}$), and the lagged dependent variable ($OP_{z,t}$) for portfolio z at time t. All versions of models include both portfolio and year fixed effects (α_z and γ_t, respectively). The standard errors used to compute the t-statistics (in brackets) are double clustered by portfolio and year. *, **, and *** denote significance at 10%, 5%, and 1%, respectively. For the detailed definitions of variables refer to Table 1.

	(i) $ROA_{z,t+1}$	(ii) $SG_{z,t+1}$
$\boldsymbol{\beta_{z,t}}$	**0.217*** (2.76)**	**0.165 (1.23)**
$Q_{z,t}$	-2.24*** (-9.33)	-1.551** (-2.48)
$CF_{z,t}$	0.908*** (13.46)	0.366** (2.06)
$\ln(Asset_{z,t})$	1.373*** (5.21)	-0.252 (-0.55)
$INS_{z,t}$	-1.262 (-0.70)	0.291 (0.09)
$INSTR_{z,t}$	-15.523*** (-3.88)	-6.623 (-0.88)
$ROA_{z,t}$	0.080** (2.37)	-
$SG_{z,t}$	-	0.788*** (16.94)
N obs.	240	240
R^2	67%	88%

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