The Real Effects of Algorithmic Trading

by

Huihao Yan

Business Administration
Duke University

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Dissertation submitted in partial fulfillment of
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ABSTRACT

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Abstract

Prior literature finds that algorithmic trading (AT) benefits the financial market by improving liquidity and accelerating the incorporation of existing information into prices. This paper shows that AT also has negative real effects: it reduces the sensitivity of corporate investment to stock prices. Moreover, firms' future operating performance deteriorates following periods of high AT activity. The evidence is consistent with algorithmic traders crowding out fundamental traders' information acquisition, leading to less information in prices for managers to learn and hence worse investment efficiency. Supporting evidence is also observed among financial analysts, who also learn less from stock prices when making forecast revisions.

Dedication

I dedicate this dissertation to my parents, Bicheng Yan and Xinchun Lu.

Contents

List of Tables

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I am deeply indebted to my dissertation committee. I would like to express my sincere gratitude to my co-supervisors, Qi Chen and Bill Mayew, not only for their continuous guidance throughout my Ph.D. studies, but also the opportunity to work as co-authors on several research projects. I learned a great deal from them on how to think critically and conduct rigorous research. I am grateful for the invaluable support from my committee members, Alon Brav and Rahul Vashishtha. Alon led me into academic research when I was a master's student and has been an inspiration to me ever since. Rahul provided crucial feedback at each stage of my dissertation and other papers. I greatly appreciate helpful comments and suggestions from Scott Dyreng, Zhaoyang Gu, Cam Harvey, John Heater, Zeqiong Huang, Xu Jiang, Suresh Nallareddy, Katherine Schipper, Eddie Watts, Brian Weller, Hao Xue, my fellow Ph.D. colleagues, and workshop participants at Baruch College, the Chinese University of Hong Kong, Duke University, the University of Pittsburgh, Rice University, the University of Rochester, and the Singapore Management University. Last but not least, I thank my family, especially Feng Bao, for their unconditional support throughout the years, and all my friends who encouraged me to strive for my goal.

1. Introduction

Modern securities trading is highly automated. Algorithmic trading (AT), defined as the use of computer algorithms to automatically execute certain trading strategies (Hendershott et al. (2011)), has become a dominant component of the current market structure (SEC (2010)). In fact, high frequency trading (HFT), a prominent subset of AT, accounts for around 60% of daily US equity trading volume alone (Meyer et al. (2018))[1]. Whether algorithmic traders (ATs) benefit or hurt market quality is hotly debated among regulators, in the media, and in a rapidly growing academic literature (Menkveld (2016)). The debate, however, so far has focused exclusively on the impact of AT in the financial markets. In this paper, I ask a question that has received little attention: does AT affect decision making in the real economy?

I propose that AT can have real consequences through information feedback effects from stock prices to decision makers (Dow and Gorton (1997), Subrahmanyam and Titman (2001), Bond et al. (2012)). Prices aggregate information acquired by heterogeneously informed traders (Hayek (1945)), some of which may be new to firm managers[2]. Therefore, managers have incentives to learn from "the wisdom of crowds" to guide their actions (Luo (2005), Chen et al. (2007), Bakke and Whited (2010), Zuo (2016)). In this paper, I consider

[1] HFT refers to trading strategies that use extraordinarily high-speed and sophisticated computer algorithms to establish and liquidate positions during very short time frames (SEC (2010), p. 45).
[2] For example, traders as a collection may possess superior information on macroeconomic conditions, consumer demand and industry competition. Allen (1993) argues that market information has become more useful as production processes have become more complex. Rappaport (1987) provides anecdotal evidence on how managers use the information in prices for investment decisions.

the possibility that AT influences the informativeness of stock prices to managers by affecting traders' costly information acquisition.

To understand how AT can influence the informativeness of stock prices, consider the Bond et al. (2012) framework that distinguishes between two types of price efficiency: Forecasting Price Efficiency (FPE) and Revelatory Price Efficiency (RPE). FPE is defined as the extent to which prices reflect future cash flows (i.e., the total amount of information in prices), while RPE refers to the extent to which prices reveal new information to managers. RPE is more valuable for real decisions than FPE, because prices with high FPE may contain information already known to managers. Prior work has examined the role of AT in the price discovery process, most of which documents that AT accelerates the incorporation of *existing* information into prices[3](i.e., AT improves FPE). However, this literature does not speak to another dimension of the price discovery process, i.e., the acquisition of *new* information by traders. If AT deters the production of new information unknown to managers, RPE will decrease and in turn inhibit what managers can learn from prices when making real decisions.

A priori, theory provides ambiguous predictions about the effects of AT on private information acquisition, because algorithms are used for many different reasons and

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[3] Carrion (2013) finds that it takes less time for stock prices to incorporate information from order flow and market index returns on days when ATs are more active. Brogaard et al. (2014) find that ATs tend to trade in the opposite direction to transitory pricing errors and in the same direction as future permanent price moves, pushing prices closer to fundamentals. Chadboud et al. (2014) document a similar effect in the foreign exchange market, where ATs reduce arbitrage opportunities and excess volatility.

strategies[4]. On the one hand, theoretical models (Hoffman (2014), Han et al. (2014), Ait-Sahalia and Saglam (2017)) predict that competition among algorithmic market makers, coupled with their ability to better screen informed order flows and update stale quotes, would lead to narrowed quoted spreads, reduced price impact of trades, and diminished short-term volatility. These predictions are supported by empirical evidence (Hendershott et al. (2011), Hasbrouck and Saar (2013), Lyle and Naughton (2016), Boehmer et al. (2018), Malinova et al. (2018)). Prior literature (Grossman and Stiglitz (1980), Fang et al. (2009)) suggests that liquid markets reduce trading costs and stimulate information acquisition by traders, predicting a positive association between AT and information production (the liquidity channel).

On the other hand, there are models that feature opportunistic liquidity-taking ATs who employ order anticipation strategies[5] to profit at the expense of non-ATs (Baldauf and Mollner (2018), Yang and Zhu (2017)). In his popular book *Flash Boys*, Michael Lewis vividly depicts a real-life scenario where an experienced trader from the Royal Bank of Canada was ambushed by an AT:

> *"Watch closely. I am about to buy one hundred thousand shares of AMD. I am willing to pay four dollars a share. There are currently one hundred thousand shares of AMD being offered at four dollars a share – ten thousand on BATS, thirty-five thousand on the New York Stock Exchange, thirty thousand on Nasdaq, and twenty-five thousand on Direct Edge. You could see it all on the screens. We'd all sit there and stare at the screen and I'd have my finger over the Enter*

[4] Hagstromer and Norden (2013) and Hasbrouck and Saar (2013) categorize AT into agency and proprietary (typically associated with HFT). HFT strategies can be further categorized into market making and opportunistic trading.

[5] Order anticipation strategies refer to "the employment of sophisticated pattern recognition software to ascertain from publicly available information the existence of a large buyer (seller), or the sophisticated use of orders to ping different market centers in an attempt to locate and trade in front of large buyers and sellers" (SEC (2010)).

button. I'd count out loud to five … Then I'd hit the Enter button and – boom! – all hell would break loose. The offerings would all disappear, and the stock would pop higher."

These strategies are also documented in several empirical studies to be associated with increased trading costs to large institutional traders (Korajczyk and Murphy (2018), Hirschey (2018), van Kervel and Menkveld (2018)). The opportunistic ATs essentially free ride on the information collected by non-ATs, and can crowd out the latter's incentive for fundamental research (the crowding out channel)[6]. The models and empirical evidence echo the concern raised in Stiglitz (2014), who argues that the improvement in "nanosecond" price discovery associated with AT comes at the expense of other traders who have spent resources to obtain information about the real economy, resulting in an overall less informative stock market.

Whether the liquidity channel or the crowding out channel dominates in the equity market is an important empirical question as it determines whether managers can glean more or less information from prices to guide their real decisions. I investigate this question by examining the effect of AT on investment sensitivity to prices, a common approach adopted in the literature to study how learning from prices can affect real investment decisions[7] (e.g., Morck et al. (1990), Chen et al. (2007), Foucault and Fresard (2012),

[6] The models in Baldauf and Mollner (2018) and Yang and Zhu (2017) unambiguously predict a decline in fundamental information acquisition due to order anticipation strategies. Empirically, Weller (2017) finds that traders reduce information acquisition up to one month before earnings announcements. Lee and Watts (2018) find that a tick size increase reduces AT and increases fundamental information acquisition in the pre-announcement period. Anecdotal evidence also suggests that mutual funds are replacing fundamental portfolio managers with quantitative and tech-driven funds (Hunnicutt (2017)).
[7] Morck et al. (1990) provide four interpretations on the association between future investment and stock prices. I discuss each of them in Section 5.4.

Edmans et al. (2017), Jayaraman and Wu (2018)). A positive (negative) association between AT and investment-price sensitivity indicates that AT strengthens (weakens) the response of investment to price signals, which is consistent with AT encouraging (deterring) the acquisition of new information (unknown to managers) by non-ATs.

To empirically investigate this issue, I construct AT proxies using the Market Information Data Analytics System (MIDAS), made publicly available by the SEC since 2012. MIDAS collects and processes order book data of the 13 national equity exchanges time-stamped to the microsecond. Following Weller (2017), I construct four proxies for AT: odd lot volume ratios (i.e., the fraction of volume coming from trades of less than 100 shares), order-to-trade ratios, cancel-to-trade ratios, and trade-to-volume ratios (i.e., the inverse of trade size). Existing literature suggests that ATs tend to continuously submit and cancel orders within short time intervals (SEC (2010), Hasbrouck and Saar (2013)), and their trade sizes are relatively small (Hendershott (2011), Carrion (2013), O'Hara et al. (2014)). Therefore, a higher value of each of the four proxies indicates a higher level of AT activity.

I find a negative association between AT and investment-*q* sensitivity in the OLS regressions, consistent with AT crowding out information production so that managers base investment less on prices. However, this specification potentially suffers from reverse causality, as ATs may select into firms with lower investment-*q* sensitivity where more informed traders are present (Edmans et al. (2015)).

To overcome this limitation, I follow the instrumental variables (IV) technique of Weller (2017) and use the log of the average stock prices as an instrument for exogenous AT activities. The relevance condition requires that stock prices are correlated with AT. This follows from the "sub-penny" rule (SEC Rule 612) mandating a minimum price increment of one cent for orders in stocks covered by Reg NMS. ATs continually monitor and update quotes. They are expected to participate more in trading stocks with higher prices all else equal, because a small change in stock value with low price may require no actions by algorithms as the magnitude of change does not reach the one penny tick size. The exclusion restriction requires that controlling for covariates such as market capitalization and cash flows, variation in lagged stock prices should relate little to investment-q sensitivity. A priori, there is little theoretical foundation to oppose this assumption. The results from the IV regressions confirm that corporate investment is less sensitive to stock prices when the level of AT activity is high, establishing a causal link that AT reduces the production of information unknown to managers, and hence RPE.

To provide additional evidence on the underlying crowding out mechanism, I conduct several cross-sectional tests. First, theory suggests that opportunistic ATs' order anticipation strategies are more likely to drive out fundamental traders' information acquisition (Baldauf and Mollner (2018), Yang and Zhu (2017)). Since ATs' aggressive liquidity-taking activities are more prevalent in illiquid stocks (Hirschey (2018)), I expect and find a greater reduction in investment-q sensitivity for these stocks. Second, the crowding out effects should be stronger in stocks where the initial information rents to informed traders were larger (Chen et al. (2007)). Consistent with this expectation, I find that the decrease in investment-*q* sensitivity concentrates in firms with low analyst coverage. Finally, I explore whether accounting conservatism affects the extent to which AT reduces investment-*q* sensitivity. Chen et al. (2018) theoretically show that more conservative accounting system attracts more informed trading and thus facilitates managerial learning. If AT indeed crowds out informed traders, the reduction in investment-*q* sensitivity would be greater in these firms. The evidence is consistent with this prediction as well.

While a reduction in investment-*q* sensitivity indicates less managerial learning from prices and hence worse investment efficiency, it is not a direct measure. To further investigate the real implications of AT, I examine the effect of AT on future operating performance (Chen et al. (2007), Jayaraman and Wu (2018)). If AT reduces information production by informed traders, managers will not be able to learn much information from prices and their investment decisions are more likely to be incorrect. Using 1 and 2-year ahead ROA, sales growth and asset turnover as proxies for future operating performance, I find that AT is negatively associated with these performance measures, consistent with the hypothesis that AT crowds out the production of information useful for managerial learning.

I further explore the commonality and diversity in the underlying strategies that drive the four AT proxies by performing a Principal Component Analysis (PCA). Two principal components can explain 96% of total variations for the four AT proxies. The first component is positively associated with all of the four AT proxies, while the second component is positively associated with Order/Trade and Cancel/Trade but negatively associated with Oddlot and Trade/Volume. Since market-making ATs are more likely to submit and cancel a large amount of orders relative to actual trades, while liquidity-taking ATs tend to constantly execute trades in small sizes, I conjecture that the first principal component is more consistent with liquidity taking activities and the second principal component is more representative of market-making AT. Consistent with my intuition, I find that the reduction in investment-q sensitivity is driven by the first component, but not the second.

The crowding out effect of AT also inhibits what financial analysts can learn from prices. I find that AT reduces the sensitivity of analysts' long-term growth forecast revision to past stock returns. This implies that the detrimental effects of AT on information production generalize to classes of market participants beyond firm management.

This paper makes three contributions. First, it advances the growing literature in AT. Prior studies generally focus on the effects of AT on various measures of capital market quality. While these studies highlight the role AT plays in improving liquidity and accelerating the incorporation of existing information into prices (Carrion (2013), Brogaard et al. (2014), Chadboud et al. (2014), Zhang (2018)), they are silent about the production of new information by traders[8]. I document that reduced information

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[8] One exception is Weller (2017), who examines how AT affects information acquisition around quarterly earnings announcements. Using price jump ratios as a proxy for traders' information acquisition activity, he

asymmetry comes with a price: the diminished production of information useful for managers' investment decisions.

Second, beyond the real effects of AT on information production, my consideration of how AT's real effects are moderated by accounting conservatism adds to the accounting literature that studies how financial reporting attributes impact capital allocation (Konodia and Lee (1998), Dye and Sridhar (2002), Kanodia and Sapra (2016), Leuz and Wysocki (2016)).

Third, this paper contributes to the broader literature on both the real effects of financial markets (Dow and Gorton (1997), Subrahmanyam and Titman (2001), Bond et al. (2012)) and studies that examine the effect of technological advancement in financial markets on price efficiency and economic efficiency. Bai et al. (2016) document that the US financial markets have become more informative during 1960 to 2014, largely due to increased information production by market participants. However, the recent trend towards automated trading and passive index investing is crowding out fundamental research (Gider et al. (2016), Israeli et al. (2017)), which can be detrimental to the efficiency of real resource allocation. My study shows that this is indeed the case: fast speed and sophisticated algorithms facilitated by advanced technology have unintended

finds AT reduces information acquisition up to one month before earnings announcements. However, he proxies for the total amount of acquirable information using returns around earnings announcements, which should be already known by managers.

consequences as predicted in Stiglitz (2014), leading to less informative markets and diminished real efficiency.

The rest of the paper proceeds as follows. Section 2 develops my main hypothesis and discusses the empirical design. Section 3 describes the data and sample construction procedure. Section 4 presents the main empirical results. Section 5 performs additional analyses and Section 6 concludes.

2. Hypothesis development and empirical approach

2.1 Price efficiency and economic efficiency

Price efficiency and economic efficiency are closely linked (Dow and Gorton (1997), Bond et al. (2012)). Stock prices not only reflect market participants' assessment of managers' past decisions, but also provide valuable information to guide their future investment (i.e., the learning perspective). While insiders have access to all the firm-specific information, dispersed traders as a collection may possess better information than firm managers on certain aspects, such as macroeconomic conditions, industry competition, and demand growth. Moreover, large sample evidence is empirically documented that managers indeed use price signals to guide their real decisions, both in big corporate events such as M&A (Luo (2005), and day-to-day investments (Chen et al. (2007), Jayaraman and Wu (2018)).

Bond et al. (2012) term the extent to which prices reveal new information to managers as "Revelatory Price Efficiency (RPE)". They distinguish it from another type of price efficiency, Forecasting Price Efficiency (FPE), defined as the extent to which prices reflect future cash flows (i.e., the total amount of information in prices)[9]. They argue that it is RPE, rather than FPE, that matters more for real decisions, because prices with high FPE may contain information already known to managers. A desirable level of RPE

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[9] The different between FPE and RPE is analogous to the different between "informational efficiency" and "informativeness" in Brunnermeier (2005), where information efficiency measures the extent to which prices reflect all information currently available to market participants, and informativeness refers to the absolute level of information contained in prices.

can only be achieved when traders are willing to incur costs to produce and trade on information about future profitability. In this paper, I study whether advances in technology, represented by the rise of AT in electronic trading venues, influence traders' incentive to acquire information, which in turn affects RPE and thus real efficiency.

2.2 AT and information acquisition

2.2.1 Category of AT strategies

A priori, the effect of AT on information acquisition is ambiguous. AT strategies are diverse and have different implications for information production. Prior literature generally categorizes AT activity into agency and proprietary (Hagstromer and Norden (2013), Hasbrouck and Saar (2013)). The former is typically a service provided to buy-side institutions to minimize the cost of executing trades (e.g., algorithms that break up large orders into pieces and send them over to multiple trading venues). Proprietary algorithms are used by technologically sophisticated firms to profit from the trading process itself. Featured with super-low-latency infrastructure and large amounts of trading during short time frames, these high-frequency traders (HFTs) have received heightened attention from the regulators, the media, and academic researchers. HFTs both supply and take liquidity in trading (Hagstomer and Norden (2013), Hendershott and Riordan (2013)). Theory suggests that they can have different effects on private information acquisition depending on their role in trading.

2.2.2 Market-making AT and information acquisition

When ATs are market makers, the sophisticated algorithms enable them to quickly update stale quotes in response to the arrival of new information, reducing the risk of being picked off by informed traders (Hoffmann (2014), Han et al. (2014), Ait-Sahalia and Saglam (2017)). Consistent with theoretical predictions, empirical evidence shows that AT narrows bid-ask spreads and reduces both the price impact of trades and short-term volatility (Hendershott et al. (2011), Hasbrouck and Saar (2013), Lyle and Naughton (2016), Boehmer et al. (2018), Malinova et al. (2018)). The presence of algorithmic market makers improves market liquidity and reduces the trading costs to all traders, which encourages more information acquisition (Grossman and Stiglitz (1980), Fang et al. (2009)), implying increased RPE and real efficiency. I refer to this possible AT effect as the liquidity channel.

2.2.3 Opportunistic AT and information acquisition

On the other hand, the ultra-fast speed of ATs can put non-ATs at a disadvantage. As algorithmic market makers become better able to screen informed order flows and update stale quotes, the information rents to non-ATs decrease. Additionally, opportunistic liquidity-taking ATs may employ order anticipation strategies to profit at the expense of non-ATs (Baldauf and Mollner (2018), Yang and Zhu (2017)). In these cases, ATs essentially free ride on the information collected by other traders, which eventually should crowd out their fundamental research. Empirically, such order anticipation strategies are documented to be employed by ATs across several equity markets, leading to higher transaction costs of non-AT institutions (Korajczyk and Murphy (2018), Saglam (2017), Hirschey (2018), van Kervel and Menkveld (2018)). If the returns to investing in information are reduced, traders will produce less forward-looking information, and managers have less to learn from prices. As a result, RPE will decline in the presence of AT. I refer to this possible AT effect as the crowding out channel.

2.3 Empirical approach

I examine the real effects of AT in the context of firm investment, a major corporate decision. Following prior literature (Tobin (1969), Morck et al. (1990), Chen et al. (2007), Foucault and Fresard (2012), Edmans et al. (2017), Jayaraman and Wu (2018)), I test the competing hypotheses by examining how AT activity affects a firm's investment-q sensitivity. The greater the new information in stock prices (i.e., RPE), the more managers will condition their investment on stock prices. Therefore, a positive association between AT and investment-q sensitivity is consistent with the liquidity channel being dominant, while a negative association between AT and investment-q sensitivity is consistent with the crowding out channel being dominant. Specifically, I estimate the following regression:

$$I_{i,t+1} = \alpha_i + \eta_t + \beta_1 q_{i,t} + \beta_2 AT_{i,t} * q_{i,t} + \beta_3 AT_{i,t} + \beta_4 size_{i,t} + \beta_5 CFO_{i,t} + \beta_6 AT_{i,t} * CFO_{i,t} + \epsilon_{i,t} \quad (1)$$

where $I_{i,t+1}$ is firm *i*'s investment in year t+*1*, α_i is firm fixed effects, η_t is year fixed effects, $q_{i,t}$ is the normalized price of firm i in year t calculated as the market value of equity plus book value of assets minus book value of equity scaled by book assets, $AT_{i,t}$ is the proxy for AT activity (details in Section 3) during year t, and control variables include $AT_{i,t}$, $size_{i,t}$(log market capitalization), $CFO_{i,t}$ (cash flows from operations) and

$AT_{i,t} * CFO_{i,t}$. The coefficient of interest is β_2. The liquidity channel predicts a positive β_2, while the crowding out channel predicts a negative β_2. Cash flows is a non-price-based measure of a firm's investment opportunities. Since the level of AT activity should only operate through the price signals, β_6 is expected to be insignificantly different from zero.

3. Data and sample construction

The data sources in this paper include: accounting data and executive compensation from Compustat; stock prices, returns, and liquidity data from CRSP; analyst forecasts data from IBES; and order book data from the Market Information Data Analytics System (MIDAS). In response to the Flash Crash on May 6, 2010, The SEC launched MIDAS in 2012 with the aim of more efficiently collecting and analyzing order book data for equities and futures. MIDAS collects and processes data from the consolidated tapes as well as from the proprietary feeds[10] of the 13 national equity exchanges time-stamped to the microsecond. Specifically, MIDAS collects posted orders and quotes on national exchanges, modifications/cancellations of those orders, trade executions against those orders, and off-exchange trade executions. MIDAS summarizes these billions of messages into aggregates by date, stock, and exchange. While MIDAS does not specifically identify whether an order submission/cancellation is initiated by an algorithmic trader, it is the most comprehensive publicly available data source to trace their activity[11].

[10] According to the SEC, every day MIDAS collects about 1 billion records from these proprietary feeds. They are typically used by only the most sophisticated market participants such as market makers and high-frequency traders. Most institutional investors, retail investors and academics generally do not consume this data as it is extremely voluminous and requires specialized data expertise.

[11] A number of papers (e.g., Broggard et al. (2014), Carrion (2013), Hirschey (2018)) use proprietary data provided by NASDAQ that identifies a subset of high frequency traders. This data set is limited to a stratified sample of 120 stocks in 2008 and 2009. Kirilenko et al. (2017), Baron et al. (2018) and Clark-Joseph (2013) examine transaction level data with trader identifiers on a single security, the E-Mini, during short time-frames ranging from 3 days to 2 months in 2010. SEC (2014) provides a review on papers that use data sets with HFT identifiers.

Following Weller (2017) and SEC guidelines, I construct four proxies for AT from MIDAS: (1) the odd lot volume ratio is the total volume associated with odd lot trades[12] divided by the total trade volume, (2) the order-to-trade volume ratio is the total volume across all orders placed divided by the total trade volume, (3) the cancel-to-trade ratio is the number of full or partial cancellations divided by the number of trades, and (4) the trade-to-volume is the number of trades divided by the total trade volume (i.e., inverse of trade size)[13]. Existing literature suggests that ATs tend to continuously submit and cancel orders within short time intervals (SEC (2010), Hasbrouck and Saar (2013)), and their trade sizes are relatively small and often in odd lots (Hendershott et al. (2011), Carrion (2013), O'Hara et al. (2014)). Therefore, higher values of each of the four proxies indicate higher level of AT activity. All four proxies are computed by aggregating daily order book data during a year[14] and then taken the natural logarithm to reduce right skewness.

Appendix A provides the sample construction procedure. The sample includes all firm-years in the intersection of Compustat, CRSP and MIDAS from 2012-2017. Each firm-year is required to have at least 63 trading days with non-missing AT proxies and

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[12] An odd lot is an order amount for a security that is less than a round lot, i.e., the normal unit of trading for that particular asset. A round lot is defined as 100 shares for all but three tickers: BRK.A (Berkshire Hathaway Inc.) and SEB (Seaboard Corp) have a round lot of one, and BH (Biglari Holdings Inc.) has a round lot of 10.

[13] NYSE and AMEX use the level-book method for order book reporting, while the other exchanges use the more granular order-based method. Several ratios are not directly comparable under the two book reporting mechanisms. Following the guideline of the SEC, I exclude NYSE and AMEX when calculating the odd lot ratio, the cancel-to-trade ratio, and the trade-to-volume ratio. More details regarding the MIDAS methodology is available at: https://www.sec.gov/marketstructure/mar_methodology.html.

[14] For example, assume there are 252 trading days for firm i in year t, then $OddLotRatio_{i,t} = \frac{\sum_{k=1}^{252} OddLotVolume_{i,t,k}}{\sum_{k=1}^{252} TotalVolume_{i,t,k}}$.

stock prices. The final sample includes 12,737 firm-years with non-missing variables to estimate Equation (1).

Panel A of Table 1 presents summary statistics of variables used to estimate equation (1). All variables are winsorized at 1% and 99% to remove the impact of outliers. The dependent variable, corporate investment, is measured as capital expenditure scaled by beginning net PP&E[15], expressed in percentage points. Panel B reports the pairwise correlations among the four AT proxies. All the correlations are highly positive, consistent with them capturing the same underlying construct. To further validate the commonality among the AT proxies, I perform a Principal Component Analysis. As shown in Panel C, the first principal component alone explains 66% of the total variance. Moreover, it is positively correlated with all the four proxies, suggesting that it is a good summary statistic for the underlying phenomenon of AT activity. Therefore, I include the first principal component scores (*PC1*) as an additional proxy for AT in subsequent analyses.

[15] The results are robust to alternative measures of investment, e.g., the sum of capital expenditure and R&D scaled by beginning total assets. Section 5.5 provides results for the robustness tests.

Table 1: Descriptive Statistics

Panel A of this table reports the summary statistics of the variables used in equation (1). See variable definition in Appendix B. Panel B reports the pairwise correlations between the four AT proxies, and their correlations with the log average prices during year *t*. Panel C reports the results from the Principal Component Analysis on the four AT proxies. Components with eigenvalues greater than 1 are retained. The correlations between the components and the four AT proxies as well as the explanatory proportions of each component are tabulated.

Panel A: Summary statistics

Variable	N	Mean	S.D.	25th	Median	75th
CAPEX/Net PPE	12737	31.12	40.14	10.76	19.6	35.45
q	12737	2.05	1.59	1.07	1.48	2.3
CFO	12737	0.03	0.19	0.01	0.06	0.12
size	12737	6.59	2.08	5.08	6.59	8.01
oddlot	12737	-2.55	0.86	-2.96	-2.37	-1.93
order to trade	12737	3.73	0.62	3.3	3.7	4.13
cancel to trade	12737	3.35	0.62	2.94	3.26	3.7
trade to volume	12737	-4.8	0.47	-4.99	-4.64	-4.48

Panel B: Correlation matrix

Variables	*oddlot*	*order/trade*	*cancel/trade*	*trade/volume*	*log price*
oddlot	1				
order/trade	0.584	1			
cancel/trade	0.320	0.805	1		
trade/volume	0.953	0.506	0.160	1	
log price	0.798	0.459	0.143	0.816	1

Panel C: Principal component analysis of four AT proxies

Principal Components	*oddlot*	*order/trade*	*cancel/trade*	*trade/volume*	Explanatory Proportion
First Component	0.544	0.531	0.404	0.509	0.663
Second Component	-0.400	0.389	0.660	-0.503	0.297

4. Empirical Results

4.1 AT and investment-price sensitivity

Table 2 reports the results from estimating equation (1). To facilitate the comparison of economic magnitude among different specifications, $AT_{i,t}$ is standardized to have mean zero and unit standard deviation, so that β_2 can be interpreted as the incremental sensitivity of investment to q for an average firm when AT increases by one standard deviation. Column (1) confirms the positive investment-q and investment-CFO relations (Morck et al. (1990)) without any AT proxy. Column (2)-(5) include each of the four AT proxies at a time, as well as its interaction with q and CFO. The coefficient on $AT * q$ is negative across all AT measures, and two of them (*oddlot* and *trade/volume*) are statistically significant[16]. In terms of economic magnitude, a one standard deviation increase in AT is associated with a reduction in investment-q sensitivity by 25% (1.669/6.748) in column (2) and by 29% (1.921/6.727) in column (5). Column (6) uses the first principal component score across the four AT measures (*PC1*) to moderate investment sensitivity to price. The coefficient on $AT * q$ is also significantly negative with a similar economic magnitude – a one standard deviation increase in *PC1* is associated with a reduction in investment-q sensitivity by 20% (1.354/6.606). Across all the specifications, the coefficient on $CFO * AT$ is insignificant. To the extent that CFO provides a non-price

[16] Section 5.2 discusses potential reasons for why the coefficients on *order/trade* and *cancel/trade* are insignificant.

based signal for firms' general investment opportunities, this result is expected as AT should only affect managers' ability to learn from prices (i.e., q) rather than non-price based signals (i.e., CFO).

Table 2: OLS Regressions

This table reports the results from estimating the following regression:

$$I_{i,t+1} = \alpha_i + \eta_t + \beta_1 q_{i,t} + \beta_2 AT_{i,t} * q_{i,t} + \beta_3 AT_{i,t} + \beta_4 size_{i,t} + \beta_5 CFO_{i,t} + \beta_6 AT_{i,t} * CFO_{i,t} + \epsilon_{i,t} \quad (1)$$

See variable definition in Appendix B. AT is standardized to have zero mean and unit standard deviation. Firm fixed effects and year fixed effects are included. Standard errors are double clustered at the firm and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
AT		*oddlot*	*order/trade*	*cancel/trade*	*trade/volume*	*PC1*
q	7.496***	6.748***	7.147***	7.071***	6.727***	6.606***
	(7.836)	(6.890)	(6.608)	(5.943)	(7.077)	(6.339)
*AT*q*		-1.669***	-0.415	-0.667	-1.921***	-1.354**
		(-2.716)	(-0.647)	(-0.776)	(-2.877)	(-2.326)
AT		0.821	1.839*	1.874	1.946	2.661**
		(0.634)	(1.805)	(1.526)	(1.486)	(2.308)
size	2.454**	3.519***	2.403**	2.542**	3.210***	2.615***
	(2.534)	(3.736)	(2.470)	(2.598)	(3.044)	(2.745)
CFO	19.914**	24.103***	23.329***	19.946**	25.804***	25.151***
	(2.101)	(2.867)	(2.795)	(2.359)	(2.824)	(3.086)
*AT*CFO*		2.992	4.319	-0.022	4.627	4.453
		(0.462)	(0.893)	(-0.005)	(0.751)	(0.720)
firm FE	Y	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y	Y
N	12,297	12,297	12,297	12,297	12,297	12,297
adj. R-sq	0.420	0.422	0.420	0.420	0.422	0.421

Taken together, the results in Table 2 are consistent with the crowding out channel: ATs drive out fundamental traders, which reduces information production and price informativeness, and thus managers learn less from prices when making investment decisions.

4.2 The IV regression

Equation (1) potentially suffers from reverse causality, as ATs may select into firms with low investment to price sensitivity. Edmans et al. (2015) provide such a channel. In the presence of feedback effects from stock prices to managers, informed traders tend to trade on good news while refraining from trading on negative information, because managers' corrective actions would hurt speculators' profits when they trade on bad news. The implication is that informed traders are more likely to trade in firms where managers are less likely to take corrective actions following information in prices, i.e., firms with lower investment-q sensitivity. Therefore, the results in Table 2 are confounded by the possibility that the causality runs in the other direction where firms with lower investment-q sensitivity attracts informed traders, as well as their predators – the ATs. In order to make causal inference on the effects of AT on investment-q sensitivity, it is crucial to identify exogenous variations in AT.

Following Weller (2017), I use the log of the average stock price during year t as an instrument for AT activity. The relevance condition requires a strong correlation between the instrument variable (i.e., log price) and the endogenous variable (i.e., AT proxies). The "sub-penny" rule (SEC Rule 612) mandates a minimum price increment of one cent for displayed orders in stocks covered by Reg NMS, and it creates exogenous variation in AT across stocks with different price levels. To illustrate, consider two stocks, one traded at $100 and the other traded at $10. The minimum price increment on the $100 stock is 1 basis point, while the minimum price increment on the $10 stock is 10 basis points. If the algorithm automatically updates quotes whenever there is a 5 basis points change in the underlying stock value, then we would expect more quote updates for the $100 stock than for the $10 stock – because a 5 basis points change in the latter stock does not reach the smallest price impact and thus require no action by traders. Therefore, ATs are more likely to participate in trading stocks with higher prices all else equal. Panel B of Table 1 confirms the strong positive relationship between stock prices and the four AT proxies.

The exclusion condition requires that the variation in stock prices is not related to traders' incentives to acquire information or managers' tendency to react to prices, after controlling for covariates such as market capitalization and cash flows. While a priori there is little theoretical foundation why the level of stock prices should matter for managerial response to prices, I acknowledge that the exclusion condition is an inherently untestable assumption[17].

I estimate the following 2SLS regression:

[17] Section 5.5 provides additional tests for the validity of the exclusion condition.

$$AT_{i,t} = \theta_{11}LnP_{i,t} + \theta_{12}LnP_{i,t} * q_{i,t} + \theta_{13}LnP_{i,t} * CFO_{i,t} + \lambda_1\Gamma_{i,t} + \delta_{1i,t}$$
$$AT_{i,t} * q_{i,t} = \theta_{21}LnP_{i,t} + \theta_{22}LnP_{i,t} * q_{i,t} + \theta_{23}LnP_{i,t} * CFO_{i,t} + \lambda_2\Gamma_{i,t} + \delta_{2i,t}$$
$$AT_{i,t} * CFO_{i,t} = \theta_{31}LnP_{i,t} + \theta_{32}LnP_{i,t} * q_{i,t} + \theta_{33}LnP_{i,t} * CFO_{i,t} + \lambda_3\Gamma_{i,t} + \delta_{3i,t}$$
$$I_{i,t+1} = \beta_2\widehat{AT}_{i,t} * q_{i,t} + \beta_3\widehat{AT}_{i,t} + \beta_6\widehat{AT}_{i,t} * CFO_{i,t} + \lambda\Gamma_{i,t} + \epsilon_{i,t} \tag{2}$$

where $LnP_{i,t}$ is the log of the average stock prices of firm *i* during year *t*, and the remaining variables are the same as in Equation (1) with $\Gamma_{i,t} = \{\alpha_i, \eta_t, q_{i,t}, size_{i,t}, CFO_{i,t}\}$ denoting the set of control variables including firm and year fixed effects.

Table 3 reports the results from estimating equation (2). Across all specifications, the K-P rk LM statistics reject the under-identification hypothesis at 1%, suggesting that log prices is a strong instrument for AT. The coefficients on *AT*q* are consistently negative and significant across Column (1) – (5). The economic magnitude estimated from the IV regression is also stronger compared to the OLS regression. As shown in Column (5), a one standard deviation increase in *PC1* leads to a 35% (2.153/6.084) decrease in investment-*q* sensitivity. As observed previously in Table 2, the coefficients on *AT*CFO* remain insignificant, consistent with the hypothesis that AT only affects managers' investment decisions through price-based signals.

Table 3: IV Regressions

This table reports the results from estimating the following 2SLS regression:

$$AT_{i,t} = \theta_{11} LnP_{i,t} + \theta_{12} LnP_{i,t} * q_{i,t} + \theta_{13} LnP_{i,t} * CFO_{i,t} + \lambda_1 \Gamma_{i,t} + \delta_{1i,t}$$

$$AT_{i,t} * q_{i,t} = \theta_{21} LnP_{i,t} + \theta_{22} LnP_{i,t} * q_{i,t} + \theta_{23} LnP_{i,t} * CFO_{i,t} + \lambda_2 \Gamma_{i,t} + \delta_{2i,t}$$

$$AT_{i,t} * CFO_{i,t} = \theta_{31} LnP_{i,t} + \theta_{32} LnP_{i,t} * q_{i,t} + \theta_{33} LnP_{i,t} * CFO_{i,t} + \lambda_3 \Gamma_{i,t} + \delta_{3i,t}$$

$$I_{i,t+1} = \beta_2 \widehat{AT}_{i,t} * q_{i,t} + \beta_3 \widehat{AT}_{i,t} + \beta_6 \widehat{AT}_{i,t} * CFO_{i,t} + \lambda \Gamma_{i,t} + \epsilon_{i,t} \quad (2)$$

where $\Gamma_{i,t} = \{\alpha_i, \eta_t, q_{i,t}, size_{i,t}, CFO_{i,t}\}$. See variable definition in Appendix B. AT is standardized to have zero mean and unit standard deviation. Firm fixed effects and year fixed effects are included. Standard errors are double clustered at the firm and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

	(1)	(2)	(3)	(4)	(5)
AT	*oddlot*	*order/trade*	*cancel/trade*	*trade/volume*	*PC1*
q	6.733***	4.862***	3.716**	6.771***	6.084***
	(6.612)	(3.465)	(2.217)	(6.689)	(5.446)
*AT*q*	-1.902**	-3.305**	-5.580***	-2.099**	-2.153**
	(-2.545)	(-2.547)	(-2.904)	(-2.500)	(-2.575)
AT	5.344*	9.277*	17.997***	5.902*	6.153*
	(1.921)	(1.767)	(2.678)	(1.912)	(1.999)
size	2.036	2.563**	2.954***	1.889	2.207*
	(1.460)	(2.613)	(3.452)	(1.264)	(1.802)
CFO	28.491***	40.989***	41.823***	28.583***	30.915***
	(3.426)	(3.162)	(2.922)	(3.497)	(3.547)
*AT*CFO*	7.030	26.582	47.108	7.004	(-2.575)
	(1.061)	(1.370)	(1.291)	(1.070)	9.699
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
N	12,297	12,297	12,297	12,297	12,297
K-P rk LM	7.095***	6.877***	6.874***	6.999***	7.202***
K-P rk Wald F	352.735	19.609	30.913	268.005	132.311

4.3 Cross-sectional tests

The results in Table 3 are consistent with the crowding out channel, which reduces the amount of new information in prices that managers can use to guide their investment decisions. This section further explores the underlying mechanism in the cross section. All the tests are motivated by prior theoretical and empirical literature on AT and managerial learning.

First, while prior literature documents that algorithmic liquidity suppliers tend to concentrate on the most traded and liquid stocks, aggressive liquidity-taking activities are more prevalent in illiquid stocks (Hirschey (2018)). Theory suggests that opportunistic ATs' order anticipation strategies are more likely to drive out fundamental traders' information acquisition (Baldauf and Mollner (2018), Yang and Zhu (2017)). Therefore, I expect the reduction in price informativeness and investment-*q* sensitivity to be larger in illiquid stocks with wider bid-ask spreads.

Second, the crowding out effects should be stronger in stocks where learning is more valuable, i.e., where the level of informed trading is higher (Chen et al. (2007), Jayaraman and Wu (2018)). If the decrease in investment-*q* sensitivity is due to less learning, then the effect is expected to be stronger for firms with more informed trading. I use analyst coverage as the proxy for the amount of private information in prices. The crowding out channel predicts that the reduction in investment-*q* sensitivity should be greater in stocks with lower analyst coverage.

Finally, I explore whether accounting conservatism affects the extent to which AT reduces investment-q sensitivity. This test is motivated by Chen et al. (2018), who show that in the presence of feedback effects, more conservative accounting system would encourage traders to trade more on bad news so that prices would be more informative and managers can learn more from prices. The implication from their model is that informed traders are more likely to be present in firms with more conservative accounting. If AT indeed crowds out informed traders, the reduction in investment-q sensitivity would be greater in more conservative firms.

Empirically, I sort firms into quartiles based on three measures: (1) average daily closing bid-ask spreads during year *t-1*, (2) the number of analysts covering firm *i* during year *t-1,* and (3) the average C-score of firm *i* during the past five years, which is a firm-year measure of accounting conservatism proposed by Khan and Watts (2009). The observations in the top and the bottom quartiles for each of the three measures are used to form a sub-sample. Then I augment equation (2) by adding a dummy variable, which equals 1 if the observation is in the top quartile and 0 if it is in the bottom quartile, as well as its interaction with q, *AT*, and q**AT*. A significant coefficient on the triple-interaction term suggests that AT's effects on investment-q sensitivity vary with the cross-sectional variables of interest.

Table 4 reports the results of the cross-sectional tests. The results in Panel A suggest that AT only leads to a reduction in investment-q sensitivity for firms with high bid-ask spreads (the coefficient on $HighSpread * q * AT$ is consistently negative across the 5 AT proxies), consistent with aggressive algorithmic liquidity takers crowding out fundamental traders in illiquid stocks. The results in Panel B indicate that AT only reduces investment-q sensitivity for firms with low analyst coverage (the coefficient on $HighAnalyst * q * AT$ is consistently positive across the 5 AT proxies[18]), consistent with ATs driving out information acquisition in stocks with more informed trading initially. Panel C presents the results for high vs. low accounting conservatism. Across all the AT proxies, the coefficient on $HighConsv * q * AT$ is significantly negative, consistent with more conservative firms experiencing a greater loss of informed traders, and hence a greater reduction in managerial learning.

Together, these results provide additional supporting evidence for the crowding out channel: ATs employ order anticipation strategies and reduce profits available for non-ATs, which deters their fundamental information production and ultimately reduces the amount of new information managers can learn from prices.

Table 4: Cross-Sectional Tests

This table reports the results from estimating an augmented version of equation (2). See variable definition in Appendix B. Firms are sorted into quartiles based on three different measures from Panel A to Panel C. The observations in the top and the bottom quartiles for each of the three measures are used to form a sub-sample. Equation (2) is augmented with a dummy variable, which is equal to 1 if the observation is in the top quartile and 0 if in the bottom quartile, as well as interactions of the dummy variable with *q, AT,* and *AT*q*. AT is standardized to have zero mean and unit standard deviation. Firm fixed effects and year fixed effects are included. Standard errors are double clustered at the firm and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

[18] F-test suggests that the sum of $q * AT$ and $HighAnalyst * q * AT$ is not statistically different from zero.

Table 4: Cross-Sectional Tests (Cont'd)

Panel A: High versus low bid-ask spreads

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
q	3.801	2.277	3.106	3.912	3.373
	(1.490)	(0.967)	(1.520)	(1.384)	(1.381)
*AT*q*	-0.227	0.229	-0.003	-0.350	-0.058
	(-0.173)	(0.102)	(-0.001)	(-0.181)	(-0.039)
*HighSpread*AT*q*	-3.658**	-9.273**	-8.044	-3.828*	-4.445**
	(-2.060)	(-2.285)	(-1.657)	(-1.776)	(-2.152)
AT	2.555	-3.448	-29.187	5.323	1.420
	(0.681)	(-0.495)	(-1.303)	(0.916)	(0.332)
*HighSpread*q*	-4.874	-8.041	-5.628	-5.242	-5.397
	(-1.119)	(-1.192)	(-0.955)	(-1.177)	(-1.130)
*HighSpread*AT*	7.220	28.645**	67.895*	4.872	10.314*
	(1.576)	(2.035)	(1.742)	(0.847)	(1.722)
size	5.113**	7.601***	14.300***	4.644*	5.778***
	(2.277)	(3.399)	(2.668)	(1.980)	(2.667)
CFO	11.468	29.430	6.119	11.616	15.190
	(1.073)	(1.624)	(0.493)	(1.088)	(1.322)
*AT*CFO*	5.771	38.747	73.429	5.291	10.145
	(0.865)	(1.297)	(1.349)	(0.811)	(1.108)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
N	5,494	5,494	5,494	5,494	5,494

Table 4: Cross-Sectional Tests (Cont'd)

Panel B: High versus low analyst coverage

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
q	1.442	-0.262	-2.475	1.473	1.145
	(0.417)	(-0.065)	(-0.310)	(0.441)	(0.319)
*AT*q*	-4.460***	-6.715***	-7.910**	-4.630***	-4.600***
	(-4.495)	(-4.051)	(-2.523)	(-4.713)	(-4.467)
*HighAnalyst*AT*q*	4.652***	8.045***	10.490	4.973***	5.004***
	(3.604)	(2.961)	(1.594)	(3.039)	(3.360)
AT	11.474***	20.293***	43.403**	11.658***	12.657***
	(3.445)	(3.188)	(2.071)	(3.560)	(3.480)
*HighAnalyst*q*	2.643	3.568	6.434	2.640	2.723
	(0.724)	(0.858)	(0.778)	(0.749)	(0.728)
*HighAnalyst*AT*	-11.327***	-28.047**	-76.743*	-10.034**	-13.935***
	(-2.829)	(-2.656)	(-1.747)	(-2.271)	(-2.787)
size	3.704**	5.796***	12.519**	3.255*	4.384***
	(2.216)	(3.400)	(2.550)	(1.850)	(2.768)
CFO	36.017***	48.782***	17.602	36.182***	38.696***
	(3.636)	(4.003)	(0.908)	(3.719)	(3.714)
*AT*CFO*	17.385***	59.384***	171.912	15.273***	23.876***
	(4.366)	(3.774)	(1.476)	(3.721)	(4.784)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
N	5,659	5,659	5,659	5,659	5,659

Table 4: Cross-Sectional Tests (Cont'd)

Panel C: High versus low conservatism

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
q	0.791	0.874	2.072	0.686	0.964
	(0.701)	(0.524)	(1.197)	(0.575)	(0.945)
*AT*q*	1.573*	7.130*	6.490*	1.967*	2.144**
	(1.836)	(1.843)	(1.957)	(1.918)	(2.119)
*HighConsv*AT*q*	-5.084***	-19.045*	-22.383*	-5.791***	-6.662**
	(-2.682)	(-1.883)	(-1.683)	(-2.818)	(-2.615)
AT	-4.338	-16.351**	-27.059*	-4.842	-5.580
	(-1.290)	(-2.063)	(-1.692)	(-1.116)	(-1.665)
*HighConsv*q*	-0.668	-9.402	-9.390	-0.767	-2.316
	(-0.191)	(-1.216)	(-1.048)	(-0.212)	(-0.567)
*HighConsv*AT*	9.002**	32.363*	61.587	9.907**	11.746**
	(2.359)	(1.825)	(1.321)	(2.521)	(2.368)
size	6.228***	6.984***	10.665**	6.079***	6.328***
	(3.413)	(4.613)	(2.270)	(3.084)	(3.847)
CFO	16.909*	34.937	39.326	16.503*	20.137*
	(1.745)	(1.619)	(1.442)	(1.698)	(1.840)
*AT*CFO*	6.914	37.262	119.478	6.292	10.480
	(0.812)	(1.273)	(1.092)	(0.791)	(1.023)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
N	4,759	4,759	4,759	4,759	4,759

5. Additional Analyses

5.1 Future operating performance

Thus far, I interpret the reduced investment-q sensitivity as evidence of managers learning less from prices due to smaller amount of new information impounded into prices by informed traders (i.e., lower RPE). While a reduction in investment-q sensitivity indicates less efficient investment decisions, it is not a direct measure. Following prior literature (Chen et al. (2007), Jayaraman and Wu (2018)), I examine the effect of AT on future operating performance. If AT reduces RPE and hence causes managers to make worse investment decisions, we should expect that AT will have a negative effect on firms' future operating performance.

Empirically, I regress measures of future operating performance on q, size, current operating performance, and AT proxies (instrumented with average stock prices):

$$AT_{i,t} = \xi + \theta LnP_{i,t} + \lambda_1 q_{i,t} + \lambda_2 size_{i,t} + \lambda_3 Op_{i,t} + \delta_{i,t}$$
$$Op_{i,t+1} = \alpha_i + \eta_t + \beta_1 q_{i,t} + \beta_2 size_{i,t} + \beta_3 Op_{i,t} + \beta_4 \widehat{AT}_{i,t} + \epsilon_{i,t} \quad (3)$$

I use 1 and 2-year ahead ROA, sales growth, and asset turnover as proxies for future operating performance. The results are reported in Table 5. All the three future operating performance measures over 1 and 2-year horizons deteriorate following periods of high AT activity for all the five AT proxies, suggesting that AT indeed worsens operational efficiency.

Table 5: Future Operating Performance

This table reports the results from estimating the following 2SLS regression:

$$AT_{i,t} = \xi + \theta LnP_{i,t} + \lambda_1 q_{i,t} + \lambda_2 size_{i,t} + \lambda_3 Op_{i,t} + \delta_{i,t}$$

$$Op_{i,t+1} = \alpha_i + \eta_t + \beta_1 q_{i,t} + \beta_2 size_{i,t} + \beta_3 Op_{i,t} + \beta_4 \widehat{AT}_{i,t} + \epsilon_{i,t} \quad (3)$$

The dependent variables are 1- and 2-year ahead ROA, sales growth and asset turnover in Panel A and B, respectively. AT is standardized to have zero mean and unit standard deviation. Firm fixed effects and year fixed effects are included. Standard errors are double clustered at the firm and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

Panel A: 1-year ahead future operating performance and AT

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
Dependent variable: ROA_{t+1}					
AT	-0.036***	-0.064***	-0.073***	-0.042***	-0.040***
	(-4.722)	(-4.987)	(-4.887)	(-4.813)	(-4.952)
q	0.006***	0.008***	0.007***	0.006***	0.006***
	(3.582)	(5.030)	(4.268)	(3.252)	(3.959)
size	0.027***	0.019***	0.014***	0.029***	0.024***
	(4.160)	(3.619)	(3.057)	(4.174)	(4.061)
ROA_t	0.041	0.047	0.046	0.042	0.043
	(0.385)	(0.435)	(0.431)	(0.392)	(0.404)
N	11,603	11,603	11,603	11,603	11,603

Table 5: Future Operating Performance (Cont'd)

Panel A: 1-year ahead future operating performance and AT (Cont'd)

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
Dependent variable: SalesGrowth_{t+1}					
AT	-0.114**	-0.190**	-0.216**	-0.132**	-0.122**
	(-2.221)	(-2.362)	(-2.275)	(-2.269)	(-2.281)
q	0.032**	0.037***	0.036***	0.030**	0.033***
	(2.571)	(3.005)	(2.729)	(2.468)	(2.682)
size	0.128***	0.106***	0.089***	0.134***	0.120***
	(5.108)	(5.315)	(4.452)	(4.919)	(5.309)
$SalesGrowth_t$	-0.240***	-0.236***	-0.235***	-0.237***	-0.238***
	(-3.232)	(-3.164)	(-3.174)	(-3.211)	(-3.204)
N	11,413	11,413	11,413	11,413	11,413

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
Dependent variable: Turnover_{t+1}					
AT	-0.133***	-0.153***	-0.082***	-0.080***	-0.072***
	(-3.50)	(-3.41)	(-3.41)	(-3.48)	(-3.41)
q	0.089***	0.091***	0.091***	0.088***	0.089***
	(9.910)	(10.777)	(10.443)	(9.722)	(10.138)
size	-0.081***	-0.096***	-0.106***	-0.077***	-0.086***
	(-7.164)	(-9.218)	(-9.493)	(-6.381)	(-7.979)
$Turnover_t$	-0.071***	-0.125***	-0.141***	-0.083***	-0.078***
	(-3.613)	(-3.741)	(-3.699)	(-3.613)	(-3.703)
N	11,635	11,635	11,635	11,635	11,635

Table 5: Future Operating Performance (Cont'd)

Panel B: 2-year ahead future operating performance and AT

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
Dependent variable: $ROA_{(t,t+2)}$					
AT	-0.025***	-0.039***	-0.047***	-0.029***	-0.027***
	(-3.337)	(-3.621)	(-3.663)	(-3.379)	(-3.489)
q	0.005***	0.006***	0.007***	0.005***	0.006***
	(3.326)	(3.857)	(4.110)	(3.074)	(3.547)
size	0.012	0.007	0.002	0.014	0.010
	(1.504)	(1.036)	(0.289)	(1.641)	(1.353)
ROA_t	-0.101***	-0.102***	-0.100***	-0.099***	-0.100***
	(-3.348)	(-3.533)	(-3.608)	(-3.230)	(-3.419)
N	8,438	8,438	8,438	8,438	8,438

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
Dependent variable: $SalesGrowth_{(t,t+2)}$					
AT	-0.102***	-0.153***	-0.182***	-0.117***	-0.106***
	(-3.348)	(-3.510)	(-3.461)	(-3.466)	(-3.468)
q	0.040***	0.044***	0.047***	0.038***	0.041***
	(3.833)	(4.015)	(3.982)	(3.643)	(3.883)
size	0.047	0.027	0.006	0.054*	0.039
	(1.646)	(1.141)	(0.306)	(1.813)	(1.485)
$SalesGrowth_t$	-0.263***	-0.262***	-0.261***	-0.261***	-0.262***
	(-11.663)	(-11.322)	(-10.935)	(-11.654)	(-11.509)
N	8,331	8,331	8,331	8,331	8,331

Table 5: Future Operating Performance (Cont'd)

Panel B: 2-year ahead future operating performance and AT (Cont'd)

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
Dependent variable: $\text{Turnover}_{(t,t+2)}$					
AT	-0.088***	-0.137***	-0.163***	-0.101***	-0.093***
	(-4.591)	(-4.542)	(-4.092)	(-4.609)	(-4.593)
q	0.052***	0.056***	0.059***	0.051***	0.054***
	(4.890)	(5.292)	(5.084)	(4.848)	(4.990)
$size$	-0.064***	-0.084***	-0.101***	-0.058***	-0.072***
	(-4.995)	(-6.985)	(-8.020)	(-4.324)	(-5.782)
$Turnover_t$	-0.014	-0.009	-0.016	-0.012	-0.012
	(-0.340)	(-0.208)	(-0.397)	(-0.293)	(-0.306)
N	8,487	8,487	8,487	8,487	8,487

5.2 The second principal component

The results in Table 3 show that for each of the four AT proxies as well as the first principal component, AT reduces the investment-q sensitivity, suggesting that the crowding out mechanism is the major force at work. In practice, AT strategies are highly diverse (Hagstomer and Norden (2013), Boehmer et al. (2018)), and may have distinct implications for price informativeness. Notably, algorithmic market-making is shown to improve liquidity and reduce trading costs both theoretically and empirically (Ait-Sahalia and Saglam (2017), Hendershott et al. (2011), Hasbrouck and Saar (2013)), while algorithmic liquidity-taking is associated with free-riding on information and increased trading costs to institutional investors (Baldauf and Mollner (2018), Yang and Zhu (2017), van Kervel and Menkveld (2018)). This section further explores the potential commonality and dissimilarity underlying the four AT proxies by taking a closer look at the Principal Component Analysis (PCA).

In general, PCA is used to detect and summarize the pattern of correlations among variables. It produces common components that are potentially the underlying phenomena (i.e., common strategies in the AT context) that drive the data. Panel C of Table 1 presents the results from PCA on the four AT proxies. I retain components with eigenvalues greater than 1, which results in two principal components accounting for 96% of total variances: the first component explains 66% of the total variance and the second explains 30%. Moreover, while the first component is positively correlated with all the four AT proxies, the second component is negatively associated with *Oddlot* and *Trade/Volume* while positively associated with *Order/Trade* and *Cancel/Trade*. Intuitively, the second component appears to be more consistent with algorithmic market-making strategies, where ATs constantly submit and cancel orders, generating high ratios of orders and cancellations relative to actual trades. On the other hand, the high incidents of oddlot trades and smaller trade sizes are more consistent with opportunistic ATs taking liquidity by small amounts in a non-systematic fashion. Therefore, I conjecture that the first principal component is more likely to capture liquidity demanding AT, while the second component is more representative of market-making AT. If this is indeed the case, we should expect the reduction in investment-*q* sensitivity to be mainly driven by the first component rather than the second.

The results in Table 2 and Table 3 already confirm the first aspect of the above conjecture, that the first principal component is negatively associated with investment-*q* sensitivity. To test the second aspect, I drop the individual AT proxies in equation (1) and (2) and simultaneously include the scores for both the first (*PC1*) and the second (*PC2*) principal components. The results in Table 6 are consistent with my intuition: the coefficient on $q * PC1$ is significantly negative in both specifications, while the coefficient on $q * PC2$ is insignificant. The PCA suggests that diversity in AT strategies does exist and may be differentially associated with various proxies. More importantly, it seems that the strategies employed by liquidity taking ATs are driving the reduction in price informativeness, while the market-making ATs do not inhibit what managers can learn from price. However, I caution against putting too much weight on the economic interpretation of the results in this section because they are largely data-driven rather than theoretically based.

Table 6: The Second Principal Component

This table reports the results from estimating modified versions of equation (1) and (2), where AT is replaced by the principal component scores of the first and second principal components. For the modified equation (2), only *PC1* is instrumented. Firm fixed effects and year fixed effects are included. Standard errors are double clustered at the firm and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

	(1)	(2)
	OLS	IV with *PC1*
q	6.875***	6.760***
	(6.068)	(5.723)
*PC1*q*	-1.439**	-1.714**
	(-2.486)	(-2.427)
*PC2*q*	1.228	1.195
	(1.211)	(1.186)
PC1	1.614	5.419**
	(1.355)	(2.175)
PC2	0.013	-1.185
	(0.010)	(-0.658)
size	3.489***	2.289
	(3.366)	(1.616)
CFO	25.681***	28.918***
	(3.070)	(3.697)
*PC1*CFO*	3.874	6.509
	(0.607)	(0.991)
*PC2*CFO*	-1.226	-1.881
	(-0.260)	(-0.406)
firm FE	Y	Y
year FE	Y	Y
N	12,297	12,297

5.3 AT and analysts' long-term growth forecast revisions

If the crowding out effect of AT limits the information in prices, managers should not be the only agents who are impacted. Equity analysts represent another class of agents who should also be affected by AT, given they interpret stock prices changes and predict firm fundamentals, continually revising their short-run and long-run forecasts in response to the arrival of new information.

Empirically, I examine whether the sensitivity of analysts' long-term growth forecast revisions to firms' past returns is affected by AT. The choice of long-term growth forecast is intentional, as it is more likely to be affected by the same pieces of forward-looking market wide and industry specific information unknown to managers. Specifically, I estimate the following regression:

$$Rev_{i,j,t} = \alpha_j + \eta_t + \beta_1 Ret_{i,t-1} + \beta_2 AT_{i,t-1} * Ret_{i,t-1} + \beta_3 AT_{i,t-1} + \gamma Days + \epsilon_{i,j,t} \quad (4)$$

Where $Rev_{i,j,t}$ is analyst *j*'s revision (i.e., forecast at date *t* minus forecast at date *t-1*) of long-term growth forecast on firm *i* issued at date *t*, α_j is analyst fixed effects, η_t is year fixed effects, $Ret_{i,t-1}$ is the stock return of firm *i* between date *t-1* and *t*, and $AT_{i,t-1}$ is the proxy for AT activity between *t-1* and *t* defined the same as in (1) and (2). *Days* is the log number of days between the two forecasts. The coefficient of interest is β_2. I also use the log of the average stock price between *t-1* and *t* as an instrument for AT activity and estimate the following 2SLS regression:

$$AT_{i,t-1} = \theta_{11} LnP_{i,t-1} + \theta_{12} LnP_{i,t-1} * Ret_{i,t-1} + \lambda_1 CONTROL + \delta_{1i,t-1}$$
$$AT_{i,t-1} * Ret_{i,t-1} = \theta_{21} LnP_{i,t-1} + \theta_{22} LnP_{i,t-1} * Ret_{i,t-1} + \lambda_2 CONTROL + \delta_{2i,t-1}$$
$$Rev_{i,j,t} = \beta_2 \widehat{AT}_{i,t-1} * Ret_{i,t-1} + \beta_3 \widehat{AT}_{i,t-1} + \gamma CONTROL + \epsilon_{i,j,t} \quad (5)$$

where $CONTROL = \{\alpha_j, \eta_t, Ret_{i,t-1}, Days\}$.

Panel A of Table 7 presents the results from estimating Equation (4). The coefficient on $Ret * AT$ is significantly negative across all AT measures, consistent with AT reducing analysts' long-term growth forecast revision to past returns sensitivity. In terms of economic magnitude, an analyst's revision-return sensitivity declines by 13.9% (=0.892/6.4) when there is a one standard deviation increase in *PC1*.

Panel B of Table 7 reports the results from estimating equation (5). The IV estimates confirm that analysts are learning less from prices in revising their long-term growth forecasts in the presence of AT, implying that AT crowds out the acquisition of forward looking, long-term fundamental information.

Table 7: Long-Term Growth Forecast Revisions to Past Returns

Panel A of this table reports the results from estimating the following regression:

$$Rev_{i,j,t} = \alpha_j + \eta_t + \beta_1 Ret_{i,t-1} + \beta_2 AT_{i,t-1} * Ret_{i,t-1} + \beta_3 AT_{i,t-1} + \gamma Days + \epsilon_{i,j,t} \quad (4)$$

AT is standardized to have zero mean and unit standard deviation. Analyst fixed effects and year fixed effects are included. Standard errors are double clustered at the analyst and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

Panel A: OLS Regression

	(1)	(2)	(3)	(4)	(5)	(6)
AT		*oddlot*	*order/trade*	*cancel/trade*	*trade/volume*	*PC1*
Ret	6.585***	6.449***	6.449***	6.430***	6.431***	6.400***
	(17.77)	(18.67)	(17.81)	(17.67)	(17.96)	(18.22)
*AT*Ret*		-0.823**	-0.700***	-0.819***	-0.819***	-0.892***
		(-3.24)	(-7.19)	(-7.09)	(-7.13)	(-13.80)
AT		0.054	0.052	0.095*	0.066	0.078
		(0.83)	(1.55)	(2.62)	(1.27)	(1.35)
Days	-0.235***	-0.235***	-0.237***	-0.241***	-0.234***	-0.237**
	(-5.54)	(-5.12)	(-5.27)	(-5.12)	(-4.63)	(-4.51)
analyst FE	Y	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y	Y
N	50555	50555	50555	50555	50555	50555

Table 7: Long-term Growth Forecast Revisions to Past Returns – Cont'd

Panel B of this table reports the results from estimating the following 2SLS regression:

$$AT_{i,t-1} = \theta_{11}LnP_{i,t-1} + \theta_{12}LnP_{i,t-1} * Ret_{i,t-1} + \lambda_1 CONTROL + \delta_{1i,t-1}$$

$$AT_{i,t-1} * Ret_{i,t-1} = \theta_{21}LnP_{i,t-1} + \theta_{22}LnP_{i,t-1} * Ret_{i,t-1} + \lambda_2 CONTROL + \delta_{2i,t-1}$$

$$Rev_{i,j,t} = \beta_2 \widehat{AT}_{i,t-1} * Ret_{i,t-1} + \beta_3 \widehat{AT}_{i,t-1} + \gamma CONTROL + \epsilon_{i,j,t} \qquad (5)$$

where $CONTROL = \{\alpha_j, \eta_t, Ret_{i,t-1}, Days\}$. AT is standardized to have zero mean and unit standard deviation. Analyst fixed effects and year fixed effects are included. Standard errors are double clustered at the analyst and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

Panel B: IV Regression

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
Ret	6.406***	6.266***	6.263***	6.375***	6.343***
	(22.07)	(21.18)	(21.14)	(22.13)	(22.01)
*AT*Ret*	-1.087*	-1.664*	-1.834*	-1.115*	-1.184*
	(-2.18)	(-2.49)	(-2.33)	(-2.20)	(-2.27)
AT	0.061	0.096	0.104	0.065	0.068
	(0.65)	(0.75)	(0.74)	(0.64)	(0.68)
Days	-0.235***	-0.237**	-0.235**	-0.233***	-0.235***
	(-5.40)	(-4.27)	(-3.79)	(-5.38)	(-4.75)
analyst FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
N	50555	50555	50555	50555	50555

5.4 Alternative interpretations of investment-q sensitivity

Morck et al. (1990) provide four interpretations on the association between future investment and stock prices: (1) the stock market is a passive predictor of future activity that managers do not rely on to make investment decisions, (2) managers rely on the stock market as a source of information in making investment decisions, (3) stock market affects investment through its influence on the cost of funds and external financing, and (4) the managers cater to investors' opinions in order to protect their jobs. While I interpret the reduced investment-*q* sensitivity as evidence of managers learning less from prices due to smaller amounts of new information impounded into prices by informed traders (i.e., interpretation (2)), I discuss the plausibility of the other interpretations in this section, and design a battery of tests to examine their empirical validity.

5.4.1 FPE channel

Interpretation (1) suggests that AT does not necessarily reduce managerial learning. Instead, it can inject excess noise into prices which makes prices less correlated with the information managers use in investment, i.e., AT leads to reduced FPE rather than RPE. I perform two sets of additional analyses to test this alternative explanation.

First, I examine whether AT reduces the future earnings response coefficients (FERC), i.e., the ability of current returns to anticipate future earnings, a common proxy for FPE in prior literature (Israeli et al.(2017)). Specifically, I estimate the following regression:

$$\text{Ret}_{i,t} = \alpha_i + \eta_t + \beta_1 Earn_{i,t-1} + \beta_2 Earn_{i,t} + \beta_3 Earn_{i,t+1} + \beta_4 AT_{i,t} * Earn_{i,t-1} + \beta_5 AT_{i,t} * Earn_{i,t} + \beta_6 AT_{i,t} * Earn_{i,t+1} + \beta_7 AT_{i,t} + \beta_8 \Gamma_{i,t} + \epsilon_{i,t} \qquad (6)$$

where $\text{Ret}_{i,t}$ is the buy-and-hold returns for firm *i* during year t, α_i is the firm fixed effects, η_t is the year fixed effects, $\text{Earn}_{i,t}$ is the income before extraordinary items scaled by the beginning market capitalization, and $\Gamma_{i,t}$ is a set of control variables including future returns $\text{Ret}_{i,t+1}$, size and the growth rate of assets during year t. $\text{AT}_{i,t}$ and interaction terms including $\text{AT}_{i,t}$ are instrumented with log stock prices, $lnP_{i,t}$.

Table 8 presents the results from estimating Equation (6). Most of the coefficients on $\text{AT} * \text{Earn}_{i,t}$ are significantly positive, while all of the coefficients on $\text{AT} * \text{Earn}_{i,t+1}$ are statistically insignificant, suggesting that AT enables current returns to better reflect current earnings without affecting FERC. The evidence is inconsistent with interpretation (1) that AT reduces FPE.

Table 8: AT and FERC

This table reports the results from estimating Equation (6). See variable definition in Appendix B. AT is standardized to have zero mean and unit standard deviation. Analyst fixed effects and year fixed effects are included. Standard errors are double clustered at the analyst and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
AT	*oddlot*	*order/trade*	*cancel/trade*	*trade/volume*	*PC1*
$Earn_{t-1}$	-0.821***	-0.677**	1.081	-0.815***	-0.821***
	(-7.388)	(-2.048)	(0.128)	(-7.723)	(-6.412)
$Earn_{t}$	-0.094	1.085**	1.026	-0.157*	0.174
	(-1.040)	(2.084)	(0.299)	(-1.949)	(1.535)
$Earn_{t+1}$	0.077	0.476**	0.048	0.055	0.233**
	(0.926)	(2.258)	(0.020)	(0.767)	(2.277)
$AT * Earn_{t-1}$	-0.340***	-0.103	22.114	-0.394***	-0.345***
	(-4.435)	(-0.143)	(0.255)	(-5.608)	(-3.153)
$AT * Earn_{t}$	0.193***	1.949**	3.941	0.122*	0.408***
	(2.858)	(2.502)	(0.590)	(1.906)	(4.126)
$AT * Earn_{t+1}$	0.045	0.662	3.073	0.047	0.155
	(0.657)	(1.617)	(0.356)	(0.701)	(1.591)
AT	-1.041***	-1.466***	0.810	-1.206***	-1.065***
	(-7.971)	(-6.425)	(0.130)	(-7.630)	(-7.673)
Ret_{t+1}	-0.268***	-0.220***	-0.766	-0.246***	-0.252***
	(-4.199)	(-2.927)	(-0.446)	(-3.806)	(-3.983)
size	0.647***	0.381***	-0.818	0.711***	0.561***
	(11.596)	(4.142)	(-0.201)	(11.140)	(9.918)
AssetGrowth	0.009	-0.010	-0.266	0.018	0.011
	(0.228)	(-0.159)	(-0.330)	(0.427)	(0.237)
N	11,479	11,479	11,479	11,479	11,479

Second, I directly control for FPE proxies in the investment-q sensitivity specification. Following Edmans et al. (2017), I use two proxies for FPE: (1) firm-specific return variation (i.e., $1 - \mathrm{R}^2$ as in Chen et al. (2007), where R^2 is the R-squared from regressing firm-level daily returns on market excess returns and average industry returns), and (2) the fraction of non-zero return trading days (*NZRET*) during year *t*.

Panel A of Table 9 presents the results when $1 - \mathrm{R}^2$ and $\mathrm{q} * (1 - \mathrm{R}^2)$ are added to Equation (2) as additional controls. The coefficient on $\mathrm{q} * (1 - \mathrm{R}^2)$ is significantly positive, consistent with firms with higher FPE indeed having higher investment-q sensitivity. The coefficients on $\mathrm{q} * \mathrm{AT}$ remain significantly negative across all the specifications, suggesting that the crowding out effect of AT is responsible for the reduction in investment-q sensitivity.

Panel B of Table 9 presents the results when *NZRET* and *q*NZRET* are included as additional controls to Equation (2). Due to the lack of variation in *NZRET*, I sort all the firm-years into quartiles based on *NZRET*, and create two dummy variables: (1) *NZRET_HI* = 1 if the firm-year is in the top quartile, and (2) *NZRET_LO = 1* if the firm-year is in the bottom quartile. After controlling for FPE, *q*AT* is still significantly negative across all the specifications, supporting the AT effects through the RPE channel.

Table 9: Controlling for FPE

This table reports the results from estimating Equation (2) with additional controls for FPE, which is firm-specific return variation ($1 - \mathrm{R}^2$) in Panel A, and the fraction of non-zero return trading days (NZRET) in Panel B. See variable definition in Appendix B. AT is standardized to have zero mean and unit standard deviation. Analyst fixed effects and year fixed effects are included. Standard errors are double clustered at the analyst and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

Panel A: Firm-specific return variation as proxy for FPE

	(1)	(2)	(3)	(4)	(5)
AT	*oddlot*	*order/trade*	*cancel/trade*	*trade/volume*	*PC1*
q	2.658	0.590	-1.114	2.611	1.884
	(1.089)	(0.209)	(-0.353)	(1.071)	(0.753)
*AT*q*	-1.370*	-2.255*	-3.477**	-1.477*	-1.511*
	(-1.935)	(-1.926)	(-2.045)	(-1.884)	(-1.957)
AT	4.785*	8.095	14.382**	5.260*	5.412*
	(1.720)	(1.493)	(2.247)	(1.706)	(1.752)
size	2.510*	3.167***	3.629***	2.375	2.727**
	(1.820)	(3.250)	(4.250)	(1.603)	(2.243)
CFO	28.217***	38.336***	38.644***	28.369***	30.316***
	(3.389)	(3.075)	(3.003)	(3.471)	(3.488)
*AT*CFO*	6.958	22.976	38.790	7.105	9.191
	(1.038)	(1.219)	(1.183)	(1.067)	(1.108)
$1 - R^2$	0.590	1.219	0.095	0.295	0.448
	(0.123)	(0.236)	(0.018)	(0.062)	(0.093)
$q * (1 - R^2)$	5.317*	6.221*	7.701**	5.436*	5.710*
	(1.826)	(1.995)	(2.275)	(1.874)	(1.956)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
N	12,297	12,297	12,297	12,297	12,297

Table 9: Controlling for FPE (Cont'd)

Panel B: NZRET as proxy for FPE

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
q	6.091***	4.044***	2.957**	6.181***	5.351***
	(5.893)	(3.280)	(2.024)	(6.091)	(5.044)
*AT*q*	-2.362***	-3.689***	-5.927***	-2.608***	-2.567***
	(-3.105)	(-2.944)	(-3.231)	(-3.034)	(-3.092)
AT	5.725*	9.342*	17.958***	6.339*	6.481*
	(1.930)	(1.673)	(2.817)	(1.893)	(1.988)
size	2.084	2.545**	2.899***	1.930	2.231*
	(1.508)	(2.623)	(3.251)	(1.295)	(1.855)
CFO	27.842***	40.922***	41.423***	27.942***	30.429***
	(3.296)	(3.229)	(2.940)	(3.359)	(3.467)
*AT*CFO*	6.808	27.082	47.285	6.661	9.670
	(1.054)	(1.426)	(1.331)	(1.053)	(1.201)
NZRET_HI	-3.337**	-3.251*	-2.933*	-3.076**	-3.204**
	(-2.327)	(-2.002)	(-1.848)	(-2.184)	(-2.192)
*q*NZRET_HI*	1.425*	1.305	1.143	1.312	1.335
	(1.760)	(1.472)	(1.353)	(1.626)	(1.627)
NZRET_LO	-1.448	-2.436	-2.590	-1.204	-1.713
	(-0.474)	(-0.820)	(-0.915)	(-0.394)	(-0.575)
*q*NZRET_LO*	-0.040	0.572	0.709	-0.099	0.162
	(-0.022)	(0.330)	(0.411)	(-0.055)	(0.092)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
N	12,297	12,297	12,297	12,297	12,297

5.4.2 External financing channel

Interpretation (3) is empirically documented by Baker et al. (2003), who find that investment-q sensitivity increases monotonically as firms become more equity-dependent, as they need external equity to finance marginal investments. By this view, the association between AT and reduced investment-q sensitivity may be due to AT making firms less financially constrained, potentially by improving liquidity. However, this would imply an improvement in operational efficiency, inconsistent with what I find in Section 5.1. I also perform two additional analyses to test this alternative explanation. First, I examine whether AT has differential effects on investment-q sensitivity for constrained and unconstrained firms. The empirical design is similar to that in Section 4.3, with the cross-sectional variable replaced by the proxy for financial constraints from Hadlock and Pierce (2010). The results are presented in Panel A, Table 10. Across all the AT proxies, the coefficient on $HighFinConst * q * AT$ is insignificant, suggesting that the external

Table 10: External Financing Channel

Panel A of this table reports the results from estimating a similar model as in Table 4, where the cross-sectional variable is financial constraints. Panel B of this table reports the results from estimating a similar model as in Table 5, where $Op_{i,t+1}$ is replaced by $Eqiss_{i,t+1}$. AT is standardized to have zero mean and unit standard deviation. Firm fixed effects and year fixed effects are included. Standard errors are double clustered at the firm and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

Table 10: External Financing Channel (Cont'd)

Panel A: High versus low financial constraints

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
q	2.927	2.012	1.487	2.804	2.731
	(1.213)	(1.179)	(0.897)	(0.981)	(1.352)
*AT*q*	-0.044	-0.300	-2.494	0.607	0.212
	(-0.015)	(-0.087)	(-0.587)	(0.155)	(0.073)
*HighFinConst*AT*q*	-1.540	-2.390	-2.770	-2.386	-2.014
	(-0.456)	(-0.477)	(-0.676)	(-0.538)	(-0.578)
AT	5.181	7.412	0.657	5.620	5.526
	(0.899)	(0.967)	(0.047)	(0.794)	(0.972)
*HighFinConst*q*	4.119*	3.406	2.501	4.226	3.777
	(1.735)	(1.174)	(0.724)	(1.565)	(1.637)
*HighFinConst*AT*	-3.136	-3.029	37.756	-3.680	-2.729
	(-0.470)	(-0.160)	(0.933)	(-0.472)	(-0.354)
size	1.428	0.808	4.375	1.456	1.160
	(0.671)	(0.523)	(1.166)	(0.629)	(0.609)
CFO	30.963***	62.463***	73.910**	30.565***	35.832***
	(3.007)	(2.959)	(2.289)	(3.007)	(3.207)
*AT*CFO*	10.121	48.749*	102.535	9.647	14.407
	(1.423)	(1.858)	(1.558)	(1.436)	(1.571)
N	5,816	5,816	5,816	5,816	5,816

Table 10: External Financing Channel (Cont'd)

Panel B: Future equity issuance

	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
AT	-0.001	-0.002	-0.003	-0.002	-0.001
	(-0.069)	(-0.069)	(-0.069)	(-0.069)	(-0.069)
q	0.135***	0.135***	0.135***	0.135***	0.135***
	(13.450)	(13.643)	(13.580)	(13.379)	(13.495)
size	-0.184***	-0.184***	-0.184***	-0.183***	-0.184***
	(-7.307)	(-7.595)	(-7.673)	(-7.219)	(-7.434)
N	12,238	12,238	12,238	12,238	12,238
Year FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y

financing channel does not drive the reduced investment-*q* sensitivity. Second, I examine whether high AT firms tend to issue more equity in the following year. The empirical design is similar to equation (3), with $Op_{i,t+1}$ replaced by $Eqiss_{i,t+1}$. The results are presented in Panel B, Table 10. I find that AT has no effect on future equity issuance, inconsistent with the prediction of the external financing channel.

5.4.3 Managerial catering channel

Finally, interpretation (4) suggests that the reduction in investment-*q* sensitivity is due to less managerial catering to investors, which is related to the agency channel (i.e., since prices do not accurately reflect managerial efforts, managers care less about prices and cater less to investors, leading to lower investment-*q* sensitivity). If this is the underlying channel, then the reduction in investment-*q* sensitivity should be greater for firms with high pay-for-performance sensitivity. Using the same empirical design as in Section 4.3 with the cross-sectional variable replaced by pay-for-performance sensitivity (i.e., *Delta* from Core and Guay (2002)), I do not find a significant difference in the effect of AT on investment-*q* sensitivity between high and low *Delta* firms (Table 11), suggesting that this is not likely to be the underlying mechanism.

Table 11: High versus Low Pay-for-Performance Sensitivity

This table reports the results from estimating a similar model as in Table 4, where the cross-sectional variable is pay-for-performance sensitivity. AT is standardized to have zero mean and unit standard deviation. Firm fixed effects and year fixed effects are included. Standard errors are double clustered at the firm and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

AT	(1) *oddlot*	(2) *order/trade*	(3) *cancel/trade*	(4) *trade/volume*	(5) *PC1*
q	13.666***	11.797***	9.835**	13.774***	12.552***
	(3.649)	(3.400)	(2.494)	(3.690)	(3.569)
*AT*q*	-5.127	-6.265	-8.071	-5.936	-4.937
	(-1.579)	(-1.594)	(-1.262)	(-1.646)	(-1.564)
*HighDelta*AT*q*	-1.690	-6.227	-3.936	-2.386	-2.545
	(-0.345)	(-0.655)	(-0.478)	(-0.405)	(-0.505)
AT	5.838	7.773	9.360	6.401	5.675
	(1.165)	(0.905)	(0.678)	(1.215)	(1.053)
*HighDelta*q*	-3.899	-4.834	-7.179	-3.467	-4.290
	(-0.788)	(-1.077)	(-1.541)	(-0.673)	(-0.996)
*HighDelta*AT*	5.779	14.617	10.483	7.802	7.338
	(0.641)	(0.775)	(0.537)	(0.681)	(0.772)
size	2.447	2.336	2.919	2.483	2.473
	(1.046)	(0.996)	(1.151)	(1.113)	(1.092)
CFO	-0.412	-6.424	1.596	0.004	-1.064
	(-0.035)	(-0.347)	(0.104)	(0.000)	(-0.089)
*AT*CFO*	8.893	0.528	18.853	11.599	8.163
	(0.678)	(0.020)	(0.454)	(0.778)	(0.560)
N	2,752	2,752	2,752	2,752	2,752

5.5 Robustness Checks

This subsection provides several robustness checks to the original empirical specification.

5.5.1 Alternative measure of investments

Table 12 presents the results when the dependent variable in Equation (3) is replaced by *(CAPX+R&D)/Asset.* The coefficients on *AT*q* remain significantly negative and the economic magnitude is similar to that documented in Table 3. For example, a one standard deviation increase in *PC1* is associated with a 39% (=0.703/1.797) reduction in investment-q sensitivity.

Table 12: Alternative Measure of Investments

This table reports the results from re-estimating Equation (2), where the dependent variable is replaced by (CAPX+R&D)/Assets. AT is standardized to have zero mean and unit standard deviation. Firm fixed effects and year fixed effects are included. Standard errors are double clustered at the firm and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

	(1)	(2)	(3)	(4)	(5)
AT	*oddlot*	*order/trade*	*cancel/trade*	*trade/volume*	*PC1*
q	2.008***	1.426***	1.100***	2.009***	1.797***
	(10.970)	(7.044)	(4.990)	(11.420)	(10.228)
*AT*q*	-0.632***	-1.015***	-1.707***	-0.708***	-0.703***
	(-6.545)	(-5.421)	(-5.405)	(-6.398)	(-6.480)
AT	1.213**	1.723**	4.831***	1.326**	1.396***
	(2.570)	(2.051)	(4.087)	(2.582)	(2.796)
size	-0.574	-0.546	-0.560*	-0.589	-0.566
	(-1.335)	(-1.446)	(-1.813)	(-1.345)	(-1.395)
CFO	-8.363***	-2.450	-2.436	-8.421***	-7.229***

	(-4.409)	(-0.858)	(-0.732)	(-4.417)	(-3.556)
*AT*CFO*	3.635***	12.859***	21.574***	3.594***	4.872***
	(2.850)	(3.160)	(2.736)	(2.749)	(3.049)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
N	12,297	12,297	12,297	12,297	12,297

5.5.2 Additional control variables in IV specification

While I use the average log prices as an instrument for IV activity, prices themselves can be an endogenous choice by managers. For example, management may have incentives to control nominal stock prices due to liquidity (Conroy et al. (1990), Angel (1997)) or catering rationales (Baker et al. (2009)). Following Weller (2017), I explicitly control for bid-ask spreads and institutional ownership to address these concerns. The results in Table 13 suggest that the inclusion of these two additional control variables has little impact on the coefficients of *q*AT*.

Table 13: Additional Controls in IV

This table reports the results from re-estimating Equation (2) with two additional control variabls, bid-ask spreads and institutional ownership. AT is standardized to have zero mean and unit standard deviation. Firm fixed effects and year fixed effects are included. Standard errors are double clustered at the firm and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

	(1)	(2)	(3)	(4)	(5)
AT	*oddlot*	*order/trade*	*cancel/trade*	*trade/volume*	*PC1*
q	6.051***	4.280***	3.437**	6.073***	5.453***
	(5.940)	(3.078)	(2.041)	(6.029)	(4.832)
*AT*q*	-1.799**	-3.192**	-5.234***	-1.956**	-2.042**
	(-2.308)	(-2.498)	(-2.752)	(-2.218)	(-2.373)

AT	7.173**	12.307**	19.309***	8.262**	8.048***
	(2.647)	(2.622)	(3.386)	(2.621)	(2.753)
size	3.514**	4.086***	3.947***	3.432**	3.707***
	(2.492)	(3.498)	(3.634)	(2.384)	(2.840)
CFO	26.810***	37.019***	40.398***	26.957***	28.933***
	(3.307)	(3.027)	(2.911)	(3.369)	(3.436)
*AT*CFO*	5.701	21.770	44.193	5.724	7.996
	(0.848)	(1.138)	(1.195)	(0.858)	(0.960)
Spread	165.252**	37.547	-110.222	210.868**	116.328
	(2.105)	(0.393)	(-0.862)	(2.495)	(1.560)
Inst	-24.662***	-25.776***	-23.463***	-26.053***	-25.189***
	(-3.385)	(-3.570)	(-2.997)	(-3.450)	(-3.449)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
N	12,120	12,120	12,120	12,120	12,120

5.5.3 Alternative aggregation period of AT

In the main analyses, I assume that managers base their future investment decisions on information from stock prices over the entire year. Table 14 presents the results when the window of learning (i.e. the aggregation period of AT) is shortened to 6 months (i.e. AT is instrumented with the average log prices during the last 6 months instead of a whole year). The coefficients on *AT*q* remain significantly negative and the economic magnitude is little changed compared to Table 3.

Table 14: Alternative Aggregation Period of AT

This table reports the results from re-estimating Equation (2), where AT is instrumented with the log average prices during the last 6 months of the year. AT is standardized to have zero mean and unit standard deviation. Firm fixed effects and year fixed effects are included. Standard errors are double clustered at the firm and year level. t-statistics are reported in parentheses under coefficient estimates. ***, **, and * denote two-sided test of significance level of less than 0.01, 0.05, and 0.1, respectively.

	(1)	(2)	(3)	(4)	(5)
AT	*oddlot*	*order/trade*	*cancel/trade*	*trade/volume*	*PC1*
q	6.889***	4.543***	3.308*	6.998***	6.180***
	(7.136)	(3.375)	(1.829)	(7.245)	(5.903)
*AT*q*	-2.015**	-4.100***	-6.568***	-2.158**	-2.353***
	(-2.649)	(-2.809)	(-2.690)	(-2.580)	(-2.706)
AT	9.121***	17.954***	26.404***	10.157***	10.404***
	(2.702)	(2.779)	(2.971)	(2.719)	(2.794)
size	0.211	2.013**	3.571***	-0.145	0.828
	(0.131)	(2.066)	(3.634)	(-0.082)	(0.626)
CFO	26.151***	33.968***	32.117***	26.953***	27.584***
	(3.113)	(2.970)	(3.230)	(3.291)	(3.263)
*AT*CFO*	4.370	19.834	32.243	4.934	6.292
	(0.727)	(1.020)	(1.047)	(0.822)	(0.841)
firm FE	Y	Y	Y	Y	Y
year FE	Y	Y	Y	Y	Y
N	12,288	12,288	12,288	12,288	12,288

6. Conclusion

I provide evidence that algorithmic trading (AT) has real effects: it reduces the sensitivity of corporate investment to stock price. I hypothesize that this is because ATs put fundamental traders at a disadvantage and crowd out their information acquisition, leading to less new information in stock prices for managers to learn. In the cross section, I find that the reduction in investment-price sensitivity concentrates in illiquid stocks, stocks with more informed trading and firms with higher level of accounting conservatism, lending support to the crowding out channel over the liquidity channel. I further document that firms' future operating performance deteriorates following periods of higher AT activity, which is another piece of evidence for AT's detrimental effects on real efficiency. Principal Component Analysis provides further supporting evidence that liquidity-taking ATs rather than market-making ATs are driving the reduction in investment-q sensitivity. Finally, I find that equity analysts' long term growth forecasts are less sensitive to the stock returns of firms with high AT activities, indicating that they also learn less from stock prices about firms' long-run prospects (likely to be unknown by managers).

One caveat of this study is that while AT spans a broad range of trading strategies, some of the competing hypotheses pertain to certain types of HFT strategies (e.g., market making versus order anticipations), which are not separately identified in the MIDAS data. However, I argue that the noise in the empirical proxies is not likely to undermine the documented results. First, HFT is the dominant form of AT that has attracted most scrutiny from investors and regulators (SEC (2010)); in this regard, the real effects of AT largely depend on the real effects of HFT. Second, some of the AT proxies (e.g., *Order/Trade* and *Cancel/Trade*) are closely linked to HFT strategies, providing more direct support for the theoretical predictions. Lastly, other types of low-frequency AT strategies (e.g., agency AT and fundamental-based AT) are more likely to reduce trading costs and improve price informativeness, which would bias against the results I find.

My findings provide empirical support for the proposition put forward by Stiglitz (2014), that improvement in nanosecond price discovery comes at the expense of fundamental traders who have spent resources to obtain information about the real economy. While AT improves liquidity and accelerates the incorporation of existing information into prices, it discourages information production, leads to a less informative market, and reduces the extent to which managers are able to learn from prices in making investment decisions. This real effects of AT provide a new angle to evaluate the technological advances in financial markets.

Appendix A: Sample Construction

Criteria	Observations
Firm-years in Compustat/CRSP Merged dataset with fiscal year ending between 2012-2017	29,053
Exclude observations with less than 63 days of available order book data from MIDAS	13,297
Exclude observations with less than 63 days of available prices from CRSP	13,256
Exclude observations with missing variables for equation(2)	12,737

Appendix B: Variable Definition

Variable	Definition
$I_{i,t+1}$	Firm i's capital expenditure (CAPX) during yeat t+1 scaled by the net PP&E (PPENT) at the end of year t
$q_{i,t}$	Firm i's market value of equity (PRCC_F*CSHO) plus book value of liabilities (AT - CEQ) scaled by book assets (AT) at the end of year t
$size_{i,t}$	Firm i's market capitalization in natural logarithm (ln(PRCC_F*CSHO)) at the end of year t
$CFO_{i,t}$	Firm i's cash flow from operations scaled by total assets at the end of year t (OANCF/AT)
$AT_{i,t}$	Four proxies for algorithmic trading of firm i's stock during year t as described below:
$Oddlot\ ratio$	The total volume associated with odd lot trades divided by the total trade volume
$Ordertotrade\ ratio$	The total volume across all orders placed divided by the total trade volume
$Canceltotrade\ ratio$	The number of full of partial cancellations divided by the number of trades
$Tradetovolume\ ratio$	The number of trades divided by the total trade volume
$PC1_{i,t}$	The first principal component scores based on a principal component analysis of the four AT proxies
$PC2_{i,t}$	The second principal component scores based on a principal component analysis of the four AT proxies
$LnP_{i,t}$	The log of the average stock prices of firm i during year t
$HighSpread_{i,t}$	An indicator variable that is equal to 1 if the average closing daily bid-ask spreads of firm i is in the top quartile of the sample for year t, and 0 if in the bottom quartile
$HighAnalyst_{i,t}$	An indicator variable that is equal to 1 if the number of analysts that cover firm i during year t is in the top quartile of the sample, and 0 if in the bottom quartile
$HighConsv_{i,t}$	An indicator variable that is equal to 1 if the average C-score for firm i, calculated following Khan and Watts (2009), during the past five years is in the top quartile of the sample, and 0 if in the bottom quartile
$Op_{i,t+1}$	Firm i's operating performance during year t+1, described below:
$ROA_{i,t+1}$	Firm i's operating income before depreciation during year t +1 divided by total assets at the end of year t (OIBDP/AT)

$SalesGrowth_{i,t+1}$	Firm i's growth in sales revenue during year t+1 ($\frac{REVT_{i,t+1}}{REVT_{i,t}} - 1$)
$Turnover_{i,t+1}$	Firm i's sales revenue during year t+1 divided by total assets at the end of year t
$Rev_{i,j,t}$	Analyst *j*'s revision of long-term growth forecast on firm *i* issued at date *t*, defined as the forecast at date *t* minus the forecast at date *t-1*
$Ret_{i,t-1}$	The stock return of firm *i* between date *t-1* and date *t*
$Days_{i,j,t}$	The log number of days between the two forecasts issued by analyst *j* on firm *i*
$Earn_{i,t}$	The income before extraordinary items of firm *i* during year *t* scaled by the market capitalization of firm *i* at the beginning of year *t*
$1 - R^2_{i,t}$	R^2 is the R-squared from regressing firm *i*'s daily returns on the market returns and industry returns during year *t*
$NZRET_{i,t}$	The fraction of non-zero return trading days for firm *i* during year *t*
$HighFinConst_{i,t}$	An indicator variable that is equal to 1 if the financial constraint measure for firm i calculated following Hadlock and Pierce (2010) is in the top quartile of the sample during year t, and 0 if in the bottom quartile
$Eqiss_{i,t+1}$	Firm i's equity issuance during year t+1, measured as $(CEQ_{i,t+1} - CEQ_{i,t} + RE_{i,t} - RE_{i,t+1})/AT_{i,t}$
$HighDelta_{i,t}$	An indicator variable that is equal to 1 if firm i's pay-for-performance sensitivity calculated following Core and Guay (2002) is in the top quartile of the sample for year t, and 0 if in the bottom quartile
$Inst_{i,t}$	The average quarterly institutional ownership for firm *i* during year *t*

References

Ait-Sahalia, Y., & Saglam, M. (2017). High frequency market making: implications for liquidity. *Working Paper*.

Allen, F. (1993). Stock markets and resource allocation. In C. Mayer & X. Vives (Eds.), *Capital Markets and Financial Intermediation* (pp. 81-108). Cambridge: Cambridge University Press.

Angel, J. J. (1997). Tick Size, Share Prices, and Stock Splits. *The Journal of Finance*, 52(2), 655-681.

Bai, J., Philippon, T., & Savov, A. (2016). Have financial markets become more informative? *Journal of Financial Economics, 122*(3), 625-654.

Baker, M., Stein, J. C., & Wurgler, J. (2003). When Does the Market Matter? Stock Prices and the Investment of Equity-Dependent Firms. *The Quarterly Journal of Economics, 118*(3), 969-1005.

Baker, M., Greenwood, R., & Wurgler, J. (2009). Catering through Nominal Share Prices. *The Journal of Finance, 64*(6), 2559-2590.

Bakke, T.-E., & Whited, T. M. (2010). Which Firms Follow the Market? An Analysis of Corporate Investment Decisions. *The Review of Financial Studies, 23*(5), 1941-1980.

Baldauf, M., & Mollner, J. (2018). High-frequency trading and market performance. Working Paper.

Baron, M., Brogaard, J., Hagströmer, B., & Kirilenko, A. (2018). Risk and return in high-frequency trading. *Journal of Financial and Quantitative Analysis, Forthcoming*.

Boehmer, E., Li, D., & Saar, G. (2018). The Competitive Landscape of High-Frequency Trading Firms. *The Review of Financial Studies, 31*(6), 2227-2276.

Bond, P., Edmans, A., & Goldstein, I. (2012). The Real Effects of Financial Markets. *Annual Review of Financial Economics*, *4*(1), 339-360.

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-Frequency Trading and Price Discovery. *The Review of Financial Studies, 27*(8), 2267-2306.

Brunnermeier, M. K. (2005). Information Leakage and Market Efficiency. *The Review of Financial Studies, 18*(2), 417-457.

Carrion, A. (2013). Very fast money: High-frequency trading on the NASDAQ. *Journal of Financial Markets*, *16*(4), 680-711.

Chaboud, A. P., Chiquoine, B., Hjalmarsson, E., & Vega, C. (2014). Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market. *The Journal of Finance*, *69*(5), 2045-2084.

Chen, Q., Goldstein, I., & Jiang, W. (2007). Price Informativeness and Investment Sensitivity to Stock Price. *The Review of Financial Studies*, *20*(3), 619-650.

Chen, Q., Huang, Z., Jiang, X., Zhang, G., & Zhang, Y. (2018). The effects of asymmetric disclosure on price informativeness and firm performance. Working Paper.

Clark-Joseph, A. D. (2013). Exploratory trading. *Job Market Paper*.

Conroy, R. M., Harris, R. S., & Benet, B. A. (1990). The Effects of Stock Splits on Bid-Ask Spreads. The Journal of Finance, 45(4), 1285-1295.

Core, J., & Guay, W. (2002). Estimating the Value of Employee Stock Option Portfolios and Their Sensitivities to Price and Volatility. *Journal of Accounting Research*, *40*(3), 613-630.

Dow, J., & Gorton, G. (1997). Stock market efficiency and economic efficiency: is there a connection? *Journal of Finance, 52*(3), 1087-1129.

Dye, R., & Sridhar, S. (2002). Resource Allocation Effects of Price Reactions to Disclosures. *Contemporary Accounting Research*, *19*(3), 385-410.

Edmans, A., Goldstein, I., & Jiang, W. (2015). Feedback Effects, Asymmetric Trading, and the Limits to Arbitrage. *American Economic Review*, *105*(12), 3766-3797.

Edmans, A., Jayaraman, S., & Schneemeier, J. (2017). The source of information in prices and investment-price sensitivity. *Journal of Financial Economics*, *126*(1), 74-96.

Fang, V. W., Noe, T. H., & Tice, S. (2009). Stock market liquidity and firm value. *JOurnal of Financial Economics*, *94*(1), 150-169.

Foucault, T., & Frésard, L. (2012). Cross-Listing, Investment Sensitivity to Stock Price, and the Learning Hypothesis. *The Review of Financial Studies*, *25*(11), 3305-3350.

Gider, J., Schmickler, S., & Westheide, C. (2016). High-frequency trading and fundamental price efficiency. *Working Paper*.

Grossman, S., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *American Economic Review, 70*(3), 393-408.

Hadlock, C. J., & Pierce, J. R. (2010). New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index. *The Review of Financial Studies, 23*(5), 1909-1940.

Hagströmer, B., & Nordén, L. (2013). The diversity of high-frequency traders. *Journal of Financial Markets, 16*(4), 741-770.

Han, J., Khapko, M., & Kyle, A. S. (2014). Liquidity with high-fequency market making. *Working Paper*.

Hasbrouck, J., & Saar, G. (2013). Low-latency trading. *Journal of Financial Markets, 16*(4), 646-679.

Hayek, F. A. (1945). The Use of Knowledge in Society. *American Economic Review* 35 (4):519-530.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does Algorithmic Trading Improve Liquidity? *The Journal of Finance, 66*(1), 1-33.

Hendershott, T., & Riordan, R. (2013). Algorithmic Trading and the Market for Liquidity. *Journal of Financial and Quantitative Analysis, 48*(4), 1001-1024.

Hirschey, N. (2018). Do high-frequency traders anticipate buying and selling pressure? *Working Paper*.

Hoffmann, P. (2014). A dynamic limit order market with fast and slow traders. *Journal of Financial Economics, 113*(1), 156-169.

Hunnicutt, T. March 28, 2017. BlackRock cuts fees and jobs; stockpicking goes high tech. Reuters. https://www.reuters.com/article/us-blackrock-funds/blackrock-cuts-fees-and-jobs-stockpicking-goes-high-tech-idUSKBN16Z2X9

Israeli, D., Lee, C. M. C., & Sridharan, S. A. (2017). Is there a dark side to exchange traded funds? An information perspective. *Review of Accounting Studies, 22*(3), 1048-1083.

Jayaraman, S., & Wu, J. S. (2018). Is Silence Golden? Real Effects of Mandatory Disclosure. *The Review of Financial Studies*, Forthcoming.

Kanodia, C., & Lee, D. (1998). Investment and disclosure: the disciplinary role of periodic performance reports. *Journal of Accounting Research, 36*(1), 33-55.

Kanodia, C., & Sapra, H. (2016). A Real Effects Perspective to Accounting Measurement and Disclosure: Implications and Insights for Future Research. *Journal of Accounting Research, 54*(2), 623-676.

Khan, M., & Watts, R. L. (2009). Estimation and empirical properties of a firm-year measure of accounting conservatism. *Journal of Accounting and Economics, 48*(2), 132-150.

Kirilenko, A., Kyle, A. S., Samadi, M., & Tuzun, T. (2017). The Flash Crash: High-Frequency Trading in an Electronic Market. *The Journal of Finance, 72*(3), 967-998.

Korajczyk, R. A., & Murphy, D. (2018). High frequency market making to large institutional trades. *The Review of Financial Studies, Forthcoming*.

Lee, C. M. C., & Watts, E. M. (2018). Tick size tolls: Can a trading slowdown improve price discovery? Working Paper.

Leuz, C., & Wysocki, P. D. (2016). The Economics of Disclosure and Financial Reporting Regulation: Evidence and Suggestions for Future Research. *Journal of Accounting Research, 54*(2), 525-622.

Lewis, M. (2014). Flash boys: A Wall Street revolt: W. W. Norton & Company.

Luo, Y. (2005). Do Insiders Learn from Outsiders? Evidence from Mergers and Acquisitions. *The Journal of Finance, 60*(4), 1951-1982.

Lyle, M. R., & Naughton, J. P. (2016). How does algorithmic trading improve market liquidity? Working Paper.

Malinova, K., Park, A., & Riordan, R. (2018). Do retail investors suffer from high frequency traders? *Working Paper*.

Menkveld, A. J. (2016). The Economics of High-Frequency Trading: Taking Stock. *Annual Review of Financial Economics, 8*(1), 1-24.

Meyer, G., Bullock, N. & Rennison, J. January 1, 2018. How high-frequency trading hit a speed bump. Financial Times. https://www.ft.com/content/d81f96ea-d43c-11e7-a303-9060cb1e5f44).

Morck, R., Shleifer, A., & Vishny, R. (1990). The stock market and investment: is the market a sideshow? Brookings Papers on Economic Activity, 21(2), 157-216.

O'Hara, M., Yao, C., & Ye, M. (2014). What's Not There: Odd Lots and Market Data. *The Journal of Finance, 69*(5), 2199-2236.

Rappaport, A. (1987). Stock market signals to managers. *Harvard Business Review* (November).

Saglam, M. (2017). Order anticipation around predictable trades. *Working Paper*.

SEC. (2010). Concept release on equity market structure. *Concept Release 34-61358, File S7-02-10*.

SEC. (2014). Equity market structure literature review Part II: high frequency trading.

Stiglitz, J. E. (2014). Tapping the brakes: are less active markets safer and better for the economy? *Working Paper*.

Subrahmanyam, A., & Titman, S. (2001). Feedback from Stock Prices to Cash Flows. *The Journal of Finance, 56*(6), 2389-2413.

Tobin, J. (1969). A General Equilibrium Approach To Monetary Theory. *Journal of Money, Credit and Banking, 1*(1), 15-29.

van Kervel, V., & menkveld, A. J. (2018). High-frequency trading around large institutional orders. *Journal of Finance, Forthcoming*.

Weller, B. (2017). Does algorithmic trading reduce information acquisition? *Review of Financial Studies*.

Yang, L., & Zhu, H. (2017). Back-running: Seeking and hiding fundamental information in order flows. *Working Paper*.

Zhang, S. S. (2018). Need for speed: Hard information processing in a high-frequency world. *Journal of Futures Markets*, 38(1), 3-21.

Zuo, L. (2016). The informational feedback effect of stock prices on management forecasts. *Journal of Accounting and Economics, 61*(2), 391-413.

Biography

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