Algorithmic Trading and High Frequency Trading

Hao Zhou

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Centre for Applied Financial Studies

UniSA Business School

University of South Australia

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Hao Zhou

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Declaration of Authorship

I hereby declare that this thesis contains no material which has been accepted for the award of any other degree or diploma in any university or other institution and that, to the best of my knowledge this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

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Abstract

This thesis provides one standalone survey essay and three empirical essays on algorithmic trading (AT) and its effect on market qualities. The survey essay reviews the theoretical, empirical, and policy studies on algorithmic and high frequency trading. We review the theoretical literature relating to: (1) market maker–taker dynamics, (2) information content of trades and quotes, and (3) recently incurred or proposed market structural changes. We aim to provide a comprehensive roadmap for future research by surveying the empirical literature with an emphasis on how data and causal events can be identified. Our conclusion includes a brief discussion of policy implications and suggestions for future work.

The first empirical essay investigates the role algorithmic trading on days when the absolute value of the market return is more than 2%. We find that the abnormal return of a stock is related to the stock's AT intensity, that high AT intensity stocks experience less price drops (surges) on days when the market declines (increases) for more than 2%. This result is consistent with the view that AT minimizes price pressures and mitigates transitory pricing errors.

The second empirical essay examines algorithmic execution strategy and the effects of algorithmic trading order imbalances. We find that, *ex-ante*, algorithmic traders execute their trades according to the prevailing Volume-Weighted Average Price (VWAP), they are more likely to execute buy (sell) orders when the prevailing VWAP moves lower (higher) compared to the prevailing stock price. This implies a contrarian strategy which may mitigate the short-term price trends. Further analyses show that AT order imbalances have a smaller price impact compared to non-AT order imbalances. These effects are robust on days when the absolute value of the market return is more than 2%.

The last empirical essay considers the role of algorithmic trading in the price discovery process. We estimate a state space framework that decomposes stock prices into permanent price series and transient pricing error via state space frameworks. We find that algorithmic traders contribute more to the permanent price processes and less to the transient pricing errors compared to other traders. Our results show that AT facilitates the price discovery process by contributing to permanent price movements. Our results are robust on days when the absolute value of the market return is more than 2%.

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Abbreviations

ARIMA Autoregressive Intergraded Moving Average

ARMA Autoregressive Moving Average

ASX Australian Securities Exchange

AT Algorithmic Trading

CAR Cumulative Abnormal Return

CFTC Commodity Futures Trading Commission

CT Computerized Trading

E-mini E-mini S&P 500 Futures

FTT Financial Transactions Tax

HFT High Frequency Trading

IV Instrumental Variable

NASDAQ National Association of Securities Dealers Automated Quotations

NYSE New York Stock Exchange

SEC Securities and Exchange Commission

SIRCA Securities Industry Research Centre of Asia-Pacific

VAR Vector Autoregression

VWAP Volume-Weighted Average Price

Chapter 1

Introduction and overview

1.1 Introduction

Financial markets are experiencing a major transition due to the advance of Algorithmic Trading (AT) technologies. The traditional views regarding the roles and the responsibilities of market participants, the characteristics of market qualities, and the determinants of security prices all need to be re-investigated. For example, O'Hara (2015) argue that, in a high frequency environment, short term information and price changes might not just be asset value-related but also motivated by investors' order flows. Many of these changes can be directly attributed to AT. This thesis surveys the recent literature on AT and High Frequency Trading (HFT) and investigates the characteristics of AT in a turbulent post-global financial crisis period on the Australian Securities Exchange (ASX).

This thesis consists of one standalone survey chapter and three empirical chapters. The survey chapter reviews around 100 recent theoretical, empirical, and policy studies on AT and HFT. The theoretical literature review highlights the heterogeneity in the assumptions and the modeling approaches and the resulting differences in the conclusions. Most of the theoretical literature models computerized traders as fast traders which differ in terms of the roles they play, the information contents they possess, and their trading environments. Therefore, we review the theoretical papers based on three criteria: market maker–taker dynamics, level of information content, and market structural changes. We review the empirical and policy literature with the aim of providing a comprehensive roadmap to future researchers. Specifically, we focus on the two major empirical challenges faced by computerized trading researchers: The data identification and the causal inferences. We first introduce the empirical papers based on how AT or HFT is identified. We then discuss the papers in relation to their causal techniques and exogenous events. In addition, we summarize and contrast the current empirical findings around various market quality measures. Finally, we identify the gaps in the literature and suggest several directions for future research.

The first empirical chapter investigates the effects of AT on individual stock returns during turbulent periods. We identify 39 turbulent days defined as the days when the absolute value of the market return exceeds 2%. We then assess the relation between AT and individual stock returns on turbulent days. We find that, on days when the market moves up by more than 2%, stocks with high AT intensity experience less upward price pressures. On market down days, the prices of high AT intensity stocks decline less. Our results are economically significant: On market down days, a 10% (or a half standard deviation) increase in algorithmic selling, on average, corresponds to a 12 basis point smaller price drop in individual stocks. The economic significance is similar on market up days. Furthermore, in the five-day period post market down days, stocks with less AT experiences more return reversals. Taken together, we find that AT negatively relates to individual stock price swings on turbulent days. Our results supports the view that algorithmic traders minimize the price pressures of their transactions and mitigate transient price pressures from the market.

The second empirical chapter examines AT execution strategy and order imbalances. We relate AT execution strategy to the Volume-Weighted Average Price (VWAP). The VWAP is a common metric for traders to assess their execution performances. We construct intraday VWAPs and apply a logit model to assess the choice of AT order submission in relation to the prevailing VWAP. We find that algorithmic traders are more likely to initiate transactions when intraday VWAP moves more favorably. Specifically, a buy (sell) order lower (higher) than the VWAP is considered favorable. AT is more likely to initiate buy (sell) orders when the prevailing VWAP moves lower (higher). Our result implies that, compared to other traders, algorithmic traders are more contrarian and AT may mitigate the price trends over the short-term. We then assess AT order imbalances and its effect on stock prices. We show that the price impact of AT order imbalances are smaller compared to non-AT order imbalances. The effects documented in this chapter are robust on turbulent days.

The last empirical chapter analyze the role of AT in the process of price discovery. To isolate the efficient (permanent) price discovery process from the short-term noises, We apply state space models to decompose the observed price series into an unobserved efficient price component and a transient error component. The efficient price component, modeled as a martingale, captures information arrivals relevant to the permanent price. The transient error component, modeled as an autoregressive process, represents the short-term noises such as temporary liquidity shocks and market microstructure noises. We assess the contribution of AT to both the efficient price discovery process and transient pricing errors. We find that AT facilitates the efficient price discovery process by trading more in the direction of efficient price changes and less in the direction of transient pricing errors.

1.2 Contributions

This thesis contributes to the literature in several ways. First, we provide the most comprehensive survey of the recent and emerging AT and HFT literature, to the best of our knowledge. Biais and Woolley (2011) and Jones (2013) provide early reviews on the topic of HFT. Goldstein, Kumar, and Graves (2014) describe the history of automated trading over the last decade and survey several AT and HFT papers. SEC (2014) summarizes the empirical HFT literature from a policy making perspective. O'Hara (2015) and Stiglitz (2014) discuss the broader perspectives of market microstructure research and social welfare economics respectively. We add to this burgeoning literature by reviewing the recently published and working papers, and contribute in terms of both depth and breadth. Specifically, we aim to provide a complete picture on the topic of computerized trading by reviewing the empirical and theoretical literature on AT and HFT. We also decompose the theoretical modeling approaches and offer a deeper understanding of the diversity of the theoretical conclusions.

Second, we highlight the effects of AT over time intervals relevant to non-algorithmic investors. Regulatory agencies have been expressing concerns about the implications of AT to non-AT, which has longer trading horizons than AT. Whether the recent changes of the equity market structure due to AT are detrimental or not for the rest of the investment community, as pointed out in a note by the U.S. regulator, is an important issue that deserves further investigation (SEC, 2010). However, most of the AT and HFT studies have focused on ultra-short-term effects, ranging from milliseconds to minutes.[1] For instance, Hendershott and Riordan (2013) relate AT to intraday liquidity measures such as the bid–ask spread and order book depth. Hasbrouck and Saar (2013) propose a framework for identifying HFT and assess its intraday effects. Brogaard, Hendershott, and Riordan (2014) assess the impact of HFT on market qualities on a second-by-second basis and, more specifically, report the effect of HFT in the 20 seconds around public announcements. It is relevant and intuitive to analyze automated trading at ultra-high frequencies since many proprietary trading strategies emphasize the exploitation of small and fleeting

[1] A subset of AT, HFT is generally distinguished from AT by its clear emphasis on trading speed.

opportunities in the market. There are reasons to suggest the longer-term implications of AT. Some computerized traders follow an extension of traditional trading strategies, such as value, momentum, and pairs trading. These strategies often involve holding positions over days and longer horizons. Moreover, according to the ASX (2010), execution algorithms make up the majority of AT.[2] These execution algorithms are services provided to buy-side clients to minimize the price impact of trading and thus the intention to trade is expressed by human traders. Therefore, the inference of these trades could be studied over horizons longer than a few minutes. We show the association between AT and price fluctuations on the turbulent days and five days immediately after the turbulent days.

Third, we provide empirical evidence of the relationship between AT and daily price fluctuations during the most turbulent trading days of the global financial crisis. To the best of our knowledge, our study is the first to investigate the impact of AT on daily stock returns. Hendershott, Jones, and Menkveld (2011) show that AT reduces the price impact of trades over the next 5 to 30 minutes. We differ in research design by focusing on turbulent periods and longer-term effects. Our findings suggest that AT is negatively related to stock price swings on days with extreme price movements and the stock return reversal over the subsequent days.

Fourth, we contribute to the literature by empirically showing the difference between AT and non-AT order imbalances. A rich literature exists on the impact of order imbalances on stock markets (e.g., Hasbrouck and Seppi, 2001; Chordia, Roll, and Subrahmanyam, 2002; Chordia and Subrahmanyam, 2004). We extend this literature by providing evidence of heterogeneity based on order imbalances from different investor groups. We find that nonAT order imbalances are more persistent compared to AT order imbalances; however, AT order imbalances have significantly less impact on stock returns. After controlling for trade size and the total level of trading activity, we find that, *ceteris paribus*, the impact of order imbalances by nonAT is 50% larger than by AT.

In addition, we investigate the execution strategy of AT that could affect stock price fluctuations. A number of studies have suggested that AT and HFT could follow VWAP strategies to optimize the timing of their trades (e.g.

[2] Algorithms can be separated into execution algorithms and situational algorithms (ASX, 2010). Execution algorithms (or agency algorithms) seek to reduce the costs of executing large orders by minimizing the market impact of trades. In contrast, situational algorithms (or proprietary algorithms) profit by monitoring and analyzing market data and news. HFT is a subset of situational algorithms.

Domowitz and Yegerman, 2005; Hendershott et al., 2011; Easley, Lopez de Prado, and O'Hara, 2012). Carrion (2013) uses end-of-day VWAP metrics to show that, ex post, HFT times the market successfully. We differ from Carrion (2013) by using the intraday dynamic VWAP, which continuously updates throughout a trading session. We show that, ex ante, the execution decisions of algorithms are highly sensitive to the prevailing VWAP at the time of the trade.

Finally, provided that AT is more widely adopted and incorporates longer-term trading strategies compared to HFT. Our results on AT price discovery compliments the results of Brogaard, Hendershott, and Riordan (2014) on HFT price discovery. High frequency traders rely on expensive low latency technologies and compete to be a fraction of a second faster than the others (Biais, Foucault, and Moinas, 2015). Therefore, HFT is mostly adopted by a small number of highly sophisticated proprietary traders and electronic market makers, whereas AT technology has been widely adopted by buy-side funds and brokerages due to its lower cost and less reliance on infrastructure.

Chapter 2

Algorithmic and High Frequency Trading: A Review of the Literature

Chapter Summary

Algorithmic trading is a specialized trading activity in which quotes and trades are computer generated to follow certain strategies. As a subset of algorithmic trading, high frequency trading is generally distinguished from algorithmic trading by its clear emphasis on trading speed. Our paper reviews the theoretical, empirical, and policy studies on algorithmic and high frequency trading. We review the theoretical literature relating to: (1) market maker–taker dynamics, (2) information content of trades and quotes, and (3) recently incurred or proposed market structural changes. We aim to provide a comprehensive roadmap for future research by surveying the empirical literature with an emphasis on how data and causal events can be identified. Our conclusion includes a brief discussion of policy implications and suggestions for future work.

2.1 Introduction

The past decade has seen a tremendous proliferation of AT and HFT in financial markets.[3] The growth in automated trading technology has restructured the way we trade securities now. Computer systems have replaced trading floors and fast moving machines have taken over the role of intermediation by human market makers. However, these developments are not without controversy. Many unprecedented events, such as the "flash crash" and the "Knight Capital glitch", have exposed the vulnerability of the new trading ecosystem.[4] Large scale and negative media coverage have brought these phenomena into the public eye. Academics are keen to understand this new phenomena. To the best of our knowledge, there have been around 100 papers on the topics of AT and HFT written over the last few years.

Figure (2.1) illustrates the public attention on HFT via a Google trend analysis. Over the long term, Google search frequency has elevated substantially post the global financial crisis. The "flash crash", its related media coverage, and regulatory releases are correlated with several initial spikes of search frequencies. Public attention peaked around the release of the popular book: "Flash Boys" (Lewis, 2014), which generated significant scepticism over HFT.

We aim to provide a comprehensive review of the recent and emerging AT and HFT literature. Biais and Woolley (2011) and Jones (2013) provide early reviews on the topic of HFT. Biais and Woolley (2011) focus on the policy implications of HFT and propose several principles of HFT regulation. Jones (2013) emphasizes the diversity of HFT strategies and the impact of HFT on market quality, particularly market fragility issues related to the "flash crash" and similar incidents. Goldstein, Kumar, and Graves (2014) describe the evolution of automated trading over the past decade and survey several AT and HFT studies. SEC (2014) examines the empirical HFT

[3]The percentage of AT volume has increased from about non-existent in 2003 to about 70% in 2007 for euro, dollar, and yen currency exchange trading on Electronic Broking Services (Chaboud, Chiquoine, Hjalmarsson, and Vega, 2014). ASIC (2013) estimates that HFT accounts for 27% of Australian equity market turnover in 2012.

[4]On May 6, 2010, US stock market indices dropped by more than 5%, only to recover 30 minutes later. This incident, known as the "flash crash", is widely discussed in the literature. See, e.g., Biais and Woolley (2011); Kirilenko, Kyle, Samadi, and Tuzun (2017); Jones (2013); Goldstein, Kumar, and Graves (2014); and SEC (2014). On October 16, 2013, Knight Capital's order routing system glitch generated more than 4 million trades in 45 minutes when processing 212 small retail orders (SEC, 2013).

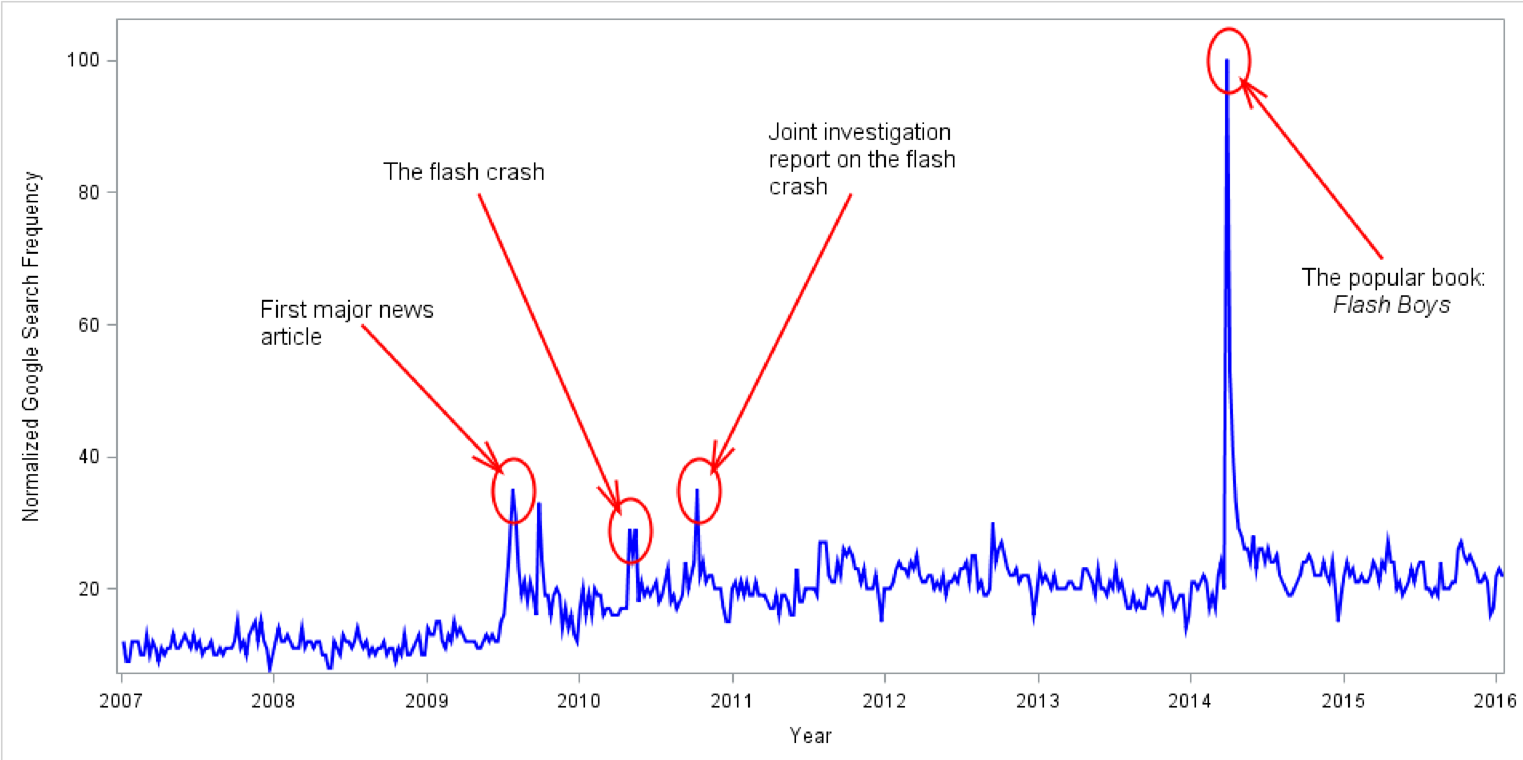

Figure 2.1: HFT Public Information Demand Analysis via Google Trend.
This figure shows the time series of normalized Google search frequency of the key words 'HFT' and 'High Frequency Trading' between 2007 and 2016. The blue line is global Google search frequency normalized to a maximum of 100. The red circles denote several crucial times when HFT has entered the public sphere.

literature and focuses on US stock market to an audience of regulators, practitioners, and academics. O'Hara (2015) considers the market microstructure changes in light of computerized trading technology. The author discusses how the trading world has changed and how market microstructure research should adapt. Stiglitz (2014) provides a theoretical discussion on the broader social welfare effects of HFT and other recent financial innovations. We add to this burgeoning literature by reviewing the previous work, and contribute in terms of both depth and breadth. In particular, we review empirical HFT studies in conjunction with AT and theoretical literature. We also emphasise on the diversity of the modeling approaches given that the theoretical literature features a variety of different computerized trading strategies, our goal is to compare, contrast and assimilate the literature. Another objective of our paper is to provide a roadmap for future research. Therefore, we focus on the two main challenges in the empirical literature: identifying AT/HFT trades and establishing causal relation between AT/HFT and market quality metrics.

Trading algorithms can generally be divided into execution algorithms and situational algorithms (ASX, 2010). Execution algorithms, also called agency algorithms, seek to reduce the costs of executing large orders by minimizing the market impact of trades and they account for the bulk of AT. In contrast, situational algorithms, also known as proprietary algorithms, profit by monitoring and analyzing market data and news announcements. HFT is a subset of AT that predominantly utilizes situational algorithms.[5] SEC (2014) lists four broad categories of HFT strategies. Passive market making generally involves the submission of limit orders that provide liquidity in the marketplace. Directional strategies aim to profit from direction change in security prices via long or short positions. High frequency arbitrageurs scan the related products, often in different markets, to identify arbitrage opportunities due to temporary pricing misalignments and rely on their low latency trading technology to be the first to seize the opportunity. Structural strategies seek to exploit structural vulnerabilities in markets or in other market participants. For instance, traders with fast trading technologies may be able to profit by trading against stale orders submitted by slower traders. These strategies are discussed in the empirical, and to a larger extent, in the theoretical literature.

We use the term "Computerized Trading (CT)" when the subject matter concerns both AT and HFT throughout this paper in order to improve the precision of our discussions. Since AT encompasses HFT, when one refers to AT, one technically also refers to HFT. However, simply using the term "AT" when referring to an effect found in both AT and HFT studies would be inaccurate, since the reader may assume that the effect is only found in AT studies. Therefore, we specify the term "CT" to avoid the redundant phrase "both AT and HFT" or the imprecise term "AT" when referring to both trading groups.[6]

In this paper, we review the theories on CT regarding three aspects: market maker–taker dynamics, the level of information content, and market structural changes. Under mild assumptions, the theoretical studies model specific CT strategies. As a result, there exists a large diversity in modeling approaches and hence a variety of

[5]Although there is no clear definition, HFT generally have the following attributes: (1) acting in a proprietary capacity and executing large amount of trades; (2) using high-speed and sophisticated computer programs; (3) holding positions for a very short time; (4) submitting numerous orders and cancelling them almost instantly; (5) ending the trading day with almost no inventory; (6) minimizing latencies using colocation services (SEC, 2010).

[6]The introduction of "CT" allows us to leave the exclusivity function of the terms "AT" and "HFT" intact. Nevertheless, we use "AT" or "HFT" whenever possible to highlight the significant differences between AT and HFT.

predictions. In other words, the conclusions reached in a theoretical study often depend on which computerized traders groups are targeted by the authors. The modeling approaches of theoretical papers differ in the following aspects. First, CT can be modeled as liquidity providers or liquidity consumers (e.g., Foucault, Hombert, and Roşu 2016; Jovanovic and Menkveld 2016b). Second, the literature also models CT with different levels of private information, i.e., informed about future order flows (Aït-Sahalia and Saglam, 2014), or uninformed (Cvitanic and Kirilenko, 2010). Third, several studies also link market structural changes related to CT, such as the introduction of maker–taker pricing schemes (Foucault, Kadan, and Kandel, 2013), or increased degree of market fragmentation (Biais, Foucault, and Moinas, 2015). To accommodate these three characteristics, our survey focuses on how the models are constructed and what type of CT is discussed. We survey the theoretical literature based on whether the targeted computerized traders are liquidity suppliers, liquidity consumers, or a mixture of both. Next, our paper discusses the different levels of private information assumed in the literature. Last, we survey the literature that relates CT to recently incurred or proposed market structural and policy changes.

We then survey the empirical studies on CT. The challenges faced by the empirical literature can be categorized into two aspects. First, empirical researchers have to either proxy for CT or use datasets that flag computerized trades. However, proxies for CT provide limited level of details for researchers to target specific questions. Moreover, data identifying CT are usually hard to obtain and unavailable through public databases. Second, like most other market microstructure topics, the causation between CT and market quality metrics is difficult to establish. In the absence of direct theoretical predictions, empirical researchers can rely on "natural experiments" that cause exogenous shocks to AT or HFT activities. In the current literature, instrumental variable regressions are constructed based on carefully selected market events under the assumption that these events are uncorrelated with the market quality metrics. However, some instrumental variables are not strictly exogenous. For example, colocation is the most widely used instrument for AT and HFT. Brogaard, Hagströmer, Nordén, and Riordan (2015) find that not only do high frequency traders employ colocation services, but many other types of traders also use these services. To assist future research, we survey the empirical literature outlining how CT data can be identified and introduce causal identification instruments employed in CT studies. We then summarize the effects of CT on market quality metrics.

Although we aim to exhaust the literature on CT, it is beyond the scope of our paper to assign all existing studies to each aspect that we discuss. Instead, we introduce recent CT studies based on the aforementioned three theoretical and two empirical aspects. It is intended that this systemized approach would be more useful than listing the contributions of individual studies in detail. Section 2.2 discusses existing literature review and policy papers. In Section 2.3, we consider the theoretical literature with respect to three aspects of CT, namely market maker–taker dynamics, the level of information content, and recently incurred or proposed market structural changes. In Section 2.4, we explain the data identification and causal techniques in empirical studies. Section 2.5 examines the effects of CT on market quality and Section 2.6 provides a conclusion and suggestions for future research.

2.2 Review and policy studies

In this section, we discuss the existing survey and policy literature on CT according to the following criteria: First, several papers discuss the recent trading issues in the perspective of the computerized traders. The CT literature forms a basis for their discussion in terms of various related market phenomena. Second, few studies discuss the recent changes in market structure and its implication in social welfare, but these papers take the broader perspectives of market designers and policy makers. Last, regulatory agencies and exchange operators have released a number of policy papers addressing the growing popularity of CT.

2.2.1 CT review papers

Biais and Woolley (2011) provide an early review of HFT with the aim of contributing to policy debate while drawing evidence from several theoretical and empirical studies. Specifically, the authors argue that, under *laissez-faire* conditions, further development in HFT may trigger an arms' race to minimize latency or impose systemic risk in the market. The authors then propose potential regulatory interventions such as monitoring and taxing HFT, imposing minimum latency, regulatory oversight, and capital requirements. Jones (2013) reviews theoretical and empirical research on HFT and liquidity. Based on the available empirical research on HFT, the author argues that HFT has significantly improved market liquidity and lowered trading cost for all investors. At the same time, Jones warns that HFT may not be beneficial during extremely volatile periods such as the "flash crash". Goldstein, Kumar, and Graves (2014) survey a large body of literature on CT and describe its evolution as well as the recent suspected decline of HFT. In addition, the authors discuss the effects of rapid computerized traders on market fairness and market stability, giving a detailed list of market glitches during the years 2010–2013. Goldstein, Kumar, and Graves provide additional information by quoting substantially from several reputable news agencies (e.g., Reuters, the Wall Street Journal, and the New York Times). Menkveld (2016) provides in-depth survey of the theory by grouping theoretical studies into seven subtopics relating to the speed advantage of HFT. The author then discuss the empirical findings relevant to these subtopics.

2.2.2 Review papers from broader perspectives

Kirilenko and Lo (2013) survey the history and roots of AT and HFT since the beginning of quantitative finance in the 1950s. The authors provide in-depth discussions of the extreme market events such as the "quant meltdown", the "flash crash", and the "Knight Capital glitch". Kirilenko and Lo point out that these incidents are facilitated by the growth of AT and propose financial regulation principles to strengthen the robustness of financial markets. Specifically, the authors recommend four AT regulation design principles: engineering based systems, heavy safeguards, high levels of transparency, and neutral platform.

Stiglitz (2014) discusses whether recent financial innovations including CT lead to welfare improvements. On the topic of HFT, the author argues that the acceleration price discovery do not translate into social welfare gains. Furthermore, citing the seminal insights from Grossman and Stiglitz (1980), Stiglitz asserts that high frequency traders are able to extract information from trades at the expense of other traders who have spent resources to acquire information from the real economy.[7] Consequently, high frequency traders dissuade others from acquiring costly new information and thus do not contribute to better price discovery. The author also argues that HFT can lead to less liquidity since the informational advantage of high frequency traders deters other traders from submitting and keeping limit orders in the markets.

O'Hara (2015) describes the new market microstructure and how it is shaped by high frequency technologies. Specifically, the author challenges the traditional definition of private information and argues that short-term

[7] Grossman and Stiglitz (1980) show that prices cannot reflect all information since information is costly to acquire. Stiglitz argues that high frequency traders extract "information rents" from that would otherwise benefit other traders who had invested in acquiring information.

information in the high frequency world is not necessarily motivated by the fundamental value of assets. Instead, informed trading is multidimensional in that trading opportunities can be motivated by traders anticipating each other's (or even their own) order flows. O'Hara then proposes several important market microstructure research agendas such as market linkage and market fairness.

Kauffman, Hu, and Ma (2015) review the technological, institutional, and regulatory forces that contributed to the development of HFT. The authors then assess the extent to which HFT has emerged in the Asian regional financial markets. Kauffman, Hu, and Ma find that, overall, the implementation of HFT is slower in Asian markets compared to those of the U.S. and Europe. Furthermore, the authors do not observe significant effects of HFT on Asian markets. However, Japanese and Australian markets have the technological and institutional support for further HFT growth.

2.2.3 Policy papers

Regulators and exchange operators have launched numerous investigations on the development and effects of CT. SEC (2010) evaluates the U.S. equity market structure in light of HFT. The agency lists several characteristics of HFT including the execution of large amounts of trades in a proprietary capacity, using high-speed and sophisticated computer programs, holding short-term positions, submitting and cancelling numerous orders, maintaining a low end-of-day inventory position, and the tendency to use colocation services. ASX (2010) assesses the impact of AT and changes in market structure on the ASX. The report also raises concerns about balancing the interests of short-term algorithmic traders with those of other investors. ASIC (2013) examines the impact of dark trading and HFT on Australian financial markets. The agency find that HFT accounts for 27% of the market and some of the common negative perceptions about HFT seem to be overstated. Specifically, the order-to-trade ratios have only experienced moderate increase and only 1.2% of high frequency traders hold positions for an average of 2 minutes or less. ESMA (2014) estimates the level of HFT activity in European markets. HFT activities are measured in two ways: The direct approach identifies HFT on an institutional level based on the institutions' business models. The indirect approach identifies HFT according to trading behavior such as lifetime order-to-trade ratio. The paper finds that there are significant differences in the amount of estimated HFT between the direct and indirect approach. Finally, SEC (2014) provides an extensive survey of HFT empirical literature and discusses some limitations of the literature such as the challenges of collecting data and the difficulties in distinguishing different HFT strategies.

2.3 Theoretical studies

The theories on CT are new and emerging. Due to the diversity of CT strategies, theoretical models generally do not attempt to capture the overarching impact of AT or HFT on security markets. Instead, the literature focuses on incorporating one or few salient characteristics of CT into standard trading games. The most prevalent and generally agreed characteristic is that computer algorithms are faster than human traders. However, beyond the notion that computerized traders are fast traders, the literature has not reached a consensus on what characteristics of CT should be modeled. Therefore, the generated predictions, which are based on different assumptions, can often be distinct and sometimes contradictory. The differences in the modeling approaches can be summarized in three ways: First, computerized traders are modeled as liquidity providers, liquidity consumers, or a mixture of both. Second, computerized traders can be uninformed, partially informed, or fully informed, so their information content varies across papers. Third, some papers assess the market design changes in the presence of computerized traders. In this section, we survey the growing theoretical literature in order of the three CT aspects: market maker–taker dynamics, the level of information content, and recently incurred or proposed market structural changes.[8] It is important to note that the theoretical literature mainly discusses HFT. While some studies explicitly model HFT (e.g., Jovanovic and Menkveld, 2016b; Jarrow and Protter, 2015), other papers implicitly target HFT by modeling "fast traders"(see, among others, Biais, Foucault, and Moinas, 2015; Hoffmann, 2014).

2.3.1 Market maker–taker dynamics

One of the aspects of contrast is whether CT provides or supplies liquidity. CT can specialize anywhere on the continuum between pure market makers and pure market takers. An array of literature models CT as either speculators that only consume liquidity, market makers that try to minimize adverse selection risks, or a mixture of both.

[8]Menkveld (2016) employs a similar approach that groups the theoretical HFT literature into seven categories. For each category, the author also discusses several related empirical papers.

HFT can employ pure liquidity consuming strategies. The theoretical model by Foucault, Hombert, and Roşu (2016) studies a "fast trader" who closely resembles the directional high frequency speculators. The authors extend Kyle's (kyle1985continuous) model by incorporating heterogeneity in the speed of speculators reaction to new information. The model features a fast or slow informed trader and a competitive dealer who are both continuously trading a risky asset. The informed trader faces short and long run price movements that could have opposite signs depending on the latest news signal and the informed trader's forecast of the asset's long-term payoff.[9] If the latest news signal for the risky asset is negative and the risky asset is overvalued in the long-term, the asset price will move in a "U" shape trajectory. A slow trader, due to insufficient computing power or reaction speed, can only execute a buy trade according to the long run price projection. However, a fast trader who possesses superior reaction speed can quickly carry out round-trip trades and profit from the short-term dip as well as the long-term rise. The model predicts that the net positions of fast traders are more volatile and related to short term price in comparison to those of slow traders. When news becomes more informative, fast traders increase their amount of trades and liquidity improves.

High frequency traders can be modeled as market makers. Jovanovic and Menkveld (2016b) model high frequency traders as the machine middlemen between a human buyer and a human seller. In their model, the seller and the buyer enter the market sequentially due to their opportunity costs. Without the machine, the seller would enter the market first and post a quote. The buyer would enter later and decide whether to buy at the quoted price. The machine is assumed to have no opportunity cost and thus can be present during both periods. After the introduction of the machine, the seller can use the market order against the machine's quote. The machine is specified to possess "hard" information about the risky asset that is unavailable to human traders. Jovanovic and Menkveld (2016b) argue that the machine middleman is more useful if its "hard" information (information that is easily accessible and quantifiable by computers) accounts for a larger fraction of the risky asset value. Their empirical analysis shows that the entry of HFT reduces adverse selection cost by 23% and increases the amount of

[9]We note that the theoretical definition of "news" often means news from the latest price change, the price change is not necessarily caused by a news announcement. We draw a distinction between "news feed/annoucement" in the general sense and the theoretical "news" throughout our paper. We reserve the term "news" for the news in a theoretical context, while we use "news announcement" or "news feed" when we discuss the news in general. We thank the reviewer for pointing out this important distinction and other highly constructive suggestions.

trades by 17%. The authors also advocate a double auction mechanism instead of the prevalent limit order book market structure.

Fast traders can be liquidity suppliers and consumers at the same time. Hoffmann (2014) extends Foucault (1999) and features fast and slow traders who can submit limit orders and market orders. A risky asset is traded by sequentially arrived fast and slow traders over an infinite time horizon. Slow traders can choose to either submit a limit order or a market order, then leave before the next trader arrives. Since fast traders can better monitor the market and react to new information, they can revise their orders before the next trader arrives if the next trader is a slow trader. It is implied in the model that slow traders can endogenously react to the speed advantage of fast traders. Hoffmann predicts that, overall, fast traders reduce price inefficiencies and create more trades. However, slow traders are worse off in equilibrium due to their reduced bargaining power. When the cost of fast trading technology is considered similar to that described in Biais, Foucault, and Moinas (2015), the investment in fast technology is likely to result in a social welfare loss. Hoffmann recommends policies that can reduce the bargaining power of fast traders such as randomized speed bumps.

Menkveld and Zoican (2017) study the interaction between market makers and speculators when both trader groups employ HFT technologies. The authors incorporate high frequency market makers, high frequency speculators (or bandits), and liquidity traders into a trading game on a single risky asset. The game is repeated on a fixed time interval which represents the latency of the exchange. High frequency speculators and market makers only submit or cancel orders at the beginning or the ending of each time interval. During the time interval, both HFT groups are not allowed to access the market but the market makers can decide whether to pay the monitoring cost. Liquidity traders might arrive to consume the quote posted by market makers, while news could occur to change the price of the asset. These two events happen independently with a probability proportional to the length of the time interval. The model predicts that as the time interval becomes shorter (the latency diminishes) the high frequency market maker encounters speculators more often. Therefore, the spread increases due to a higher adverse selection cost.

In their "white" paper, the Securities and Exchange Commission (SEC) expressed concerns about the possibility of proprietary "front running" algorithms (p. 54, SEC, 2010). To address this concern about front running practice of HFT, Cartea and Penalva (2012) assume high frequency traders as pure surplus extractors who stand between liquidity traders and market makers. The model is a three-stage trading game, in which two liquidity traders seek to trade with the market makers to absorb their liquidity shock in Period 1 and Period 2 respectively. However, liquidity traders' orders cannot reach the market maker before being "front run" by machine traders and vice versa. Consequently, both liquidity traders and the market makers take a "haircut" by the machine traders. Cartea and Penalva (2012) find that HFT extracts trading profits from liquidity traders and causes a greater price impact on liquidity trades. The market maker suffers increased trading costs due to HFT extractions but gains expected returns through higher liquidity discounts. Baldauf and Mollner (2015) model the interaction between anticipatory high frequency traders, an analyst, and liquidity investors on multiple exchanges. The analyst collect private information at a cost and submit orders to profit from the costly information while high frequency traders anticipate the analyst's orders. In equilibrium, high frequency traders profit by free-riding on the analyst's information. The authors argue that the anticipatory behavior of HFT discourages information acquisition and the prices become less informative.

2.3.2 Information content

An alternative aspect of contrast is the degree of private information possessed by computerized traders. Traders with high frequency technology can be assumed to possess private information about future order flow from other traders. Aït-Sahalia and Saglam (2014) construct a trading game in which high frequency traders are liquidity suppliers posting limit orders and other traders demand liquidity by posting market orders. In their model, high frequency market makers periodically receive signals about the direction of future order flow from slow traders. The authors find that high frequency market makers can optimally adjust their limit orders based on observed frequency and quality of the order flow signals. Aït-Sahalia and Saglam (2014) then expand their model to include both high frequency and low frequency market makers. High frequency traders exert adverse selection risk on slower market makers and low frequency market makers respond by posting wider bid–ask spreads. Overall, Aït-Sahalia and Saglam (2014) find that better HFT technology can improve profits, liquidity provision, and generate a higher order cancellation rates in normal times. However, the liquidity provision of HFT would deteriorate in light of increased price volatility.

High frequency traders can acquire information and become informed about price impact by submitting "exploratory" trades. Clark-Joseph (2014) updates the study of specialist's price experimentation behavior by Leach and Madhavan (1992) and Leach and Madhavan (1993) in the context of modern limit order book markets with high frequency technologies.[10] Specifically, Clark-Joseph (2014) constructs an order-driven market to analyze the motivation for exploratory trades. The model is a two period (t_1 and t_2) trading game that features a high frequency trader, the aggressive order flows, and an uncertain liquidity state. There are two possible liquidity states: good or bad state. The liquidity state does not change between t_1 and t_2. The high frequency trader can test the prevailing liquidity state by submitting a small but costly exploratory trade. The aggressive order flow arrives at t_2, the high frequency trader is informed about this order flow and has a chance to trade ahead of it. At t_1, the high frequency trader faces the trade-off between submitting a costly exploratory trade at t_1 to acquire information about the liquidity state and front–running the predicted order flow at t_2 without knowledge of the liquidity state. If the high frequency trader chooses the latter, then high frequency trades would not be profitable if the liquidity state is bad. In other words, the high frequency trader can choose to submit a small exploratory trade at a minor cost, in order to avoid potential large costs from unfavorable order executions due to the lack of liquidity in the market. The empirical part of Clark-Joseph (2014) tests and validates the existence of exploratory HFT.

Li (2015) studies the competition among high frequency traders who possess persistent private information about a risky asset's value. Extending Kyle (1985) and Holden and Subrahmanyam (1992), Li models a risky asset that is traded by multiple informed high frequency traders, liquidity traders, and a risk neutral market maker. The asset is traded over discrete periods. The informed traders observe private information about the value of the asset and submit orders accordingly, whereas the liquidity traders' order flows are normally distributed. The designated market maker sets prices at each period based on the order flows of informed traders and liquidity traders. The author finds that, when the time interval between trades reduces, the order size of both informed traders and liquidity traders decreases. In contrast to Holden and Subrahmanyam (1992), Li finds that the competition

[10] Leach and Madhavan (1992) and Leach and Madhavan (1993) propose theoretical models in which market making specialists can adjust their price quotes to induce informed order flow and expedite the price formation process. The model by Clark-Joseph (2014) extends this idea by assuming that high frequency traders would submit small marketable transactions to gain information about the liquidity state of the market.

between informed traders does not eliminate the rent from private information at equilibrium. Overall, the result provides an explanation for the persistent profitability of HFT, despite the increasing competition between high frequency traders.

Some high frequency traders are assumed to be uninformed. Cvitanic and Kirilenko (2010) analyze the price formation process in a limit order book with and without an uninformed machine trader. The authors assume that the machine trader is extremely fast in its order submissions and cancellations. The machine trader employs a "sniping" strategy to "pick-off" stale orders in the limit order book. By following this strategy, the machine repeatedly submits orders to the limit order book and immediately cancels any orders that are not executed. This behavior is empirically documented by Hasbrouck and Saar (2013). Cvitanic and Kirilenko (2010) find that, even in the absence of new information, the average transaction price is likely to change following the machine trader's entrance. The presence of a machine trader changes the human-to-human transaction price distribution into a mixture of human-to-human and machine-to-human transaction price distributions.

Jarrow and Protter (2015) investigate high frequency traders' informational advantages in an arbitrage-free environment. The authors model a continuous trading economy with ordinary traders, sophisticated traders, and high frequency traders. The high frequency traders are allowed to trade continuously due to their speed advantage, whereas ordinary traders and sophisticated traders are assumed to trade in discrete times. The authors find that, under the arbitrage-free condition, HFT can profit by executing market orders at limit order prices. HFT can also "front run" slower market orders by submitting limit orders. In a similar environment, Jarrow and Protter (2012) show that HFT can increase volatility and create stock price deviations from their fundamental values.

2.3.3 Recently incurred or proposed market structural changes

Recent changes in market structure and design often contribute to the proliferation of AT and HFT.[11] For example, the degree of market fragmentation is increasing in equity markets across the world. The cost of monitoring order books and executing trades across markets have substantially increased, despite the generally

[11]The popularity of AT and HFT have also significantly altered the market structure, see O'Hara (2015) for a detailed survey on the recent and predicted market microstructure changes brought by the development of high frequency technologies.

beneficial effects of increased competition across trading venues.[12] This gives rise to computer algorithms that are designed to efficiently trade under conditions of market fragmentation. Brokers employ execution algorithms to seek optimal prices for their clients, whereas proprietary traders rely on low latency technologies to identify and trade on any arbitrage opportunities before others. Due to competition among trading venues, lower trading costs can induce traders to post more limit orders (Colliard and Foucault, 2012). CT benefits more from limit orders due to their higher monitoring capacities. Biais, Foucault, and Moinas (2015) capture the advantage of CT in fragmented markets. The authors extend Grossman and Stiglitz (1980) and endogenize the trading decisions of financial institutions on the trade-off between the gains from trade and the costs of adverse selection and information acquisition. In their model, financial institutions seek to profit by trading a risky asset based on their private valuation of the asset. However, the asset is traded in multiple venues and only a fraction of those venues are liquid enough to have attractive quotes. Institutions are then at risk of not finding an attractive quote due to their limited monitoring capacities. Financial institutions can invest in fast trading technologies to search across venues and guarantee trading against an attractive quote. Biais, Foucault, and Moinas find that fast traders generate a negative externality upon slow traders. In equilibrium, institutions overinvest in fast trading technologies which results in social welfare loss. The authors also argue that, due to the benefit of fast trading technologies in facilitating quote searches, a complete ban on fast trading is not advised but Pigovian taxes on investment in fast trading technology are recommended.

An additional effect of increased market fragmentation is a heightened competition between exchanges. To increase liquidity and attract investors, many exchanges have introduced market maker–taker price schemes, which are two-level pricings that offer lower transaction fees to liquidity providers compared to liquidity consumers. Foucault, Kadan, and Kandel (2013) provide an explanation for this scheme. The authors model market makers as specialized high frequency liquidity providers. Market takers are assumed to behave like buy-side investors or their brokers employing execution algorithms to break a large order into multiple small trades. In this model, a new quote submitted by market makers creates a trading opportunity for market takers as they can trade against this

[12]For instance, Shkilko, Van Ness, and Van Ness (2012) study the competition between National Association of Securities Dealers Automated Quotations (NASDAQ) and three major electronic communication networks. The authors find that the probability of executions on all four venues have increased due to the competition among exchanges.

quote. Similarly, a new trade is a profit opportunity for market makers as a quoting opportunity arises in the absence of a consumed quote. A maker (taker) is more likely to quote (trade) when his/her monitoring intensity increases. Therefore, trading and quoting reinforces each other, thus makers and takers exert positive externalities on each other. The trading rate is then determined by the aggregate monitoring intensity and trading cost on both sides. If the aggregate monitoring intensity of makers decreases compared to those of takers, the quoting intensity would decrease as makers struggle to find quoting opportunities. The trading rate would then decrease, since lower quoting intensity generates fewer opportunities for takers and vice versa. Exchanges could then charge a lower fee on market making via maker–taker pricing.[13]

2.4 Empirical studies

Despite the exponential growth of empirical AT and HFT studies, the research on CT still faces two major challenges. First, the data of CT are difficult to define and identify. AT and HFT are technological tools which have the purpose to assist trading rather than distinct strategies or confined trader groups. Therefore, algorithmic traders, and to a larger extent high frequency traders, are not clearly defined. For instance, Brogaard, Hagströmer, Nordén, and Riordan (2015) analyze two different definitions of HFT and one widely used HFT event and find that these three measures have substantial differences in many cases. Furthermore, many of the data used in AT and HFT studies are not publicly available. Second, the empirical literature is placing an increasing emphasis on causal inferences. Techniques such as instrumental variables and difference-in-difference regressions, although not new, have received increased attention in the literature. CT studies generally relate trading activities to market quality metrics. In a typical regression setup, a significant coefficient can arise because CT causes changes in market quality metrics. However, the same result can be observed if CT simply reacts to changes in the market conditions. Therefore, it is important to identify the direction of the causal relations between CT and market quality metrics.

Given the challenges in AT and HFT empirical literature, we first survey recent studies based on how CT is identified or proxied and then discuss the events used as causal instruments and other causal establishing techniques. We argue that, at least in the current state of the literature, AT and HFT studies cannot be discussed in isolation

[13]Brolley and Malinova (2012) find that a decrease in maker fee increases liquidity but decreases market participation by investors. However, it is uncertain whether maker–taker fee structure would receive wider adoption (see, e.g., Lam, 2015; ASIC, 2014).

from each other. First, proxies of AT and HFT could be correlated. The proxies introduced by Hendershott, Jones, and Menkveld (2011) and Hasbrouck and Saar (2013) both measure, in different ways, the intensity of order submissions, revisions, cancellations, and trades. Second, HFT makes up a significant portion of AT and there are many similar results found on the aggregate effect of AT and HFT. Hendershott and Riordan (2013) and Carrion (2013) find that AT and HFT, respectively, provide liquidity when it is expensive and consume liquidity when it is cheap. Both studies also incorporate information from the futures markets into the spot markets (see, among others, Hendershott and Riordan, 2013; Zhang, 2013).

2.4.1 Empirical studies by data identification

2.4.1.1 Studies that use CT proxies

Compared to human trading, CT generally creates larger amounts of message traffic, in terms of order submissions, revisions, and cancellations. For instance, Hasbrouck and Saar (2013) find that high frequency traders tend to generate "fleeting orders" to the market by repeatedly submitting limit orders only to cancel them in the next milliseconds. SEC (2010) and SEC (2014) also list "bursts of order cancellation and modification" as a trait for identifying HFT. Therefore, CT is likely more prevalent when there are large amounts of quoting and trading activities compared to dollar value exchanges. Researchers exploit this trait and proxy CT as the amount of market activities scaled by dollar volume traded. The use of proxies enables researchers to leverage publicly available data to conduct large scale studies. However, the drawback is clear: these proxies are a "catch all" type of measure that allows the observation only of aggregate CT effects with noise. Microstructure intricacies such as trade imbalance and order aggressiveness cannot be uncovered via proxies.

The most widely used proxy is *message traffic* introduced by Hendershott, Jones, and Menkveld (2011):

$$AT_{i,t}^{HJM} = -\frac{DollarVolume_{i,t}}{Messages_{i,t}}, \tag{1}$$

where $AT_{i,t}^{HJM}$ is the message traffic proxy for AT and $messages_{i,t}$ is the electronic message traffic sent to the exchange.[14] Electronic message traffic includes quote submissions, cancellations, and trades. Boehmer, Fong, and

[14]To differentiate each proxy, we added the author's surname initials "HJM" (and "AAFH", "HF" in Equation (2), Equation (3)

Wu (2015) apply this proxy in 42 exchanges internationally over the period between 2001 and 2011. The authors find AT increases liquidity and price discovery, but causes higher volatility. Boehmer, Fong, and Wu (2013) use a similar dataset to describe the relation between AT and the ability of firms to raise new capital. The authors find that greater AT intensity is associated with declines in equity capital over the next year. Frino, Mollica, Monaco, and Palumbo (2017) use $AT_{i,t}^{HJM}$ to proxy AT around earnings announcements and find that liquidity is more resilient during periods when the level of AT activities is high.

Using a similar AT proxy, Skjeltorp, Sojli, and Tham (2015) study the effect of AT on asset prices of U.S. listed stocks during the period 1999–2012. The authors find that the returns of low AT stocks are higher compared to those of high AT stocks. Scholtus, van Dijk, and Frijns (2014) use the amount message traffic, the number of orders submitted and canceled shortly after, and the number of order executions as AT proxies around macroeconomic news announcements. Their study highlights the importance of speed during news announcements, and shows that an additional latency of 300ms can cause an annualized loss of 1.94%. Scholtus, van Dijk, and Frijns also find that AT increases trading volume and market depth at the best quotes, but also increases volatility and causes a decline in the overall market depth.

Lepone and Sacco (2013) employs order-to-trade ratio as an AT proxy to investigate the impact of the exogenous implementation of a message traffic tax by the regulators in Chi-X Canada. Order-to-trade ratio is measured as the amount of raw message traffic over the number of trades. The authors find that the trading cost increase due to the message traffic tax coincides with the deterioration of liquidity.

Harris (2015) propose *cancel-to-trade ratio* as an alternative proxy to message traffic:

$$AT_{i,t}^{AAFH} = \frac{Cancellations_{i,t}}{Trades_{i,t}}, \tag{2}$$

where $AT_{i,t}^{AAFH}$ is the order cancellation proxy for AT. $Cancellations_{i,t}$ is the number of cancellations for orders that are within the first 10 levels of the limit order book. $Trades_{i,t}$ is the number of transactions within the same time interval t. The authors argue that the cancel-to-trade ratio is a superior AT proxy to order-to-trade (Hendershott, Jones, and Menkveld, 2011) because it is less correlated with HFT according to a Hausman test. The

respectively) as superscripts. These superscripts do not exist in original studies.

authors then construct a simultaneous equations system for market integrity violations (measured by closing price manipulation and information leakage during public announcements), market efficiency (measured by effective spread), and AT. (Hendershott, Jones, and Menkveld, 2011) find that AT reduces the incidence of closing price manipulation and information leakage. AT also improves market efficiency by reducing effective spreads.

HFT can be proxied as the intensity of "strategic runs". Hasbrouck and Saar (2013) show that high frequency traders conduct strategic runs when they quickly submit a series of linked quotations, cancellations, and executions. The authors proxy HFT as the time-weighted number of strategic runs:

$$HFT_{i,t}^{HS} = \frac{TimeofRuns_{i,t}}{TimeInterval_{i,t}}, \tag{3}$$

where $HFT_{i,t}^{HS}$ is the strategic runs proxy for HFT $TimeofRuns_{i,t}$ is the amount of time during which strategic runs are occurring in stock i and time interval t. $TimeInterval_{i,t}$ is the amount of time in interval t. For example, if we observed two strategic runs during a 10-minute interval t in stock i, and these two runs lasted for 1 minute and 2 minutes respectively, then $HFT_{i,t}^{HS}$ equals 0.3 (3/10). Hasbrouck and Saar (2013) compare this proxy with the HFT data identified by NASDAQ (Brogaard, Hendershott, and Riordan, 2014). The authors find that the proxy is highly correlated with the observed HFT activities. Hasbrouck and Saar then apply this metric to analyze market quality of NASDAQ stocks from October, 2007 to June, 2008. The authors show that HFT is positively associated with liquidity and volatility measures.

2.4.1.2 Studies that classify CT on aggregate

The majority of the recent studies use data that directly flag each trade or quote as CT or human trading. These data are usually provided by exchanges to academics on a non-disclosure agreement. The exchanges identify CT by leveraging their specialized knowledge about the account-level trading and quoting activities by their market participants. The advantage of these data is that they allow researchers to perform more detailed analysis in intraday and high frequency context. The drawback is that the effect of CT is assessed on aggregate. In other words, it is difficult to analyze the heterogeneity of CT beyond a simple separation of liquidity-taking and liquidity-providing trades (SEC, 2014). In this section, we introduce CT studies by the datasets used.

AT datasets: Hendershott and Riordan (2013) use an AT dataset provided by the Deutsche Boerse. The dataset contains the quotes and trades submitted by algorithms in the top 30 stocks of the German stock market. The time period is January 1 to January 18, 2008. The authors analyze the order submission strategies of AT and non-AT by order types. Compared to non-AT, AT is more likely to initiate trades when spreads are small and more likely to provide liquidity when spreads are wide. Hendershott and Riordan then further validate the finding via a probit regression in event-time (trade-by-trade). The dependent variable is equal to 1 if the trade is initiated by AT (or supplied/cancelled by AT in later variations). The regressors are market conditions and the recent DAX futures returns. The authors confirm the earlier results: algorithms are more likely to trade when it is cheaper to trade. Furthermore, algorithmic traders are more likely to buy (sell) if the recent futures returns are positive (negative). These results imply that AT monitors the market better than non-AT, since algorithmic traders submit quotes and trades based on the spot market conditions as well as the returns in the corresponding futures markets.

Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) employ quotes and trades data provided by Electronic Broking Services. The paper analyzes the effect of AT on price efficiency of the triangular exchanges rate of EUR-JPY-USD between September 2003 to December 2007. High frequency Vector Autoregression (VAR) is constructed to assess the effects of AT on triangular arbitrage opportunities and autocorrelation in returns. The authors find that AT reduces both triangular arbitrage opportunities and autocorrelation in return series. More interestingly, the decreases in arbitrage opportunities are attributed to algorithmic trades that consume liquidity whereas autocorrelation reductions are caused by algorithmic trades that supply liquidity. The result implies that algorithmic traders engage in arbitrage strategies; they scan the market for temporary price misalignments in related financial products and profit by initiating trades, thus AT improves price efficiency by speeding up price discovery.

Frino, Prodromou, Wang, Westerholm, and Zheng (2017) use a transaction level dataset provided by the Australian Securities Exchange and assess the information content of AT by linking it to corporate earnings announcements between October 2008 to October 2009. The authors use VAR to model the series of return, AT volume imbalance, and non-AT volume imbalance around earnings announcements. The paper finds that non-AT volume imbalance leads AT volume imbalance prior to corporate earnings announcements but the lead direction reverses immediately after the announcements. AT also reacts faster to public information arrivals since their trades are more profitable after earnings announcements. This dataset is also used in Zhou, Kalev, and Lian (2016). The authors investigate the effect of AT during the volatile periods around the global financial crisis. The study finds that on volatile days, when the absolute value of the market return exceeds 2%, AT is negatively related to stock price fluctuations. The paper also finds that order imbalances from AT have a smaller effect on stock returns compared to those from non-AT. Last, Zhou, Kalev, and Lian show that AT tends to follow intraday volume weighted average price metrics as suggested by Domowitz and Yegerman (2005).[15]

Using the same dataset, Duong, Kalev, and Sun (2016) study earnings announcements and the subsequent information transmission among related stocks. The announcing stocks are matched with their rivals within the same industry. The authors apply a VAR framework to examine the AT order flows between the announcing stocks and the rival stocks. Duong, Kalev, and Sun show that, during the earnings announcements period, AT incorporates information in other stocks that compete with the announcing stock. Their results imply that AT synchronizes public information among related stocks.

HFT datasets: Many studies use a proprietary dataset provided by NASDAQ. This dataset is first acquired by Terrence Hendershott and Ryan Riordan.[16] The sample of stocks are stratified based on their market capitalization. The stocks are evenly assigned into large-cap, mid-cap, and small-cap groups with 40 stocks in each group. Each market cap group contains 20 New York Stock Exchange (NYSE) listed stocks and 20 NASDAQ listed stocks. NASDAQ manually identified 26 HFT firms based on its knowledge of the firms and their trading activities, such as daily net positions, order-to-trade ratio, and order durations. The time period covers 2008 and 2009.[17] This dataset allows accurate identification of HFT firms without relying on proxies or quantitative classifications. The limitation of this dataset is that not all high frequency traders are identified, since this classification technique is only applied at the firm level. Other traders with high frequency technologies that conduct their trading in conjunction with activities in the same firm are not included. For example, a proprietary trading desk that is part of a large non-HFT institution is not identified since the trades from the proprietary trading desk cannot be

[15]The volume weighted average price is commonly used by the practitioners to measure the execution quality of their trades. See Madhavan (2002) for a comprehensive survey.

[16]See Brogaard, Hendershott, and Riordan (2014) for a detailed description of the NASDAQ dataset.

[17]SEC (2014) provides the most comprehensive survey of the empirical literature that uses the NASDAQ dataset.

separately identified. A similar situation can arise if a small HFT firm routes its orders through a non-HFT firm.

Brogaard, Hendershott, and Riordan (2014) use the NASDAQ dataset to study the relation between HFT and the price formation process, applying state space methods to decompose the stock price series into a permanent component and a transitory component. The permanent component reflects the underlying "efficient" stock price. Changes in the permanent prices indicate the new information arrivals. The transitory component captures pricing errors or liquidity shocks that are uncorrelated with the "efficient" price process. Brogaard, Hendershott, and Riordan then estimate the effects of HFT and non-HFT on these two components via the Kalman filter and smoother, and maximum likelihood. The authors find that both HFT and non-HFT initiate trades in the direction of permanent price movements and in the opposite direction of transitory price movements. The effects of HFT are significantly larger than those of non-HFT. This implies that high frequency traders initiate trades to incorporate more information into the market at the same time as reducing the transitory pricing error. Brogaard, Hendershott, and Riordan then analyze the passive trades by HFT and non-HFT. The authors find that passive trades by HFT, to a larger extend compared to those by non-HFT, are negatively related to permanent price changes and positively related to transitory pricing errors. This effect is consistent with the notion that passive high frequency traders act as market makers in the modern financial markets.

Using a similar dataset, Carrion (2013) studies how high frequency traders change their trading behavior based on market conditions and other traders. The author first compares HFT-executed prices with the end-of-day VWAP metrics. VWAP metrics are widely used by practitioners to evaluate their trade performance. Carrion finds that HFT time the market better by beating the VWAP. Furthermore, similar to AT effects found by Hendershott and Riordan (2013), HFT provides liquidity when it is cheap and consumes liquidity when it is expensive. Carrion (2013) then tests the relation between HFT and price efficiency in terms of order imbalances and price delays. The order imbalance results are similar to the AT findings in Zhou, Kalev, and Lian (2016); Carrion (2013) finds that the predictive power of order imbalances on stock returns is weaker on high HFT participation days. The study also shows a significant reduction in price delays on high HFT participation days. Overall, these results indicate that HFT is positively associated with stock price efficiencies.

Hirschey (2016) also uses the NASDAQ dataset to study HFT order anticipation strategy. If HFT follows the order anticipation algorithm that aims to trade ahead of large non-HFT orders, the cost of trading for non-HFT will increase because the favorable quotes are already taken by HFT. Moreover, anticipatory HFT would increase the indirect cost of trading in the form of a higher price impact.[18] Emphasizing the initiated trades. Hirschey (2016) first sorts the stocks into deciles based on net marketable buying by high frequency traders. Net marketable buying, also known as order flow or volume imbalance in other studies, is simply the buy-trades less sell-trades initiated by a certain trader group. Non-HFT net marketable buying is then sorted by HFT net marketable buying deciles. The results indicate that HFT net marketable buying leads non-HFT net marketable buying by up to 5 minutes, at least in the top and bottom deciles of HFT net marketable buying. VAR is then constructed to estimate the lead-lag relationship among stock returns, HFT net marketable buying, and non-HFT net marketable buying. The analysis confirms that HFT leads non-HFT in order flows.

Several other studies use the NASDAQ dataset. Gerig (2015) studies how HFT synchronizes security prices among related stocks. Synchronization occurs when price changes in one security are reflected in other related securities. The author finds that prices synchronized much faster in 2010, compared to 2005 and 2000, and the increased synchronization speed is largely contributed by HFT. However, the author also notes that there is potential for HFT to "synchronize" pricing errors more than real news.[19] Gao and Mizrach (2011) examine HFT during large scale asset purchases by the Federal Reserve. The authors find that HFT is less likely to provide liquidity, measured by the frequency of HFT quotes within the bid–ask spread. HFT is also more likely to initiate trades against non-HFT firms during large scale purchases. Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov (2016) investigate HFT around price jumps, classified as 99.9% percentile of price changes during 10-second intervals, and show that its liquidity provision increases. The authors suggest that HFT can provide liquidity during price jumps due to its quicker information processing abilities.

Tong (2015) combines the NASDAQ dataset with a proprietary dataset of equity transactions by institutional investors provided by Ancerno LTD. The execution shortfalls of 204 institutions are studied between 2008 and 2009. Execution shortfall is the percentage difference between the executed price and a prevailing benchmark price when the order is submitted to the broker. The author finds that HFT is positively associated with the trading cost of traditional institutions. Moreover, institutions with better historical trading-desk performance are less

[18] A similar situation is incorporated into the theoretical model by Cartea and Penalva (2012).

[19] Moosa and Ramiah (2015) find that the short-term profitability of HFT is likely to be overstated.

affected by HFT. Zhang (2013) follows the intuition in Jovanovic and Menkveld (2016b) and investigates HFT's reaction to "hard" and "soft" information. Hard information is easily accessible and quantifiable by computers, whereas soft information is qualitative and hard for computers to interpret. The author proxies hard information by extreme price movements (shocks) in the E-mini S&P 500 Futures (E-mini) futures contracts and the VIX index. News announcements are used to proxy soft information. Zhang finds that HFT dominates non-HFT in reacting to shocks in E-mini futures and the VIX index, and non-HFT reacts better to news announcements.

O'Hara, Yao, and Ye (2014) investigate the odd-lot trades by HFT and non-HFT. Odd-lot trades are trades that are small and not reported to the consolidated tape. The authors show that although high frequency traders are more likely to use odd-lot trades, slow traders' odd-lot trades contain more information compared to high frequency odd-lot trades. This result supports the premise of execution algorithms, whereby institutions use algorithms to split up their large liquidity orders. Johnson, Van Ness, and Van Ness (2016) study odd-lot trades with the NASDAQ dataset and a more recent dataset in 2013. The authors confirm that non-HFT odd-lot trades contribute more to price discovery processes. Furthermore, odd-lot trades originated from a larger order contain less information than other trades.

O'Hara, Saar, and Zhong (2015) employ order-level NYSE DLE (Display Book Data Log Extractor) dataset that covers all trades and quotes between May and June 2012. The dataset categorizes each trading account into institutions, individuals, quantitative traders, and high frequency market makers. The authors find that HFT market makers benefit from a larger relative tick size. In a large relative tick size environment, high frequency market makers can reduce the frequency of their limit order revisions, and high frequency market makers are more likely to improve prices by undercutting existing limit orders. O'Hara, Saar, and Zhong suggests that a "one-size-fits-all" tick size regulation is not optimal. The authors recommend larger tick sizes for less liquid stocks.

2.4.1.3 Studies that classify HFT on account level

Many empirical studies quantitatively classify traders as high frequency traders or slow traders based on their trading characteristics. SEC (2010) identifies several common characteristics of HFT which can be identified via careful examination of trader accounts: (1) HFT primarily holds positions over short-term; (2) HFT generates large amounts of order submissions, revisions, and cancellations; (3) high frequency traders aim to close out the day with no inventory; (4) traders with high frequency technologies tend to employ colocation services to minimize latencies. A range of identification techniques are employed based on these principles. The advantage of quantitative identification is that it provides even more detailed data. Once HFT accounts have been identified, researchers can trace all market activities (if available) generated by these accounts, including HFT quotations, cancellations as well as the entry of new high frequency traders. These data also allow a dichotomy of aggressive and passive high frequency traders based on their order aggressiveness.[20] Moreover, these data enable enquiries into the "arms race" between different HFT accounts which are a primary concern discussed in policy documents and theoretical papers. However, this identification method may not be applicable to many public data, since public data usually do not flag activities based on individual accounts (or each proprietary firm).

Quantitative identification of HFT: Kirilenko, Kyle, Samadi, and Tuzun (2017) are the first to adopt quantitative identification. The authors apply account level identification on the E-mini trading and trader accounts data around the "flash crash" from May 3, 2010 to May 6, 2010. Kirilenko, Kyle, Samadi, and Tuzun categorize trading accounts into high frequency traders, market makers, fundamental buyers, fundamental sellers, opportunistic traders, and small traders. The 16 (out of a total of 15,422 trading accounts) HFT accounts are identified based on three criteria:

1. *Daily volume:* the number of trades is more than 9 in at least one of the three days before the "flash crash".
2. *End-of-day position:* on the days when the accounts have 10 or more trades, the end-of-day net positions are no more than 5% of the daily volume.
3. *Intraday position:* the square root of the sum of squared deviations of each minute's net holding from the end-of-day net positions does not exceed 1.5% of its total trading volume for the day.

The authors find that a non-HFT large sell order triggered the "flash crash". During the initial decline on May 6, 2010, high frequency traders provided liquidity to fundamental sellers. However, as the price declined further and high frequency traders' positions kept accumulating, they started to rewind their positions by consuming liquidity and thus exacerbated the downward price pressure. Their results suggest that high frequency traders did

[20]We use "aggressive" and "passive" as neutral terms to distinguish whether the traders predominantly initiate trades by submitting market orders or facilitate trades by submitting limit orders.

not cause the "flash crash" but that their reactions contributed to the extreme selling pressure during the episode. The "flash crash" has been extensively discussed in the literature, see Jones (2013) for a detailed description of the incident and an extensive review of the related literature. A joint investigation between Commodity Futures Trading Commission (CFTC) and SEC finds that the "flash crash" is not caused by "fat fingers" or another singular entity; it is rather the result of a severe liquidity mismatch relating to a number of market stability issues (CFTC/SEC, 2010). Furthermore, the "flash crash" is not an isolated incident, Goldstein, Kumar, and Graves (2014) provide a list of other similar incidents and numerous related news feeds.

Aggressive versus passive HFT: Baron, Brogaard, Hagströmer, and Kirilenko (2016) adopt a similar but more inclusive classification method on the E-mini data from August 2010 to August 2012. For example, instead of criteria (3) in Kirilenko, Kyle, Samadi, and Tuzun (2017), Baron, Brogaard, Hagströmer, and Kirilenko require HFT accounts to have a median net position range (maximum position less minimum position) of less than 10% of the total volume traded on that day. Furthermore, the authors distinguish the identified HFT accounts based on how often they initiate trades:[21]

1. *Aggressive high frequency traders* are HFT accounts that initiate at least 60% of their trades.
2. *Mixed high frequency traders* are those that initiate between 20% and 60% of their trades.
3. *Passive high frequency traders* are those that initiate less than 20% of their trades.

Baron, Brogaard, Hagströmer, and Kirilenko find that aggressive high frequency traders are more profitable than passive ones. The profits of aggressive HFT are concentrated towards a small number of firms. Overall, HFT firms outperform non-HFT firms and generate a median Sharpe ratio of 4.5 in August 2010. Baron, Brogaard, Hagströmer, and Kirilenko (2016) further proxy the speed of high frequency traders by how fast they switch from a passive trade to an aggressive trade. Their results suggest that speed is positively associated with profitability of HFT. Last, HFT new entrants are more likely to underperform and exit the market. This result implies that the competition among HFT firms is high.

[21] Many market makers employ HFT technologies to reduce the cost of monitoring the market, for example Menkveld (2013) finds that a single HFT market maker accounted for 64.4 % trade participation in the new trading venue, Chi-X Europe, in 2007.

Benos and Sagade (2016) further explore the heterogeneity in HFT. The authors study a dataset that contains account level information of transactions on UK markets between September 1, 2012 and December 31, 2012. A classification of 26 HFT firms on account level is generated with the assistance of the UK Financial Conduct Authority. The HFT firms are then segregated into three subcategories: aggressive HFT, neutral HFT, and passive HFT. Benos and Sagade then apply the VAR frameworks to time-series of the stock prices, the order flow initiated by the three groups of high frequency traders, and the order flow initiated by other traders to study the price discovery characteristics of HFT firms in terms of their aggressiveness. Aggressive HFT firms dominate the price discovery process followed by neutral HFT firms and market making HFT firms. The authors' event-time (trade-by-trade) analysis confirms their calendar-time results and shows that aggressive HFT contributes more to the permanent price changes in proportion to noise. The results suggest that the aggressive high frequency traders are most informed about short-term price innovations, while the passive ones use market orders primarily to re-balance their inventory.

2.4.2 Causal inferences

A common issue in CT studies is establishing causality. CT studies aim to address the effects of CT on market quality metrics using econometric tests. However, the results can be correlations instead of causations. For example, CT is found, on aggregate, to improve liquidity in terms of bid–ask spreads and market depth (see, e.g., Hendershott, Jones, and Menkveld, 2011; Hasbrouck and Saar, 2013). At the same time, Hendershott and Riordan (2013) and Carrion (2013) find that algorithmic and high frequency traders execute their transactions based on the prevailing market liquidity conditions. Therefore, the two-way causation between CT and market conditions should be disentangled. In this section, we review the techniques and the exogenous events used in the literature to establish the causal relation between CT and market quality measures.

2.4.2.1 Technological upgrades

Instrumental Variable (IV) analysis is the most commonly used causal identification technique in the empirical literature on CT. IV analysis requires an exogenous shock to the variable of interest (AT or HFT). Since CT is facilitated by technological advances, many studies use trading system upgrades and the introduction of fast trading services as an instrument for AT.

The first causal event for AT in the literature is a technology upgrade to the NYSE trading system called Autoquote. With the Autoquote upgrade, the market displays a large liquidity quote (generally more than 15,000 shares) alongside the best bid and offer (Hendershott, Jones, and Menkveld, 2011). This upgrade allows AT to better monitor the market and execute trades accordingly. Autoquote is not introduced simultaneously for all NYSE stocks. The upgrade is phased in gradually in stock batches. This allows researchers to isolate market-wide time effects from the effects of increased AT. Hendershott, Jones, and Menkveld (2011) use Autoquote as an instrument to analyze the causal effects of AT on NYSE stocks around the period of Autoquote implementation (December 2002 to July 2003). The authors find that AT improves liquidity by narrowing spreads and reducing adverse selection costs. AT reduces the price impact of trades and improves the informativeness of quotes by reducing the fraction of price discovery related to trades.

Goldstein, Kwan, and Philip (2016) investigate the effect of HFT on the transaction costs of non-HFT around a technological update introduced by the Australian Securities Exchange in April 2012. The new technology, known as ASX ITCH, enables access to ultra-low latency market information that attracts latency-sensitive traders. Their study exploits exogenous increase in the effectiveness of HFT to establish causal inference. Goldstein, Kwan, and Philip conduct difference-in-difference tests for limit order transaction costs over the three months before and three months after the introduction of ASX ITCH. The authors find that HFT increases the limit order transaction costs of non-HFT and that HFT is more successful in trading ahead of limit orders of non-HFT.

2.4.2.2 Exchange fee changes

Another possible instrumental variable is related to transaction and quotation fee changes. Many algorithmic strategies rely heavily on generating large amounts of message traffic. For instance, execution algorithms break up large orders into small packets of trades to minimize their price impact and transaction costs, whereas high frequency market makers submit large amounts of limit order quotations, revisions, and cancellations to minimize their adverse selection costs. It is conceivable that a fee change would have a larger effect on CT in comparison to human trading.

Malinova, Park, and Riordan (2013) draw their causal inference between AT and market quality via a regulatory fee change. On April 1, 2012, the Investment Industry Regulatory Organization of Canada, a regulatory body, started to charge its dealers an IT cost-recovery fee based on the message traffic generated by trading. The dealers passed on these fees to its high activity clients, including computerized traders. The authors apply the first stage IV regression on the fee change and the level of AT. Malinova, Park, and Riordan find that the fee hike exogenously decreased message traffic generated by AT. The authors then show that liquidity deteriorates in the form of increased spreads and adverse selection costs, due to the exogenous decrease in AT message traffic following the fee change.

2.4.2.3 Financial transactions tax

Many computerized algorithms rely on submitting large amounts of small trades and quotes to minimize transaction costs or profit from fleeting opportunities. Therefore, Financial Transactions Tax (FTT) on trades and especially quotes would disproportionably affect HFT. Several studies recommend implementing FTT to internalize the negative externalities of HFT (see e.g., Jones 2013 and Goldstein, Kumar, and Graves 2014). However, the efficacy of FTT is widely supported by empirical evidences. Colliard and Hoffmann (2017) analyze the implementation of a French FTT in August, 2012 and find that market quality deteriorates after the introduction of the FTT.Lepone and Sacco (2013) investigate the impact of a message traffic tax implementation in Chi-X Canada in April, 2012. A message traffic can be a quote submission, revision, or cancellation. The authors find that the trading cost increase due to the message traffic tax coincides with the deterioration of liquidity.

2.4.2.4 Colocations

The trading opportunities identified by algorithms are generally small and fleeting. To trade on these opportunities requires nearly instant connection speed with the exchange. A tiny delay may result in a non-execution if another order arrived a millisecond earlier. For instance, Goldstein, Kumar, and Graves (2014) argue that HFT strategies rely on being the first to seize profit opportunities. O'Hara (2015) asserts that high frequency traders can turn reaction speed via colocation and other technologies into informational advantage. High frequency market makers also need to minimize the delay to minimize the risk of their stale order being picked off due to new information arrivals. The desire to be the first to trade motivates exchanges and computerized traders to reduce latencies across various trading venues. Laughlin, Aguirre, and Grundfest (2014) document a three millisecond reduction of intermarket latencies between Chicago and New York from April 2010 to August 2012. The authors attribute the drop in delays to the increased presence of CT, alongside other technological infrastructure upgrades. However, the delay caused by the physical distance between the location of the exchange and the location of the trader cannot be eliminated by faster computers. For example, Garvey and Wu (2010) analyze the execution quality of traders in relation to their geographical locations. The authors find that traders with closer proximity to New York City areas experience faster order executions. To target the demand for closer proximity to the exchange servers, exchanges around the world have introduced colocation services that enable market participants to locate their machines next to the exchange server. These services aim to minimize the travel time of signals between the exchange and the computers. The level of CT is expected to increase after computerized traders employ colocation services.

Boehmer, Fong, and Wu (2015) use colocation introduction as an exogenous shock that increases the intensity of AT, and compare its market quality effects before and after the colocation event in multiple countries to establish a causal link between AT and market quality measures.[22] The authors find that AT improves liquidity and price discovery, however, AT is associated with greater volatility. Moreover, on days when AT is positively related to volatility, AT is also negatively associated with liquidity. Based on this finding, the authors argue that algorithmic activities on volatile days are not desirable since they also reduce liquidity. Boehmer, Fong, and Wu highlight the cross-sectional differences in algorithmic traders' effects stating that the benefits of AT are stronger in larger stocks, whereas AT actually reduces liquidity in the smaller stocks.

Aggarwal and Thomas (2014) study the introduction of colocation services on the Indian stock market in January 2010. Stocks that experience a large increase in AT after colocation are matched with other stocks based on market quality metrics such as market capitalisation, stock price, turnover, number of trades, and floating stocks. The authors then apply difference-in-difference methods to compare the difference of market quality measures between the matched groups. The pre-colocation period is January 2009 to December 2009 and the post-colocation period is July 2012 to August 2013. Aggarwal and Thomas find that AT reduces liquidity costs, order imbalance,

[22]See Aitken, Cumming, and Zhan (2015) for the global starting dates of colocation services.

and price volatility. Using similar colocation events, Boehmer and Shankar (2014) investigate the effect of AT on the comovement of order flow, prices, and market conditions. The authors find that AT decreases commonalities in order flow, return, liquidity, and volatility due to the more intense competition among algorithmic traders after the introduction of colocation.

2.5 Discussion on CT and market quality metrics

2.5.1 Liquidity

The studies on CT generally agree that CT, on aggregate, improves liquidity. For example, the theoretical model by Roşu (2016a) predicts that fast traders generate a large trading volume, and market liquidity increases as the number of fast traders rises. Empirically, Hendershott, Jones, and Menkveld (2011) find that AT improves liquidity by narrowing spreads and reducing adverse selections. Bershova and Rakhlin (2013) analyze the effect of buy-side HFT on Japanese and UK markets. Their results indicate that HFT is negatively associated with bid–ask spreads. However, there are different results in the literature when the heterogeneity of high frequency traders is considered. Aggressive high frequency traders primarily initiate trades to profit from short-term information, so aggressive high frequency traders could be associated with a reduction in liquidity. For example, Foucault, Kozhan, and Tham (2017) argue that the opportunistic arbitrage by HFT can impair liquidity since it exposes liquidity suppliers to the risk of being adversely selected. Passive/market making high frequency traders possess superior reaction speeds and can monitor the market cheaply. Therefore, passive HFT can outperform traditional intermediaries and improve liquidity provision. Jarnecic and Snape (2014) find that HFT market makers submit limit orders closer to the best quotes, and HFT limit order strategy improves bid–ask spread.

Despite the overall positive liquidity effect of CT, the literature also discusses how traditional liquidity measures such as bid–ask spread and market depth might be problematic due to the "quote flickering" characteristic of HFT. "Quote flickering" is an order submission strategy in which high frequency traders quickly submit limit orders and cancel any unexecuted orders within milliseconds.[23] If the market is experiencing a large amount

[23]Some papers also call this "fleeting orders" or "strategic runs". Hasbrouck and Saar (2009) show that this phenomenon is relatively recent. Cartea, Payne, Penalva, and Tapia (2016) find pervasive quote flickering episodes on NASDAQ in March 2007–2015. Table 2 of Hasbrouck and Saar (2013) provides an empirical example of "quote flickering". Blocher, Cooper, Seddon, and Van Vliet

of quote flickering, then the calculated bid–ask spread and market depth at the best quotes would vary greatly. Consequently, the liquidity metrics could be inflated since the flickering quotes generally cannot be utilized by market orders. Baruch and Glosten (2013) provide the theoretical basis for quote flickering and argue that limit order traders manage their adverse selection risk by rapidly canceling and resubmitting their quotes. Hasbrouck and Saar (2013) use quote flickering to construct proxies for HFT. Kang and Shin (2012) find that flickering quotes reduce the informational content of the limit order book. Van Ness, Van Ness, and Watson (2015) find that higher order cancellation rates are detrimental to market liquidity.

In addition, CT may decrease market stability during difficult times. The theoretical model by Cespa and Vives (2016) shows that the fragmentation of liquidity supply induced by HFT may cause traders to consume more liquidity when the cost of supplying liquidity increases. This behavior can generate market instability. Boehmer, Fong, and Wu (2015) argue that the benefit of AT liquidity provision reduces in volatile markets. Hagströmer, Nordén, and Zhang (2014) analyze order aggressiveness of high frequency market makers, high frequency speculators, and slow traders. The authors show that high frequency traders supply more liquidity when the bid–ask spread is wide. Korajczyk and Murphy (2016) investigate HFT liquidity provision in difficult times, and find that HFT liquidity provision is reduced in the presence of large, directional institutional trades. high frequency traders also provide less liquidity after they incur losses. Finally, Han, Khapko, and Kyle (2014) model the order submission and cancellation behavior of high frequency market makers. The authors argue that, since high frequency market makers impose adverse selection on slower market makers, high frequency market makers may drive out low frequency market makers, and liquidity would consequently deteriorate.

2.5.2 Price discovery and price efficiency

Due to the higher speed and cheaper monitoring, CT is able to quickly incorporate information into the prices and accelerate the price discovery process. A wide range of studies provide evidence that CT improves price discovery and reduces price inefficiencies. As described earlier in Section 2.3.2, Foucault, Hombert, and Roşu

(2016) find that high frequency traders create clusters of order cancellations by competing to get to the front of the limit order queue. Egginton, Van Ness, and Van Ness (2016) study the intense episodic spikes in quoting activity and find that these spikes are associated with lower liquidity, higher trading costs, and increased short-term volatility.

(2016) argue that fast traders can incorporate information by trading on the short-term news and long-term price forecasts whereas slow traders can only trade according to long-term price movements. Roşu (2016b) shows that informed trading improves liquidity and has no effect on the impact of orders. Boehmer, Fong, and Wu (2015) analyze a wider range of markets and find that AT improves informational efficiency across international markets. Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) show that algorithmic traders improve price efficiency: AT market orders reduce arbitrage opportunities and their passive orders reduce autocorrelations in high frequency returns. Brogaard, Hendershott, and Riordan (2014) find that high frequency traders facilitate the price discovery process by trading in the direction of permanent price changes and in the opposite direction of transitory pricing errors. In addition, the literature finds that, compared to passive HFT, aggressive HFT dominates the price discovery process. For instance, Benos and Sagade (2016) separate HFT into aggressive HFT, mixed HFT, and passive HFT. The authors show that aggressive HFT market orders are more informed than those from mixed and passive HFT. Brogaard, Garriott, and Pomeranets (2016) investigate the effects of competition between high frequency traders. The authors find that price efficiency improves after the entry of aggressive high frequency traders.

Furthermore, price discovery is increasingly caused by updates to limit order quotations without actual transactions. Hendershott, Jones, and Menkveld (2011) show that trade-correlated information declines when AT increases around the implementation of Autoquote around 2003. Chordia, Green, and Kottimukkalur (2016) investigate the role of AT around macroeconomic announcements and find that order flow becomes less informative over time as quotes respond to news directly rather than indirectly through trading. The authors also show that there are no significant incremental profits when algorithmic traders can access macroeconomic news two seconds earlier via Reuters' premium news services. However, the costs of price efficiency may outweigh its benefits. Stiglitz (2014) questions whether the improvements in price discovery translate into gains in social welfare. Chakrabarty, Jain, Shkilko, and Sokolov (2015) investigate the effects of SEC's ban on unfiltered connections to exchange servers, which slowed down the speed of a significant fraction of market participants. The authors find that both transaction costs and price efficiency have declined after the market slow down. Moreover, the reduction in trading cost is substantially larger than the increase in pricing errors.

The literature also uncovers several sources of the information advantage of computerized traders. First, computerized traders execute their orders on the spot markets based on price changes in related indices, markets, and derivatives. For example, the theoretical model by Jovanovic and Menkveld (2016b) described earlier in Section 2.3.2 assumes that machine traders possess “hard” information. Hard information such as prices of market indices is easy for computers to process. Zhang (2013) shows that HFT reacts strongly to hard information proxied by shocks in E-mini prices. Hendershott and Riordan (2013) also find that algorithmic traders can monitor prices from futures markets and execute trades on spot markets based on futures price movements. Ito and Yamada (2015) suggest that HFT contributes to the spillover effect between NASDAQ and Forex markets by incorporating common information about Forex rates. Second, CT can profit from price discrepancies in related assets. Budish, Cramton, and Shim (2015) point out that arbitrage opportunities arise due to the breakdowns in the correlations between related assets over ultra-short time intervals (i.e. 100 milliseconds). Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) provide evidence that liquidity consuming AT is negatively associated with the frequency of arbitrage opportunities in JPY-USD-EUR triangular currency exchange prices. Gerig (2015) suggests that HFT improves the speed of synchronization among related stocks. Alampieski and Lepone (2012) find that HFT trades more UK-US cross-listed stocks in the UK market when the US market opens. Last, CT can quickly adapt to public information arrivals. Frino, Prodromou, Wang, Westerholm, and Zheng (2017) demonstrate that although algorithmic traders are uninformed before corporate earnings announcements, they time trades better immediately after the earnings announcements. Jiang, Lo, and Valente (2014) show that HFT improves price efficiency and reduces liquidity during macroeconomic news announcements. Alampieski and Lepone (2011) find that HFT liquidity consuming and liquidity providing activities increase around macroeconomic announcements.

In addition, some studies also show that small trades initiated by HFT can be uninformed. Clark-Joseph (2014) argues that high frequency traders submit small exploratory trades to test the liquidity state of the market and decide whether to execute their larger trades. O’Hara, Yao, and Ye (2014) provide supporting evidence that small odd-lot trades by high frequency traders contain less information in comparison to those by other investors. Johnson, Van Ness, and Van Ness (2016) note that odd-lot trades originated from larger orders (i.e. generated by execution algorithms) contain less information in comparison to other trades.

2.5.3 Volatility

The effect of CT on short-term volatility is more divided in the literature than that on liquidity and price discovery. On one hand, Aggarwal and Thomas (2014) estimate volatility in terms of realized volatility and high-low midquote range over 5-minute intervals. The authors find that AT reduces volatility following the colocation event. Hasbrouck and Saar (2013) show that HFT reduces volatility, measured as a high-low midquote range over 10-minute intervals. Hagströmer and Nordén (2013) estimate the realized volatility over 1-minute to 15-minute intervals and separate HFT into aggressive and passive HFT. The authors find that high frequency market makers reduce volatility. On the other hand, Boehmer, Fong, and Wu (2015) calculate a wide range of volatility metrics over 10-minute, 30-minute, and daily time intervals. Their results suggest that AT increases volatility. Bershova and Rakhlin (2013) measure high-low price ranges over 5-minute, 10-minute, and 30-minute intervals and show that buy-side HFT is positively associated with volatility.

Several intricacies are noted in the CT literature on volatility. First, the "flash crash" and similar events have raised concerns about the role of CT during high volatility periods. Biais and Woolley (2011) argue that HFT may impose systemic risk to the stability of the markets. Jones (2013) describes in detail the impact of the "flash crash" on the E-mini prices and several individual stocks, and surveys relevant academic and policy papers. Goldstein, Kumar, and Graves (2014) compile an extensive list of market glitches between 2010 and 2013 associated with the rapid responses of computerized traders. Kirilenko, Kyle, Samadi, and Tuzun (2017) is the first empirical study to investigate the causes of the "flash crash". The authors find that HFT, while not triggering the "flash crash", exacerbated the price declines. Bernales (2014) provides a dynamic equilibrium model with AT in a limit order market, arguing that AT prefers volatile assets since it can generate larger profits during periods of high market volatility. Zhou, Kalev, and Lian (2016) study AT on volatile days defined as days when the market rises or declines by more than 2%. The authors find that AT is associated with smaller price fluctuations in stock prices on volatile days. Gao and Mizrach (2016) associate HFT with market breakdowns. Market breakdown days are defined as days when the stock falls by more than 10% of the 09:35 price and subsequently reverts back to within 2.5% of the 09:35 price at the end of the day. The authors show that HFT is positively associated with liquidity and volatility.

Second, volatility can arise when new information is incorporated into prices. It is, therefore, important to consider the effects of CT on both information related and noise related volatility. While Brogaard, Hendershott, and Riordan (2014) do not associate HFT with traditional volatility measures, the authors show that, compared to non-HFT, HFT initiated order flow is more positively associated with the permanent (information) component of the price changes. Moreover, the HFT initiated order flow is more negatively associated with the transitory (noise) component of the price changes.

In addition, CT, especially HFT, may have different effects on volatilities over different intervals. Hasbrouck (2015) applies wavelet transform on the time-series of bid and ask quotes in US markets. The author then extracts volatilities and variance ratios from the wavelets over different time intervals. The results indicate that during the period of 2001-2011, although volatility of bid and ask quotes measured in ultra-short horizons (i.e. 50 to 100 milliseconds) does not exhibit strong trend, the variance ratios between ultra-short horizons and longer horizons (i.e. 27 minutes) have increased. Breckenfelder (2013) estimates realized volatility over a wide range of time intervals from a few minutes to a day. Breckenfelder finds that HFT competition increases intraday volatility but has no effect on interday volatility.

2.6 Conclusion

AT and its subset, HFT, have experienced formidable growths over the past decade. In this paper, we survey the academic and policy papers on AT and HFT. First, we discuss review papers specifically on CT, review papers on broader topics that discusses CT, and policy papers. We point out the differences in terms of their perspectives and contributions. Second, We survey the theoretical literature on HFT and fast traders. Since fast trading technology can be employed by a variety of investors in the market ecosystem, theoretical studies can target various types of computerized traders. Consequently, predictions by the theoretical models depend on what types of computerized traders are considered. To synthesize these theoretical predictions, we focus on gauging how HFT is modeled. We review the theoretical literature in relation to market maker–taker dynamics, information content of fast traders, recently incurred market structural changes, and proposed market changes. Third, we review the empirical literature with an emphasis on how to identify the proxies and data used as well as the techniques employed in establishing the causal links between CT and market quality. We hope that this review provides a roadmap for future research, particularly in overcoming difficulties of identifying CT and establishing its causal relations with market quality measures. Last, we summarize and discuss the impact of CT on market quality. Given the different effects documented in the literature, we point out several issues related to measuring and interpreting the observed market quality effects.

We note that the results discussed in this paper are subject to a few caveats. Since the literature on CT is relatively new and emerging, little consensus has been reached on the effects of CT. In addition, many papers discussed are working papers, which are subject to changes as they go through the peer review processes. A more significant challenge is that the empirical studies on CT are limited by data constraints. Specifically, various proxies and datasets mainly focus on the aggregated effects of CT. Account level data are confronted by privacy issues. These data restrictions contribute to the gap between the negative public perceptions and the mixed results in the literature. Due to the extensive media coverage and popular books featuring anecdotal stories, regulatory agencies around the globe are under pressure to make substantial policy changes.[24] We advise against indiscriminate restrictions on CT such as global speed bumps and transaction fee hikes.[25] Instead, we encourage regulators to collaborate with academics by providing anonymously identified account level data, in order to promote rigorous, robust, and independent scholarly research.

Finally, we suggest some directions for future research. First, further research is needed to determine the optimal market design in the new trading environment. This line of inquiry could focus on: what is the socially optimal transaction speed;[26] and what is the best transaction fee structure. Second, with the proliferation of account level HFT data and detailed market microstructure prices and quotes, future research could focus on the finer details in terms of both HFT and microstructure metrics. For instance: how to distinguish HFT beyond our current binary aggressive/passive dichotomy; how to identify HFT based on the heterogeneity of HFT strategies; and how to link the accelerated price discovery processes to volatility metrics in different time intervals. Third, the source of the private information of computerized traders is not clear. O'Hara (2015) notes that, in a high frequency world, private information (and the associated price changes) over very short time intervals might

[24]For instance, Lewis (2014) claims that the market is "rigged", however, no computerized trader is cited. Mary Jo White, the chairwoman of the SEC, says that "the markets are not rigged" (see The Committe on Financial Services, 2014, p. 12).

[25]See Malinova, Park, and Riordan (2013) for the adverse effect of regulatory fee increases.

[26]Several theoretical studies discuss the optimal trading frequency, see, among others, Budish, Cramton, and Shim (2015); Foucault, Kadan, and Kandel (2013); Guo (2015); Bongaerts and Van Achter (2016).

not just be asset value-related but also investor's order-related. Therefore, the boundary between "informed" and "uninformed" traders could become blurry. Future studies on the source, heterogeneity, and the implications of computerized traders' information content are warranted. In addition, market fairness should attract more attention due to recent changes in the trading ecosystem. HFT can potentially impose adverse effects on other market participants and more market fairness metrics are needed to capture these effects. Last, researchers could exploit the frequent policy and market structure changes because the important changes, such as order priorities and minimum order resting time, can potentially have large adverse effects. In addition, many changes provide clean natural experiment opportunities that can enable researchers to disentangle causations from correlations.

Chapter 3

Algorithmic Trading in Turbulent Markets

Chapter Summary

We investigate the role algorithmic trading on days when the absolute value of the market return is more than 2%. We find that the abnormal return of a stock is related to the stock's AT intensity, that high AT intensity stocks experience less price drops (surges) on days when the market declines (increases) for more than 2%. This result is consistent with the view that AT minimizes price pressures and mitigates transitory pricing errors.

3.1 Introduction

Technological developments over the past decade have substantially increased the use of computer algorithms by equity investors. In light of extreme market events such as the "flash crash", academics, market regulators, and finance practitioners are keen to understand the role of AT in turbulent markets.[27] Does AT contribute to further price decline in individual stocks when there is a large drop in the overall market? The answer is not clearly answered by the literature. On one hand, algorithmic traders act as "messengers" by transmitting price movements among derivatives, indices, and related stock prices (See, e.g. Jovanovic and Menkveld, 2016b; Hendershott and Riordan, 2013; Zhang, 2013; Chaboud, Chiquoine, Hjalmarsson, and Vega, 2014). Therefore, AT would exert price pressure in individual stocks by reacting to the large drop in market indices. On the other hand, computer algorithms can minimize price pressure, reduce the price impact of trades, and mitigate pricing errors (See, e.g. Hendershott, Jones, and Menkveld, 2011; Malinova, Park, and Riordan, 2013; Brogaard, Hendershott, and Riordan, 2014). One could argue that AT would mitigate the downward price pressure from overall market drop. The answer to the question of whether AT contribute to extreme price movements is important to the stability of the new trading ecosystem. Building on the research framework of Dennis and Strickland (2002), we address this question by analyzing the relation between AT and the returns of stocks on days when there is a large movement in market indices defined as days when the absolute value of the market return exceeds 2%. Specifically, we aim to answer the following questions: Does AT contribute to the stock price decline (increase) when there is a large market drop (gain)? If so, what properties of AT are the cause?

We employ a novel dataset in which the trades are flagged based on whether they are generated by computer algorithms. We focus on the turbulent days on the ASX from October 27, 2008, till October 23, 2009. Our sample has the following advantages. First, we are able to identify AT buy and sell trades without relying on proxies such as message traffic. Second, in their seminal study, Hendershott, Jones, and Menkveld (2011) find that, overall, AT plays a beneficial role in terms of liquidity and price discovery in rising markets. At the same time, the authors warn that investigations of the characteristics of AT "in turbulent or declining markets" (p. 31) are

[27]On May 6, 2010, U.S. stock market indices and related securities experienced a sharp price drop of more than 5%, only to recover in the course of about 30 minutes. See Kirilenko, Kyle, Samadi, and Tuzun (2017) for a detailed analysis.

equally important. We study the effects of AT during the most turbulent times in decades, since our sample period is at the peak of the financial crisis and immediately after the collapse of Lehman Brothers in September 2008. Third, Biais, Foucault, and Moinas (2015) find that fast traders are better off than slow traders in fragmented markets. To highlight the effects of AT in the absence of market fragmentation, we analyze AT prior to the entry of Chi-X in October 2011 when the ASX was the only exchange operator in Australia.

We find that, controlling for size, risk, liquidity, and information, stocks sold by AT experience less downward price pressure than those sold by non-AT when there is a broad market decline of more than 2%. We obtain similar results for algorithmic buy trades when the market is up by more than 2%. Our results are economically significant. For example, we find that a 10% (or a half standard deviation) increase in AT selling, on average, corresponds to a 12 basis point increase in returns for individual stocks in bear markets. Furthermore, stocks that have low levels of AT experiences significant return reversals following market decline days. Specifically, stocks traded less by AT tend to recover from their large turbulent day price drops during the subsequent trading days. Our findings on post-event day return reversals imply that non-AT overreacts to the overall market pressure by pushing stock prices beyond their fundamental values. Overall, our evidence suggests that, compared to non-AT, AT does not contribute to price swings among individual stocks in turbulent markets.

We isolate the effect of AT on event days from the endogenous effect between AT and stock movements by applying a propensity score matching algorithm. We match event day observations (the treatment group) with non-event day observations (the control group) based on return, volatility, market cap, and liquidity. The matching effectively eliminates any meaningful difference between the treatment group and the control group in terms of these market condition covariates. We apply the matching algorithm to market up and market down days separately. This matching procedure gives us a representative control group that has market characteristics similar to those on event days. We then use a difference-in-differences method to distinguish the effects of AT on event days in comparison to a sample of stock-days with similar market conditions. We show that the negative association between AT and price fluctuation only exists in the treatment group despite the similarity between the treatment and the control groups. Furthermore, we show that this relation is unchanged in light of firm-specific news arrivals. In summary, we show that the relation between AT and market fluctuations is not driven by AT reacting to an individual stock's return, volatility, liquidity, size, or public information arrivals.

AT is associated with fewer price swings on stressful days; however, the mechanics of this relation are beyond the scope of the current chapter. While the results in this chapter imply that AT actively counteracts pricing errors, it is also possible that algorithms aim to minimize transaction costs and stay away from stocks experiencing the largest price swings.[28] However, it is sufficiently clear that AT does not exacerbate extreme price movements.

The rest of the chapter is organized as follows. Section 3.2 briefly discuss the related literature on AT and HFT. Section 3.3 describes our data. Section 3.4 presents our findings on AT in turbulent markets. Section 3.5 discusses the association between AT, market conditions, and news. Finally, Section 3.6 concludes the chapter.

3.2 Literature review

Our paper relates to the rapidly growing literature of AT/HFT. Several authors have surveyed this topic: Goldstein, Kumar, and Graves (2014) describe the evolution of automated trading over the past decade and survey several AT and HFT studies; SEC (2014) examines the empirical HFT literature and focuses on the US stock market for an audience of regulators, practitioners, and academics; O'Hara (2015) considers the market microstructure changes in light of computerized trading technology. The author discusses how the trading world has changed and how market microstructure research should adapt. The theoretical literature focuses on incorporating the "fast" nature of computerized trading into trading games. Foucault, Hombert, and Roşu (2016) argue that fast traders can incorporate information by trading on the short-term news and long-term price forecasts whereas slow traders can only trade according to long-term price movements. The theoretical model of Jovanovic and Menkveld (2016b) considers high frequency traders as the machine middlemen and finds that HFT incorporates information that is easily accessible and quantifiable by computers such as index values. Foucault, Kadan, and Kandel (2013) study maker–taker price schemes in high frequency environments. The authors find that charging market makers lower fees encourages trades and increases liquidity. Roşu (2016a) predicts that fast traders generate a large amount of trading volume, and market liquidity increases as the number of fast traders rises. Biais and Woolley (2011) argue that HFT may impose systemic risk to the stability of the markets.

The empirical literature studies the impact of AT/HFT on market quality. Overall, AT and HFT improve

[28] In support of our interpretation, Chapter 5 in this thesis show that AT trade less in the direction of transient pricing errors compared to other traders.

liquidity (see, e.g. Hendershott, Jones, and Menkveld, 2011; Hasbrouck and Saar, 2013; Brogaard, Hagströmer, Nordén, and Riordan, 2015). However, AT and HFT may retreat from liquidity provision during difficult times (for instance, Hagströmer, Nordén, and Zhang, 2014; Boehmer, Fong, and Wu, 2015; Korajczyk and Murphy, 2016). AT and HFT contribute to informational efficiency (Chaboud, Chiquoine, Hjalmarsson, and Vega, 2014; Brogaard, Hendershott, and Riordan, 2014; among others). Their information is acquired from derivatives and indices (Hendershott and Riordan, 2013; Zhang, 2013; Ito and Yamada, 2015); related assets (Budish, Cramton, and Shim, 2015; Gerig, 2015); and public announcements (Jiang, Lo, and Valente, 2014; Frino, Prodromou, Wang, Westerholm, and Zheng, 2017). Boehmer, Fong, and Wu (2015) and Breckenfelder (2013) find that AT/HFT is positively associated with volatility whereas Aggarwal and Thomas (2014) and Hasbrouck and Saar (2013) observes a reduction in volatility when AT/HFT increases. Although it is beyond the scope of our study to measure and model volatility, our research design allows us to draw inferences on price swings in a stock by investigating whether the stock experiences a larger price surge (decline) when the overall market rises (drops) by more than 2%.

3.3 Data and research design

3.3.1 Data description

We employ a novel AT dataset provided by the ASX. This dataset contains all equity transactions on the ASX between October 27, 2008, and October 23, 2009. Each trade reports the company code, trade price, trade volume, buy/sell indicator, time stamp to the nearest millisecond, and a special indicator for both sides of the transaction showing whether the trade was initiated by a computer or a human. Algorithmic trades are identified based on their digital imprints on the ASX. Specifically, trades automatically generated by computers are assigned terminal IDs different from human trades in the exchange. This classification does not completely eliminate the possibility that human traders would submit their orders through the computer based system gateway, and vice versa. Therefore, the classification in this paper is a proxy for human and computer based trading.[29] Similar to Hendershott and Riordan (2013), we merge the AT dataset with order-level data provided by Securities Industry

[29] This dataset is also used by Frino, Prodromou, Wang, Westerholm, and Zheng (2017). For more details, see Frino, Prodromou, Wang, Westerholm, and Zheng (2017).

Research Centre of Asia-Pacific (SIRCA). The SIRCA data enable the accurate identification of buy/sell trades. This combination allows us to identify whether a trade was initiated by a buyer or a seller, as well as whether the trade was algorithm driven. The return of the All Ordinaries Index (All Ords) was acquired from Thompson Reuters' tick history. The sample period is approximately one calendar year, covering the Australian stock market around the peak of the global financial crisis. The market turbulence during our sample period allows us to study AT in relation to extreme market movements.

Besides the ability to differentiate AT from non-AT transactions, the Australian data provide additional benefits. First, while many previous studies rely on Lee and Ready's (1991) algorithm, we use the "true" classification of buys and sells from order-level data provided by SIRCA.[30] Ellis, Michaely, and O'Hara (2000) and Chakrabarty, Moulton, and Shkilko (2012) find the accuracy of Lee and Ready's algorithm to be 81.05% and 69%, respectively. In the ASX, Aitken and Frino (1996) show the accuracy to be 74%. Therefore, it would be beneficial to improve the accuracy of trade direction classification. Additionally, Dennis and Strickland (2002) use quarterly sampled corporate filing data to identify the participation rate of each investor group. We utilize real-time transaction-level data, which enables us to better analyze the time-series of investor participation and control for potential autoregressive properties.

3.3.2 Stock and event day selection

To ensure that there are sufficient AT and non-AT volumes in our sample to generate robust results, we limit the sample stocks to those that were present throughout the sample period. We further delete stocks that were traded on fewer than 200 days over the 252 trading days in our sample. Our final sample contains 384 stocks.

Researchers apply a wide range of techniques to identify the turbulent trading periods. Brogaard, Hendershott, and Riordan (2014) select the top 10% of stock-days sorted by the volatility in the permanent (efficient) component of the intraday price changes. Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov (2016) detect extreme

[30] Our data include every order in the limit order book and each order is given an unique ID. Therefore, each order's time stamp can be dynamically updated upon submission, revision, cancellation, and execution. In a limit order market, a trade occurs when an ask-side order has a lower or equal price compared to a bid-side order. The trade initiator can therefore be identified by comparing the time stamps of the orders on both sides. If the time stamp of the ask-side (bid-side) is earlier, then the trade resulted from a liquidity-demanding buy (sell) order hitting the ask (bid).

price jumps as the top 0.1% of the 10-second trading intervals sorted by absolute midquote changes. Shkilko, Van Ness, and Van Ness (2012) identify episodes of intraday downward price pressures as stock-days when the individual stock prices fall for more than two standard deviations of historical intraday returns and then rebound. Our approach differs from these methods based on two objectives. First, we assess algorithmic buys (sells) in individual stocks in relation to the upward (downward) pressure from the market. Therefore, we separately identify extreme market up days and down days. Second, we analyze the longer-term effects of AT and investigate the stock prices on the event days and five days after the event days.

Similar to Dennis and Strickland (2002), we define turbulent days as days when the absolute values of the returns on the market are greater than 2%.[31] There are 19 market up days and 20 market down days. We use the All Ords as our proxy for market returns. The All Ords contains the top 500 Australian ordinary stocks and amounts to over 95% of the value of all stocks listed in the ASX. The final sample contains 9,896 stock trading days across 384 stocks. Table (3.1) and (3.2) report the event days, number of stocks for each event day, and returns of the All Ords.

The ASX is a highly concentrated market, large movements in the market index could be caused by a few of the largest firms. Consequently, the selected days may contain days when the index change does not represent a price shift among a wide range of stocks. To avoid this potential bias in our event day selection, we calculate the percentages of firms with positive returns, zero returns, and negative returns. Furthermore, we calculate the ratios of stocks with positive returns (negative returns) to those with negative returns (positive returns) for positive (negative) market return days. Table (3.1) presents the market up days, the mean percentage of positive return stocks is 72.40%, with a maximum of 81.47% on July 14, 2009, and a minimum of 57.45% on January 27, 2009. The ratio of stocks with positive returns to stocks with negative returns indicates that there are, on average, 2.75 times more stocks with positive returns than those with negative returns over our sample period. Table (3.2) presents the market down days, the findings for market down days are stronger, with a maximum of 92.68% negative return stocks on January 15, 2009. Overall, the results imply that individual stock returns are overwhelmingly positive (negative) on market up (down) days.

[31] As a robustness test, we select the same amount of turbulent days based on intraday realized variances of the market index, the results are qualitatively and quantitatively similar.

Table 3.1: Market Up Days and Returns

This table contains the dates, market returns, and number of stocks in the sample and the proportion of stocks that have positive, zero, and negative returns on days when the the return of the market portfolio rises by more than 2%. The sample period is from 27 October 2008 to 23 October 2009. Stocks are included on each event day if they were traded by both ATers and non-ATers on the day. The market portfolio is defined as the Australian All Ordinaries index. In this table, percent positive is the percentage of stocks with returns greater than zero, percent zero is the percentage of stocks with returns equal to zero, percent negative is the percentage of stocks with returns less than zero, and ratio is the ratio of percent positive (negative) to percent negative (positive) on market up (down) days. There are 19 up days and 20 down days in our sample.

Date	Market Return (%)	Number of Stocks	Percent Positive	Percent Zero	Percent Negative	Ratio
05-Nov-08	2.82	277	72.92	5.78	21.30	3.42
25-Nov-08	5.51	253	73.52	7.91	18.58	3.96
28-Nov-08	4.10	244	73.77	8.61	17.62	4.19
08-Dec-08	3.69	221	71.04	4.98	23.98	2.96
15-Dec-08	2.41	224	72.32	4.46	23.21	3.12
27-Jan-09	2.79	235	57.45	8.94	33.62	1.71
13-Mar-09	3.27	242	80.99	4.96	14.05	5.76
17-Mar-09	2.91	252	75.00	5.16	19.84	3.78
23-Mar-09	2.29	241	64.73	8.30	26.97	2.40
02-Apr-09	2.69	269	76.58	5.58	17.84	4.29
14-Apr-09	2.22	274	75.55	5.84	18.61	4.06
30-Apr-09	2.26	265	76.98	5.28	17.74	4.34
04-May-09	2.89	266	73.31	5.64	21.05	3.48
19-May-09	2.12	274	67.52	6.93	25.55	2.64
10-Jun-09	2.10	277	67.51	10.11	22.38	3.02
14-Jul-09	3.23	259	81.47	8.11	10.42	7.81
13-Aug-09	2.74	340	73.75	5.01	21.24	3.47
16-Sep-09	2.32	334	71.56	8.68	19.76	3.62
07-Oct-09	2.15	330	69.70	8.48	21.82	3.19

Table 3.2: Market Down Days and Returns

This table contains the dates, market returns, and number of stocks in the sample and the proportion of stocks that have positive, zero, and negative returns on days when the the return of the market portfolio drops by more than 2%. The sample period is from 27 October 2008 to 23 October 2009. Stocks are included on each event day if they were traded by both ATers and non-ATers on the day. The market portfolio is defined as the Australian All Ordinaries index. In this table, percent positive is the percentage of stocks with returns greater than zero, percent zero is the percentage of stocks with returns equal to zero, percent negative is the percentage of stocks with returns less than zero, and ratio is the ratio of percent negative to percent positive. There are 20 down days in our sample.

Date	Market Return (%)	Number of Stocks	Percent Positive	Percent Zero	Percent Negative	Ratio
06-Nov-08	−4.22	233	13.30	3.00	83.69	6.29
07-Nov-08	−2.43	236	34.75	5.51	59.75	1.72
11-Nov-08	−3.40	224	15.18	2.68	82.14	5.41
13-Nov-08	−5.44	220	8.64	5.00	86.36	10.00
17-Nov-08	−2.32	225	22.67	6.22	71.11	3.14
18-Nov-08	−3.47	238	15.13	5.88	78.99	5.22
20-Nov-08	−4.32	266	14.29	5.64	80.08	5.61
26-Nov-08	−2.68	225	23.56	8.44	68.00	2.89
02-Dec-08	−4.02	217	13.82	5.53	80.65	5.83
12-Dec-08	−2.31	211	29.38	5.21	65.40	2.23
08-Jan-09	−2.27	220	20.91	4.55	74.55	3.57
15-Jan-09	−4.07	205	2.93	4.39	92.68	31.67
20-Jan-09	−3.00	223	15.25	4.04	80.72	5.29
23-Jan-09	−3.83	216	13.43	6.48	80.09	5.97
02-Mar-09	−2.82	225	22.22	7.11	70.67	3.18
08-Apr-09	−2.22	255	20.78	4.71	74.51	3.58
21-Apr-09	−2.40	265	19.25	2.64	78.11	4.06
14-May-09	−3.43	277	13.72	2.17	84.12	6.13
23-Jun-09	−3.01	308	11.04	6.17	82.79	7.50
02-Oct-09	−2.04	331	9.37	4.23	86.40	9.23

Although the numbers of stocks included for each event day are not identical, the sample size for each event day is sufficiently large. The minimum is 205 on January 15, 2009, and the maximum is 340 on both August 14, 2009, and September 17, 2009. The distribution of market up days is relatively spread out throughout the year. For market down days, however, there is a cluster of event days in November 2008.[32]

3.4 AT intensity and abnormal returns

In this section, we investigate whether the intensities of AT is associated with the returns in individual stocks when the overall market experiences large surges or declines. Therefore, the cross-sectional distribution of individual stock returns will be a function of AT intensity. We first analyze the univariate properties of AT and then report the multivariate regression results.

3.4.1 Univariate analysis

Figure (3.1) (Figure (3.2)) presents AT and non-AT buy (sell) volume statistics for all days, market up days, and market down days. The volume statistics are calculated as the mean of the daily trading volume across all stocks in our sample.

Figure (3.1) and Figure (3.2) indicate that, on market up and down days, the fraction of AT liquidity-demanding and liquidity-supplying trades compared to non-AT trades does not change significantly. The findings support our premise that AT does not drastically change their trading behavior compared to non-AT in light of extreme market movements.

Table (3.3) reports descriptive statistics. We measure trading activity by volume traded and the number of transactions. We then separate buy-initiated trades from sell-initiated trades to identify additional information from the trade direction. Panel A presents the cross-sectional averages of volume, the number of transactions, and various AT volume (number of trades) ratios measured by the AT-initiated volume (number of trades) over the total volume (number of trades). The daily statistics are reported for all 252 trading days, including 19 up days and 20 down days. In line with Chordia and Subrahmanyam (2004), the number of buy trades is slightly higher than the number of sell trades, with means of 118 and 107, respectively. AT trade size is much smaller than that

[32] This turbulent period is attributed to the collapse of Lehman Brothers and the peak of the financial crisis (Longstaff, 2010).

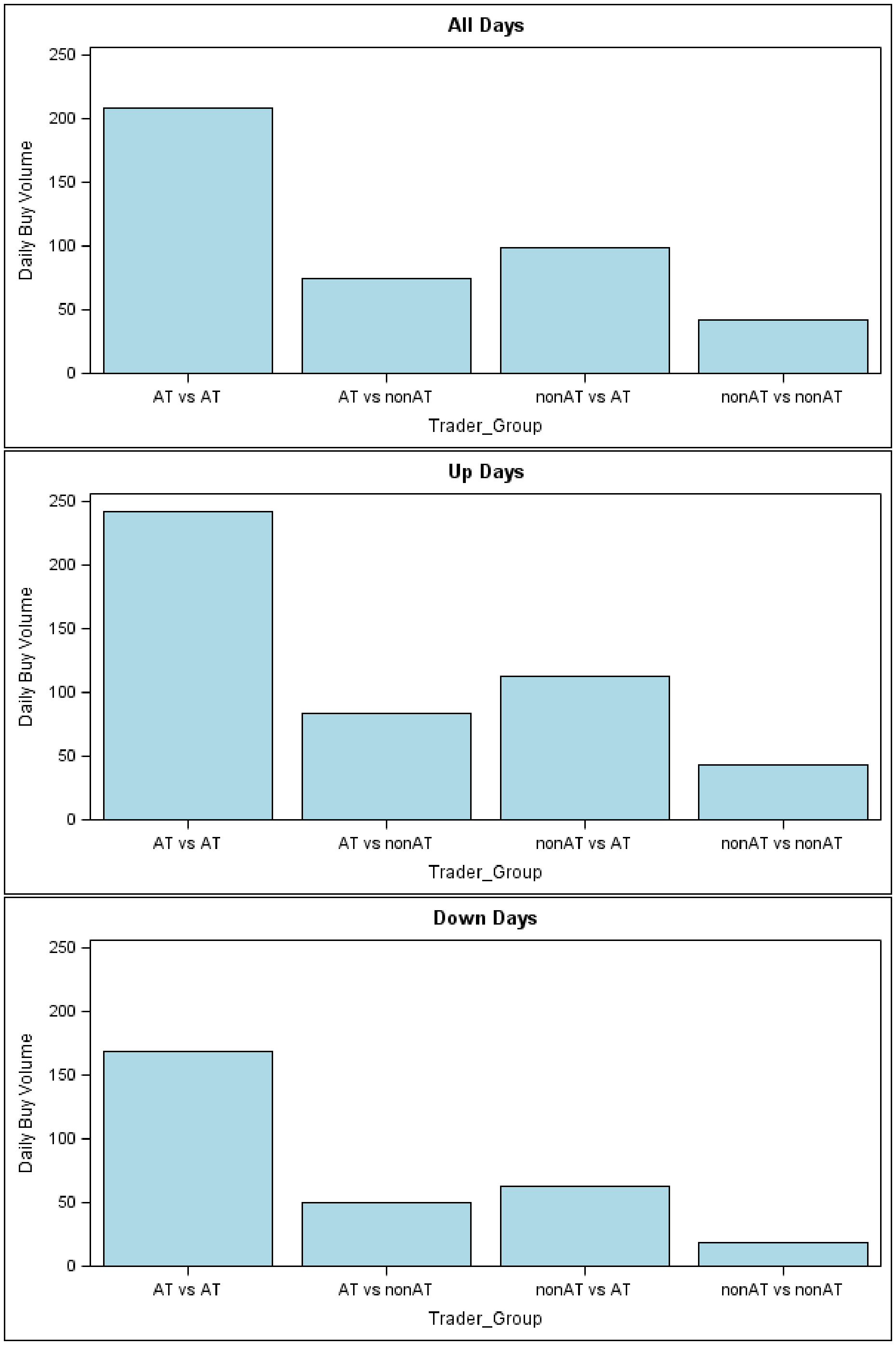

Figure 3.1: AT and non-AT Buy Volume by Event Days.

These figures contain AT and non-AT buy volume statistics by event days from 27 October 2008 to 23 October 2009. The up (down) days are defined as the days when the market returns exceed 2% (-2%). Trader group ‘AT vs non-AT’ denotes the group of trades that are initiated by AT, and non-AT is on the passive side. Other trader groups are defined analogously. Volume is presented in millions of shares.

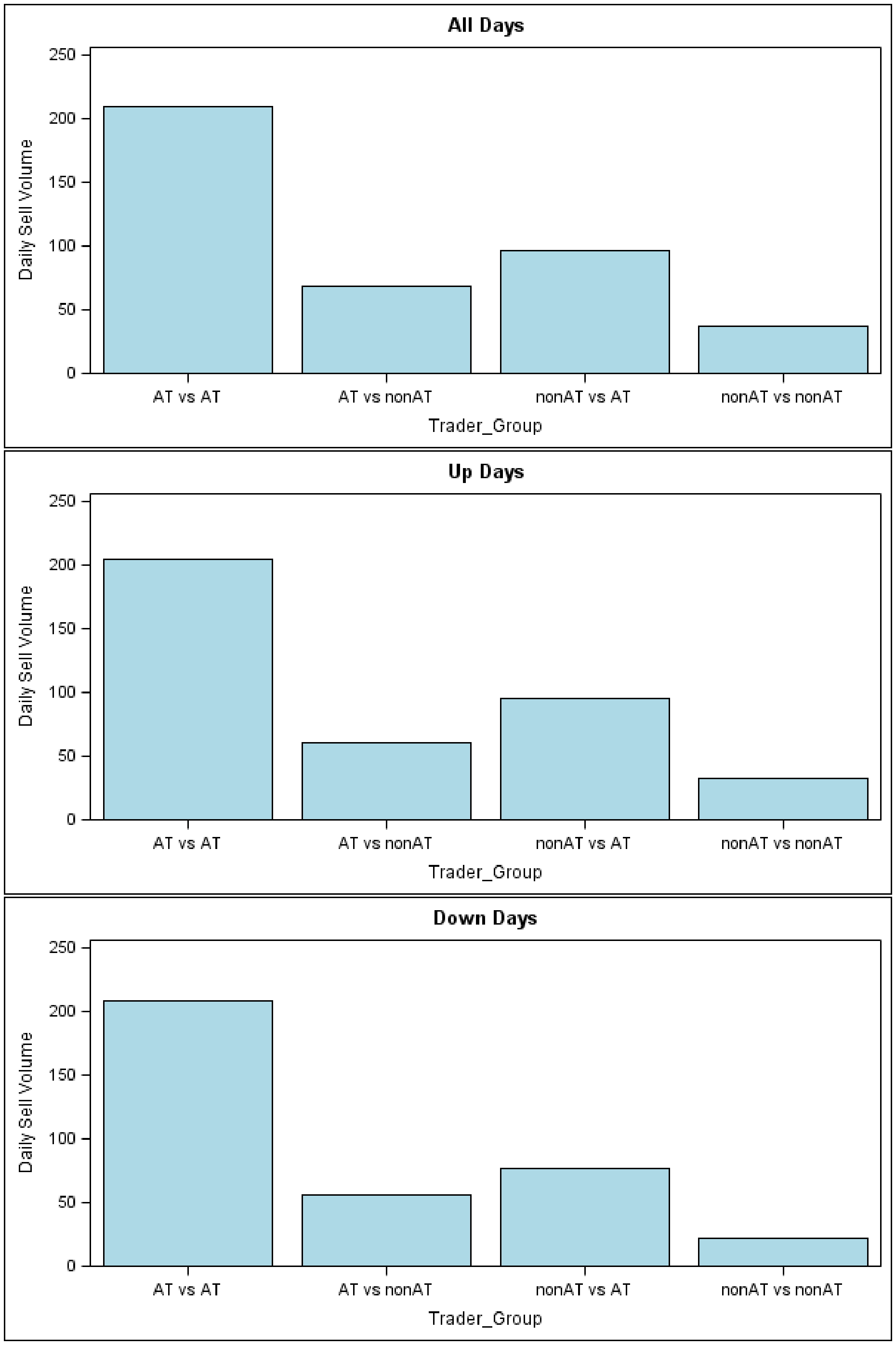

Figure 3.2: AT and non-AT Sell Volume by Event Days.

These figures contain AT and non-AT sell volume statistics by event days from 27 October 2008 to 23 October 2009. The up (down) days are defined as the days when the market returns exceed 2% (-2%). Trader group 'AT vs non-AT' denotes the group of trades that are initiated by AT, and non-AT is on the passive side. Other trader groups are defined analogously. Volume is presented in millions of shares.

of non-AT. This finding is consistent with Hendershott and Riordan (2013), in that algorithmic traders break their orders into smaller packets to achieve the best prices.

The average daily volume differences between regular days and event days can be interpreted based on the first two rows of Panel A in Table (3.3). Consistent with the notion that large market returns should correlate with elevated trading volume, the average buy volume on market up days is 13.44% higher than those on all days. On market down days, the proportion of sell volume to overall volume increased to 54.81% compared to 49.28% on regular days. This increase implies that traders are responding to the market downward pressure by disproportionately selling stocks. However, the overall trading volume decreased by 20.57%. This abnormal decline in volume is likely a result of the highly turbulent sample period: several of the market down days are in November 2008, at the height of the Global Financial Crisis first originated in the U.S. markets. It is an unusual time period for the U.S. and the global economy. Australian investors were reasonably uncertain about the severity of impact on Australian companies.

Panel B of Table (3.3) presents the cross-sectional means of individual stock time-series correlations and autocorrelations between all AT trade, AT buy, and AT sell ratios, measured by the number of trades and volume. The corresponding ratios measured by the number of trades and volume are highly correlated, with correlations of 0.672, 0.666, and 0.680 for all AT trades, AT buys, and AT sells, respectively. The correlations between AT buys and AT sells measured by the number of trades and volume are 0.093 and 0.110, respectively. Panel C contains the cross-sectional average autocorrelations of AT ratios measured by volume and the number of trades. The autocorrelation of the ratio of AT trades to all trades is substantially high; the first-lag autocorrelation is 0.211. The autocorrelations of AT buys and AT sells are smaller but also significant: 0.167 and 0.176, respectively. The autocorrelations decay at a moderate speed.

For the majority of this chapter, we focus on AT liquidity-demanding trades for the following reasons.[33] First, during our sample period, buy-side execution algorithms account for the majority of AT (ASX, 2010). large institutions employ execution algorithms to minimize the price impact of pre-existing large orders (Menkveld, 2016). Unlike many HFT firms, these buy-side institutions generally do not specialize in liquidity provision.[34] The

[33]We use Section 3.4.4 to explore the net effects of AT liquidity demand and supply.

[34]Menkveld (2013) characterizes the trading strategy of one large HFT firm in the European markets. The author finds that over

Table 3.3: Descriptive Statistics

This table contains summary statistics for daily AT ratios between 27 October 2008 and 23 October 2009. The sample comprises 384 stocks. The event days are defined as the days when the absolute values of the market returns exceed 2%. Panel A presents the means and standard deviations of trading volume and the AT volume ratios. Buy (sell) volume is the mean of the total daily buy (sell) volume across all stocks in our sample. The AT volume ratio is defined as the daily ratio between the AT volume and the overall volume. Other ratios are defined analogously. Panels B and C present the cross-sectional means of the individual stock time-series correlations and autocorrelations. There are 252 trading days, 19 up days, and 20 down days.

Panel A: Descriptive Statistics

	All Days		Up Days		Down Days	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Buy Volume (,000,000)	424	145	481	141	300	74
Sell Volume (,000,000)	412	121	393	99	364	89
No. of Buy Trades (,000)	118	25	133	29	115	28
No. of Sell Trades (,000)	107	21	101	15	108	20
AT Volume Ratio (%)	68.25	17.26	69.97	16.76	71.56	15.89
AT Buy Volume Ratio (%)	68.22	18.27	69.74	17.46	69.64	16.38
AT Sell Volume Ratio (%)	67.24	19.01	67.21	18.91	69.86	17.25
AT No. of Trades Ratio (%)	80.84	11.75	81.40	11.33	81.75	10.47
AT No. of Buy Trades Ratio (%)	79.56	12.46	80.67	11.53	80.08	10.85
AT No. of Sell Trades Ratio (%)	79.32	12.84	79.06	12.68	80.43	11.62

Panel B: Correlations

	AT Buy Volume Ratio	AT Sell Volume Ratio	AT No. of Trades Ratio	AT No. of Buy Trades Ratio	AT No. of Sell Trades Ratio
AT Volume Ratio	0.622	0.678	0.672	0.440	0.484
AT Buy Volume Ratio		0.093	0.435	0.666	0.090
AT Sell Volume Ratio			0.441	0.090	0.680
AT No. of Trades Ratio				0.649	0.643
AT No. of Buy Trades Ratio					0.110

Panel C: Autocorrelations

	AT Volume Ratios			AT No. of Trades Ratios		
lag	All Trades	Buy Trades	Sell Trades	All Trades	Buy Trades	Sell Trades
1	0.211	0.167	0.176	0.254	0.211	0.204
2	0.149	0.118	0.109	0.191	0.150	0.142
3	0.116	0.085	0.082	0.159	0.117	0.113
4	0.100	0.075	0.071	0.140	0.102	0.093
5	0.087	0.059	0.056	0.127	0.086	0.085

major sell-side electronic market makers have yet to enter the ASX. For example, two major global electronic market makers, Global Electronic Trading Company (GETCO) and Virtu Financial, entered the ASX in May and August 2011 respectively (ASX 2011a and ASX 2011b). Second, our data identify AT on a trade-by-trade basis instead of order-by-order basis, the coarseness of our data limits us from fully interpreting the liquidity provision results. For example, an execution of a passive AT sell order can be viewed as AT providing liquidity to inpatient buyers. Alternatively, it is possible that the passive sell order is stale and is being picked off by other traders. With order level data, the intentions and implications of limit order activities can be better teased out. We leave the issues of automated market making for future studies with more granulated datasets.

Similar to Dennis and Strickland (2002), our main variable of interest is the level of AT activity in proportion to total trading activity. We define rAT as the ratio of the AT volume divided by the total trading volume:

$$rAT_{i,t} = \frac{ATvolume_{i,t}}{Totalvolume_{i,t}}, \tag{4}$$

where $ATvolume_{i,t}$ is AT initiated volume for stock i on day t. $Totalvolume_{i,t}$ is the total volume for stock i on day t. $rATbuy$ and $rATsell$ are defined analogously for AT buy and sell volume. Throughout the paper, we focus on AT liquidity-demanding trades instead of AT liquidity-supplying trades for the following reasons.[35] First, buy-side execution algorithms, which primarily initiates trades constitute the majority during our sample period (ASX, 2010). On the other hand, sell-side algorithms such as HFT market makers, do not account for a significant fraction during our sample period. Second, our robustness tests show that liquidity-supplying trade contains insignificant information. Third, based on the results in Figure (3.1), AT does not supply more liquidity than the amount of liquidity it consumes. Our measures are aggregated daily. The daily frequency optimally reflects the richness of transaction data and the relevance of our results to the longer-term investors. Buy-side agency execution algorithms remain the majority among automated algorithms during our sample period (ASX, 2010). These algorithms tend to split large orders into smaller trades. The number of trade measures would be biased, since the algorithms would split a large order into multiple trades. Therefore, we use volume ratios instead of the

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75% of its trades are liquidity providing trades.

[35]Similar to Brogaard, Hendershott, and Riordan (2014), we classify a trade as AT liquidity-demanding (supplying) if AT is on the aggressive (passive) side of the trade.

number of trades.

We assess the univariate relation between rAT and the stock returns on turbulent days. Figure (3.3) presents the association between rAT and individual stock returns on market up days and down days.

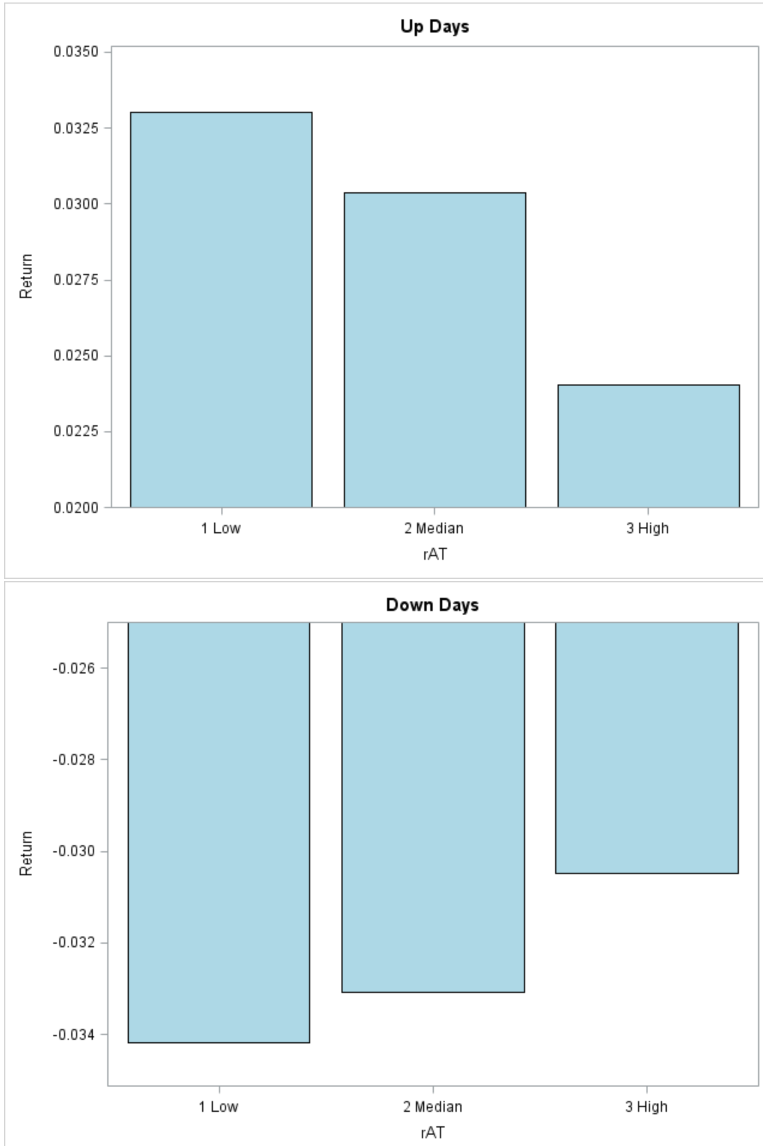

Figure 3.3: AT and non-AT Trading Volume on Up Days and Down Days.
These figures illustrate the univariate relation between AT and event day stock returns. The up (down) days are defined as the days when the market returns exceed 2% (-2%). The top (bottom) panel is for up (down) days.

Consistent with the notion that AT minimizes price pressure and reduce the price impact of trades, we find that low rAT stocks experience less upward (downward) pressure when the market goes up (down) by more than 2% (Hendershott, Jones, and Menkveld, 2011 and Malinova, Park, and Riordan, 2013).

3.4.2 Multivariate analysis

In the regression analyses, we define the intensity of AT, iAT, as the value of rAT on the event day less the mean of rAT over the past five days:[36]

$$iAT_t = rAT_t - \frac{1}{5}\sum_{i=t-5}^{t-1} rAT_i. \tag{5}$$

The decision to use abnormal values as opposed to raw values is based on the autoregressive properties reported in Table (3.3). Specifically, we find that AT and non-AT consistently prefer certain stocks to others. Applying the raw values on the event day for the cross-section of stocks would incorporate the information about these preferences. The lag length is determined by autocorrelation analysis, wherein the lag length is determined by the Akaike information criterion.

To assess how the trading activities of different investor groups correlate to individual stock returns in a turbulent market, we model the market-adjusted return on each event day as a function of the AT intensity and control variables. The most efficient estimation method for our panel data would be a pooled ordinary least squares estimator. However, possible cross-sectional correlations in the error terms could be a problem. To mitigate this issue, we follow Dennis and Strickland (2002) and use Fama–MacBeth (1973) regression on each event day:

$$ar_i = \alpha + \beta_1 iAT_i + \beta_2 size_i + \beta_3 turnover_i + \beta_4 idiovar_i + \beta_5 beta_i + \epsilon_i, \tag{6}$$

where ar_i is the market-adjusted return for stock i on the event day, iAT_i is the intensity of AT, $size_i$ is the logarithm of the market value of stock i five days prior to the event day, $turnover_i$ is the ratio of the daily volume over the number of shares outstanding on the event day, $idiovar_i$ is the idiosyncratic variance of the market model residual of stock i on days $[-125, -5]$, and $beta_i$ is the beta of stock i for days $[-125, -5]$. In Panel A of Table (3.4),

In Panel B of Table (3.4), iAT_i is further segregated into $iATbuy_i$ and $iATsell_i$, corresponding to AT buy

[36] We obtain similar regression results using rAT.

intensity and AT sell intensity, respectively:

$$ar_i = \alpha + \beta_1 iATbuy_i + \beta_2 iATsell_i + \beta_3 size_i + \beta_4 turnover_i + \beta_5 idiovar_i + \beta_6 beta_i + \epsilon_i. \quad (7)$$

We include beta as an independent variable, which is calculated based on historical returns over the past year. The magnitude of beta is directly associated with market-adjusted returns and volatility. There are two reasons to include turnover in our regression. First, previous studies have established the link between stock trades and stock price changes (for a detailed survey, see Karpoff, 1987). Although our main variables capture AT/non-AT trading effects, we include turnover to account for overall liquidity effects. Second, the theoretical model of Foucault, Kadan, and Kandel (2013) predicts a strong association between AT and trading rates. Empirically, AT is reported to follow a liquidity-driven strategy (Hendershott and Riordan, 2013). If AT is correlated with liquidity in our sample, omitting turnover would likely force our main variables to become proxies for liquidity effects. Therefore, we include turnover to ensure that the estimated relation between iAT and returns is robust to pricing and proxy effects.

As for turnover, we include size in the regression to account for its possible association with return and iAT.[37] Moreover, the All Ords, a value-weighted index, places more weight on larger stocks. Therefore, including size could alleviate potential biases of returns toward larger stocks. We also include idiosyncratic variance in our regression. Dierkens (1991) suggests using idiosyncratic volatility as a measure of informational effects. If AT has an informational advantage, as argued by Biais, Foucault, and Moinas (2015), it will be correlated with idiosyncratic variance.

Our main variable of interest is the intensity of AT in individual stocks in light of large market movements. We measure the association between AT and market-adjusted returns for each stock. When the market suffers from a price decline of more than 2%, further decline in a given stock represented by a decrease in market-adjusted return would indicate its higher downward price pressure. If we find more AT in stocks that have a smaller market-adjusted return, then AT would cause price fluctuations by exerting further downward pressure on individual stocks. Alternatively, if AT levels are positively associated with market-adjusted returns on market decline days,

[37] Banz (1981) finds size to be a significant factor of stock returns.

then AT would be beneficial to stock price stability. To emphasize the importance of trade direction, we then segregate trading volume into buy and sell volumes. We expect the buy (sell) volume to be more relevant than the sell (buy) volume on market up (down) days.

Table (3.4) presents the results. Panel A reports the estimations with unsigned AT intensity. The signs of the coefficients for the AT intensity (iAT) are as expected: negative for market up days and positive for market down days. The coefficients suggest that non-AT creates price pressure in the direction of market movement. However, the AT intensity (iAT) is marginally insignificant (p-value of 0.113) on market up days and insignificant (p-value of 0.181) on market down days. To further disentangle the informativeness in trade signals, we report the estimations for the AT buy intensity ($iATbuy$) and the AT sell intensity ($iATsell$) in Panel B. On market up days, the AT buy intensity is significant and the AT sell intensity is highly insignificant, whereas the distribution of significance reverts on market down days. This result suggests that the predictive power of the buy (sell) volume on up (down) days is diluted by not assigning trade direction in Panel A. Taken together, the AT buy intensity is negatively correlated with the market-adjusted return on up days, whereas the AT sell intensity is positively correlated with the market-adjusted return on down days. This finding supports the notion that stocks with less AT buying (selling) would incur a greater upward (downward) price swing on up (down) days. As a result, stocks with higher levels of AT would reduce volatility on event days.

Economically, the association between AT intensity and market-adjusted returns are substantial. The economic significance is most pronounced when we segregate the trades into buy- and sell-initiated trades. The coefficient of the AT buy intensity on market up days is 1.61, which implies a decrease of 16 basis points in the predicted abnormal returns for a 10% (or 0.53 standard deviation) increase in the AT buy intensity. Likewise, the coefficient of the AT sell intensity on market down days indicates that a 10% (or 0.49 standard deviation) increase in AT selling, on average, corresponds to a 12 basis point increase in abnormal returns. The coefficients of the control variables in Panels A and B of Table (3.4) are similar in magnitude and significance. As expected, turnover is positively (negatively) related to market-adjusted returns on market up (down) days. However, the association on market down days is not significant, implying that market up days are more likely to be liquidity driven compared to market down days. Size and idiosyncratic variance are not significantly related to market-adjusted returns.

Table 3.4: Event Day Market-Adjusted Return Regressions on Abnormal AT Ratios

This table presents coefficient estimates from Fama–MacBeth regressions using the following model:

$$ar_i = \alpha + \beta_1 iAT_i + \beta_2 size_i + \beta_3 turnover_i + \beta_4 idiovar_i + \beta_5 beta_i + \epsilon_i,$$

where ar_i is the market-adjusted abnormal return for stock i on the event day. The event days are defined as the days when the absolute values of market returns exceed 2%. In Panel A, iAT_i is the abnormal volume ratio between the AT volume and the overall volume on the event day less the mean volume ratio over the past five days. The term $size_i$ is the logarithm of the market value of stock i five days prior to the event day and $turnover_i$ is the ratio of the daily volume over the number of shares outstanding on the event day. The variable $idiovar_i$ is the idiosyncratic variance of the market model residual of stock i on days $[-125, -5]$ and $beta_i$ is the beta of stock i for days $[-125, -5]$. The event days are segregated into 19 up days and 20 down days. In Panel B, iAT_i is further segregated into $iATbuy_i$ and $iATsell_i$ corresponding to the abnormal buy volume ratio and the abnormal sell volume ratio, respectively:

$$ar_i = \alpha + \beta_1 iATbuy_i + \beta_2 iATsell_i + \beta_3 size_i + \beta_4 turnover_i + \beta_5 idiovar_i + \beta_6 beta_i + \epsilon_i.$$

The control variables are identical to those in Panel A. The coefficients for iAT_i, $iATbuy_i$, $iATsell_i$, and $beta_i$ are multiplied by 100 in both panels. The coefficients for $size_i$ are multiplied by 1,000. The p-values are reported from a t-test of the mean coefficient being different from zero.

	Up Days				Down Days			
	Mean	p-value	Min	Max	Mean	p-value	Min	Max
Panel A: Aggregated AT Ratio								
iAT	−1.01	0.113	−5.22	3.98	0.73	0.181	−2.83	6.47
beta	1.86	0.000	−0.12	4.74	−1.93	0.000	−4.66	0.29
turnover	0.60	0.001	−0.72	1.94	−0.36	0.239	−3.54	2.57
size	−0.19	0.838	−5.10	10.49	0.09	0.889	−4.42	8.40
idiovar	0.42	0.380	−3.61	4.53	−0.58	0.316	−3.71	5.22
Panel B: Segregated Buy/Sell Ratio								
iATbuy	−1.61	0.005	−6.54	1.43	−0.31	0.579	−3.61	6.18
iATsell	−0.13	0.764	−3.52	2.80	1.19	0.011	−2.58	5.05
beta	1.86	0.000	−0.11	4.80	−1.95	0.000	−4.58	0.52
turnover	0.59	0.002	−0.91	1.98	−0.33	0.272	−3.68	2.66
size	−0.24	0.803	−5.35	10.46	0.13	0.848	−4.13	8.41
idiovar	0.39	0.427	−3.69	4.57	−0.61	0.300	−3.63	5.20

3.4.3 Post-event day analysis

The empirical findings on event days indicate that the absolute value of individual stock returns with lower AT intensity exceeds that of returns with higher AT intensity. In this section, we show the post-event return differences between stocks with high and low AT intensity. The return difference on the event day could be explained by non-AT reactions to information and driving prices to their fundamental values. If this is the case, we should observe no return reversal during the period immediately after the event day for stocks with lower AT intensity compared to those with higher AT intensity. If, however, there are significant return reversals among stocks with lower AT intensity, then non-AT increases price fluctuations and causes prices to deviate from their fundamental values.

The time span of our data dictates that longer-term analysis is not feasible; nevertheless, we provide a post-event cumulative return analysis over the five days immediately after each event day. We sum post-event market-adjusted returns as Cumulative Abnormal Returns (CARs) for each stock and partition them into quartiles based on their event day AT intensity. We then calculate the mean difference between CARs of higher and lower AT intensity. The intuition is that if the return effects on event days are temporary, we will observe significantly higher CARs in low AT stocks, compared to high AT stocks, immediately after market down days. Alternatively, if the return effects are fundamental on event days, we will observe insignificant differences in post-event CARs.

Table (3.5) contains the results of the post-event CAR differences. In Panel A, the first (third) row contains the mean CAR difference between the top and bottom 50% (25%) based on AT activities. The second and fourth rows report the p-values corresponding to a test of a null hypothesis that the CARs from high/low AT quartiles are identical. On market down days, the post-event CAR difference is significantly negative. This finding implies significant return reversals in stocks of low AT intensity.

Table 3.5: Post-Event Cumulative Abnormal Returns

This table presents the results of post-event CAR analysis for stocks ranked by AT activity quartiles. The event days are defined as the days when the absolute values of market returns exceed 2%. In Panel A, the CAR for stock i is the market-adjusted return over five days after each event day. The CARs for individual stocks are partitioned into quartiles based on the AT buy (sell) volume market share on each up (down) day. The mean CAR difference between high- and low-AT stocks are presented. In Panel B, the CAR for stock i is calculated as the five-day post-event return for stock i less the mean five-day returns for all stocks in the same beta quartile as stock i on the event day. The p-values in parentheses correspond to a test of a null hypothesis that the CARs from high/low-AT quartiles have identical means.

	Up Days		Down Days	
	5 Days	5 Days (Indep)	5 Days	5 Days (Indep)
Panel A: Post Event CAR Partitioned by AT Activities				
Top Less Bottom Half (%)	−0.201	−0.249	−0.690	−1.000
	(0.595)	(0.446)	(0.027)	(0.017)
Top Less Bottom Quartile (%)	−0.095	0.348	−0.775	−1.380
	(0.817)	(0.607)	(0.084)	(0.024)
Panel B: Post Event CAR Partitioned by AT Activities (Robustness)				
Top Less Bottom Half (%)	−0.337	−0.227	−0.775	−1.080
	(0.219)	(0.480)	(0.011)	(0.009)
Top Less Bottom Quartile (%)	−0.090	−0.180	−0.832	−1.420
	(0.820)	(0.700)	(0.058)	(0.018)

3.4.4 Net effects of AT liquidity demand and supply

In this section, we assess the net effect of AT liquidity demand and supply on turbulent days. Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov (2016) use an activity metric that nets liquidity supply and demand from HFT. We apply a similar metric for AT. To measure AT demand and supply, we use AT volume imbalances of liquidity demanding and supplying trades respectively:

$$\begin{aligned} dAT_{i,t} &= dATbuy_{i,t} - dATsell_{i,t} \\ sAT_{i,t} &= sATbuy_{i,t} - sATsell_{i,t}, \end{aligned} \tag{8}$$

where $dAT_{i,t}$ ($sAT_{i,t}$) is the volume imbalance of liquidity demanding (supplying) AT for stock i on day t. $dATbuy_{i,t}$ ($dATsell_{i,t}$) is the buy (sell) initiated trading volume where the initiator is AT. $sATbuy_{i,t}$ ($sATsell_{i,t}$) is the buy (sell) initiated trading volume where the seller (buyer) is an algorithmic trader. The difference between liquidity demand and liquidity supply volume imbalances is our main metric:

$$netAT_{i,t} = dAT_{i,t} - sAT_{i,t}. \tag{9}$$

A positive net AT imbalance, $netAT_{i,t}$, indicates net trading activity of AT in the direction of the positive returns. I.e., A positive net AT imbalance results from either AT demands more liquidity by initiating more buy trades than sell trades (positive $dAT_{i,t}$) or AT supplies more liquidity to buy-initiated trades compared to sell-initiated trades (negative $sAT_{i,t}$).

On market up (down) days, most storks experience positive (negative) returns. A positive (negative) net AT imbalance shows that AT facilitates trades in the direction of the upward (downward) price movements. Similar to Equation (6), we apply Fama–MacBeth (1973) regression on event days:

$$ar_i = \alpha + \beta_1 netAT_i + \beta_2 size_i + \beta_3 turnover_i + \beta_4 idiovar_i + \beta_5 beta_i + \epsilon_i, \tag{10}$$

where ar_i is the abnormal return for stock i. The main variable of interest is $netAT_i$, which measures the net effect of AT liquidity demand and supply. Table (3.6) presents the association between abnormal return of individual stocks on event days and the net AT imbalance. On both market up and down days, the coefficients of $netAT$ are negatively significant. These results imply that AT liquidity demand and supply activities are inversely associated with upward (downward) price swings in individual stocks on market up (down) days.

3.4.5 Robustness tests

We perform several tests to assess the robustness of our results. We first test an alternative construction of the AT intensity, iAT. Madhavan, Richardson, and Roomans (1997) argue that innovation in the order flow is more indicative for security prices if the order flow is correlated. Innovation is modeled as the "surprise" component: the raw value less the expected value from the previous period. We follow a methodology similar to that of Brogaard, Hendershott, and Riordan (2014) and model the innovation in rAT, $innAT$, as the residual of a five-lag autoregressive model. The number of lags is determined by the Akaike information criterion. The innovations in the AT buys ($innATbuy$) and AT sells ($innATsell$) are obtained analogously. Table (3.7) presents the results.

The re-estimation results in Table (3.7) are quantitatively and qualitatively similar to the initial results in

Table 3.6: Event Day Market-Adjusted Return Regressions on Net AT Imbalances
This table presents coefficient estimates from Fama–MacBeth regressions using the following model:

$$ar_i = \alpha + \beta_1 netAT_i + \beta_2 size_i + \beta_3 turnover_i + \beta_4 idiovar_i + \beta_5 beta_i + \epsilon_i,$$

where ar_i is the market-adjusted abnormal return for stock i on event days. The event days are defined as the days when the absolute values of market returns exceed 2%. $netAT_i$ is the net effect of AT liquidity demand and supply defined in Equation (8) and (9). $size_i$ is the logarithm of the market value of stock i five days prior to the event day and $turnover_i$ is the ratio of the daily volume over the number of shares outstanding on the event day. The variable $idiovar_i$ is the idiosyncratic variance of the market model residual of stock i on days [−125, −5] and $beta_i$ is the beta of stock i for days [−125, −5]. The event days are segregated into 19 up days and 20 down days. The coefficients for $netAT_i$ are scaled by 10,000,000. The coefficients of $beta_i$ ($size_i$) are multiplied by 100 (1000). The p-values are reported from t-tests of the mean coefficient being different from zero.

	Up Days				Down Days			
	mean	p-value	min	max	mean	p-value	min	max
netAT	-0.859	0.001	-2.194	2.015	-0.832	0.000	-2.559	0.523
beta	1.792	0.000	0.001	0.041	-1.921	0.000	-0.050	0.003
turnover	0.552	0.001	-0.689	1.873	-0.477	0.027	-3.266	0.582
size	0.142	0.884	-0.006	0.010	0.303	0.654	-0.006	0.009
idiovar	0.481	0.298	-3.722	3.801	-0.316	0.567	-3.402	5.519

Table (3.4): *innAT* is statistically insignificant when we do not distinguish buy-initiated from sell-initiated trades and *innATbuy* (*innATsell*) is significantly related to abnormal returns on market up (down) days, with similar coefficients. The re-estimation confirms that our finding is robust with regard to the measurement of AT.

We also provide a sensitivity analysis of the event day selection criteria. In Table (3.8), we relax the threshold of event day selection criteria from an absolute market return of more than 2% to a range between 1.5% and 2.5%. Furthermore, if the market moves during the day but reverses toward the initial value at closing, the daily market return would not capture these days. Therefore, we replace the daily market return with the daily high (low) to open price return to capture the extreme price increase (decline) in the intraday. This measure allows us to include stocks that rose (fell) more than 2% in the intraday but reversed below 2% at the end of the day.

We then delete all consecutive event days to eliminate the effect of interday fluctuations. In addition, we further limit our sample of stocks to those that have at least ten trades initiated by both AT and non-AT in Table (3.9). Finally, the result is also robust to day-of-the-week effects, firm fixed effects, and double clustering of the standard error in stocks and days.

All robustness results in Tables (3.8) and (3.9) are quantitatively and qualitatively similar to those estimated using the initial specifications described in Section 3.4.2.

Table 3.7: Event Day Market-Adjusted Return Regressions on Innovation in AT Intensity

This table presents coefficient estimates from Fama–MacBeth regressions using the following model:

$$ar_i = \alpha + \beta_1 innAT_i + \beta_2 size_i + \beta_3 turnover_i + \beta_4 idiovar_i + \beta_5 beta_i + \epsilon_i,$$

where ar_i is the market-adjusted abnormal return for stock i on the event day. The event days are defined as the days when the absolute values of market returns exceed 2%. In Panel A, $innAT_i$ is volume ratio innovation obtained as the residual of an autoregressive model with five lags applied to the individual stock volume ratios. The term $size_i$ is the logarithm of the market value of stock i five days prior to the event day and $turnover_i$ is the ratio of the daily volume over the number of shares outstanding on the event day. The variable $idiovar_i$ is the idiosyncratic variance of the market model residual of stock i on days $[-125, -5]$ and $beta_i$ is the beta of stock i for days $[-125, -5]$. The event days are segregated into 19 up days and 20 down days. In Panel B, $innAT_i$ is further segregated into $innATbuy_i$ and $innATsell_i$, corresponding to the abnormal buy volume ratio and the abnormal sell volume ratio, respectively:

$$ar_i = \alpha + \beta_1 innATbuy_i + \beta_2 innATsell_i + \beta_3 size_i + \beta_4 turnover_i + \beta_5 idiovar_i + \beta_6 beta_i + \epsilon_i.$$

The coefficients for $innAT_i$, $innATbuy_i$, $innATsell_i$, and $beta_i$ are multiplied by 100 in both panels. The coefficients for $size_i$ are multiplied by 1,000. The p-values are reported from a t-test of the mean coefficient being different from zero.

	Up Days				Down Days			
	Mean	p-value	Min	Max	Mean	p-value	Min	Max
Panel A: Aggregated AT Ratio								
innAT	−0.93	0.160	−5.43	4.30	0.48	0.378	−3.22	5.58
beta	1.86	0.000	−0.15	4.75	−1.94	0.000	−4.66	0.32
turnover	0.60	0.001	−0.71	1.94	−0.36	0.235	−3.54	2.56
size	−0.15	0.871	−4.87	10.42	0.09	0.891	−4.52	8.42
idiovar	0.42	0.391	−3.74	4.54	−0.56	0.338	−3.65	5.28
Panel B: Segregated Buy/Sell Ratio								
innATbuy	−1.65	0.005	−6.48	1.58	−0.49	0.398	−4.06	5.52
innATsell	0.10	0.820	−2.98	3.57	0.94	0.059	−3.44	5.17
beta	1.87	0.000	−0.12	4.80	−1.95	0.000	−4.64	0.59
turnover	0.59	0.002	−0.85	2.02	−0.35	0.255	−3.71	2.62
size	−0.11	0.902	−4.91	10.49	0.11	0.871	−4.34	8.38
idiovar	0.36	0.462	−3.90	4.52	−0.58	0.319	−3.50	5.29

Table 3.8: Sensitivity Test for Event Day Selection

This table presents coefficient estimates from Fama–MacBeth regressions using the following model:

$$ar_i = \alpha + \beta_1 iATbuy_i + \beta_2 iATsell_i + \beta_3 size_i + \beta_4 turnover_i + \beta_5 idiovar_i + \beta_6 beta_i + \epsilon_i.$$

Sensitivity analysis of the event day selection method is presented based on the absolute value of market returns exceeding the range from 1.5% to 2.5%. In the last column, we estimate the event days when the absolute difference between intraday high/low prices exceed 2%. The variable ar_i is the market-adjusted abnormal return for stock i on the event day; $iATbuy_i$ ($iATsell_i$) is the abnormal volume ratio between the AT buy (sell) volume and the overall buy (sell) volume on the event day less the mean volume ratio over the past five days; $size_i$ is the logarithm of the market value of stock i five days prior to the event day; $turnover_i$ is the ratio of the daily volume to the number of shares outstanding on the event day; $idiovar_i$ is the idiosyncratic variance of the market model residual of stock i on days $[-125, -5]$; and $beta_i$ is the beta of stock i for days $[-125, -5]$. The coefficients for $iATbuy_i$, $iATsell_i$, and $beta_i$ are multiplied by 100 in both panels. The coefficients for $size_i$ are multiplied by 1,000. The p-values are reported in parentheses from a t-test of the mean coefficient being different from zero.

	1.50%	1.75%	2%	2.25%	2.50%	high/low
No. of Up Days	32	25	19	14	10	23
No. of Down Days	29	24	20	18	13	31
Panel A: Market Up Days						
iATbuy	−1.199	−1.528	−1.606	−1.834	−1.592	−1.510
	(0.012)	(0.008)	(0.005)	(0.016)	(0.101)	(0.002)
iATsell	−0.202	−0.104	−0.128	−0.137	0.064	0.041
	(0.494)	(0.772)	(0.764)	(0.775)	(0.923)	(0.920)
beta	1.527	1.664	1.865	1.901	1.705	1.632
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
turnover	0.475	0.539	0.587	0.642	0.611	0.461
	(0.000)	(0.001)	(0.002)	(0.008)	(0.042)	(0.007)
size	−0.800	−1.320	−0.236	0.105	0.746	0.328
	(0.313)	(0.142)	(0.803)	(0.929)	(0.646)	(0.721)
idiovar	0.163	0.194	0.387	0.334	0.565	0.645
	(0.663)	(0.645)	(0.427)	(0.601)	(0.406)	(0.897)
Panel B: Market Down Days						
iATbuy	−0.485	−0.475	−0.313	−0.416	−0.854	−0.301
	(0.246)	(0.345)	(0.579)	(0.532)	(0.246)	(0.495)
iATsell	0.829	0.790	1.194	1.117	1.260	0.827
	(0.021)	(0.057)	(0.011)	(0.027)	(0.036)	(0.021)
beta	−1.719	−1.796	−1.953	−2.004	−2.126	1.447
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
turnover	−0.315	−0.426	0.330	−0.368	−0.394	−0.434
	(0.239)	(0.175)	(0.272)	(0.277)	(0.396)	(0.124)
size	−0.884	0.047	0.130	−0.012	0.375	0.398
	(0.218)	(0.937)	(0.848)	(0.988)	(0.701)	(0.532)
idiovar	−0.663	−0.531	−0.610	−0.526	−1.205	0.417
	(0.155)	(0.298)	(0.300)	(0.411)	(0.084)	(0.451)

Table 3.9: Panel Data Regressions for Abnormal Volume Ratios

This table presents coefficient estimates from panel data regressions using the following model:

$$ar_{i,t} = \alpha + \beta_1 iATbuy_{i,t} + \beta_2 iATsell_{i,t} + \beta_3 size_{i,t} + \beta_4 turnover_{i,t} + \beta_5 idiovar_{i,t} + \beta_6 beta_{i,t} + \epsilon_{i,t}.$$

The variable $ar_{i,t}$ is the market-adjusted abnormal return for stock i on the event day; $iATbuy_{i,t}$ ($iATsell_{i,t}$) is the abnormal volume ratio between the AT buy (sell) volume and the overall buy (sell) volume on the event day less the mean volume ratio over the past five days; $size_{i,t}$ is the logarithm of the market value of stock i five days prior to the event day; $turnover_{i,t}$ is the ratio of the daily volume to the number of shares outstanding on the event day; $idiovar_{i,t}$ is the idiosyncratic variance of the market model residual of stock i on days $[t-125, t-5]$; and $beta_{i,t}$ is the beta of stock i for days $[t-125, t-5]$.

In the first (second) column, we included stocks that has at least 1 (10) AT and non-AT initiated trades on each event day. In the third column, we exclude consecutive event days. In the last column, we include weekday dummies to control for day of the week effect. The coefficients for $iATbuy_i$, $iATsell_i$, and $beta_i$ are multiplied by 100 in both panels. The coefficients for $size_i$ are multiplied by 1,000. The standard errors are clustered by stock and day. The p-values are reported in parentheses.

	All	10 Trades	Non-consec Days	Day of the Week
Panel A: Market Up Days				
iATbuy	−1.400	−1.270	−1.580	−1.400
	(0.014)	(0.045)	(0.013)	(0.014)
iATsell	−0.050	0.520	−0.240	−0.090
	(0.893)	(0.266)	(0.586)	((0.818))
beta	1.500	1.400	1.450	1.500
	(0.000)	(0.000)	(0.000)	(0.000)
turnover	0.546	0.000	0.572	0.537
	(0.268)	(0.314)	(0.271)	((0.269))
size	−0.200	−1.500	−0.100	−0.200
	(0.810)	(0.102)	(0.935)	(0.843)
idiovar	1.503	2.031	1.633	1.478
	(0.003)	(0.023)	(0.002)	(0.002)
adjusted R^2	0.052	0.058	0.058	0.057
Panel B: Market Down Days				
iATbuy	−0.280	−0.698	−0.080	−0.290
	(0.577)	(0.203)	(0.898)	(0.555)
iATsell	1.270	1.636	0.980	1.280
	(0.010)	(0.004)	(0.068)	(0.010)
beta	−1.790	−1.901	−1.670	−1.800
	(0.000)	(0.000)	(0.000)	(0.000)
turnover	−0.080	−0.005	−0.080	−0.080
	(0.462)	(0.691)	(0.439)	(0.458)
size	−0.100	0.472	0.500	−0.100
	(0.909)	(0.574)	(0.627)	(0.937)
idiovar	−1.380	−1.384	−1.547	−1.333
	(0.011)	(0.013)	(0.012)	(0.015)
adjusted R^2	0.050	0.058	0.053	0.052

3.5 AT, news announcements, and market conditions

While we observe economically large and robust results for AT intensity and price fluctuations, the results could be driven by the reactions of AT or non-AT to relevant market conditions and information rather than AT reducing price fluctuations. In this section, we explore plausible mechanisms through which market conditions and information might influence AT and non-AT.

3.5.1 Matched event day versus non-event day difference-in-differences analysis

Algorithmic traders may react to the return, liquidity, size, and volatility of a particular stock and adjust their execution accordingly. This may alter our inference about AT intensity and stock price swings. For example, computerized traders may choose to buy more stocks that have lower returns and not as many higher-return stocks. Consequently, on market up days, we observe a negative association between AT buy intensity and upward price swings. We aim to address this issue using a difference-in-differences regression between event and non-event days. We separate our sample into event days as our treatment group and non-event days as our control group. However, we cannot directly compare the treatment and control groups since the market conditions in terms of return, liquidity, and volatility could be significantly different. To avoid traders with AT technologies reacting to these differences, we match the treatment group with a subset of the control group based on market conditions. Specifically, we acquire propensity scores based on a logit regression on a set of covariates. The dependent variable is a dummy indicating whether the observation is on an event day. The independent variables are the market-adjusted return, size, turnover, beta, and idiosyncratic variance. We then match each observation in the treatment group with two observations in the control group that have similar market characteristics.[38] Table (3.10) presents the market condition differences before and after the match.

We perform the matching analysis for market up days and down days separately, with the results presented in Panels A and B of Table (3.10), respectively. The left-hand columns show the difference prior to the match and the right-hand column show the difference after the match. All differences in market conditions becomes

[38]We apply a 1:2 match because we have a large control group compared to the treatment group. We also performed a 1:1 match as a robustness check, the results of which are available upon request. The implications are unchanged.

Table 3.10: Propensity Score Matching Diagnostics

This table shows the diagnostics for propensity score matching between event days and non-event days. The sample is separated into up (down) days as the treatment group and non-event days as the control group. Each stock-day in the treatment group is matched with a stock-day in the control group based on their propensity scores. The propensity score is acquired from the logit regression for the treatment and control group. The dependent variable is a dummy that takes 1 if the observation is on a event day and 0 otherwise. The set of covariates are presented in the first column: $ar_{i,t}$ is the market-adjusted abnormal return for stock i on day t; $size_{i,t}$ is the logarithm of the market value of stock i five days prior to day t; $turnover_{i,t}$ is the ratio of the daily volume to the number of shares outstanding on day t; $idiovar_{i,t}$ is the idiosyncratic variance of the market model residual of stock i on days $[t-125, t-5]$; and $beta_{i,t}$ is the beta of stock i for days $[t-125, t-5]$. Panel A (B) presents the diagnostics for market up (down) days. Column 2-4 (5-7) presents pairwise comparison of the covariates and their difference before (after) propensity matching. Ar and Turnover are in percentages. The p-values for the differences in each covariates between treatment and control groups are reported in parentheses.

Panel A: Market Up Days

	Pre-Match			Post-Match		
	Control	Treatment	Difference	Control	Treatment	Difference
ar	0.168	0.122	0.046	0.098	0.122	-0.024
			(0.562)			(0.798)
beta	0.865	0.976	-0.111	0.980	0.976	0.004
			(0.000)			(0.697)
turnover	0.256	0.353	-0.097	0.313	0.353	-0.040
			(0.000)			(0.717)
size	19.933	20.315	-0.382	20.337	20.315	0.022
			(0.000)			(0.432)
idiovar	0.231	0.240	-0.009	0.237	0.240	-0.003
			(0.014)			(0.434)
No. of observations	79,488	5,076	84,564	10,152	5,076	15,228

Panel B: Market Down Days

	Pre-Match			Post-Match		
	Control	Treatment	Difference	Control	Treatment	Difference
ar	0.168	-0.104	0.272	-0.119	-0.104	-0.015
			(0.000)			(0.858)
beta	0.865	0.978	-0.113	0.995	0.978	0.017
			(0.000)			(0.213)
turnover	0.256	0.302	-0.046	0.314	0.302	0.012
			(0.000)			(0.500)
size	19.933	20.448	-0.515	20.420	20.448	-0.028
			(0.000)			(0.335)
idiovar	0.231	0.228	0.003	0.232	0.228	0.004
			(0.391)			(0.340)
No. of observations	79,488	4,820	84,308	9,640	4,820	14,460

Table 3.11: Matched Event Day and non-Event Day Diff-in-Diff Test

This table shows the results for the difference-in-difference test on market up days and down days using following model:

$$\begin{aligned} ar_{i,t} &= \alpha + \beta_1 iATbuy_{i,t} + \beta_2 iATsell_{i,t} + \beta_3 up_t + \beta_4 up_t \cdot iATbuy_{i,t} + \beta_5 up_t \cdot iATsell_{i,t} \\ &\quad + \beta_6 size_{i,t} + \beta_7 turnover_{i,t} + \beta_8 idiovar_{i,t} + \beta_9 beta_{i,t} + \epsilon_{i,t}, \end{aligned}$$

over a sample in which each event day is matched with two non-event days based on the criteria described in Table (3.10). $ar_{i,t}$ is the market-adjusted abnormal return for stock i on the event day; $iATbuy_{i,t}$ ($iATsell_{i,t}$) is the abnormal volume ratio between the AT buy (sell) volume and the overall buy (sell) volume on the event day less the mean volume ratio over the past five days; $size_{i,t}$ is the logarithm of the market value of stock i five days prior to the event day; $turnover_{i,t}$ is the ratio of the daily volume to the number of shares outstanding on the event day; $idiovar_{i,t}$ is the idiosyncratic variance of the market model residual of stock i on days $[t-125,\ t-5]$; and $beta_{i,t}$ is the beta of stock i for days $[t-125,\ t-5]$; up_t is a dummy variable that takes 1 if day t is a market up day. Column 2 and 3 presents the results for matched market up days. In column 3 and 4, we repeat the analysis on market down days. The coefficients for $iATbuy_i$, $iATsell_i$, and $beta_i$ are multiplied by 100 in both panels. The coefficients for $size_i$ are multiplied by 1,000. In order to control for correlations in cross-section and time-series, we cluster the standard errors by stock and day. The p-values are reported in parentheses.

	Up Days		Down Days	
	Coefficient	p-value	Coefficient	p-value
iATbuy	0.490	(0.197)	-0.350	(0.126)
iATsell	-0.420	(0.197)	0.050	(0.836)
up	0.050	(0.816)		
iATbuy*up	-1.950	(0.005)		
iATsell*up	0.340	(0.488)		
down			-0.010	(0.949)
iATbuy*down			0.030	(0.956)
iATsell*down			1.150	(0.021)
beta	0.420	(0.005)	-0.350	(0.009)
turnover	0.306	(0.251)	0.064	(0.440)
size	-0.200	(0.592)	0.400	(0.324)
idiovar	0.762	(0.026)	-0.487	(0.062)
adjusted R^2	0.013		0.005	

insignificant after the propensity matching algorithm is applied.

We then run a difference-in-differences regression on the matched sample to show whether there is a differential effect of AT intensity on event days compared to non-event days, given that the observations on event and non-event days have similar market characteristics. Specifically, we interact the AT intensity variables with event day dummy variables to assess the marginal effect of AT on price fluctuations in light of overall market pressure. The standard errors are two-way clustered to control for persistent effects in the stock and time dimensions (Thompson, 2011). Table (3.11) presents the coefficient estimates.

On market up days, the AT intensity variables ($iATbuy_{i,t}$ and $iATsell_{i,t}$) are not significant, whereas the interaction between the market up dummy (up_t) and AT buy intensity ($iATbuy_{i,t}$) is negatively significant. These two results imply that, despite the treatment and control groups having similar market characteristics, the association between AT intensity and abnormal return only exists when there is overall market pressure. The results and implication on market down days are similar. The adjusted R -squared is artificially low because we include two observations in the control group for each one in the treatment group.[39]

While beyond the scope of this chapter, it is worth mentioning that the effects of AT differ during episodes of market-wide pressure in our treatment group compared to idiosyncratic shocks in our control group. Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov (2016) find that high frequency traders on average switch to liquidity demanding when more than one stock simultaneously experiences extreme price movements. Our evidence suggests that the liquidity demanding AT is associated with individual stock returns during market-wide shocks.

Overall, the matching algorithm eliminates any meaningful differences in market condition measures between event day and non-event day observations. The difference-in-differences regression highlights the contrast of AT effects between event and non-event days. More importantly, the analyses provide confidence that the association between AT and price fluctuation is exogenous to the market condition measures in individual stocks.

3.5.2 AT and news arrivals

While we observe an economically large effect between AT and stock price fluctuation on event days, it is possible that this effect is information driven. For instance, Hendershott and Riordan (2013) suggest that, due to the cheaper monitoring costs of AT, AT may quickly incorporate relevant market information. Frino, Prodromou, Wang, Westerholm, and Zheng (2017) find that non-AT volume imbalance leads AT volume imbalance prior to corporate earnings announcements but AT can quickly adjust trades immediately after the announcements. To the best of our knowledge, the literature does not have a consensus on whether AT is more informed compared to non-AT. However, we need to consider the possibility that one party is more informed than the other.[40] If non-AT is more informed compared to AT, then non-AT may incorporate price-relevant information during announcement

[39] The adjusted R-squared is between 5% and 6% in the previous sections when we include only event days.

[40] The literature has not decided whether AT is more informed compared to non-AT. This question, however, is beyond the scope of the current paper.

periods. Therefore, the observed association between AT and stock price fluctuation may be a manifestation of non-AT incorporating information. To assess the effect of public information arrivals, we include firm-specific and price-sensitive announcements as dummy variables and interact with our main AT variables. An announcement is included if it occurred during the period between the closing of the last trading day and the closing of the current day. Our sample includes 293 announcements on market up days and 291 announcements on market down days. If event day returns are driven by AT or non-AT reacting to public information arrivals, we would observe significant coefficients for the interaction variable.

Table (3.12) presents panel regression results for public information arrivals. To control for correlations in the stock and time dimensions, the standard errors are clustered by stock and date (Thompson, 2011).

The interaction variables are not significant in Table (3.12), which implies that the correlation between AT and price fluctuation observed in Table (3.4) is not driven by traders reacting to information. Furthermore, all announcement stock days in the third column of up and down days are excluded. We observe qualitatively and quantitatively similar results compared to Table (3.4). Overall, the results suggest that the association between AT and information is not driven by trader groups reacting to public information arrivals.

3.5.3 Causal implications

While we have excluded several plausible alternatives to the premise of AT reducing price fluctuation on turbulent days, it would be ideal to establish causal implications directly via instrumental variables that are exogenous to price fluctuation on turbulent days. For example, an instrument for AT is the introduction of the "autoquote" on the New York Stock Exchange.[41] This technological improvement enables faster dissemination of information for AT and is introduced in batches of stocks. Another popular instrument is the co-location services provided by the exchanges.[42] This service enables specialized low-latency driven traders to achieve near-instantaneous execution speeds for a substantial fee. For example, Boehmer, Fong, and Wu (2013) use co-location events as an instrument to assess the impact of AT on various market quality metrics. However, autoquotes and similar technological events are not available in our sample. In addition, co-location services

[41] See Hendershott, Jones, and Menkveld (2011) for the application and details.

[42] See Aitken, Cumming, and Zhan (2015) for a comprehensive survey on the starting dates of co-location services internationally.

Table 3.12: AT and Firm Specific News Arrival

This table presents coefficient estimates from panel data regressions using the following model:

$$ar_{i,t} = \alpha + \beta_1 iATbuy_{i,t} + \beta_2 iATsell_{i,t} + \beta_3 size_{i,t} + \beta_4 turnover_{i,t} + \beta_5 idiovar_{i,t} + \beta_6 beta_{i,t} + \epsilon_{i,t}.$$

The variable $ar_{i,t}$ is the market-adjusted abnormal return for stock i on the event day; $iATbuy_{i,t}$ ($iATsell_{i,t}$) is the abnormal volume ratio between the AT buy (sell) volume and the overall buy (sell) volume on the event day less the mean volume ratio over the past five days; $size_{i,t}$ is the logarithm of the market value of stock i five days prior to the event day; $turnover_{i,t}$ is the ratio of the daily volume to the number of shares outstanding on the event day; $idiovar_{i,t}$ is the idiosyncratic variance of the market model residual of stock i on days $[t-125,\, t-5]$; and $beta_{i,t}$ is the beta of stock i for days $[t-125,\, t-5]$.

In the second column of up days and down days, we proxy public information arrival by including price sensitive firm specific announcements as dummy variables and interact with our main AT variables. In the third column of up days and down days, stocks that have firm specific announcements during the event days are excluded. The coefficients for $iATbuy_i$, $iATsell_i$, and $beta_i$ are multiplied by 100 in both panels. The coefficients for $size_i$ are multiplied by 1,000. The p-values are reported in parentheses, which are calculated based on standard errors clustered by stock and day to control for correlations in cross-section and time-series.

	Up Days			Down Days		
	Without Interaction	With Interaction	Exclude News Days	Without Interaction	With Interaction	Exclude News Days
iATbuy	-1.400	-1.370	-1.410	-0.280	-0.280	-0.280
	(0.012)	(0.004)	(0.004)	(0.577)	(0.589)	(0.589)
iATsell	-0.050	-0.070	-0.070	1.270	0.850	0.860
	(0.841)	(0.865)	(0.867)	(0.010)	(0.032)	(0.032)
iATbuy*news		-1.030			-0.970	
		(0.742)			(0.717)	
iATsell*news		0.350			5.450	
		(0.877)			(0.182)	
news		1.330			0.320	
		(0.093)			(0.586)	
beta	1.500	1.490	1.570	-1.790	-1.790	-1.800
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
turnover	0.545	0.533	0.405	-0.080	-0.081	-0.035
	(0.268)	(0.264)	(0.248)	(0.462)	(0.454)	(0.618)
size	-0.200	-0.200	0.500	-0.100	-0.100	0.300
	(0.810)	(0.814)	(0.536)	(0.909)	(0.917)	(0.755)
idiovar	1.503	1.484	1.160	-1.380	-1.364	-1.360
	(0.003)	(0.003)	(0.012)	(0.011)	(0.013)	(0.018)
adjusted R^2	0.052	0.054	0.053	0.050	0.052	0.057

were only available on the ASX at the start of our sample in November 2008, which eliminates the possibility of a pre–post implementation comparison. Besides autoquotes and co-location, the literature uses many other instruments. For instance, Hasbrouck and Saar (2013) use other stocks' HFT activity as an instrument of the target stock's HFT activity in an attempt to circumvent the endogeneity between the target stock's market quality and HFT activity. Aitken, Cumming, and Zhan (2015) use "permanent change" in trade size as one of the instruments. The permanent change event is defined as the first of four continuously declining months in average market trading size or the biggest single drop from the previous month. Aggarwal and Thomas (2014) compare market quality measures from January 2009 to December 2009 against those from July 2012 to August 2013. These two periods are chosen to be around the co-location event in January 2010. These methods are not suitable for our analysis. We further explored other technological upgrades and trading rule amendments and were unable to find suitable instruments for the two-stage least squares analysis.

Our approach is to exclude the most probable alternatives. First, we match the observations on the event days, as the treatment group, with those that have similar market characteristics on non-event days, as the control group. We then use a difference-in-differences approach to show that the effects are observed only in the treatment group, despite the control group not being meaningfully different in terms of market conditions. Second, we show that the effect is not driven by algorithmic traders' reactions to firm-specific news arrivals. Third, the effects are not likely to be caused by situational algorithms, since the significant effects of AT buys (sells) were observed only on market up (down) days. Specifically, unlike execution algorithms, which have a pre-existing intention to buy or sell, situational algorithms tend to be indifferent in terms of profiting from buy trades or sell trades. For example, many HFT algorithms frequently switch between buy and sell trades and maintain a low level of inventory ((Brogaard, Garriott, and Pomeranets, 2016)). If situational algorithms buy more stocks with lower returns to exploit the cross-sectional return differences on market up days, these algorithms are likely to also sell less (more) of the same (other) stocks. As a result, we would observe significant results in both buy and sell trades on event days. Overall, the evidence suggests that the association between AT intensity and price fluctuation is not driven by algorithmic traders' reactions to market conditions in terms of return, liquidity, volatility, and firm-specific information arrivals.

3.6 Conclusions

In this paper we examine the impact of AT during the most turbulent trading days on the Australian Securities Exchange from October 2008 till October 2009. Building on Dennis and Strickland (2002), we define turbulent days as days when the absolute values of the market returns are greater than 2%. We identify 39 event days of extreme market movements during the sample period - there are 19 trading days when the market gains at least 2% and 20 trading days when the market drops by at least 2%. For those turbulent days we analyze how individual stock returns correlate with the level of AT intensity, which is measured as the abnormal ratio of trading volume of AT to the total volume traded.

We show that the level of AT intensity in individual stocks is significantly related to abnormal returns in turbulent markets. In particular, stocks with lower levels of AT intensity experience greater price swings when the absolute return of the market exceeds 2%. Moreover, these effects are economically very large. We find that with an increase of 10% (or half standard deviation) in AT buying on average, there is a decrease of 16 basis points in market adjusted returns for individual stocks when the market goes up by 2% or more. To isolate the effects of AT on market adjusted returns, We perform a difference-in-difference method on the event day observations with a propensity score matched sample of non-event day observations. We show that the effects of AT exists only on turbulent days, despite the fact that the matched non-event day sample is similar in terms of stock size, return, liquidity, and volatility.

Our study is subject to a few caveats. First, while the sample period covers the most turbulent time in decades, the sample size is limited to a time span over one year. Second, although we find beneficial effects of AT during turbulent times based on AT' characteristics, we do not support the premise that AT is harmless in other periods or other aspects of the financial market. In other words, while we observe the majority of AT to consist of benign execution algorithms, we do not exclude the possibility of market disruption caused by manipulative situational algorithms or high-frequency algorithms. Overall, our findings have important policy implications. Since AT, as a whole, plays a beneficial role in turbulent markets, we advise against indiscriminate restrictions on AT. Future research could focus on heterogeneity among AT groups, identify nefarious algorithms, and explore the effects of AT in an international, multi-year context.

Chapter 4

Algorithmic Execution Strategy and Order Imbalances

Chapter Summary

We examine algorithmic execution strategy and the effects of algorithmic trading order imbalances. We find that, *ex-ante*, algorithmic traders execute their trades according to the prevailing volume-weighted average prices, they are more likely to execute buy (sell) orders when the prevailing volume-weighted average price moves lower (higher) compared to the prevailing stock price. This implies a contrarian strategy which may mitigate the short-term price trends. Further analyses show that AT order imbalances have a smaller price impact compared to non-AT order imbalances. These effects are robust on days when the absolute value of the market return is more than 2%.

4.1 Introduction

In this chapter, we analyze the execution strategy and order imbalances of AT. Hendershott, Jones, and Menkveld (2011) suggest that execution algorithms may track the VWAP metric to reduce execution costs. The VWAP is the average price of each transaction over a certain time horizon (typically one day) weighted by the volume of each trade. The executed price of each trade can then be compared with the VWAP to evaluate the trade's execution performance.[43] By monitoring the VWAP, algorithmic traders are more likely to trade when the relative position between the VWAP and the stock price becomes more favorable. A favorable position is one in which the price moves downward (upward) relative to the VWAP for buy (sell) trades. AT execution strategy would effectively be contrarian by design. Specifically, in the initial surge of a large market-wide drop, stock prices would unfavorably deviate downward compared to the VWAPs and human traders would be more likely to sell. After the initial surge, the VWAPs would catch up with prices as more trades are executed and algorithmic traders would be more likely to trade based on this favorable VWAP movement. Therefore, algorithmic traders would be less likely to herd with human traders. As a result, AT would smooth out the liquidity demand and would not contribute to further price declines. After controlling for market conditions, we find that this is exactly the case. In particular, we estimate logit models of AT execution and show that traders with AT technologies are more likely to buy (sell) when the difference between the stock price and the intraday VWAP at the time becomes smaller (larger) on market decline days, market rise days, and other days in our sample. This finding is consistent with the notion that AT does not exacerbate the price pressure from the overall market.

We then investigate the effects of AT order imbalances on stock prices. Trades initiated by AT and non-AT may exert different levels of price pressure. To explore this hypothesis, we extend Chordia and Subrahmanyam (2004) and model market-adjusted returns as a function of order imbalances from AT and non-AT. After controlling for trade size and the total level of trading activity, we find that, on average, the impact of order imbalances by non-AT is 58% larger than that by AT on event days. This finding highlights the heterogeneity in the price impacts of order imbalances from different investor groups.

The rest of the chapter is organized as follows. Section 4.3 presents the VWAP-tracking algorithms and their

[43]The VWAP was first proposed by Berkowitz, Logue, and Noser (1988). See Madhavan (2002) for a comprehensive survey.

effects on the characteristics of AT in turbulent markets. Section 4.4 reports our findings on order imbalances. Section 4.5 provides the conclusion to the chapter.

4.2 Data and event day selection

The dataset used in the current chapter is similar to the dataset used in Chapter 3.4. Briefly speaking, we combine Australian equity market data provided by SIRCA with a novel dataset that classifies the traders on both sides of each stock transaction into algorithmic and non-algorithmic traders. The sample period is between October 27, 2008, and October 23, 2009. We focus on the stocks that are present throughout the sample period and have more than 200 active trading days out of the 252 trading days during the sample period.

To assess the characteristics of AT when the market is volatile, we define turbulent days as days when the absolute values of the returns on the market are greater than 2% (Dennis and Strickland, 2002). During our sample period, there are 19 (20) days when the market surges (declines) for more than 2%. Our final sample contains 9,896 stock-days across 384 stocks and 252 trading days. Refer to Section 3.3 for a detailed discussion on the data and the filtering process.

4.3 AT execution strategy and the VWAP metric

In this section, we investigate the possible strategies that AT could employ. Easley, Lopez de Prado, and O'Hara (2012) suggest that execution algorithms track the VWAP metric to reduce execution costs. The VWAP is the average price of each transaction over a certain time horizon (typically one day) weighted by the volume of each trade. The executed price of each trade can then be compared with the VWAP to evaluate the trade's execution performance. A buy (sell) trade is considered favorable if the transacted price is lower (higher) compared to the VWAP. If algorithms closely monitor the intraday VWAP, then AT would act as counter-trend traders. Although VWAP-tracking algorithms do not trade less than usual, they would optimize their execution timing based on the VWAP-to-price relation. Therefore, AT would smooth out the liquidity demand and would not contribute to further price swings.

By way of illustration, Figure (4.1) highlights the prices of trades initiated by AT and non-AT and the intraday dynamics of the VWAP on an event day (the top graph) and a non-event day (the bottom graph). In terms of

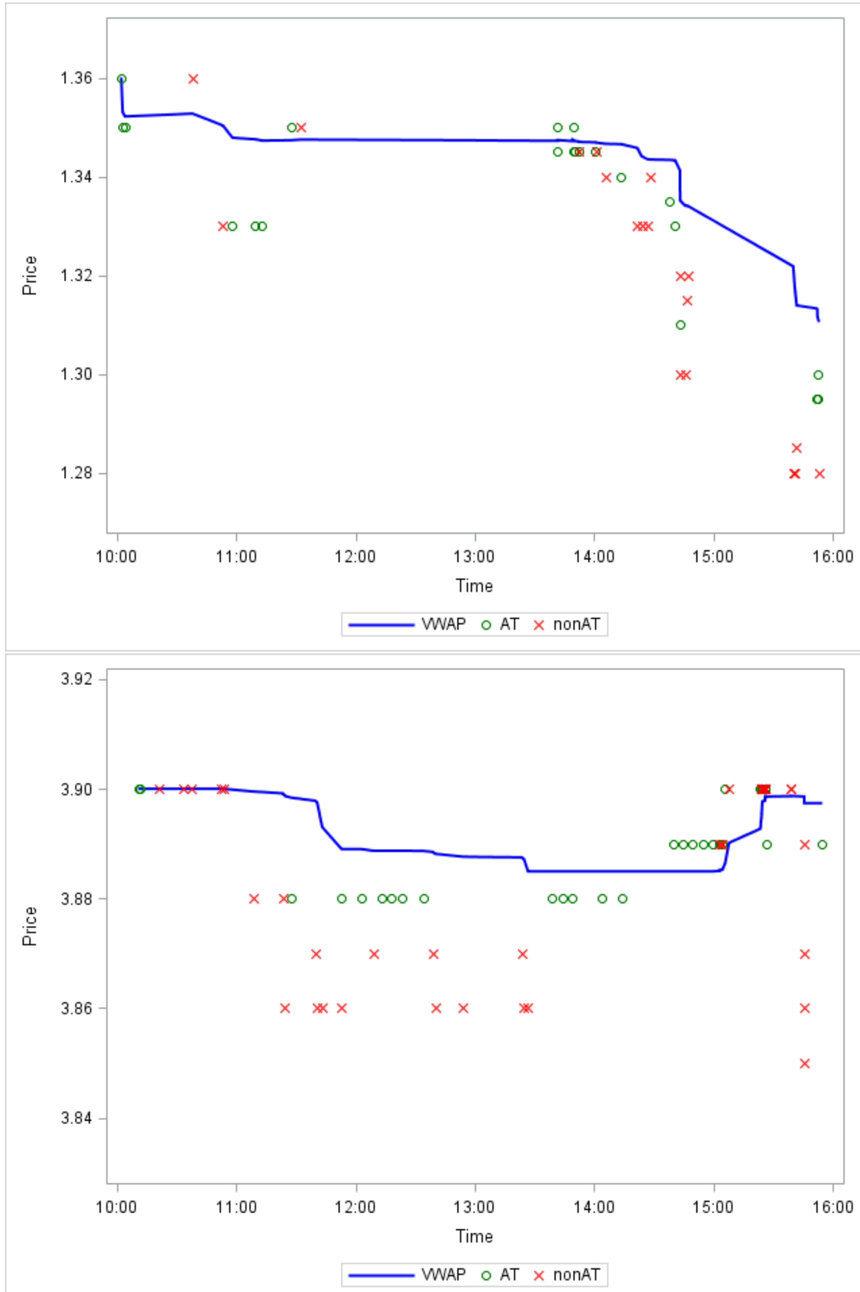

Figure 4.1: The VWAP, AT, and non-AT of One Event Day and One non-Event Day.
These figures illustrate the intraday dynamics of the VWAP and AT and non-AT prices for one event day (November 6, 2008) and one non-event day (January 21, 2009) for stocks ALS and PMV, respectively.

trading volume, both algorithmic traders and human traders initiated similar amounts of transactions. However, algorithmic traders initiated trades when the price was much closer to the VWAP, compared to human traders. This finding implies that a substantial portion of AT monitored the VWAP, whereas non-AT did not track the VWAP as much.

We reset the VWAP benchmark on a daily basis for the following reasons. First, Berkowitz, Logue, and Noser (1988), who initially proposed the VWAP as a measure of transactions cost, calculate the VWAPs on a daily basis. Second, Carrion (2013) applies end-of-day VWAP metrics that resets every day to assess how HFT times the market. Third, we have contacted several day traders and funds managers about their application of VWAP metric. These practitioners confirm that the daily VWAP is the a commonly used metric to assess day traders' performance.

We start the analysis by testing whether algorithmic traders traded closer to the VWAP compared to human traders. Table (4.1) shows the univariate results for the relation between the intraday VWAP and trades initiated by AT and non-AT. Panel A reports the average variance from the VWAP ($var_{i,t}$), defined as the squared difference between the transacted price and the prevailing VWAP weighted by the prevailing VWAP at the time of the transaction, for both AT and non-AT. On event and non-event days, $var_{i,t}$ is significantly smaller for AT than for non-AT. Algorithms therefore trade significantly closer to the VWAP compared to human traders. This finding suggests that algorithmic traders employ a VWAP-tracking strategy. During turbulent markets, algorithmic traders do not alter their strategy and therefore do not exacerbate price fluctuations.

In Panel B of Table (4.1) , we explore whether algorithmic traders buy (sell) lower (higher) than the VWAP compared to human traders. Specifically, variance from the VWAP is replaced with deviation from the VWAP ($devi_{i,t}$), which measures the signed difference between the prevailing VWAP and the transaction price weighted by the VWAP. Deviation from the VWAP is interacted with an indicator variable ($I_{i,t}$) that equals one (-1) if the trade is buyer (seller) initiated. The term $I_{i,t} \cdot devi_{i,t}$ is positive when a buy (sell) trade occurs in which the stock price is below (above) the prevailing VWAP. Therefore, $I_{i,t} \cdot devi_{i,t}$ can gauge whether and by how much each trade can beat the VWAP metric. Although the average value of the measure is negative for AT and non-AT, algorithms beat human traders in regard to the intraday VWAP metric.

Table 4.1: AT versus non-AT Variance from the VWAP

This table presents the variance from the VWAP from AT and non-AT. The VWAP for stock i at time t is defined as

$$vwap_{i,t} = \frac{\sum_{j=1}^{t} vol_{i,j} price_{i,j}}{\sum_{j=1}^{t} vol_{i,j}},$$

where $vol_{i,j}$ and $price_{i,j}$ are the volume and price of the trade at time j ($j = 1, 2, \ldots, t-1, t$) for stock i, respectively. $vwap_{i,t}$ resets every trading day. I.e., the prevailing VWAP at time t is the volume weighted average of all transactions from the beginning of the day up to the current trade at time t.

We then calculate the variance of each trade relative to the prevailing VWAP at the time (without incorporating the trade at the time):

$$var_{i,t} = (\frac{price_{i,t} - vwap_{i,t-1}}{vwap_{i,t-1}})^2.$$

Panel A contains the variance from the VWAP ($var_{i,t}$) per trade for AT and non-AT on all days, non-event days, and event days. In Panel B, variance from the VWAP is replaced by deviation from the VWAP ($devi_{i,t}$) with a buy/sell indicator ($I_{i,t}$) that is one (or -1) if the trade is initiated by a buyer (or seller):

$$devi_{i,t} = \frac{vwap_{i,t-1} - price_{i,t}}{vwap_{i,t-1}}.$$

The coefficients in Panel A (B) are multiplied by 10,000 (100). The p-values in parentheses correspond to a test of a null hypothesis that the variances of AT and non-AT trades have same means.

	All Days	Nonevent Days	Up Days	Down Days
Panel A: Variance from the VWAP ($var_{i,t}$)				
AT	0.168	0.158	0.197	0.238
non-AT	0.327	0.332	0.317	0.389
AT less non-AT	-0.159	-0.174	-0.120	-0.151
	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Deviation from VWAP with Buy/Sell Indicator ($I_{i,t} \cdot devi_{i,t}$)				
AT	-0.144	-0.138	-0.183	-0.161
non-AT	-0.178	-0.177	-0.192	-0.176
AT less non-AT	0.034	0.039	0.009	0.015
	(0.000)	(0.000)	(0.004)	(0.000)

Table 4.2: Logit Regression for AT and the VWAP

This table presents the coefficient estimates from logit regression using the following model:

$$at_{i,t} = \alpha + \beta_1 idevi_{i,t-1} \cdot I_{i,t-1} + \beta_2 spread_{i,t-1} + \beta_3 size_{i,t-1} + \beta_4 depth_{i,t-1} + \beta_5 vola_{i,t-1} + \beta_5 vol_{i,t-1} + \epsilon_{i,t}, \qquad (11)$$

where $at_{i,t}$ equals one if the trade of stock i at time t is AT initiated and zero otherwise; $idevi_{i,t-1}$ is the innovation of deviation from the VWAP ($devi_{i,t-1}$, defined in Table (4.1)), and is measured as the residual of an AR(8) autoregression multiplied by 100; $I_{i,t-1}$ is an indicator variable which is equal to one (-1) for a buy (sell) trade; $spread_{i,t-1}$ is the quoted bid–ask spread divided by 10; $size_{i,t-1}$ is the dollar volume of the trade divided by 100,000; $depth_{i,t-1}$ is the market depth at the best bid and ask in 10 million dollars; and $vola_{i,t-1}$ and $vol_{i,t-1}$ are the lagged volatility and lagged volume, respectively, in the 15 minutes before the trade. Lagged volatility is measured as the absolute value of the stock return over the interval and lagged volume is the total volume in 10 million shares over the interval. The odds ratios are calculated based on the regression coefficient. The odds ratios and marginal effects are omitted for the control variables and are available upon request. Time of day dummies for each half-hour of the trading day are included but not reported. The p-values are included in parentheses.

	All Days	Nonevent Days	Up Days	Down Days
idevi*I	0.279	0.292	0.299	0.145
−odds ratio	1.322	1.339	1.349	1.156
−marginal effect	2.613	2.547	2.654	1.305
−p-value	(0.000)	(0.000)	(0.000)	(0.000)
spread	0.024	0.024	0.025	3.972
−p-value	(0.000)	(0.000)	(0.005)	(0.346)
size	−0.696	−0.688	−0.705	−0.771
−p-value	(0.000)	(0.000)	(0.000)	(0.000)
depth	−0.144	−0.150	−0.104	0.594
−p-value	(0.161)	(0.146)	(0.496)	(0.503)
vola	−2.076	−1.993	−1.546	−3.471
−p-value	(0.108)	(0.135)	(0.379)	(0.036)
vol	−0.410	−0.361	−0.705	−1.312
−p-value	(0.124)	(0.195)	(0.000)	(0.002)

To more formally establish the statistical association between the intraday VWAP and the strategy of AT, we estimate logit regressions for algorithm-initiated trades. Following Hendershott and Riordan (2013), we control for market conditions by including the bid–ask spread, trade size, market depth, lagged volatility, and lagged volume. Also included but do not reported are the time-of-day dummies for each half-hour period. To control for correlations across stocks and across time, standard errors are double clustered in the cross-section and time-series (Thompson, 2011).

The key variable in Table (4.2) is $idevi_{i,t-1} \cdot I_{i,t-1}$, where $I_{i,t-1}$ is an indicator variable that equals one (-1) if the trade is buyer (seller) initiated. As for Brogaard, Hendershott, and Riordan (2014), $idevi_{i,t-1}$ is the deviation innovation obtained as the residual of an eight-lag autoregressive model on the time-series of $devi_{i,t-1}$. The number of lags is determined by the Akaike information criterion. The term $idevi_{i,t-1} \cdot I_{i,t-1}$ measures whether the price–VWAP relation becomes favorable. A positive $idevi_{i,t-1} \cdot I_{i,t-1}$ indicates that the stock price has decreased (increased) compared to the VWAP just before a trader buys (sells) stock i at time t. The marginal effect of $idevi_{i,t-1} \cdot I_{i,t-1}$ on all days show that AT is 2.613% more likely to execute buy (sell) trades when the price decreases (increases) by 1% compared to the VWAP. The marginal effects on up days and non-event days are similar to that on all days. AT is less sensitive to changes in the VWAP on market down days. Overall, the logit regression presented in Table (4.2) show that AT is more likely to initiate buy (sell) trades when the price decreases (increases) compared to the VWAP.

4.4 AT and non-AT order imbalances

In this section, we analyze the impact of AT order imbalances on stock prices. Our premise is that trades from AT exert less price pressure and order imbalance from AT would have less of a price impact compared to non-AT order imbalance. As a result, the stock price would fluctuate less during periods of high AT intensity. We model market-adjusted returns as a function of order imbalances from AT and non-AT and explore our hypothesis.

Order imbalances are measured as the scaled and unscaled imbalances in the number of transactions and volume. The unscaled volume imbalance is defined as the daily buy volume less the daily sell volume. The scaled volume imbalance is defined as the unscaled volume imbalance divided by the total daily volume. We separately measure each order imbalance metric for AT and non-AT on a daily basis. The cross-sectional averages of the correlations between various order imbalance metrics are reported in Panel A of Table (4.3). The correlations between scaled and unscaled order imbalances are high. For example, the correlations between the unscaled and scaled volume imbalances for AT and non-AT are 0.705 and 0.730, respectively. The correlations between volume imbalances and the number of trades imbalances are lower (0.427 and 0.570, respectively, for AT and non-AT). The correlations between AT and non-AT are very small across different metrics. The largest value (in absolute terms) for AT versus non-AT correlations is -0.071. This finding highlights the heterogeneity in the trading strategies of AT and non-AT.

Panel B of Table (4.3) presents the cross-sectional averages of the autocorrelation of AT and non-AT order imbalances measured by the number of trades and volume. Domowitz and Yegerman (2005) argue that a substantial

Table 4.3: Correlations and Autocorrelations for Order Imbalances

This table presents summary statistics for daily AT and non-AT order imbalances between 27 October 2008 and 23 October 2009. *atoib* (*atoibs*) is the (scaled) order imbalance in the volume traded by AT, *nonatoib* (*nonatoibs*) is the (scaled) order imbalance in the volume traded by non-AT. We then replace *atoib* and *nonatoib* with *atnoib* and *nonatnoib*, corresponding to order imbalance measured in number of trades for AT and non-AT, respectively. The unscaled AT volume imbalance is defined as the daily AT buy volume less the daily AT sell volume. The scaled AT volume imbalance is defined as the daily AT buy volume less the daily AT sell volume divided by the daily total volume. Number of trades imbalances are defined similar to volume imbalances (replace volume figures with number of trades). Panel A presents the cross-sectional means of the individual stock time-series correlations and Panel B contains the autocorrelations.

Panel A: Correlations

	nonatoib	atoibs	nonatoibs	atnoib	nonatnoib	atnoibs	nonatnoibs
atoib	−0.071	0.705	−0.062	0.427	−0.061	0.430	−0.058
nonatoib		−0.055	0.730	−0.019	0.570	−0.024	0.503
atoibs			−0.057	0.401	−0.055	0.641	−0.052
nonatoibs				−0.019	0.520	−0.016	0.726
atnoib					−0.018	0.756	−0.020
nonatnoib						−0.027	0.738
atnoibs							−0.021

Panel B: Autocorrelations

	Volume Imbalances				No. of Trades Imbalances			
lag	atoib	nonatoib	atoibs	nonatoibs	atnoib	nonatnoib	atnoibs	nonatoibs
1	0.122	0.142	0.120	0.144	0.182	0.183	0.170	0.156
2	0.059	0.069	0.066	0.074	0.097	0.094	0.107	0.085
3	0.033	0.046	0.048	0.047	0.074	0.058	0.085	0.060
4	0.017	0.030	0.023	0.030	0.043	0.042	0.059	0.042
5	0.015	0.018	0.014	0.023	0.049	0.030	0.040	0.034

proportion of buy-side AT uses VWAP-monitoring strategies to execute trades over time to minimize execution costs. For all but one metric, non-AT daily autocorrelations in order imbalance are larger than those for AT. This result suggests that AT does not seem to break down orders across days, which minimizes potential bias due to autocorrelation.

We model individual stock returns as a function of order imbalance by AT and non-AT. Although our order imbalance metrics have a lower autocorrelation than those of Chordia and Subrahmanyam (2004), we include four lags of order imbalance. We also use market-adjusted returns to mitigate the cross-sectional correlation in error terms. Similar to Equation ((6)), we estimate the Fama–MacBeth (1973) regression for each event day:

$$\begin{aligned} ar_{i,t} \quad = \quad & \alpha + \beta_1 atoib_{i,t} + \beta_2 nonatoib_{i,t} + \sum_{k=1}^{4} \beta_{2+k} atoib_{i,t-k} + \sum_{k=1}^{4} \beta_{6+k} nonatoib_{i,t-k} \\ & + \beta_{11} size_{i,t} + \beta_{12} turnover_{i,t} + \beta_{13} idiovar_{i,t} + \beta_{14} beta_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{12}$$

where $ar_{i,t}$ is the abnormal return for stock i on event day t and $atoib_{i,t}$ is the volume imbalance from AT in stock i on day t. The control variables are included to account for risk factors, informational effects, liquidity effects, and the potential preferences of algorithmic traders. Panel A of Table (4.4) presents the regression results. The results for lagged order imbalances are mostly insignificant and in line with the findings of Chordia and Subrahmanyam (2004). Therefore, the coefficients for lagged metrics are omitted. In Panel B, we replace the volume imbalance ($atoib_{i,t}$ and $nonatoib_{i,t}$) metrics in Equation (12) with a number of trades imbalance metrics for AT ($atnoib_{i,t}$) and non-AT ($nonatnoib_{i,t}$).

The core variables of interest are the order imbalance metrics from AT and from non-AT. The relation between market-adjusted returns and imbalance from the order flow can be expected to be similar to that from the previous literature (e.g., Chordia, Roll, and Subrahmanyam, 2002): Higher-order imbalance would create more price pressure on the buy side and cause prices to go up. In this regression, however, our objective is to find out whether order imbalances from AT and non-AT affect abnormal return differently. In other words, if the coefficients for AT imbalance ($atoib_{i,t}$) are larger than the coefficients for non-AT imbalance ($nonatoib_{i,t}$), then the implication is that AT exerts greater price pressure compared to non-AT and the market responds differently to imbalances from the different trading groups. We expect, however, non-AT imbalances to exert greater price pressure compared to AT

Table 4.4: Event Day Market-Adjusted Return Regressions on Order Imbalances

This table reports the coefficient estimates from Fama–MacBeth regressions using the following model:

$$\begin{aligned} ar_{i,t} &= \alpha + \beta_1 atoib_{i,t} + \beta_2 nonatoib_{i,t} + \sum_{k=1}^{4} \beta_{2+k} atoib_{i,t-k} + \sum_{k=1}^{4} \beta_{6+k} nonatoib_{i,t-k} \\ &\quad + \beta_{11} size_{i,t} + \beta_{12} turnover_{i,t} + \beta_{13} idiovar_{i,t} + \beta_{14} beta_{i,t} + \epsilon_{i,t}, \end{aligned}$$

where $ar_{i,t}$ is the market-adjusted abnormal return for stock i on event day t. The event days are defined as the days when the absolute values of market returns exceed 2%. In Panel A, $atoib_{i,t}$ is the order imbalance in the volume traded by AT, $nonatoib_{i,t}$ is the order imbalance in the volume traded by non-AT, $size_{i,t}$ is the logarithm of the market value of stock i five days prior to event day t, $turnover_{i,t}$ is the ratio of the daily volume over the number of shares outstanding on event day t for stock i, $idiovar_{i,t}$ is the idiosyncratic variance of the market model residual of stock i on days $[t-125, t-5]$, and $beta_{i,t}$ is the beta of stock i for days $[t-125, t-5]$. The event days are segregated into 19 up days and 20 down days. The coefficients for $atoib_{i,t}$ and $nonatoib_{i,t}$ are scaled by 100,000,000.

In Panel B, $atoib_{i,t}$ and $nonatoib_{i,t}$ are replaced by $atnoib_{i,t}$ and $nonatnoib_{i,t}$, corresponding to order imbalance measured in number of trades for stock i on event day t for AT and non-AT, respectively. The coefficients for $atnoib_{i,t}$ and $nonatnoib_{i,t}$ are multiplied by 10,000. The control variables are identical to those in Panel A. The coefficients for $beta_{i,t}$ ($size_{i,t}$) are multiplied by 100 (1,000). The p-values are reported from a t-test of the mean coefficient being different from zero.

	Up Days				Down Days			
	mean	p-value	min	max	mean	p-value	min	max
Panel A: Volume Imbalance								
atoib	1.43	0.001	0.12	5.22	1.28	0.000	−0.33	4.87
nonatoib	2.13	0.000	0.25	8.15	2.53	0.000	0.42	7.76
beta	1.71	0.000	−0.02	4.52	−1.79	0.000	−4.34	0.65
turnover	0.36	0.001	−0.15	1.23	−0.76	0.147	−8.16	1.36
size	−0.55	0.590	−6.50	9.75	0.25	0.701	−4.25	7.99
idiovar	0.49	0.307	−3.57	4.42	−0.01	0.984	−4.72	4.78
Panel B: Number of Trades Imbalance								
atnoib	0.20	0.000	−0.04	0.63	0.14	0.051	−0.39	0.74
nonatnoib	1.09	0.000	−0.48	2.44	0.62	0.006	−0.61	2.57
beta	1.75	0.000	−0.40	4.78	−1.78	0.000	−4.62	0.69
turnover	0.62	0.002	−0.35	2.23	−0.53	0.063	−3.39	1.48
size	−1.44	0.181	−7.31	11.08	0.46	0.512	−5.39	6.83
idiovar	0.37	0.430	−3.88	4.56	−0.69	0.204	−4.62	4.23

All the contemporaneous imbalance metrics in Table (4.4) are significant. The results for market up and market down days are quantitatively and qualitatively similar. Therefore, we discuss the results on up and down days together. For volume imbalance, the average coefficients of imbalances from AT and non-AT are 1.35 and 2.33, respectively, corresponding to a 72.59% difference in effects. The results from the number of trades order imbalance regression are similar. Overall, the results from the estimation are consistent with our expectation that the abnormal returns of an individual stock are related to the stock's level of AT intensity. Specifically, AT executes trades that minimize the price pressure compared to non-AT. As a result, stocks with higher AT trading experience lower price swings on turbulent days.

To further highlight the heterogeneity effects of AT and non-AT order imbalances, we repeat the analysis by explicitly modeling the difference between AT and non-AT order imbalances. We replace $atoib_{i,t}$, $nonatoib_{i,t}$, and their lags with $difoib_{i,t}$, $oib_{i,t}$, and their corresponding lags, respectively. The key variable is the difference between the AT and non-AT order imbalances ($difoib_{i,t}$). A positive (negative) coefficient for this variable can be interpreted, given the same level of overall order imbalance, as meaning that stocks that have more AT (non-AT) order imbalance experience more price movement. Table (4.5) contains the coefficient estimates of the differences between AT and non-AT order imbalances.

Consistent with the findings of Chordia and Subrahmanyam (2004), the overall order imbalance ($oib_{i,t}$) is the main predictor of stock returns. The coefficients for the differences between AT and non-AT ($difoib_{i,t}$) are significantly negative on up and down days measured by the volume and number of trades. This result is as expected: Controlling for market conditions and overall order imbalance, we find that stocks with larger AT order imbalances experience fewer price swings on turbulent days. Finally, the result is robust to nonconsecutive event day selection, event day selection based on daily high/low prices, day-of-the-week effects, and double clustering of the standard error in stocks and days. For brevity, the results are not reported here but are available upon request.

4.5 Conclusions

In this chapter, we investigate AT execution strategy in relation to the VWAP metrics and the price impact of AT order imbalances. We first analyze the determinants of AT executions using a logit model. Specifically, we relate algorithmic trades to the prevailing VWAP changes and other market quality measures. The VWAP is the

Table 4.5: Event Day Return Regressions on Differences Between AT and non-AT Order Imbalances
This table reports the coefficient estimates from Fama–MacBeth regressions using the following model:

$$ar_{i,t} = \alpha + \beta_1 difoib_{i,t} + \beta_2 oib_{i,t} + \sum_{k=1}^{4} \beta_{2+k} difoib_{i,t-k} + \sum_{k=1}^{4} \beta_{6+k} oib_{i,t-k} + \beta_{11} size_{i,t} + \beta_{12} turnover_{i,t} + \beta_{13} idiovar_{i,t} + \beta_{14} beta_{i,t} + \epsilon_{i,t},$$

where $ar_{i,t}$ is the market-adjusted abnormal return for stock i on event day t. The event days are defined as the days when the absolute values of market returns exceed 2%. In Panel A, $difoib_{i,t}$ is the AT order imbalance less non-AT order imbalance measured in volume traded, $oib_{i,t}$ is the overall order imbalance measured in volume traded, $size_{i,t}$ is the logarithm of the market value of stock i five days prior to event day t, $turnover_{i,t}$ is the ratio of the daily volume over the number of shares outstanding on event day t for stock i, $idiovar_{i,t}$ is the idiosyncratic variance of the market model residual of stock i on days $[t-125, t-5]$, and $beta_{i,t}$ is the beta of stock i for days $[t-125, t-5]$. The event days are segregated into 19 up days and 20 down days. The coefficients for $difoib_{i,t}$ and $oib_{i,t}$ are scaled by 100,000,000.
In Panel B, $difoib_{i,t}$ and $oib_{i,t}$ are replaced by $diffnoib_{i,t}$ and $noib_{i,t}$, corresponding to AT less non-AT order imbalance and overall order imbalance measured in number of trades for stock i on event day t. The coefficients for $diffnoib_{i,t}$ and $noib_{i,t}$ are multiplied by 10,000. The control variables are identical to those in Panel A. The coefficients for $beta_{i,t}$ ($size_{i,t}$) are multiplied by 100 (1,000). The reported p-values are based on testing the null hypothesis that the mean is equal to zero.

	Up Days				Down Days			
	mean	p-value	min	max	mean	p-value	min	max
Panel A: Volume Imbalance								
difoib	−0.35	0.015	−1.47	0.42	−0.62	0.016	−3.03	0.93
oib	1.78	0.000	0.25	6.69	1.91	0.000	0.47	6.31
beta	1.71	0.000	−0.02	4.52	−1.79	0.000	−4.34	0.65
turnover	0.36	0.001	−0.15	1.23	−0.76	0.147	−8.16	1.36
size	−0.55	0.590	−6.50	9.75	0.25	0.701	−4.25	7.99
idiovar	0.49	0.307	−3.57	4.42	−0.01	0.984	−4.72	4.78
Panel B: Number of Trades Imbalance								
diffnoib	−0.44	0.000	−1.09	0.43	−0.24	0.033	−1.48	0.38
noib	0.64	0.000	−0.07	1.50	0.38	0.002	−0.47	1.23
beta	1.75	0.000	−0.40	4.78	−1.78	0.000	−4.62	0.69
turnover	0.62	0.002	−0.35	2.23	−0.53	0.063	−3.39	1.48
size	−1.44	0.181	−7.31	11.08	0.46	0.512	−5.39	6.83
idiovar	0.37	0.430	−3.88	4.56	−0.69	0.204	−4.62	4.23

average price of each transaction over a certain time horizon weighted by the volume of each trade. We find that, on average, algorithmic traders are more likely to submit market buy (sell) orders when the VWAP decreases (increases) compared to the stock price. Our results imply that algorithmic traders follow VWAP tracking and short-term contrarian strategies, consistent with the notion that AT minimizes its impact to stock prices. Based on the prior literature and our discussion with the industry practitioners, we apply the VWAP that resets on a daily basis. Therefore, our findings are subject to the assumption that VWAP generally resets on a daily basis.

We then investigate the reasons for the effects of AT on market adjusted returns. We extend Chordia and Subrahmanyam (2004) by separating order imbalances in individual stocks into AT and non-AT order imbalances. We find that AT order imbalances have smaller price impacts compared to non-AT order imbalances. This finding implies that, consistent with Hendershott, Jones, and Menkveld (2011), the effect of AT on stock returns is likely caused by AT exerting less price pressure.

Chapter 5

State Space Models for AT and Price Discovery

Chapter Summary

We investigate the role of algorithmic trading (AT) in the price discovery process. We estimate a state space framework that decomposes stock prices into permanent price series and transient pricing error via state space frameworks. We find that algorithmic traders contribute more to the permanent price processes and less to the transient pricing errors compared to other traders. Our results show that AT facilitates the price discovery process by contributing to permanent price movements. Our results are robust on days when the absolute value of the market return is more than 2%.

5.1 Introduction

Price discovery is the process by which the actions of buyers and sellers determine the price of an asset in a market (O'Hara, 2003). This process is one of the essential functions provided by financial markets. Asset pricing and market efficiency relies on the speed and accuracy of price discovery processes in financial markets. The proliferation of CT has important implications on the price discovery processes. Due to computerized traders' higher speed and cheaper monitoring, CT is able to quickly incorporate information to the prices and accelerate the price discovery process. However, short-term information incorporated through accelerated price discovery process may not be motivated by the fundamental value of assets (O'Hara, 2015). In today's high frequency world, security prices are more suspectable to short-term noises such as liquidity shocks and inventory constraints. We analyze the characteristics of AT in relation to the efficient component and the noise component of the price discovery process.

We apply state space models to analyze the relation between AT, non-AT, and stock price discoveries (Brogaard, Hendershott, and Riordan, 2014). The state space models decompose observed stock price series into unobserved permanent price components and transient pricing errors. The permanent (or efficient) price series is modeled as a martingale to capture information arrivals that affect the permanent value of a stock. The transient pricing error series represents the short-lived price deviations that is not driven by fundamental value related information. The transient price changes are assumed to be stationary with an autoregressive component. We then relate AT and non-AT order flows to the increments of efficient and transitory components. We find that AT contributes more to the permanent price discovery process on a per dollar volume basis compared to non-AT. For large stocks, transient pricing errors are mitigated by AT whereas non-AT contributes to the pricing errors.

Our findings on AT compliments the results of Brogaard, Hendershott, and Riordan (2014) on HFT in several ways. First, we provide empirical evidence on AT, which is a broader computerized trading group. While high frequency traders consist of mainly the proprietary trading desks and specialized electronic market makers, AT technology has been widely adopted by buy-side institutions due to its less reliance on ultra low latency infrastructure. Second, one major advantage for computerized traders is that they can sift through the prices in dozens of trading venues and related securities to execute on small and fleeing arbitrage opportunities (Biais, Foucault, and Moinas, 2015). This advantage is most pronounced in highly fragmented markets such as the U.S. market. By studying AT in Australian market, we are able to assess their performance on a more leveled playing field.[44]

The rest of the chapter is organized as follows. Section 5.2 discusses the related literature on CT and price discovery. Section 5.3 provides descriptive statistics. Section 5.4 briefly describes the the state space models. Section 5.5.2 discusses the empirical decomposition of the observed price series and the estimation results. Section 5.6 concludes the chapter.

5.2 Literature review

Several studies provide evidence that CT improves price discovery and reduces price inefficiencies. Foucault, Hombert, and Roşu (2016) argue that fast traders can incorporate information by trading on the short-term news and long-term price forecasts whereas slow traders can only trade according to long-term price movements. Boehmer, Fong, and Wu (2015) analyze a wider range of markets and find that AT improves informational efficiency across international markets. Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) show that AT improves price efficiency: AT market orders reduce arbitrage opportunities and their passive orders reduce autocorrelations in high frequency returns. Brogaard, Hendershott, and Riordan (2014) find that HFT facilitates the price discovery process by trading in the direction of permanent price changes and in the opposite direction of transitory pricing errors. In addition, the literature finds that, compared to passive HFT, aggressive HFT dominates the price discovery process. For instance, Benos and Sagade (2016) separate HFT into aggressive HFT, mixed HFT, and passive HFT. They show that market orders placed by aggressive HFT are more informed than those placed by mixed and passive HFT. Brogaard, Garriott, and Pomeranets (2016) find that price efficiency improves after the entry of aggressive HFT.

The literature also uncovers several sources of computerized traders' information advantage. First, computerized traders execute their orders on the spot markets based on price changes in related indices and derivatives. For example, the theoretical model by Jovanovic and Menkveld (2016b) assumes that machine traders possess "hard" information. Hard information is easy for computers to process such as prices of market indices. Zhang (2013)

[44]The ASX was the only securities exchange in Australia during our sample period.

shows that HFT reacts strongly to hard information proxied by shocks in E-mini prices. Hendershott and Riordan (2013) also find that AT can monitor prices from futures markets and execute trades on spot markets based on futures price movements. Second, CT can profit from price discrepancies in related assets. Budish, Cramton, and Shim (2015) point out that arbitrage opportunities arise due to the breakdowns in the correlations between related assets over ultra-short time intervals (i.e. 100 milliseconds). Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) provide evidence that liquidity consuming AT is negatively associated with the frequency of arbitrage opportunities in JPY-USD-EUR triangular currency exchange prices. Gerig (2015) suggests that HFT improves the speed of synchronization among related stocks. Alampieski and Lepone (2012) find that aggressive HFT trade more UK-US cross-listed stocks in the UK market when the US market opens. Last, CT can quickly adapt to public information arrivals. Frino, Prodromou, Wang, Westerholm, and Zheng (2017) demonstrate that although AT is uninformed before corporate earnings announcements, they time their trades better immediately after the earnings announcements. Alampieski and Lepone (2011) find that HFT liquidity consuming and liquidity providing activities increase around macroeconomic announcements.

In addition, some studies also show that small trades initiated by HFT can be uninformed. Clark-Joseph (2014) argues that computerized traders submit small exploratory trades to test the liquidity state of the market and decide whether to execute their larger trades. O'Hara, Yao, and Ye (2014) provide supporting evidence that small odd-lot trades by HFT contain less information in comparison to those by non-HFT. Johnson, Van Ness, and Van Ness (2016) note that trades originated from larger orders (i.e. generated by execution algorithms) contain less information in comparison to other trades.

5.3 Data and descriptive statistics

In this chapter, we use the same raw data as those used in Chapter 3.4. I.e., we employ a novel AT dataset provided by the ASX that classifies each stock transaction into algorithmic and non-algorithmic trades. We compliment the AT dataset with equity market data provided by SIRCA. Our sample period is between October 27, 2008, and October 23, 2009. We filter out stocks that are not present throughout the sample period or have less than 200 active trading days out of the 252 trading days in our sample. Figure (5.1) presents the sorted market capitalisations of the 384 remaining stocks after our initial selection criteria.

The Australian stock market is highly concentrated with the top 200 stocks account for approximately 95% of the total market value. The highest valued stocks such as BHP Billiton and Commonwealth Bank have market capitalisation over $100 Billion. The size of the stocks quickly diminishes pass the few largest stocks.

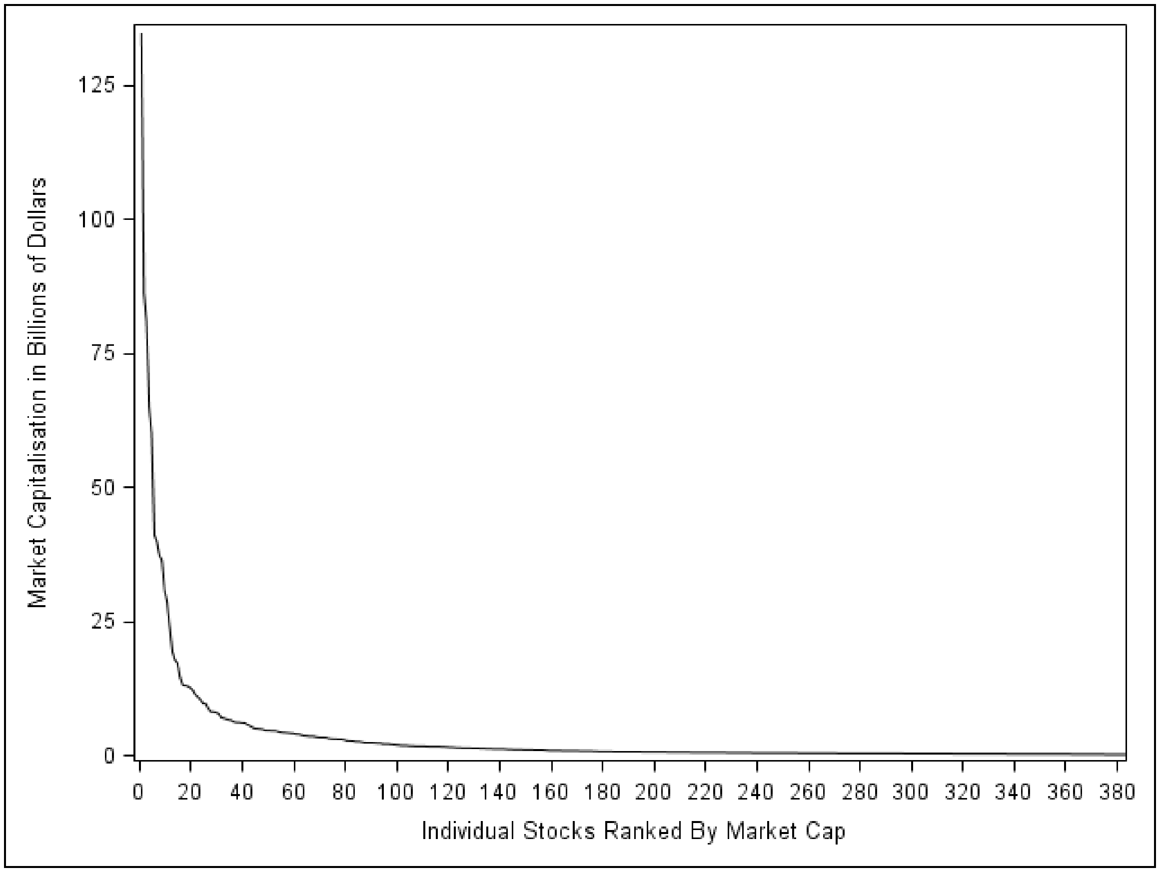

Figure 5.1: Market Capitalisation of Individual Stocks in the ASX.
This figure provides the market capitalisation of 384 stocks in the ASX on October 23 2009. The stocks are sorted by market capitalisation. The X axis represents the rank of the stock whereas the Y axis is the market capitalisation in billions of dollars.

We form large, medium, and small stock groups with 30 stocks each. The large group consists of the top 30 stocks in our sample. The medium (small) group includes the 50^{th} to the 80^{th} (140^{th} to the 170^{th}) stocks. By separating the stocks into size groups, we provide additional evidences in terms of cross-sectional variations in AT effects. Table (5.1) presents the descriptive statistics of the three size groups.

Table 5.1: Descriptive Statistics

This table reports the descriptive statistics of 30 large, medium, and small stock in the ASX from 27 October 2008 to 23 October 2009. The large group contains the top 30 stocks in Australia by market capitalization, the stock symbols are: AMP, ANZ, AXA, BHP, BXB, CBA, CCL, CSL, FGL, FMG, IAG, LEI, MQG, NAB, NCM, NWS, ORG, ORI, OSH, QBE, RIO, SGP, STO, SUN, TLS, WBC, WDC, WES, WOW, and WPL. The medium group consists of the 51st to the 80th largest stocks, their stock symbols are: AOE, BBG, BEN, BLD, BOQ, COH, CTX, DJS, DOW, DXS, EQN, FBU, FXJ, GMG, HVN, IPL, JHX, MIG, MTS, NHC, OST, PDN, PRY, PTM, RMD, SGM, SOL, TAH, TEL, and TTS. The small group contains the 141–170th largest stocks, the stock symbols are: ABP, AHD, AIX, AND, AWB, BKN, BPT, BWP, CAB, CDU, CRG, CXP, CZA, ENV, ESG, EWC, FKP, GNS, GWT, IRE, KCN, LNC, MBN, MCW, MIN, OMH, REA, SLX, SOT, and WSA. Market capitalisation is calculated based on the closing price on 23 October 2009 in billions of dollars. Relative bid–ask spread is in percentages. Dollar volumes are scaled by 1,000,000.

	Stock size group		
	Large	Medium	Small
Panel A: Market conditions			
Market capitalisation	29.285	3.590	0.862
Price	18.320	6.891	2.826
Bid–ask spread	0.017	0.014	0.013
Relative bid–ask spread	0.150	0.353	0.730
Panel B: AT and non-AT dollar volumes			
AT total	92.810	12.074	2.318
AT active	45.017	5.844	1.127
AT passive	47.793	6.230	1.191
non-AT	22.355	3.296	0.856
non-AT active	12.620	1.858	0.462
non-AT passive	9.735	1.438	0.394

5.4 The state space model backgrounds

The state space methods are applied in a variety of research disciplines such as engineering, biology, medicine, and physics. In this section, we present the quantitative backgrounds specific to our market microstructure applications. The notations used in this exposition generally follow those in Durbin and Koopman (2012).[45] I also limit this presentation to linear and Gaussian state space models. Last, this exposition does not cover the most general case of the linear and Gaussian state space methods, e.g. the error structure is mostly assumed to be diagonal.

5.4.1 Model representation

Suppose we sequentially observe a set of variables, represented by $p \times 1$ vector $y = (y_1, y_2, y_3 \ldots, y_p)'$, which denotes $p-$variate response values. The observed $p-$variate vector at time t, is modeled by the *observation equation*, which describes the relationship between the observed vector, the regression effects, and the unobserved state vector:

$$y_t = Z_t \alpha_t + X_t \beta_t + \epsilon_t, \tag{13}$$

where α_t is an unobserved $m \times 1$ vector called *state vector*.

Z_t is a $p \times m$ matrix that corresponds to the *state effect* on the observed series. Z_t represents effect of $m-$dimensional states on the observed $p-$dimensional response variables.

X_t is a $p \times k$ matrix the *regression effect* on the observed series. For each variable in the $p-$dimensional vector y_t, there are k predictors.

β_t is an $k \times 1$ vector of regression coefficients associated with the predictors in matrix X_t.

ϵ_t is the error vector called *observation disturbances.* ϵ_t is usually assumed to be serially independent, zero-mean, and Gaussian random vectors.

[45] Durbin and Koopman (2012) provides an extensive treatment of the state space approach to time-series analyzes, see chapter 3-6 for a general form of the state space representation. As a more accessible material, Commandeur and Koopman (2007) gives a brief but intuitive introduction.

The state vector hidden states in vector α_t is then modeled as a Markov process by a *state transition equation*:

$$\alpha_{t+1} = T_t \alpha_t + \eta_{t+1}. \tag{14}$$

The state transition equation assumes that a new states vector α_{t+1} is determined by its previous instance, α_t, a transition matrix, and an error vector.

T_t is a $m-$dimensional square matrix called *state transition matrix*. T_t can depend on the past observations $y_{t-1}, y_{t-2}, \ldots, y_1$.

η_{t+1} is a $m-$dimensional *state disturbances*. The variance-covariance matrix of the state disturbances is Ω. η_t is usually assumed to be serially independent, zero-mean, and Gaussian random vectors with covariance matrix Q_t. ϵ_t and η_t are assumed to be mutually independent. Elements in state effect matrix Z_t, regression coefficients vector β_t, state transition matrix T_t, and the variance matrix of the state vector α_t can be specified as unknown parameters of interest.

Kalman filter is applied to Equations (13) and (14) to estimate state vectors $\alpha_2, \alpha_3, \ldots, \alpha_T$ recursively. Whereas the initial state vector α_1 follows the *initial condition equation*:

$$\alpha_1 = \alpha + A_1 \delta + \eta_1, \tag{15}$$

where α is a $m-$dimensional vector of known constants.

δ is a $q-$dimensional vector of unknown quantities.

A_1 is a m by q selection matrix. The initial states are often assumed to be diffuse (the covariances are arbitrarily large e.g. 10^7).

Although the state space models appear complex in this representation, the presented format incorporates many salient aspects of the model employed in most empirical uses. In practice, many matrices will be either omitted or reduced to diagonal or identity matrices. Furthermore, the state space models can be readily adapted for Box-Jenkins style time-series analysis. Many widely known models, such as Autoregressive Moving Average (ARMA) models, can be written in state space form.[46]

[46] See Durbin and Koopman (2012) for detailed discussion about ARMA and Autoregressive Intergraded Moving Average (ARIMA)

5.4.2 Model estimation

Kalman filter and smoother algorithms are the main tools to estimate the state vectors and the log likelihood is maximised numerically for any unknown parameters. Kalman filter and smoother are recursive algorithms that provides forward and backward passes through the data:

1. The Kalman filter is used as the forward pass through the data, from $t = \{1, 2, \ldots, T\}$ using a recursive algorithm that calculates each state vector α_{t+1} based on the information in observations at time $t = \{t, t-1, t-2, \ldots, 1\}$.
2. The Kalman smoother is used as the backward pass through the data, from $t = \{T, T-1, t-2, \ldots, 1\}$ using a recursive algorithm that calculates each state α_t and disturbance ϵ_t vectors based on the output from the Kalman filter.

The Kalman filter is proposed by Kalman (1960), in which the idea of the state space representation is also formulated. The filtered state $alpha_{t+1}$ and its error variances are obtained using the following array of equations:

$$
\begin{aligned}
\upsilon_t &= y_t - Z_t \alpha_t, \\
F_t &= Z_t P_t Z_t' + H_t, \\
K_t &= T_t P_t Z_t' F_t^{-1}, \\
L_t &= T_t - K_t Z_t, \\
\alpha_{t+1} &= T_t \alpha_t + K_t \upsilon_t, \\
P_{t+1} &= T_t P_t L_t' + R_t Q_t R_t',
\end{aligned}
\tag{16}
$$

where υ_t is the $P \times 1$ one-step forecast error that is the difference between y_t and the expected value of y_t given the information up to $t-1$ ($E(y_t|Y_{t-1})$).

α_{t+1} is the $m \times 1$ one-step ahead expected value of the state vector $E(\alpha_{t+1}|Y_t)$.

models in state space forms.

P_{t+1} is the $m \times m$ one-step ahead error variance matrix of the state vector $Var(\alpha_{t+1}|Y_t)$.

The goal of the kalman filter is to recursively calculate one-step ahead conditional distribution of the state vector given all past information including past state vector α_t and past state vector error variance P_t. The state vector α_{t+1} obtained in these equations is called *filtered state*. Filtered state and its error variances are then used in a backward recursion:

$$\begin{aligned} r_{t-1} &= Z_t^{'} F_t^{-1} \upsilon_t + L_t^{'} r_t, \\ N_{t-1} &= Z_t^{'} F_t^{-1} Z_t + L_t^{'} N_t P_t, \\ \hat{\alpha}_t &= \alpha_t + P_t r_{t-1}, \\ V_t &= P_t - P_t N_{t-1} P_t, \end{aligned} \tag{17}$$

where $\hat{\alpha}_t$ is the $m \times 1$ conditional mean of the filtered state vector α_t, $\hat{\alpha}_t$ is obtained using all available observations. (i.e. $\hat{\alpha}_t = E(\alpha_t|y_1, y_2, \ldots, y_T) or E(\alpha_t|y)$)

V_t is the $m \times m$ error variance matrix of the filtered state vector, $V_t = Var(\alpha_t|y)$.

The state smoothing algorithms estimates the distribution of the state vectors given the entire series. The conditional mean state vector $\hat{\alpha}_t$ is calculated based on the filtered state vectors via a backward pass. The disturbance vectors ϵ_t and η_t in Equation (13) and (14) respectively are then smoothed via disturbance smoothing algorithm:

$$\begin{aligned} r_{t-1} &= Z_t^{'} F_t^{-1} \upsilon_t + L_t^{'} r_t, \\ N_{t-1} &= Z_t^{'} F_t^{-1} Z_t + L_t^{'} N_t L_t, \\ \hat{\epsilon}_t &= H_t (F_t^{-1} \upsilon_t - K_t^{'} r_t), \\ Var(\epsilon_t|y) &= H_t - H_t (F_t^{-1} + K_t^{'} N_t K_t) H_t, \\ \hat{\eta}_t &= Q_t R_t^{'} r_t, \\ Var(\eta_t|y) &= Q_t - Q_t R_t^{'} N_t R_t Q_t, \end{aligned} \tag{18}$$

where $\hat{\epsilon}_t$ is the smoothed vector of the observation disturbance in Equation (13).

$\hat{\eta}_t$ is the smoothed vector of the state disturbance in Equation (14)

The Kalman smoother for the state vector and disturbances vectors ensures that the smoothed states are estimated with not only past observations but also current as well as future observations. Unknown parameters specified in state effect matrix Z_t, regression coefficients vector β_t, state transition matrix T_t, and the variance matrix of the state vector α_t are estimated numerically via maximising the log likelihood function after the filtering phase. Once the unknown parameters are fitted into the model, another filtering phase is initiated with the fitted parameters.

5.5 The empirical analysis of AT and price discovery

This section presents the empirical modeling approach and the estimation results. We first discuss the motivations and the empirical approach to decompose stocks' intraday price series into efficient and transient components. We then measure the permanent and transitory price discovery effects of AT by incorporating AT order flow. Last, we discuss the empirical result and its implications.

5.5.1 The state space decomposition of intraday price discovery

Stock prices do not always reflect the efficient ("true") value of the company. Many causes are identified in the literature. For instance, price deviations can arise due to temporary liquidity shocks. Market makers tend to adjust their prices based on their inventory constraints. Price discreteness and other microstructure features can also affect stock prices. Agents often under- or overreact to news arrivals and market events. The state space methods is capable of efficiently incorporate multiple hidden states in a single observed time-series. Many exploit this feature to disentangle the efficient prices from transitory pricing effects. For example, Hasbrouck (1999) model the bid and ask quote series via state space procedure. Bid and ask quotes are decomposed into an implicit efficient price and a quote-exposure cost carried by market makers. Market makers pass on their quote-exposure cost to the market. And the displayed prices are the sum of the efficient prices and the market making costs. Menkveld, Koopman, and Lucas (2007) model around-the-clock price discovery process as the unobserved efficient price changes plus transitory price changes.[47] In this section, we present a simplified state space decomposition of stock prices. To minimize the effect of bid–ask bounce in the transacted price series, we measure stock prices using midquotes. Our model follows the notion that price changes arise from updates to an implicit efficient price series and a transitory price series. We decompose intraday price series into two components in our observation equation:

$$p_{i,t} = m_{i,t} + s_{i,t}, \tag{19}$$

where $p_{i,t}$ is the logarithm of the intraday midquote at the time t for stock i. $m_{i,t}$ is the permanent price component at the time t for stock i and $s_{i,t}$ is the transitory price component. Both $m_{i,t}$ and $s_{i,t}$ are modeled as hidden states. The state equation for $m_{i,t}$ is:

$$m_{i,t} = m_{i,t-1} + \mu_{i,t}, \tag{20}$$

where $m_{i,t}$ is a martingale that captures the efficient price changes. The transitory component of the observed price series, $s_{i,t}$, is specified as a stationary hidden state:

$$s_{i,t} = \phi_i s_{i,t-1} + \nu_{i,t}, \tag{21}$$

where $\phi_i s_{i,t-1}$ is an autoregressive term that characterizes the transitory aspect of $s_{i,t}$. ϕ_i is the autoregressive coefficient. We allow ϕ_i to vary between 0 and 1 to capture the mean-reverting feature of the process. $\mu_{i,t}$ and $\nu_{i,t}$ are mutually independent Gaussian process with zero mean and variances of σ_μ^2 and σ_ν^2 respectively.

Based on base on the above specifications, we rewrite our empirical model in state space form presented in Equation (13) and Equation (14). The observation vector $y_{i,t}$ is reduce to a scalar and the state vector $\alpha_{i,t}$ in our case is a 2×1 vector:

$$\begin{aligned} y_{i,t} &= p_{i,t}, \\ \alpha_{i,t} &= (m_{i,t}, s_{i,t})'. \end{aligned} \tag{22}$$

[47]Similar decomposition are featured in Hendershott and Menkveld (2014) and Brogaard, Hendershott, and Riordan (2014).

The state effect $Z_{i,t}$ in Equation (13) is reduced to a 1×2 vector; The state transition matrix $T_{i,t}$ in Equation (14) is a 2×2 matrix; The variance covariance matrix $\Omega_{i,t}$ is a diagonal matrix:

$$
\begin{aligned}
Z_{i,t} &= (1, 1), \\
T_{i,t} &= \begin{pmatrix} 1 & 0 \\ 0 & \phi_i \end{pmatrix}, \Omega_{i,t} = \begin{pmatrix} \sigma_\mu^2 & 0 \\ 0 & \sigma_\nu^2 \end{pmatrix}.
\end{aligned}
\tag{23}
$$

We use Kalman filter and smoothers to estimate the hidden states $m_{i,t}$ and $s_{i,t}$ that correspond to the efficient and transitory component of the intraday midquotes. The autoregressive coefficient in the transitory process (θ_i), and the variances of the error terms in permanent and transitory processes (σ_μ^2 and σ_ν^2, respectively) are treated as unknown parameters in the likelihood functions. These parameters are estimated numerically via maximum likelihood estimation.

By way of illustration, Figure (5.2) decomposes a representative intraday stock price series (National Australian Bank) using the state space approach. The observed logarithm price series is decomposed into a martingale efficient price series and an autoregressive transient price series. The model leverages the Kalman filter and smoother, which estimates the unobserved efficient price conditional on all intraday observations. Specifically, the unobserved efficient price at time j, $m_{i,j}$, is estimated based on the past prices ($p_{i,t<j}$), future prices ($p_{i,t<j}$), and the current price ($p_{i,t=j}$).

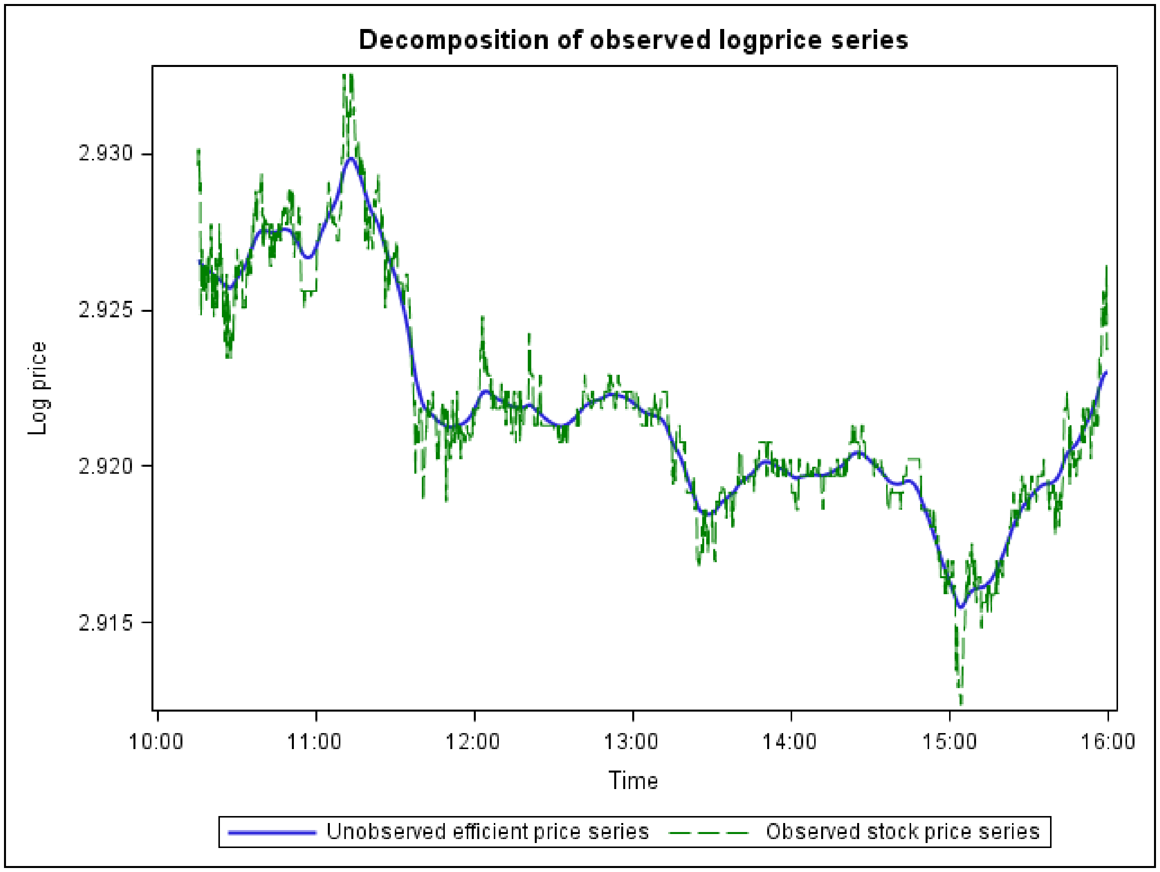

Figure 5.2: Intraday Price Series and Hidden Efficient Price Series in One Trading Session. This figure illustrates the intraday dynamics of the observed logarithm price series and the unobserved efficient component of the price series for the stock National Australia Bank Ltd. (stock symbol NAB) on January 29, 2009.

Figure (5.3) highlights the magnitudes of the two hidden components ($m_{i,t}$ and $s_{i,t}$) of the observed logprice series. While the transient component, $s_{i,t}$, contributes to a small fraction of the overall price process, it is consistently present throughout the trading day.

Overall, Figure (5.2) and (5.3) show that the decomposition allows for a more accurate measure of the permanent price discovery process and motivates the decomposition of the observed price series and the advantages of the state space representation.

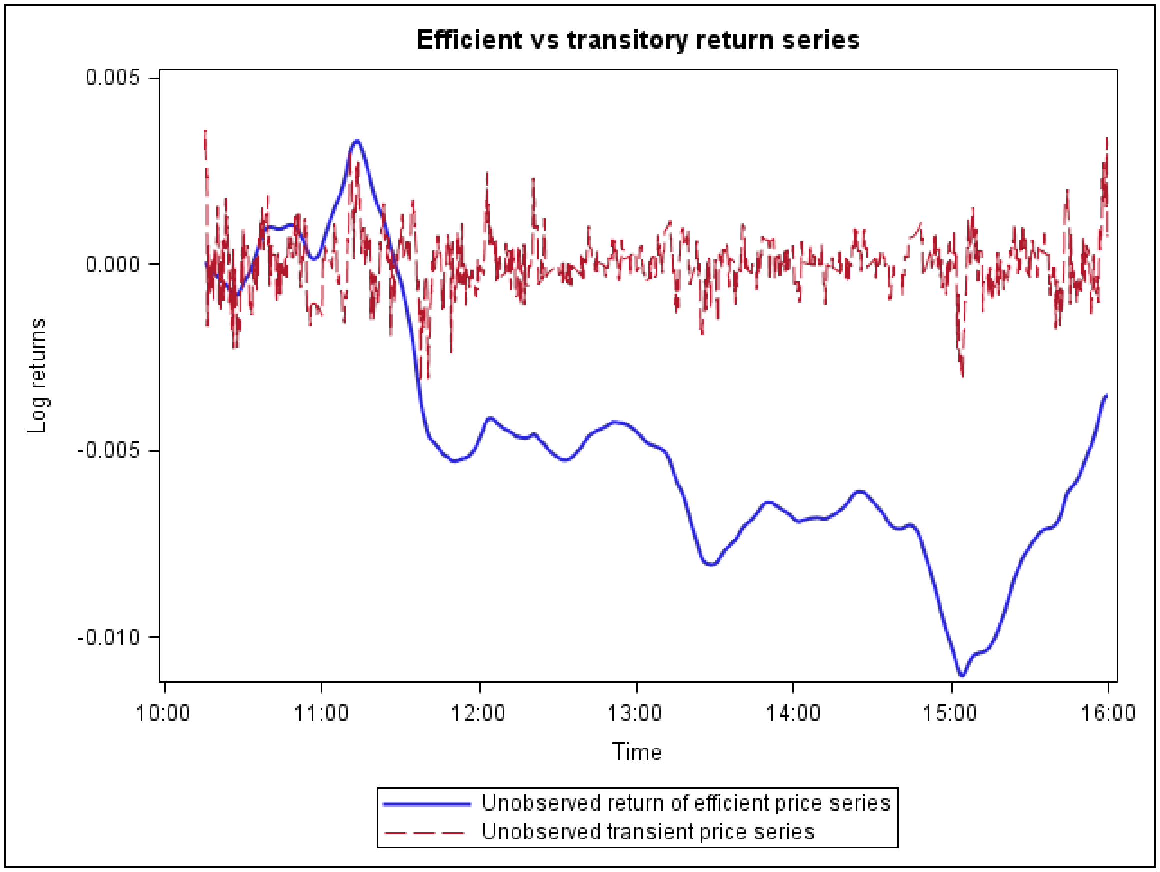

Figure 5.3: Intraday Return of the Efficient Component vs the Transitory Component in One Trading Session. This figure illustrates the intraday dynamics of the unobserved efficient price series returns and the unobserved transitory price series for the stock National Australia Bank Ltd. (stock symbol NAB) on January 29, 2009.

5.5.2 The price discovery of AT order flow

To assess the effect of AT and non-AT on the efficient and transitory components of price changes, we extend our model in Section 5.5.1 by incorporating the net order flow of AT and non-AT.

We model our observation equation as follows:

$$p_{i,t} = m_{i,t} + s_{i,t}, \tag{24}$$

where $p_{i,t}$ is the log midquote at the time t for stock i. $m_{i,t}$ is the permanent price component at the time t for stock i and $s_{i,t}$ is the transitory price component. Both $m_{i,t}$ and $s_{i,t}$ are modeled as hidden states. The state equation for $m_{i,t}$ is:

$$m_{i,t} = m_{i,t-1} + \omega_{i,t}, \tag{25}$$

where $m_{i,t}$ is a martingale. $\omega_{i,t}$ characterizes the permanent price increments. The price relevant information arrival for stock i between time t and time $t-1$ is captured by $\omega_{i,t}$. We include the effects of AT and non-AT in the process of permanent price changes ($\omega_{i,t}$):

$$\omega_{i,t} = \theta_i iat_{i,t} + \tau_i inonat_{i,t} + \mu_{i,t}, \tag{26}$$

where $iat_{i,t}$ and $inonat_{i,t}$ are the innovation of AT and non-AT net order flows respectively. The innovation of AT and non-AT are obtained as the residuals of autoregressive processes following Brogaard, Hendershott, and Riordan (2014). θ_i and τ_i are the main variable of interest, which quantifies the effect of AT and non-AT on the permanent price process respectively. $\mu_{i,t}$ is the component of $\omega_{i,t}$ unrelated to trading. The transitory component of the observed price series, $s_{i,t}$, is specified as a stationary hidden state:

$$s_{i,t} = \phi_i s_{i,t-1} + \kappa_i at_{i,t} + \varphi_i nonat_{i,t} + \nu_{i,t}, \tag{27}$$

where $\phi_i s_{i,t-1}$ is an autoregressive term that characterizes the transitory aspect of $s_{i,t}$. ϕ_i is the autoregressive coefficient. We allow ϕ_i to vary between 0 and 1 to capture the mean-reverting feature of the process. $at_{i,t}$ and $nonat_{i,t}$ are the order flow of AT and non-AT at time t, which are calculated as the buy initiated dollar volume less sell initiated dollar volume at time t for AT and non-AT. The key variables of interest are κ_i and φ_i, which measures the effect of AT and non-AT on the transitory price process. $\mu_{i,t}$ and $\nu_{i,t}$ are mutually independent Gaussian process with zero mean and variances of σ_μ^2 and σ_ν^2 respectively.

We estimate 9 unknown variables of the state space representation base on the specification in Section 5.5.2. The impact of AT on the permanent process (θ_i), the impact of non-AT on the permanent process (τ_i), the impact of AT on the transitory process (κ_i), and the impact of non-AT on transitory process (φ_i) are treated as elements in the unobserved state vector (α_t). These hidden states are estimated via Kalman filter and smoothers. The autoregressive coefficient in the transitory process (θ_i), and the variances of the error terms in permanent and transitory processes (σ_μ^2 and σ_ν^2, respectively) are treated as unknown parameters in the likelihood functions. These parameters are estimated numerically via maximum likelihood estimation.

We then write our empirical model in state space form presented in Equation (13) and Equation (14). The observation vector $y_{i,t}$ is reduce to a scalar and the state vector $\alpha_{i,t}$ in our case is a 6×1 vector:

$$\begin{aligned} y_{i,t} &= p_{i,t}, \\ \alpha_{i,t} &= (m_{i,t}, s_{i,t}, \theta_i, \tau_i, \kappa_i, \varphi_i)'. \end{aligned} \tag{28}$$

The state effect $Z_{i,t}$ is reduced to a 1×6 vector; The state transition matrix $T_{i,t}$ is a 6×6 matrix; The variance covariance matrix $\Omega_{i,t}$ has a block structure:

$$\begin{aligned} Z_{i,t} &= (1, 1, 0, 0, 0, 0), \\ T_{i,t} &= \begin{pmatrix} 1 & 0 & iat_{i,t} & inonat_{i,t} & 0 & 0 \\ 0 & \phi_i & 0 & 0 & at_{i,t} & nonat_{i,t} \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}, \Omega_{i,t} = \begin{pmatrix} \sigma_\mu^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_\nu^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}. \end{aligned} \tag{29}$$

Overall, the inclusion of AT and non-AT facilitates the interpretation on the relative contribution of the two trading groups to the price formation processes. We assess and compare both the liquidity demanding trades and liquidity supplying traders using our state space representation.

5.5.3 Estimation results and discussion

The estimation results for AT and non-AT liquidity demanding order flows are presented in Table (5.2). In general, both AT and non-AT contributes to the permanent price discovery processes. Algorithmic trades provides more price discovery compared to non-algorithmic trades.

Table 5.2: State Space Model for Intraday Prices and Liquidity Demanding Order Flows

This table presents the estimates for the state space decompositions of large, median, and small stocks using the following model:

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t}, \\ m_{i,t} &= m_{i,t-1} + \omega_{i,t}, \\ \omega_{i,t} &= \theta_i iat_{i,t} + \tau_i inonat_{i,t} + \mu_{i,t}, \\ s_{i,t} &= \phi_i s_{i,t-1} + \kappa_i at_{i,t} + \varphi_i nonat_{i,t} + \nu_{i,t}, \end{aligned}$$

where i denotes stock i and t denotes time t of the day. $p_{i,t}$ is the observed log midquote which is decomposed into an unobserved efficient price, $m_{i,t}$ and a transient pricing error, $s_{i,t}$. $m_{i,t}$ is modeled as a martingale, and $\omega_{i,t}$ is the efficient price increments. $at_{i,t}$ is the order flow of liquidity demanding AT measured as the buy dollar volume less sell dollar volume at time t for stock i. $nonat_{i,t}$ is the order flow of liquidity demanding non-AT measured analogously. $iat_{i,t}$ and $inonat_{i,t}$ are the innovations of a VAR of $at_{i,t}$ and $nonat_{i,t}$. The model is estimated for the intraday stock prices on a per stock-day basis. The p-values are included in parentheses.

	Size Groups		
	Large	Medium	Small
Panel A: Permanent Component			
iat	0.714	2.504	18.550
	(0.000)	(0.000)	(0.000)
inonat	0.598	1.623	15.286
	(0.000)	(0.005)	(0.000)
iat less inonat	0.116	0.833	3.264
	(0.000)	(0.000)	(0.208)
Panel B: Transient Component			
at	-0.115	0.482	-0.441
	(0.000)	(0.075)	(0.731)
nonat	0.036	1.829	1.592
	(0.310)	(0.039)	(0.453)
at less nonat	-0.151	-1.347	-2.033
	(0.000)	(0.057)	(0.425)

Panel A of Table (5.2) reports analyzes of the permanent price component, $m_{i,t}$. The coefficients for AT and non-AT order flows ($\theta_i, \tau_i, \kappa_i, \varphi_i$) are return per dollar volume scaled by 100 million. The AT order flow coefficient θ_i for large stocks equals to 0.714, which implies that one million dollar surprise order flow corresponds to 0.714 basis points increase in the permanent price component for large stocks. Whereas the coefficient for nonAT order flow of the same amount associates with 0.598 basis points increase. The difference between AT and non-AT order flows coefficients for large stocks is 0.116 with the p-value of 0.000, which implies that AT order flows are significantly more informative compared to non-AT order flows for large stocks.

The order flow coefficients for medium and small stocks are progressively larger, consistent with the notion that prices of smaller, less often traded stocks could be moved with less dollar volume. For medium stocks, the coefficient of AT order flows is 0.833 higher than that of non-AT. For the group of small stocks, AT order flows are also more informed compared to non-AT order flows in terms of the coefficient magnitudes. However, the difference is not statistically significant. Panel A shows that overall, AT contributes more to the efficient price discovery process, especially in larger stocks.

Panel B of Table (5.2) shows the coefficients of order flows related to the transient price component. The results indicate that AT mitigates the transient pricing errors while non-AT does not reduce the pricing errors in large stocks. In smaller stocks, AT contributes less to the transient pricing errors compared to non-AT. Specifically, the coefficients of AT order flow is -0.115, which suggests that algorithmic traders initiate trades in the opposite direction of transient pricing errors. On the other hand, the results do not show the mitigating effects of non-AT for the transient pricing errors. In comparison to non-AT, AT contributes significantly less to the transient pricing error component.

Table (5.3) presents the estimations for AT and non-AT liquidity supplying order flows. The structure of Table (5.3) is analogous to that of Table (5.2).

Both AT and non-AT liquidity supplying order flows are negatively related to the permanent price components, which supports the theoretical prediction that liquidity supplying trades are adversely selected while profiting from the bid–ask spread. Hendershott, Jones, and Menkveld (2011) shows that AT is more active in larger stocks. In the large cap group, we find that AT is adversely selected to a larger extent compared to non-AT. In the medium and small groups, the adverse selection effect is similar between AT and non-AT order flows. Our finding is consistent

Table 5.3: State Space Model for Intraday Prices and Liquidity Supplying Order Flows

This table presents the estimates for the state space decompositions of large, median, and small stocks using the following model:

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t}, \\ m_{i,t} &= m_{i,t-1} + \omega_{i,t}, \\ \omega_{i,t} &= \theta_i iat_{i,t} + \tau_i inonat_{i,t} + \mu_{i,t}, \\ s_{i,t} &= \phi_i s_{i,t-1} + \kappa_i at_{i,t} + \varphi_i nonat_{i,t} + \nu_{i,t}, \end{aligned}$$

where i denotes stock i and t denotes time t of the day. $p_{i,t}$ is the observed log midquote which is decomposed into an unobserved efficient price, $m_{i,t}$ and a transient pricing error, $s_{i,t}$. $m_{i,t}$ is modeled as a martingale, and $\omega_{i,t}$ is the efficient price increments. $at_{i,t}$ is the order flow of liquidity supplying AT measured as the buy dollar volume less sell dollar volume at time t for stock i. $nonat_{i,t}$ is the order flow of liquidity supplying non-AT measured analogously. $iat_{i,t}$ and $inonat_{i,t}$ are the innovations of a VAR of $at_{i,t}$ and $nonat_{i,t}$. The model is estimated for the intraday stock prices on a per stock-day basis. The p-values are included in parentheses.

	Size Groups		
	Large	Medium	Small
Panel A: Permanent Component			
iat	-0.623	-2.276	-15.002
	(0.000)	(0.000)	(0.000)
inonat	-0.517	-1.876	-18.255
	(0.000)	(0.000)	(0.000)
iat less inonat	-0.106	-0.400	3.253
	(0.008)	(0.178)	(0.393)
Panel B: Transient Component			
at	0.020	-0.269	-1.694
	(0.445)	(0.050)	(0.440)
nonat	0.034	-0.364	0.038
	(0.349)	(0.218)	(0.990)
at less nonat	-0.013	0.095	-1.732
	(0.697)	(0.767)	(0.656)

with the notion that the algorithmic traders in our sample are primarily large buy-side institutional institutional investors who are not specialized electronic market makers (ASX, 2010).

5.5.4 Robustness test: AT on turbulent days

Although algorithmic traders increase market liquidity, it is widely suspected that AT may retreat from the market in difficult times. To assess this concern, the main analyses are repeated on turbulent days. We have identified 19 (20) days when the market index increases (decreases) by more than 2% over our sample period.[48] Table (5.4) and (5.5) present the estimation results for liquidity demanding order flows and liquidity supplying order flows on turbulent days, respectively.

Overall, the results on turbulent days are qualitatively and quantitatively similar to those on all trading days. In particular, Panel A of Table (5.4) reports the association between liquidity demanding order flows and the permanent price components. Both AT and non-AT order flows contribute to the permanent component of the prices. One million dollar surprise AT order flows contribute, on average, 0.135 basis points more to the efficient price component compared to those of non-AT in large stocks. Panel B of Table (5.4) shows the coefficients of liquidity demanding order flows related to the transient price component. In large stocks, one million dollar surprise AT order flows contribute -0.115 basis points to the transient price component. Non-AT order flows have insignificant effects on the transient price component. The difference in AT and non-AT order flow effects are less pronounced (insignificant) in mediun (small) stocks. Table (5.5) presents the coefficients for AT and non-AT liquidity supplying order flows. Both AT and non-AT liquidity supplying order flows are negatively related to the permanent price components, consistent with the notion that liquidity providers are adversely selected.

[48]See Table (3.1) and (3.2) for more details on the event days.

Table 5.4: State Space Model for Intraday Prices and Liquidity Demanding Order Flows on Turbulent Days
This table presents the estimates for the state space decompositions of large, median, and small stocks on volatile days. Volatile days are defined as the days when the absolute values of the market returns exceed 2%.

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t}, \\ m_{i,t} &= m_{i,t-1} + \omega_{i,t}, \\ \omega_{i,t} &= \theta_i iat_{i,t} + \tau_i inonat_{i,t} + \mu_{i,t}, \\ s_{i,t} &= \phi_i s_{i,t-1} + \kappa_i at_{i,t} + \varphi_i nonat_{i,t} + \nu_{i,t}, \end{aligned}$$

where i denotes stock i and t denotes time t of the day. $p_{i,t}$ is the observed log midquote which is decomposed into an unobserved efficient price, $m_{i,t}$ and a transient pricing error, $s_{i,t}$. $m_{i,t}$ is modeled as a martingale, and $\omega_{i,t}$ is the efficient price increments. $at_{i,t}$ is the order flow of liquidity demanding AT measured as the buy dollar volume less sell dollar volume at time t for stock i. $nonat_{i,t}$ is the order flow of liquidity demanding non-AT measured analogously. $iat_{i,t}$ and $inonat_{i,t}$ are the innovations of a VAR of $at_{i,t}$ and $nonat_{i,t}$. The model is estimated for the intraday stock prices on a per stock-day basis. The p-values are included in parentheses.

	Size Groups		
	Large	Medium	Small
Panel A: Permanent Component			
iat	0.742	3.015	31.343
	(0.000)	(0.000)	(0.000)
inonat	0.609	1.887	22.586
	(0.000)	(0.003)	(0.000)
iat less inonat	0.135	1.128	8.757
	(0.045)	(0.036)	(0.189)
Panel B: Transient Component			
at	-0.135	0.500	-5.3019
	(0.013)	(0.199)	(0.265)
nonat	0.037	1.480	1.531
	(0.625)	(0.018)	(0.668)
at less nonat	-0.171	-0.980	-6.833
	(0.010)	(0.075)	(0.297)

Table 5.5: State Space Model for Intraday Prices and Liquidity Supplying Order Flows on Turbulent Days
This table presents the estimates for the state space decomposition of large, median, and small stocks on volatile days. Volatile days are defined as the days when the absolute values of the market returns exceed 2%.

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t}, \\ m_{i,t} &= m_{i,t-1} + \omega_{i,t}, \\ \omega_{i,t} &= \theta_i iat_{i,t} + \tau_i inonat_{i,t} + \mu_{i,t}, \\ s_{i,t} &= \phi_i s_{i,t-1} + \kappa_i at_{i,t} + \varphi_i nonat_{i,t} + \nu_{i,t}, \end{aligned}$$

where i denotes stock i and t denotes time t of the day. $p_{i,t}$ is the observed log midquote which is decomposed into an unobserved efficient price, $m_{i,t}$ and a transient pricing error, $s_{i,t}$. $m_{i,t}$ is modeled as a martingale, and $\omega_{i,t}$ is the efficient price increments. $at_{i,t}$ is the order flow of liquidity demanding AT measured as the buy dollar volume less sell dollar volume at time t for stock i. $nonat_{i,t}$ is the order flow of liquidity demanding non-AT measured analogously. $iat_{i,t}$ and $inonat_{i,t}$ are the innovations of a VAR of $at_{i,t}$ and $nonat_{i,t}$. The model is estimated for the intraday stock prices on a per stock-day basis. The p-values are included in parentheses.

	Size Groups		
	Large	Medium	Small
Panel A: Permanent Component			
iat	-0.560	-2.541	-20.592
	(0.000)	(0.000)	(0.000)
inonat	-0.387	-2.088	-40.975
	(0.000)	(0.000)	(0.008)
iat less inonat	-0.173	-0.453	20.383
	(0.087)	(0.487)	(0.202)
Panel B: Transient Component			
at	-0.059	-0.541	-4.706
	(0.442)	(0.205)	(0.358)
nonat	-0.088	-0.572	13.294
	(0.418)	(0.325)	(0.367)
at less nonat	0.029	0.031	-18.000
	(0.770)	(0.967)	(0.270)

5.6 Conclusions

In this chapter, we investigate the role of AT in the price formation process. Building on Brogaard, Hendershott, and Riordan (2014), we apply state space framework and decompose the observed stock prices into unobserved permanent price series and transient pricing errors. A brief background on the state space models and Kalman filters and smoothers is provided. These techniques are then applied to analyze 30 large, medium, and small stocks on the Australian Securities Exchange from October 2008 to October 2009.

We find that AT order flow, calculated as buy dollar volume less sell dollar volume, is positively related to the permanent price discovery process. AT mitigates transient pricing errors by trading in the opposite direction of the transient component of the price discovery process. The contributions to the price formation processes are mainly attributed to algorithmic traders' market orders. When compared to non-AT, AT contributes more to the permanent price component and less to the transient pricing errors. Further analyzes indicate that AT's contributions remain during turbulent periods, defined as trading days when the stock market's absolute return exceeds 2%.

Our study is subject to a few caveats. First, it focuses on a single market and a broad group of algorithmic traders. Further extensions could be made comparing the longer investment horizon algorithms and the ultra fast high frequency algorithms. Second, transient pricing errors are identified by exploiting the autoregressive properties of security prices in the veins of Hasbrouck's (1991) VAR measures and Brogaard et al.'s (2014) state space frameworks. Future studies could validate and extend our results by identifying price inefficiencies through other channels such as news versus rumor comparisons and price manipulation events.

Chapter 6

Conclusion

This thesis presents one survey essay and three empirical essays on computerized trading. This chapter presents a summary of the main findings and directions for future research.

6.1 Overview and conclusions

The survey essay, presented in Chapter 2, reviews around 100 theoretical, policy, and empirical studies on the topic of AT and HFT. Besides the common theme of computerized traders being fast, the theoretical studies employ a wide range of models based on various aspects of CT. Our survey categorizes the theoretical papers in relation to market maker–taker dynamics, information content of fast traders, recently incurred market structural changes, and proposed market changes. Overall, CT can leverage its reaction speed to excel as specialized market makers, liquidity consumers, or both. CT relies on various information such as future order flows, hidden liquidity state, and machine readable information. Increased market fragmentation, market maker favoring fee structures, and other market structural shifts facilitate the widespread use of CT. The empirical literature, despite its rapid growth, is still in the early stage with many papers yet to be published. Therefore, we survey the empirical studies with an emphasise on data quality, event identification, and establishing causal links. Finally, the empirical effects of CT are critically summarized based on various market quality dimensions.

The first empirical essay, presented in Chapter 3.4, investigates the characteristics of AT on turbulent day during the periods from October 2008 to October 2009. Similar to Dennis and Strickland (2002), 19 up swing days and 20 down swing days when the market moves up or down by more than 2% are identified. We then analyze the association between individual stock returns and the level of AT intensity in those stocks. We find that AT intensity is negatively related to individual stocks' price fluctuation on turbulent days. The effects are economically significant: on average, 10% (or half standard deviation) more AT buying on days when the market return is more than 2%, corresponds to 16 basis points less up swing for individual stocks. On days when the market drops by more than than 2%, similar magnitudes are observed between AT sells and individual stock down swings. The stocks on turbulent days are then matched with those on non-turbulent days based on abnormal return, market capitalisation, liquidity, and risk. Based on a difference-in-difference analysis, we highlight the significant association between AT and individual stock returns exists on turbulent days compared to that on other days. Overall, our findings compliments the empirical findings by Hendershott, Jones, and Menkveld (2011) and Hasbrouck and Saar (2013) in that AT mitigates price pressures of individual stocks during market swings.

The second empirical essay, presented in Chapter 4.4, examines the determinants of algorithmic execution strategy and the effects of AT order imbalances. we first apply a logit model to assess the choice of submitting algorithmic trades versus other trades in relation to the prevailing VWAP movements. VWAP is a common metric to measure execution performance. Traders aim to buy (sell) at a lower (higher) price compared to VWAP at the end of the trading day. We construct the intraday VWAP time series as a determinant of AT executions. We find that AT is more likely to trade when the VWAP–price relation is more favorable. Specifically, algorithmic traders are more likely to initiate a transaction from the buy (sell) side when VWAP is lower (higher), compared to other traders. We then extend the analyses by Chordia and Subrahmanyam (2004) by separate the effects of order imbalances from AT and non-AT. We find that the price impact of AT order imbalance is smaller than those executed by non-AT.

The last empirical essay, presented in Chapter 5, analyze the role of AT in the price formation process. We distinguish the impact of AT on the efficient price discovery process and the short-term noises. A state space frame work is employed to decompose the observed stock prices into unobserved efficient price series and transient pricing errors. We provide a brief background on the applied models and investigate 30 of the large, medium, and small Australian stocks during the period between October 2008 and October 2009. We then relate AT and non-AT order flows, calculated as buy dollar volume less sell dollar volume, to both unobserved processes. We find that, compared to non-AT, AT contribute significantly more to the permanent price discovery process and less to the transient pricing errors. Moreover, our result is robust during turbulent days when the absolute value of the market return exceeds 2%.

6.2 Suggestions for future research

Finally, we suggest several directions for future research. First, further evidence is required to optimize the design of financial markets. Given the rapid growth of CT, many market structural changes are being proposed or introduced without sufficient academic enquiry. For instance, more empirical evidence is needed to determine the optimal transaction speed. The theoretical literature have offered several competing prediction on whether the markets should adopt “speed bumps” for trading.[49] Empirically, Hendershott, Jones, and Menkveld (2011) find that the increased reaction speed due to Autoquote upgrade is beneficial to the markets in terms of liquidity and price discovery. However, Chakrabarty, Jain, Shkilko, and Sokolov (2015) find that the benefits of slower markets in terms of reduced adverse selection costs outweigh the cost in terms of increased pricing errors.

Second, future research should focus on the heterogeneity of CT since the current research mostly focus on one or few aggregate groups of AT and HFT. This line of research is further justified by the apparent disconnect between the poor public perception of CT and the mostly benign effects in the literature. Specifically, several of the nefarious effects suspected by the public are not found by academic studies.[50] The poor publicity of CT may have been misplaced since the media tends to focus on the negative stories. However, further research is needed to determine the validity of these suspicions. With the proliferation of account level HFT data, the academia is equipped to uncover the broad spectrum of HFT and identify potentially hazardous HFT practices.

Third, further research is needed to identify the private information obtained by high frequency traders. Many studies find that the private information incorporate by HFT is short-lived. O’Hara (2015) notes that short-term private information and price changes might not only be fundamental value-related but also driven by investors anticipating each others’ orders. Short-term price discoveries may blur the traditional dichotomy of “informed” versus “uninformed” traders. Furthermore, to determine the economic contributions of HFT price discoveries, future studies should establish whether the price changes incorporated by HFT are related to the true value of the assets.

[49] See, e.g., Budish, Cramton, and Shim (2015); Foucault, Kadan, and Kandel (2013); Guo (2015); Bongaerts and Van Achter (2016).

[50] For instance, HFT is widely blamed for “flash crash”, however, Kirilenko, Kyle, Samadi, and Tuzun (2017) find that HFT is not the cause.

Last, we should re-evaluate the traditional market efficiency measures and propose more market fairness measures. Specifically, traditional liquidity and price discovery measures are to be re-examined due to the proliferation of CT. Several studies point out that liquidity measures such as bid–ask spread and market depth may be influenced by the "quote flickering" practice of HFT.[51] Similarly, benefits of price discovery should be measured in conjunction with its costs (Stiglitz 2014 and Chakrabarty, Jain, Shkilko, and Sokolov 2015, for example). Moreover, further analyses are needed on market fairness. CT is widely suspected to impose adverse selection costs on other market participants. However, compared to studies on market efficiency, much fewer number of papers focus on the negative impact of computerized traders on other investors. For instance, Biais, Foucault, and Moinas (2015) allow slow traders to become fast traders at a cost. They find that fast traders impose negative externalities upon slow traders. Therefore, the number of fast traders and the investment into fast trading technologies in equilibrium is likely to cause a social welfare loss. More empirical evidence is needed to address the market fairness implications of CT.

[51]See, among others, Hasbrouck and Saar (2009), Baruch and Glosten (2013), Hasbrouck and Saar (2013), and Van Ness, Van Ness, and Watson (2015).

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