Essays on High-frequency Trading

A thesis presented in partial fulfilment of the requirement for the degree of

Doctor of Philosophy

in

Finance

at Massey University, Manawatu campus,

New Zealand

Khairul Zharif Zaharudin

2023

ABSTRACT

This thesis presents a comprehensive review of the relevant literature on high-frequency trading (HFT). There is no universal definition on HFT to date, leading to inaccurate estimations of their reach and impact in the market. HFT is a specialised form of algorithmic trading with lightning-speed network and implement complex trading strategies. HFT may have both beneficial and harmful effects on the market, and their speed could disrupt the market at remarkable pace. There are several controversies related to HFT, including the 2010 flash crash, social welfare and arms race, and market-making responsibilities. Several initiatives were implemented or proposed as a response to HFT, including speed bumps, price improvement rules, and new trading mechanics to guarantee a fair and orderly market for everyone. The second essay examines the impact of relative tick size on HFT activity. Using data from Australian equity markets, relative tick size is shown to have an inverse relationship with HFT activity. The findings demonstrate that HFTs have a very low tolerance for adverse selection risk, and their risk-averse nature prioritise risk minimisation (order-undercutting) over profit maximisation (order-queuing). The results lend credence to the perception that the primary strategy of HFTs is to generate thin profits while keeping their risk exposure to an absolute minimum. The evidence imply that policymakers may implement a dynamic tick size policy to allocate HFT activity into stocks where it is most required. The third essay illustrates how expected volatility affects HFT activity, and how the resulting change in HFT activity impacts liquidity. Using data from S&P/ASX 200 VIX index (AXVI) to measure sentiment, evidence suggests that when the sentiment is negative: (i) HFTs' ability to promote trading volume on the ASX is hampered; (ii) HFTs' ability to reduce spreads on the CHIX is dampened; and (iii) HFTs' ability to reduce price impact is amplified on both markets. Overall, HFTs' presence may significantly reduce excessive price impacts when the market is fearful. Therefore, any attempt to completely ban or restrict HFT in the market might accidentally eliminate valuable market participants.

DEDICATION

To my dearest wife,

Dr. Nor Elliany Hawa Ibrahim

who has been my pillar of strength throughout this colourful journey. Your unconditional love, support, and encouragement have kept me going through the countless challenges that we have faced together. Your unwavering faith in me has been a constant source of inspiration, and I am forever grateful for the happiness and warmth that you bring into my life.

To my beloved parents,

Zaharudin Abu Nasir and *Kamsiah Zakaria*

Words cannot express the depth of gratitude and admiration I have for both of you. Your teachings on the importance of education, knowledge, and excellence have led me on this challenging yet immensely rewarding journey. Without your everlasting love and continuous prayers, none of this would have been possible. Because of you, I am who I am now, and I will forever be indebted to you.

May the Almighty recompense all of you with abundance of goodness, in this life and the Hereafter.

ACKNOWLEDGMENT

First and foremost, I would like to express my deepest gratitude to Allah, the Most Gracious, the Most Merciful. I am eternally grateful for the perseverance and fortitude granted to me to complete this thesis, and for the countless blessings bestowed upon me throughout my life. *Alhamdulillah*. Secondly, I would like to offer blessings and peace upon the Prophet Muhammad, whose exemplary life has been a constant source of inspiration for me.

My sincerest appreciation goes to my supervisors, Prof. Martin R. Young and Dr. Wei-Huei Hsu, for their invaluable guidance, encouragement, patience, and dedication to facilitating this research. It has been an immense privilege and honour to learn under their tutelage. I am also grateful for the financial support provided by Universiti Utara Malaysia and the Ministry of Higher Education of Malaysia during my stay in New Zealand, without which this achievement would not have been possible.

I would like to extend my heartfelt gratitude to my beloved wife, Dr. Nor Elliany Hawa Ibrahim, for her steadfast support and unconditional love throughout this journey. Her constant presence by my side has been instrumental in the completion of this thesis. To my loving parents, Zaharudin Abu Nasir and Kamsiah Zakaria, I cannot thank them enough for their earnest prayers, encouragement, and kindness. To my caring parents-in-law, Ibrahim Mohd Noor and Aziah Alwi, I convey my sincerest gratitude for their prayers and understanding. To my dear friends, especially Dr. Bilal Hafeez and Nadiya (Khalid's wife), I am indebted for their invaluable assistance in handling my extensive data. To my mentor, Prof. Dr. Kamarun Nisham, I am grateful for his wisdom and insights. To my siblings (Kak Wani, Dr. Zati Aqmar, Adik Hazira) and in-laws (Abang Wan, Ana, Hafiz, Aish, Abe Pi, Abe Syahir, and Pa'an), I am thankful for their encouragement, support and belief in me.

I sincerely thank all of you for the kind gestures and inspiring roles you have played in my life. Your support has given me the strength, confidence and motivation to forge ahead and make this dream a reality. Thank you.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	Definition
AETH	Australian Equities Tick History
ALGO	Algorithmic trading ratio
ASIC	Australian Securities and Investments Commission
ASX	Australian Securities Exchange
AT	Algorithmic trading
AXJO	S&P/ASX 200 index
AXVI	S&P/ASX 200 VIX index
CBOE	Chicago Board Options Exchange
CESR	Committee of European Securities Regulators
CFTC	Commodity Futures Trading Commission
CHIX	Chi-X Australia
CROSS	Tick size crossing event
CSHL	Corwin-Schultz high-low spread
DIFF	Difference
DIFF-IN-DIFF	Difference-in-difference
DMMs	Designated market makers
ELPs	Endogenous liquidity providers
FINRA	Financial Industry Regulatory Authority
HFO	High-frequency order identifiers
HFOR	HFO’s message ratio
HFT	High-frequency trading
HFTs	High-frequency traders
ILLIQ	Amihud illiquidity ratio
ITCH	ASX ITCH dataset
LSE	London Stock Exchange
MiFID	Markets in Financial Instruments Directive
MPID	Market participant identifier
MTR	Message-to-trade ratio
NAFM	Netherlands Authority for the Financial Markets
NASDAQ	National Association of Securities Dealers Automated Quotation
NBBO	National Best Bid and Offer
NOMX-St	NASDAQ OMX Stockholm Exchange
NYSE	New York Stock Exchange
OrderID	Unique order identification
OTR	Order-to-trade ratio
Reg NMS	Regulation National Market System
RTS	Relative tick size
SEC	Securities and Exchange Commission
SIRCA	Securities Industry Research Centre of Asia-Pacific
TSX	Toronto Stock Exchange
UAL	United Airlines
VIX	The CBOE Volatility Index
VOLTO	Volume Turnover

CHAPTER ONE:
INTRODUCTION

This chapter provides an introduction and overview of this thesis. The chapter starts with a brief background on high-frequency trading, followed by motivations and objectives underlying the research. The chapter continues with overviews of the three essays individually, including some key findings and contributions. The chapter concludes with an outline of the thesis organisation.

1.1 Introduction

Technology has revolutionised trading. The use of fibre-optic cables and microwave towers to transmit trading information at the speed of light gave rise to high-frequency trading (HFT). In 2009, HFT accounted for 60% of U.S. equity trading, up from 20% in 2005. The proportion steadily declined to 50% in 2013 (Avramovic et al., 2017) and has remained steady at 52% in 2018. In Europe, HFT contributed practically 0% to total equity trading in 2005, peaked at 40% in 2010, and stabilised at 35% in 2014 (Kaya, 2016). In Australia, HFT is reported to be responsible for 27% of total stock market transactions in S&P/ASX 200 securities from January 2012 to March 2015, where the 10 biggest HFTs accounted for 21% of total trading turnover in 2015 (The Australian Securities and Investments Commission [ASIC], 2015).

Speed is the defining characteristic that distinguishes high-frequency traders (HFTs) from all other investors that engage in algorithmic or automated trading (AT). From spotting lucrative opportunities to implementing the right trading strategies, the trading speeds of HFTs almost approached the theoretical speed of light, which is around 300,000 kilometres per second (Angel, 2014). This capacity enables certain trading strategies to be limited to HFTs only, since other market players would be unable to replicate strategies requiring lightning-fast operation (Harris, 2013).

In addition, HFTs would employs quantitative analysts ("quants"), often from a mathematics or statistics background, to develop the numerous automated trading algorithms to capitalise on profitable trading opportunities. Moreover, due to the winner-take-all nature of the HFT industry, HFTs must constantly upgrade their infrastructures to minimise their automated trading latency (Kauffman et al., 2015). This culminates in an arms race among institutions to be the fastest, which is seen unproductive and socially wasteful, and the enormous amount of money spent to minimise trading latency raises concerns about whether HFT adds value overall (Chordia et al., 2013; Budish et al., 2015; Jones, 2013).

The business model of HFT relies on the execution of numerous trades with very thin profit margins, often as low as a few basis points; however, the massive trading volume amplified the small returns (Netherlands Authority for the Financial Markets [NAFM], 2010; Zhang, 2010). HFTs attempt to identify and profit from short-term inefficiencies and make tiny returns from each transaction through latency arbitrage; this allows them to profit from the trading environment itself, rather than from investing in financial assets (Hasbrouck & Saar, 2013). Aquilina et al. (2020) estimate that abolishing latency arbitrage from the global equities market would reduce the market's cost of liquidity by 17%, with a total stake of approximately US$5 billion annually.

HFTs have diverse trading strategies, which affects their sensitivity to inventory levels and price swings (Benos & Sagade, 2016). HFT strategies may be beneficial or harmful for the market, depending on their impact. Beneficial strategies are acceptable since they do not disrupt the market and enhance market quality. These include statistical arbitrage (value-motivated), directional trading strategies (informed trading), and market making (liquidity trading). In contrast, harmful strategies, such as front running (e.g., order anticipation, quote matching), spoofing and layering (i.e., uses fake orders to create the illusion that the market will move), and quote stuffing (i.e., congesting an exchange's network bandwidth with non-marketable limit orders to hinder competitors), generate profits at the cost of others through unscrupulous means.

For these reasons, HFT may be considered as a double-edged sword; while it may be beneficial in enhancing price informativeness or fostering liquidity via market-making activity, it may also prey on slower traders or hinder their ability to trade if they employ the harmful strategies. For instance, during the flash crash of May 6, 2010, HFTs, who normally provide liquidity, turned into liquidity takers. Although HFTs are not responsible for initiating the flash crash, they are criticised for exacerbating price falls and market volatility by generating a "hot-potato effect" in their competition for liquidity on the day of the crash (Kirilenko et al., 2017).

Furthermore, the limit order placements of HFTs resemble the harmful order-anticipation strategy in that they provide liquidity on the thick side of the order book, where depth is not required, and take liquidity on the thin side of the order book, where depth is necessary (Goldstein, et al., 2020). Thus, despite the fact that HFTs bring liquidity to the market, they do so only when it is least essential and avoid doing so when it is most crucial. Since they are not mandated by law to provide liquidity, market-making HFTs' reliability to do so is also questioned, especially during times of crisis (Anand & Venkataraman, 2013; Chung & Chuwonganant, 2018; Zhang, 2010).

Nonetheless, there is lack of agreement on the definition of HFT (NAFM, 2010), which contribute to the diverse findings on the consequences of HFT activity in the market, and an imprecise definition would be costly and harm all classes of market participants (Zaharudin et al., 2022). Therefore, it is imperative for the progression of finance research to accurately define and identify HFT in particular and AT in general, and to properly understand their impacts on the market. As remarked by Li et al. (2021, p. 980), "just as insights into human behaviour from the psychology literature spawned the field of behavioural finance, so insights into algorithmic behaviour could prompt an analogous blossoming of research in algorithmic finance."

1.2 Essay One: High-frequency Trading: Definition, Implications, and Controversies

The first essay of this thesis provides a comprehensive survey of the relevant literature on HFT, including regulatory reports, theoretical and empirical research. According to NAFM (2010), there is not a unified definition nor a consensus on HFT. This leads to inaccurate estimations of HFTs' market share, complicated research, and confusion between HFT and other forms of trading, which leads to HFT/HFTs being blamed for issues with which they have little or nothing to do, like the 2010 flash crash. Thus, this essay presents an in-depth literature review to comprehend how regulatory agencies around the world define and identify HFT.

In essence, HFT activity *can* be traced with the cooperation from exchanges and regulators, since they possess complete knowledge of the identity of each transaction message sent to the market. Alternatively, HFT may be identified by its unique characteristics; however, this method can only provide an approximation of HFTs' presence and impact in a market. In general, there are five traits are widely associated with HFT: (i) a specialised form of AT, (ii) utilisation of high-speed, sophisticated computer programmes and systems, (iii) very high order-to-transaction ratios, (iv) extremely short average holding periods, and (v) ending the trading day with flat positions.

HFT is a specialised form of AT that uses its superior speed to implement complex trading strategies. In general, the only unique aspect of HFT is its speed; the underlying mechanics are quite ordinary. Their short-term trading strategies have existed for a long time, and their methods for earning a profit on the market, such as attempting to buy low and sell high, are essentially identical to those used by other traders. Therefore, the essay also discusses HFT mechanics, strategies, and their effects on market quality from scholarly articles and reports.

Furthermore, literature suggests that HFT may have both beneficial and harmful effects on the market, and their lightning speed implies they could disrupt the market at remarkable pace. Therefore, the essay also discusses debates concerning HFT, including (i) the flash crash that occurred on May 6, 2010; (ii) issues regarding HFTs' acquisition of information, social welfare, and arms race; and

(iii) market-making responsibilities and excessive liquidity. The article concludes with regulatory and academic responses to HFT, including speed bumps, price improvement rules, and new trading mechanics to guarantee a fair and orderly market for everyone.

1.3 Essay Two: Relative Tick Size and High-frequency Trading

The second essay examines the impact of relative tick size on HFT activity. In contrast to the fixed nominal tick size established by the regulator, the relative tick size varies in reaction to stock price movements and nominal tick size values. A relative tick size may be shocked when a regulator revises an existing nominal tick size value, when a stock price naturally crosses a tick size border, or when a corporate action or informational event results in a significant stock price movement.

A larger (smaller) relative tick size suggests a higher (lower) profit margin from market-making spread and an increased (decreased) adverse selection risk from limit order placements for liquidity providers, including market-making HFTs (see e.g.: Angel, 1997; O'Hara et al., 2019; Sandås, 2001). Thus, the magnitude of a nominal or relative tick sizes would offer liquidity providers with an alternative between profit maximisation and risk minimization. This trade-off hinges on the liquidity provider's risk appetite, i.e., whether they're prepared to assume more risk for a larger return (profit maximisation) or accept a lower profit to reduce risk exposure (risk minimisation). In light of the notion that a discrepancy in tick size (small or large) is indicative of a different risk appetite and tolerance, this essay analyses the levels of HFT activity for two groups of stocks with distinct tick size values.

The study uses order-book data from the Australian equity market, which includes the Australian Securities Exchange (ASX) and Chi-X Australia (CHIX). Many empirical studies on tick size are primarily focused on the U.S. financial markets (see e.g. Angel, 1997; O'Hara et al., 2019; Schultz, 2000; Yao & Ye, 2018). However, the variations in Australian and American market architecture may affect HFTs' strategy, activity, and behaviour, driving them to perform differently in each country. The Australian market, for instance, employs a different tick size structure, lacks a designated market-maker, and has more flexible minimum trading unit requirements, all of which provide a unique playing field for HFTs. This study contributes to a better understanding of HFT, notably the impact of tick size on their activity and strategy in an order-driven market.

Additionally, the study proposes new proxies for HFT activity, namely high-frequency OrderIDs (HFO) and HFO's message ratio (HFOR). These measures are based on the fact that HFT activity often have short average holding periods and a large number of interconnected messages due to rapid order modifications. The calculation of these measures involves information that is commonly available from order-book data, thus improving its reproducibility and allowing it to be tested in other markets and over longer time periods.

The results of the second essay show that market-making HFTs in the Australian equity market favour stocks with a small relative tick size, suggesting that they are more concerned with minimising risk than maximising profit, and thus prefer the order-undercutting strategy over the order-queuing approach. Moreover, the results stand in contrast to the notion that market-making HFTs will reduce their liquidity provision in response to smaller relative tick sizes. The findings imply that policymakers may implement a dynamic tick size policy, in which stocks that may benefit from more HFT activity are allocated a smaller tick size, and those with excessive HFT activity are assigned a larger tick size.

1.4 Essay Three: Expected Volatility, High-frequency Trading, and Liquidity

The final essay illustrates how expected volatility affects HFT activity, and how the resulting change in HFT activity impacts liquidity. The CBOE Volatility Index (VIX), popularly known as the "fear index," represents *expected volatility* since it reflects investors' expectations of near-term future volatility in the stock market, and thus, it measures stock market sentiment (Reilly & Brown, 2012). Whaley (2009) highlights that the VIX and SPX move at asymmetric rates, and investors' fear of a bear market outweighs their excitement (or greed) for a bull market. This suggests that a high VIX signals investors' fear of a market crash, whereas a low VIX signifies investors' confidence.

Market-making HFTs are not legally obligated to offer liquidity at all times; consequently, they may choose to do so only when they perceive it to be profitable. Moreover, when circumstances are unfavourable for them, such as when adverse selection risks are higher amidst heightened market uncertainty (e.g. when the VIX is high), HFTs may decide to cease providing liquidity (Anand & Venkataraman, 2013; Chung & Chuwonganant, 2018; Zhang, 2010). For this reason, it is feared that HFTs' discretionary market making may worsen execution uncertainty, especially in volatile markets and in thinly traded securities. As a consequence, investors as a whole may lose confidence in the liquidity offered by HFTs, and pull out of the market completely. Using the S&P/ASX 200 VIX (AXVI) volatility index, this essay investigates whether market sentiment, as measured by the AXVI, would impact HFT activity, and whether the effect on HFT activity (if any) would then influence liquidity. In this essay, three distinct liquidity indicators are employed: the Corwin-Schultz spread, the Amihud illiquidity ratio, and the volume turnover. The findings of this research clarify whether HFTs can be trusted even during periods of heightened market volatility, and whether their activity promotes or hampers liquidity during such times.

The results indicate that when market sentiment is negative (i.e., when the VIX is high), the positive effects of HFT in promoting volume turnover on the ASX and lowering spreads on the CHIX are dampened; however, the ability of HFT to reduce the illiquidity ratio is amplified on both markets. Overall, this study support the notion that negative market sentiment does influence the impact of HFT on liquidity. Despite the fact that HFT's ability to enhance trading activity and reduce spread is impaired when the market is extremely fearful, their presence at such times has been shown to be beneficial for reducing price impact. Accordingly, the researcher believes that any initiative to completely prohibit or ban HFT in the market may be undesirable, since such actions may inadvertently eliminate valuable market participants, especially during periods of substantial market uncertainty.

1.5 Structure of the Thesis

The remainder of this thesis is structured as follows. Chapter Two presents the first essay of this thesis that surveys the literature related to high-frequency trading (HFT), including its definitions, implications, and controversies. Chapter Three discusses the second essay, which provides evidence on the effect of relative tick size HFT activity using data from Australian equity markets. The third essay, presented in Chapter Four, examines the impact of expected volatility on HFT activity, and whether changes in HFT activity due to heightened volatility level affected by liquidity. Chapter 5 concludes by summarising the key findings, as well as the implications of each of the three essays, including suggestions for future research directions and limitations of the study. The thesis closes with a section on Bibliography and Appendix used in the thesis.

CHAPTER TWO:
ESSAY ONE
HIGH-FREQUENCY TRADING: DEFINITION, IMPLICATIONS, AND CONTROVERSIES

This chapter provides a literature survey on high-frequency trading (HFT). The chapter begins with an overview of HFT, including its definition and identification. The chapter continues with a comprehensive review of literature on HFTs' trading mechanics; beneficial and harmful trading strategies; effects on market quality, including price discovery and efficiency, liquidity, volatility, and adverse selection costs; controversies surrounding HFT activity; market response to HFTs; and a conclusion.

2.1 Introduction

Technological advancement has shaped the financial world. Prior to the invention of the telegraph in 1844 and the telephone in 1876, communications in securities markets had been primitive, using humans and carrier pigeons to transmit information across markets (Markham, 2002). For nearly a century, the telegraph and telephone were used as the main channel for financial communication: data were received via telegraphic stock ticker, and orders transmitted via phone calls.

However, in recent years, fibre-optic cables and microwave towers have been used as the medium to transfer trading information at light speed. A group of traders exists, armed with complex algorithms that is willing to spend considerable amounts of money to gain access to these state-of-the-art facilities. They pay to collocate their servers close to or within stock exchanges, for example, to give them the speed advantage they need for their trading strategies that rely on being the fastest. In addition, they hire mathematicians and statisticians to work as quantitative analysts ("quants") to develop the various trading algorithms. This unique group of traders is commonly referred to as *high-frequency traders* (HFTs).

In the United States, the market share of high-frequency trading (HFT) of total equity trading peaked at around 60% in 2009, up from around 20% in 2005. The percentage gradually decreased to approximately 50% in 2013 (Avramovic et al., 2017) and has been relatively stable at this level since then, at 52% in 2018. In Europe, HFT's contribution to total equity trading was almost 0% back in 2005, before peaking at around 40% in 2010, and settled at around 35% in 2014 (Kaya, 2016). The Australian Securities and Investments Commission (ASIC) states that HFT accounted for approximately 27% of all equity market turnover in Standard & Poor's (S&P)/Australian Securities Exchange 200 securities from January 2012 until March 2015. Despite its stable HFT market share, Australia has a relatively high concentration of HFT-driven volume: the 10 largest HFTs accounted for 21% of all trading turnover in 2015, compared to 17% 3 years earlier (ASIC, 2015).

This article is a survey of the literature on HFT, which covers various HFT definitions. We discuss how HFT works and differentiates HFTs from other groups of investors, followed by a discussion on beneficial HFT strategies (e.g., market making, directional trading, and statistical arbitrage) and harmful HFT strategies (e.g., front running, spoofing, and quote stuffing). The article continues with an argument on the effects of HFT activities on market quality (e.g., price discovery, liquidity, volatility, and adverse selection costs) and discusses several critical issues associated with HFT (the flash crash of 2010, the arms race, and market-making obligations). The article concludes with a discussion on responses to HFT.

2.1.1 Defining HFT

As the U.S. Securities and Exchange Commission (SEC, 2010, 2014) notes, HFT has no clear definition. Regulators, researchers, and market participants therefore describe HFT in different ways. The term *HFT* is typically associated with *trading that utilises computer technology*, the *use of technology to execute orders, electronic trading, electronic markets, and automated trading*. While these terms are closely related to HFT, they are not the same thing and paint only an incomplete picture of HFT.

The Netherlands Authority for the Financial Markets (NAFM) states that the absence of a unanimous definition of HFT also makes classification difficult, which leads to other problems such as inaccurate estimations of the HFT market share and the inability to estimate the reach and influence of HFT in its markets. This lack of consensus on the definition of HFT complicates research in this area and contributes to the various conclusions on the effects of HFT activity in the market. The lack of a precise definition of HFT also leads to confusion between HFT and other forms of trading activity – such as algorithmic trading (AT) – with HFT consequently being blamed for matters (e.g., the flash crash of 2010) that have little or nothing to do with it (Moosa & Ramiah, 2015).

The incomplete definition of what HFT comprises is a problem for both HFT-active and HFT-free markets alike. Financial authorities need to meticulously analyse and consider the costs and benefits of HFT in their market. However, before they can effectively tackle the issue, they need to have a sound definition of HFT. An inaccurate definition would be too costly to the market: any microstructural changes introduced will likely involve substantial costs and could affect all classes of market participants, from individual investors to large mutual funds.

Different financial authorities describe HFT somewhat differently, but with considerable overlap. The SEC (2010, p. 45) refers to HFT as “professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on a daily basis.” The NAFM (2010) defines HFT as a form of automated trading based on mathematical algorithms that implement certain short-term trading strategies by utilising advanced technology, and not as a separate trading strategy itself. ASIC (2010) characterises HFT as a specialised form of AT that employs a high-speed, low-latency technology infrastructure. AT is viewed as a new form of trading, or a class of trading strategy, that relies on computer algorithms to automatically execute trading orders, using pre-programmed trading instructions that determine when (i.e., the timing) and how (i.e., the price and quantity) a certain order will be carried out and managed after its submission, with minimal or no human intervention (Aitken et al., 2017, 2018; Aquilina et al., 2016; Brogaard et al., 2014; Gider et al., 2019; Moriyasu et al., 2018). Unlike human traders, the lack of feelings in AT ensures that trading judgment is not swayed or clouded by emotions, allowing algorithmic traders to fully carry out their trading strategy (Harris, 2013; Manahov, 2016).

The London Stock Exchange Group (LSE), in response to a survey conducted by the Committee of European Securities Regulators (CESR) in 2010 to assess the impact of technology-driven developments, refers to HFT as a wide variety of different strategies utilising ultra-fast technology to conduct electronic market making and/or to seek arbitrage opportunities. The LSE (2010) also notes that HFT is very fast and requires a low-latency connection to the trading systems of exchanges. Among the regulatory body, the European Parliament and European Council's Directive 2014/65/EU – a 2014 amendment to the 2007 Markets in Financial Instruments Directive (MiFID), commonly referred to as MiFID II – provides a legal definition of HFT. Article 4(1) (40) of MiFID II describes an HFT technique as "an algorithmic trading technique."

According to the NAFM (2010), even with an accurate definition of HFT, trading platforms would still be unable to properly distinguish HFT from other forms of AT. To do so, they would need to establish the market shares of the various trading strategies that employed AT, which, based on today's technology, is not yet possible. Although not providing a conclusive definition of HFT, certain characteristics distinguishing HFT from other forms of trading can be specified.

The most agreed-upon characteristic of HFT is its use of high-speed, sophisticated computer programs (SEC, CESR, MiFID II) or strategies (NAFM, ASIC) to generate, route, and execute orders. HFT also uses sophisticated systems and efficient infrastructures to minimise network latencies (SEC, NAFM, ASIC, CESR, MiFID II) such as colocation services, individual or direct market data feeds, and proximity hosting. Other characteristics relate to the trading positions of HTF including extremely short average holding periods (SEC, NAFM, ASIC, CESR), large volumes of orders with very small profit margins (SEC, NAFM, ASIC, CESR), high amendment and cancellation rates or order-to-transaction ratios (SEC, NAFM, ASIC, MiFID II), and trading days ending with flat positions (SEC, NAFM, ASIC, CESR). Table 2.1 lists the detailed characteristics of HFT cited by each financial authority.

Table 2.1: Summary of HFT characteristics from regulatory perspectives

SEC (2010)[1]	▪ Use of extraordinarily high-speed, sophisticated computer programs for generating, routing, and executing orders ▪ Use of colocation services and individual data feeds offered by exchanges and others to minimise network and other types of latencies ▪ Very short time frames for establishing and liquidating positions ▪ Submission of numerous orders that are cancelled shortly after submission ▪ Ending the trading day in as close to a flat position as possible
NAFM (2010)	▪ Use of a trading strategy that involves rapid calculation and execution speeds ▪ Use of sophisticated systems and efficient infrastructures ▪ Use of an earnings model with very small profit margins in very large volumes ▪ Usually market-neutral (nondirectional) and delta-neutral (hedged) positions, thus, often closing out positions, with a flat position at the end of the day ▪ Very short average holding periods, ranging from seconds to several minutes ▪ Very high order-to-transaction ratios
ASIC (2010)	▪ Generation of large numbers of small orders with a high amendment and cancellation rates ▪ Hold positions typically with very short time horizons ▪ Use of a variety of trading strategies, the most common being the provision of electronic liquidity ▪ Processing of direct market feeds to obtain the fastest access to market information available ▪ Colocation of servers in data centres with the exchange market's matching engine to reduce access times ▪ Development of sophisticated trading strategies to trade on a short-term basis ▪ Typically ending the trading day with no carryover positions that use capital

[1] The SEC has never suggested that all of these characteristics should be met for a firm to be categorised as an HFT firm. A broader range of proprietary firms can, thus, be classified as high-frequency traders (SEC, 2014).

CESR (2010)	▪ Use of a form of automated trading that uses sophisticated computers and information technology programs ▪ Trades executed in a matter of milliseconds ▪ Hold new equity positions possibly down to a "subsecond" ▪ Ending the trading day with a flat position ▪ Use of own capital and not acting on behalf of clients ▪ Use of trading strategies generally geared towards extracting very small margins from hyperfast trading
MiFID II (2014)	▪ Infrastructure intended to minimise network and other types of latencies, including at least one of the following facilities for algorithmic order entry: colocation, proximity hosting, or high-speed direct electronic access ▪ System determines the order initiation, generation, routing, or execution, without human intervention, of individual trades or orders ▪ High intraday message rates constituting orders, quotes, or cancellations

2.1.2 HFT identification

Despite the lack of a uniform definition of HFT, the fact that HFT has several unique traits (see Table 2.1) allows it to be identified. One way to identifying HFT is with the help of the exchanges and regulators themselves, since they have the information on the identity behind each message submitted to the market. As Brogaard, Hendershott, and Riordan (2014, p. 2270) note, "one of the difficulties in empirically studying HFT is the availability of data identifying HFT. Markets and regulators are the only sources of these and HFTs and other traders often oppose releasing identifying data."

An example of such a dataset is that used in the studies of Hagströmer and Nordén (2013), Hagströmer et al. (2014), and Brogaard et al. (2015), who utilise access to the market participant identifier (MPID) information associated with each limit order in the NASDAQ OMX Stockholm Exchange (NOMX-St). With the help of NOMX-St in-house expertise, Hagströmer and Nordén (2013) categorise exchange member firms into (1) members who are primarily HFTs, that is, those that engage in proprietary trading and utilise algorithms in their trading strategies; (2) members who mainly trade for clients; and (3) members who engage in both proprietary and agency activities. This categorisation results in 29 members identified as HFT firms, 49 as non-HFT firms, and 22 as hybrid firms. Even though the dataset allows for the direct identification of the messages sent by HFT firms, the use of mediation trading services, such as sponsored access and/or the trading desks of banks, which consist of a mixture of HFT and non-HFT, makes it difficult to distinguish the origins of the trading activity and to interpret the results obtained from this group (Hagströmer & Nordén, 2013).

Another example is the NASDAQ HFT dataset, which covers 120 U.S. equities from 2008 to 2009, time stamped to the millisecond. The stocks in the sample were chosen by Terrence Hendershott (chair of NASDAQ's Economic Advisory Board during that period) and Ryan Riordan (a prominent HFT researcher), stratified by market capitalisation, and evenly split between NASDAQ and New York Stock Exchange (NYSE) listings. NASDAQ's access to order-level information on its market to identify the firms submitting orders was used, and 26 of the firms were manually classified as HFT firms. The dataset also categorises orders by whether the execution was aggressive (liquidity taking) or passive (liquidity providing), further grouping them into either HFTs or non-HFTs, resulting in four types of order execution: HH, HFTs that take liquidity from other HFTs; HN, HFTs that take liquidity from non-HFTs; NH, non-HFTs that take liquidity from HFTs; and NN, non-HFTs that take liquidity from other non-HFTs.

Even so, the dataset has its limitations. NASDAQ cannot identify all HFTs in the market and has possibly excluded HFT firms that also act as brokers while engaging in proprietary lower-frequency trading strategies. Thus, the orders from HFT firms routed through those large integrated firms could be excluded as well (Brogaard et al., 2014). Even with these limitations, both the NOMX-St and NASDAQ HFT datasets are still considered to be of high quality, since they allow researchers to accurately monitor HFT behaviour and estimate its impact on the market. The quality of datasets is clearly an ongoing issue in identifying and examining HFT activity, with nanosecond stock market data time stamping now becoming more common. Hasbrouck (2019) shows that 100- and 10-nanoseconds granularity dominates the one-second granularity of stock market data feeds in terms of the information obtained.

In the absence of internal information, researchers have to rely on HFT characteristics and formulate appropriate proxies to gauge HFT activity. One clear advantage of this approach is its replicability. The less binding constraint (i.e., the need for internal experts) allows the proxy to be applied in other markets and for longer periods. HFT proxies are constructed from message data that are commonly available for many markets. One widely used HFT measure is the order-to-trade ratio (OTR), which represents quoting intensity (e.g., Aquilina & Ysusi, 2016; ASIC, 2013, 2015; Brogaard et al., 2015; Friederich & Payne, 2015; Frino et al., 2015; Hagströmer & Nordén, 2013). It is defined as the number of limit order submissions and cancellations on a given day, divided by the number of executions. HFTs typically place large numbers of orders across various price levels and revise their orders with the arrival of new information in the market, resulting in large OTRs in stocks with high HFT activity.

However, Yao and Ye (2018) argue that the OTR is a poor cross-sectional proxy for HFT activity. Their findings show that stocks with a greater percentage of liquidity provided by HFT have a lower OTR, which directly contradicts the aforementioned wisdom. Yao and Ye (2018) find that HFTs provide more liquidity in stocks with larger tick sizes and have less motivation to cancel orders once these have reached the top of their queue positions. On the other hand, HFTs not only provide less liquidity in stocks with smaller tick sizes, but also tend to cancel orders more frequently, since price competition occurs on a finer grid. Based on these arguments, the conventional view of the OTR can be challenged in terms of its ability to be a proxy for HFT. O'Hara et al. (2019) also find similar results using NYSE data, suggesting that traders' order strategies differ between tick-constrained and tick-unconstrained environments.

Hasbrouck and Saar (2013, p. 646) define low-latency trading as "strategies that respond to market events in the millisecond's environment." From this definition, they introduce an alternative measure for HFT activity, *RunsInProcess*, which is based on HFT behaviour that utilises dynamic and strategic order placement strategies. The underlying component for this measure is the number of strategic runs, which are essentially links of rapid order submissions, cancellations, and executions presumed to be submitted by HFT algorithms. Orders are linked if (1) the cancelled order and the new order are in the same direction, (2) the orders have similar size, and (3) once an order is cancelled, it is quickly followed by another order within 100 milliseconds. The shortest run would have four messages: order submission (start), cancellation, second entry, and termination (end). The longest run could last the whole day, since orders are rapidly submitted and cancelled up until the market closes. Any runs shorter than 10 messages are eliminated, to reduce the possible inclusion of agency algorithms. Nonetheless, if any HFT arbitrage strategies utilise only marketable orders, this measure could exclude them (Hasbrouck & Saar, 2013).

Other proxies of traders' HFT activities are possible when the market provides message- or order-level data. An example is the data from the Investment Industry Regulatory Organization of Canada, which contain every message submitted to recognised Canadian trading venues. The detailed records of trades and orders, as well as constant identifiers, permit researchers to identify HFT, based on a number of factors, for example, short order-to-cancel times (Comerton-Forde et al., 2018; Korajczyk & Murphy, 2019), corresponding traders that submit large numbers of orders immediately following net order imbalance information (Comerton-Forde et al., 2018; Korajczyk & Murphy, 2019), and fast reaction times to other orders (Malinova & Park, 2020), along with other proxies such as the number of trades, OTR ratios (Boehmer et al., 2018), trading volumes, and the end-of-day inventory (Brogaard et al., 2019).

2.2 Trading Mechanics

HFT is a subset of AT and, thus, inherently has most (if not all) of the characteristics of its superset. What makes HFTs a unique class of investor within AT lies in their speed in observing potentially profitable trading opportunities, quickly processing new information and executing the appropriate actions, and analysing the textual context of news flow at much higher frequencies and in much shorter periods than a human is capable of. This is an important advantage that these machines (i.e., HFTs) have over humans (Menkveld, 2014). Their infrastructural and technological advantages allow for the optimisation of a wide array of complex trading strategies that can be both beneficial and detrimental to the market. According to Angel (2014), trading speeds nowadays are so fast that they have almost reached the theoretical speed of light, approximately 300 000 kilometres per second. This level of speed limits certain trading strategies exclusively to HFTs, since other types of market participants are unable to replicate such strategies (Harris, 2013). HFTs constantly strive for superior calculation and execution speeds (NAFM, 2010).

There is nothing new about the way HFT works. The short-term trading strategies employed by HFTs have long existed (NAFM, 2010). The way HFTs profit from the market is generally similar to other traders' strategies. For instance, they buy stocks at a lower price and then try selling them at a higher price. Stocks with a short selling option allow for more choices: traders can make money from either bearish or bullish stocks. For stocks with options, traders can make a profit from price disparities between the parent stocks and their option securities. Traders can also assume the role of market maker, in which case they stand ready to buy and sell securities and profit from the market-making spread. Moreover, market-making HFTs can receive rebates from certain trading venues for providing liquidity to their market.

Hasbrouck and Saar (2013) find the speed of some algorithms to be such that the time it takes to complete a trading cycle starting from the detection of a market event, its analysis, and sending an order can be as short as 2 to 3 milliseconds. This intense activity within the millisecond environment is also where computer algorithms react to each other. O'Hara (2015) states that order latencies are now measured in milliseconds (thousandth of a second), microseconds (one-millionth of a second), and even nanoseconds (one-billionth of a second). For comparison purposes, it takes the human eye 400-500 milliseconds to respond to visual stimuli, and human reaction times are generally thought to be around 200 milliseconds, which, in both cases, is far slower than HFT speeds (Kosinski, 2013; O'Hara, 2015). At such speeds, human traders cannot accurately follow the low-latency activity on their trading screens or the market dynamics that can be driven by the interactions between algorithms (Chordia et al., 2013; Hasbrouck & Saar, 2013).

To accommodate HFTs' need for speed, fast, reliable networks, and infrastructures are needed. In 2010, Spread Networks began the construction of an 826-mile (about 1,330 kilometres) straight-line fibre-optic cable connecting New

York and Chicago, estimated to have cost approximately US$300 million (Steiner, 2010). The cable has been able to reduce the round-trip communication between the two cities from 16 to 13 milliseconds. Although a 3-ms difference seems trivial to HFTs, it seems like an eternity (Budish et al., 2015). Subscribers were charged almost US$14 million for a 5-year contract, or roughly US$ 230,000 per month (Serbera & Paumard, 2016). Even though light is able to travel quickly through glass, it is faster through air. Therefore, in 2011, microwave towers were built to reduce the latency even further. Shkilko and Sokolov (2020) report that the microwave networks are approximately 30% faster than the Spread Networks cable. Albeit faster, these networks are easily disrupted by precipitation such as rain and snow. Due to the high costs, HFTs need to be able to make even greater profits to be successful in the millisecond environment.

The earnings model for HFT consists of executing many transactions with very small profit margins in very large volumes (NAFM, 2010). Using fully automated trading strategies, HFTs attempt to identify and profit from short-term irregularities, and earn small amounts of money from every trade. Even though the profit per trade is often as small as only a few basis points, it is amplified by the high trading volume (Zhang, 2010). The ability to trade at low latencies allows HFTs to profit from the trading environment itself, rather than from investing in financial securities (Hasbrouck & Saar, 2013). This strategy explains two of the common characteristics associated with HFT, which are frequent order cancellations shortly after their placement and high ratios of messages to completed trades (Budish et al., 2015).

In 2005, the Regulation National Market System (Reg NMS) was adopted to foster intermarket competition and to serve the interests of long-term investors and listed companies (SEC, 2005). At the centre of Reg NMS lies the Order Protection Rule (Rule 611), which prevents exchanges and brokers from executing orders at prices that are below the National Best Bid and Offer (NBBO). This created opportunities for alternative trading systems to compete for liquidity with the major exchanges, since orders are routed to the venues offering the best prices. Prior to Reg NMS, most shares were traded at the two major stock exchanges, NYSE and NASDAQ. However, within 5 years, NYSE's market share of trading of its listed stocks fell from 80% in 2005 to 25% in 2010 (Menkveld, 2013). This fragmentation reflects how market shares are being captured by "third markets," traded away from their listing venue (Pirrong, 2014). The trading venues are also geographically diverse; therefore, orders' arrival times at different exchanges vary.

HFT strategies rely heavily on speed, and fragmentation is viewed as a blessing to HFTs, since it increases the effectiveness of their strategies (Baldauf & Mollner, 2020). Latency issues, such as the speed of cross-market information flow and transmission speeds across geographical locations, are crucial to the success of HFTs. To utilise their trading strategies, many HFTs have multiple locations across several cities, such as New York, Chicago, and London, to gain a competitive edge against other HFTs. Brogaard and Garriot (2019) find that HFT competition promotes liquidity. HFTs' entrance to the Canadian Alpha exchange (an alternative trading system) has been found to reduce the bid–ask spreads on the exchange, and the effect is most prominent upon first entry. As the number of HFTs on Alpha grows, the spreads tighten, eventually converging to the levels reported on the Toronto Stock Exchange (TSX). Brogaard and Garriot also find that HFTs' departure from the market is associated with liquidity deterioration. On the contrary, using NOMX-St data, Breckenfelder (2019) finds that liquidity deteriorates following the market entry of HFTs and improves after their exit, due to competition among speculative HFTs.

2.3 Trading Strategies

Benos and Sagade (2016) state that HFTs exhibit variability in their trading strategies because of differences documented in their liquidity provision, end-of-day and maximum intraday positions, trading revenues, and the like. The variability in strategies also translates into different sensitivities of HFT position changes due to inventory levels and recent price changes. Brogaard et al. (2014) find that the direction of HFT is correlated with publicly available information such as macroeconomic news announcements and limit-order book imbalance. They also find that HFTs follow contrarian trading strategies, as evidenced by the negative correlation between HFTs' overall trading and past returns. Goldstein et al. (2014) state that, naturally, HFT strategies are employed by proprietary firms, the majority of which are either broker-dealer proprietary trading desks (trading units within a firm that trades using its own money), hedge funds, or proprietary trading groups. This result is logical, due to the high costs involved in employing sophisticated technology and obtaining the big data to execute HFT strategies (Kauffman et al., 2015; Moosa & Ramiah, 2015).

Aldridge (2013) generally categorises HFT strategies into three groups: (1) statistical arbitrage, also known as value-motivated strategies; (2) directional strategies, also known as informed trading; and (3) market making, also known as liquidity trading. The algorithms employed by HFTs can determine their order execution style such as being either aggressive or passive or either sending orders in one trade or splitting them up into smaller trades. An aggressive order is an order that is placed at the current market price, or a limit order with a price near the current market price. A passive order is a limit price placed that is far from the current market price. Similarly, the NAFM (2010) divides HFT strategies into market making, statistical arbitrage, and low latency. While the first two groups are similar to Aldridge's (2013), the third group classification, low latency, has a broader scope. The NAFM (2010) states that the success of the latter group is determined by the sheer speed of the users, hence, creating the need for the fastest systems and the best connections to trading venues. Harris (2013), on the other hand, categorises HFT strategies into three groups, based on their effect on the market. The first group, valuable HFT strategies, is a group of trading strategies that are acceptable to the market in general such as market making and statistical arbitrage. The other two groups, namely, harmful and very harmful HFT strategies, are intolerable groups of trading strategies. The strategies belonging to these groups benefit HFTs at the cost of other market participants (see Section 2.3.2).

Most HFT-based strategies, such as market making, promote market liquidity, while arbitrage strategies make positive contributions to price discovery and market efficiency. Therefore, any action to prevent or hamper these strategies through regulation or the imposition of specific constraints can have counterproductive effects on market quality. Regardless, regulatory bodies should always combat any predatory strategies that jeopardise market integrity or create disruptive or confusing effects for other market participants (Gomber et al., 2011).

Harris (2013) highlights that financial authorities should be meticulous in regulating the market, to avoid unintentionally harming beneficial HFT strategies.
Putniņš and Barbara (2020) find heterogeneity in the effects of AT/HFT trading strategies on institutional investors' trading costs, which can be grouped into harmful and beneficial strategies, based on their systematic effects. The authors' findings show that toxic AT/HFT strategies roughly double the cost of executing large parent orders, while the positive effects derived from beneficial trading strategies nullify this problem. However, in the aggregate, AT/HFT has little or no effect on institutional trading costs. This aggregation has masked the heterogeneity in AT/HFT strategies and hidden their actual impact on institutional trading costs. The authors' findings also suggest that market structure changes aimed at influencing AT/HFT can produce positive or negative outcomes, based on whether the changes are able to disproportionately encourage harmful or beneficial traders.

Cooper et al. (2016) examine regulatory efforts related to HFT, particularly on the issue of HFTs' deception in the market. They conclude that any action to treat a deception, even an intentional deception, as misconduct in a financial market could be a mistake. They outline three acceptable criteria for AT strategies: (1) the trading strategy should be prudent, that is, it should not be harmful to the market should HFTs behave unexpectedly; (2) the trading strategy should not block price discovery, that is, it should not interfere with the ability of other market participants to reflect their private information on the price; and (3) the trading strategy should not circumvent transparent price discovery, and strategies that conceal information from being discovered, such as using dark pools or hidden orders, should therefore be prohibited.

2.3.1 Beneficial Strategies

The following sections discuss acceptable HFT strategies, namely, statistical arbitrage, directional trading strategies, and market making. These strategies are deemed acceptable, since they do not harm the market and have positive effects on market quality.

2.3.1.1 Statistical Arbitrage

Statistical arbitrage (also known as "stat arb") is a trading strategy that is based on the theory that two similar instruments should share similar behaviour, and, therefore, any short-term divergence between their relative prices is likely to be corrected. This trading strategy is also commonly known as pairs trading and can use statistical approaches that measure the relation between two or more instruments such as cointegration or correlation analysis. The temporary divergence is more likely to be driven by momentary order imbalances in the market than by any meaningful fundamental change (Narang, 2013). This trading strategy is designed to make a profit from price disparities and temporary deviations in statistically significant relations. HFTs can consider tens or hundreds of stocks to utilise this strategy (Golub et al., 2013; Lhabitant & Gregoriou, 2015; Moosa & Ramiah, 2015). Accordingly, HFTs will hunt for opportunities that arise during periods of temporary deviation and exploit them before they disappear (Moosa & Ramiah, 2015).

Foucault et al. (2017) argue that the effect from arbitrage activities could go either way: it can be beneficial or harmful, depending on the underlying cause of arbitrage opportunities. In the event opportunities are due to transitory trade imbalances, arbitrageurs (i.e., HFTs) can exploit the situation by providing liquidity to the market. This action is deemed beneficial.[2] Consistent with this view, Gromb and Vayanos (2002) find that arbitrageur activity supplies liquidity to the market and brings prices closer to their fundamental value. On the contrary, if a temporary arbitrage opportunity arises due to lagged and asynchronous price adjustments to information arrival, then the arbitrageurs' profits in this case are the adverse selection costs that market makers must pay due to trading at stale quotes. Foucault et al. (2017) find that the market becomes more illiquid on days when the percentage of so-called toxic arbitrage opportunities is higher and arbitrageurs' speed is relatively faster. This finding supports the notion that the higher price efficiency from rapid arbitraging activities comes at the expense of market makers' increased adverse selection risk.

---

[2] For instance, trade imbalances can arise when impatient traders flood the market by submitting large volumes of bid or ask orders, leading prices to deviate from their fundamental values (Brogaard et al., 2018).

Wissner-Gross and Freer (2010) highlight the importance of minimising information transmission delays in modern-day securities trading. In their article on relativistic statistical arbitrage, they demonstrate that optimal intermediate locations exist between trading centres that host cointegrated securities, which minimises transmission delays and maximises profit potential. As traders continue striving to be the fastest, the importance of having optimal locations is even more pronounced (Donefer, 2010; Wissner-Gross & Freer, 2010). Regardless, Kozhan and Tham (2012) argue that, while competition is commonly associated with improved price discovery, competition among arbitrageurs can inflict negative externalities on each other due to the crowding effect, which, in turn, will limit efficiency.

Opportunities for statistical arbitrage can surge due to long-term investors' strategic decisions. For instance, their buying or selling certain securities can create a price impact on the securities' price, which consequently creates spillover across the markets, especially in correlated securities (Goldstein et al., 2014). The fastest trader that first notices such opportunities and trades on them will make the most, if not take all, of the profits from the situation. Therefore, speed is essential to the successful execution of this trading strategy, and HFTs that implement it are willing to spend a great deal to keep their technological capabilities up-to-date (Chung & Lee, 2016; MacKenzie, 2015). This strategy plays a key role in the market in terms of liquidity provision, as well as in price discovery and the information dissemination process (Goldstein et al., 2014). Nonetheless, Hasbrouck and Saar (2013) argue that, even though HFT helps in eliminating momentary price distortions, given that the improvement is only within the millisecond environment, the effect is deemed insubstantial.

2.3.1.2 Directional Trading

Directional trading strategies are a group of HFT strategies based on the identification of short-term trends or momentum, which includes event-driven strategies and short-term price movement prediction strategies. Directional strategies are time sensitive (Aldridge, 2013), since they need to anticipate intraday price movements, which involve taking unhedged positions based on forecasted price changes such as in exploiting the divergence between fundamental values and actual market prices. Benos and Sagade (2016) find that HFTs with neutral liquidity-taking/-making behaviour are trend chasers. They trade in the direction of short-term price changes, that is, they buy when the price is rising and sell when the price is falling, which is suggestive of momentum strategies.

Directional strategies are based on the theory that price movements have predictable directions which could be due to a trend (momentum strategies) or the reversal of a trend (mean reversion strategies). Under the momentum strategy, HFTs will identify a trend or a significant movement and will bet that the price will continue to move in the same direction, driven by the idea of a growing consensus among market participants (Narang, 2013). The mean reversion strategy, on the other hand, is built on the notion that any deviation in price, such as a trend or a consistent direction, could be temporary. Thus, price movements do not persistently move in one direction and will eventually revert and bounce back (Easley et al., 2012).

To be successful at implementing directional trading strategies, HFTs need to have superior access to information (e.g., information from paid-for news sources such as Bloomberg) and be able to immediately assess and analyse market conditions. Foucault et al. (2016) suggest that the contribution of news trading to directional traders' profit increases with news informativeness, and the fastest traders will gain the most profit. Furthermore, the competitive edge that directional traders have from early access to new information will not last long, since that information will soon be available to the public. Thus, directional traders are normally aggressive, since they use market orders or post limit prices close to the market (Aldridge, 2013).

2.3.1.3 Market Making

Market making can generally be described as the placement of limit orders on both sides of the market price – that is, to set limit orders to buy (sell) at a price slightly below (above) the market price. By continuously supplying the market with standing limit orders, market-making activities essentially provide liquidity to the market. The spreads between the limit orders to buy and to sell constitute the market makers' profit.

HFTs' market-making strategies help the market to be more efficient and have a stabilising effect on the market, since the HFTs provide buying power when others want to sell, and selling power when others want to buy (Angel, 2014). Despite the fact that the financial landscape has developed so with the evolution of technology, the general mechanics of market making still hold, even in a high-frequency world. Goldstein et al. (2014) state that market-making HFTs use automated liquidity provision, a strategy that rapidly places, cancels, and replaces bid and ask limit orders and profits from the resulting spreads. The high-frequency update process involved in the market-making process results in enormous order volumes and a high cancellation rate of 90% or more (SEC, 2010).

Aldridge (2013) states that market makers are exposed to two types of risk once their market limit orders are placed: inventory risk and adverse selection risk. Inventory risk is the risk that the inventory held by a market maker will decline in value due to natural market movements, while adverse selection risk is the possibility of the market maker trading against a party that is better informed about the true price of the stock. Thus, the market maker requires compensation, not only for providing liquidity, but also for the risks mentioned above (Aldridge, 2013; Golub et al., 2013).

Some electronic exchanges use the maker-taker pricing model to price their order-matching service (Harris, 2015). Durbin (2010, p. 206) defines the model as "a pricing policy of some exchanges where active traders pay a fee, some of which is distributed to the associated passive trader." The maker-taker pricing model is used to encourage market making, instead of market-taking activity, through incentives in the form of rebates or reduced transaction costs for market makers. The rebate is indeed important for market-making HFTs. The absence of a rebate can put HFTs in a loss position (Hendershott & Riordan, 2013), and their revenue from supplying liquidity would then be negative (Brogaard et al., 2014), which, in turn, would discourage HFTs' liquidity provision activities.

Unlike HFT that uses directional trading strategies, HFT market makers do not seek to make a directional bet, but, instead, maximise their inventory turnover by taking positions on both sides of the order book. HFT market makers typically turn over their inventory more than five times in a day, which explains their high share of volume traded in the market. To protect their investment, they will either hold a minimum or even zero inventory position at the end of a trading day.

By having very small inventories and short holding periods, HFTs can conduct their market-making activities with very little capital, while using high-speed trading to control their position risk (Easley et al., 2011). Benos and Sagade (2016) categorise HFTs based on their liquidity-taking/liquidity-making behaviour and find evidence that passive HFT activity is consistent with market-making activity, in which HFTs trade in the opposite direction (i.e., contrarian trading) of the most recent price changes, post limit orders, and use aggressive trades to make quick inventory adjustments. Regardless, the authors also find that passive HFTs have a high information-to-volume ratio, suggesting that the HFTs could be using various market-making strategies, rather than solely aggressive orders, to make the market.

Since HFT has become increasingly dominant in overall market activity and given its market-making role, it is interesting to examine the impact of this activity on the rewards to market making. Conrad and Wahal (2020) examine the price impact of common stock trades in the United States from 2010 to 2017. Their major finding is that market-maker profitability is very sensitive to speed, with profits declining over the sample period. For the shortest time horizon examined in their article, 100 milliseconds, the authors show that aggregate profits declined over the period, from 1.9 basis points of the total dollar volume to 1.0 basis point. Although this can be seen as a benefit to social welfare, concerns could be raised if HFTs were to achieve dominance in this area.

2.3.2 Harmful Strategies

Controversial strategies are those that profit at the expense of others through "dirty" means such as front running, order anticipation, quote matching, spoofing, layering, and quote stuffing. Moreover, HFTs' ability to rapidly enter and cancel orders faster than other traders makes it difficult to identify where liquidity exists across fragmented markets. This uncertainty creates even more opportunities that are profitable for HFTs at the cost of other traders (O'Hara, 2015).

2.3.2.1 Front running, order anticipation, and quote matching

Harris (2013, 2015) describes front-running strategies as very harmful trading strategies and further categorises them into order-anticipating and quote-matching strategies. Order anticipation works by examining trades and quotes to detect algorithms used by traders that intend to move large orders. For example, traders could split their large orders into smaller packages to conceal their private information and reduce the impact on the market. HFTs would then trade ahead of (i.e., front-run) the incoming large orders and profit from the anticipated direction of the price changes. This will increase (decrease) the price for incoming large buy (sell) orders, increasing the transaction costs for traders intending to execute large orders. HFTs that apply an order anticipation strategy design their algorithms to play by the book, without violation of duty, misappropriation of information, or other misconduct (SEC, 2010). Regardless, the strategy that they use is parasitic: not only does it not contribute to price discovery or liquidity, but also it preys on other traders and jeopardises large traders the most (Harris, 2015). Some institutional investors even claim that an order anticipation strategy can adversely affect their trading strategy, increasing their costs (Agarwal, 2012).

Quote matching, on the other hand, profits by posting slightly better limit orders, for example, one tick higher (lower), than slow traders' limit buy (sell) orders, which gives them price priority. In the case in which the market is moving against their position, quote-matching HFTs would trade with the slower traders' quotes (which have become the best quotes) to minimise their losses. The problem of quote matching is not new to large buy-side traders. It was an important source of profit for exchange specialists before the HFT era; the main difference today is the identity of the quote matchers (Harris, 2013). Unlike the order anticipation strategy, which requires high-quality pattern recognition algorithms, the success of a quote-matching strategy depends very much on HFTs' low-latency communication. Speed is crucial to quote matchers, to ensure that their orders are the first to be filled and to revise their unexecuted orders, should large orders be cancelled or filled by other parties. Therefore, the order anticipation strategy is dominated by the faster HFTs (Harris, 2013). Nevertheless, both strategies unnecessarily increase large traders' transaction costs (Chung & Lee, 2016) and could impede the process of impounding fundamental information into the price (Jarnecic & Snape, 2014).

Aquilina and Ysusi (2016) empirically examine HFTs' order anticipation activity using data from the LSE and find no evidence of HFTs systematically anticipating orders sent to different venues by non-HFTs and trying to front-run the orders. However, when analysing longer periods, the authors do find trading patterns consistent with HFTs anticipating non-HFTs' order flow. Regardless, the result can also mean that HFTs are able to react more quickly to news and other public information than non-HFTs can. Aquilina and Ysusi (2016, p. 26) conclude that HFTs "appear not to anticipate near-simultaneous orders … but they could be predicting the flow over longer periods."

Van Kervel and Menkveld (2019) document the behaviour of HFTs around large institutional orders executed through a series of child trades on the NOMX-St. From three theoretical standpoints, HFTs can adopt the role of market makers that provide liquidity to the market (Grossman & Miller, 1988) and/or engage in *predatory trading* activity by demanding liquidity and front-running institutional orders (Brunnermeier & Pedersen, 2005) and/or undertake back-run positions, that is, delaying their entry into the market so that privately informed orders can be sniffed out (Yang & Zhu, 2017). Their findings show that HFTs initially trade against the direction of an institutional order (i.e., acting as a liquidity supplier) before eventually trading in the same direction, to strategically ride the institutional order flow, making it costlier for the latter to impound their private information into prices. The authors also find that HFTs need considerable time (several hours) to learn about the institutional order, which is consistent with the back-run position. From one angle, HFTs' participation could make pricing more efficient in the short run, through faster price discovery. Regardless, in the long run, Van Kervel and Menkveld (2019) argue that institutional investors could have less motivation to continue costly analyst research to seek informational rents, since the projected returns from doing so is diminished by the participation of HFTs, potentially making prices less efficient in the long run.

2.3.2.2 Spoofing and layering

Spoofing and layering constitute a strategy defined as "submitting multiple orders at different prices on one side of the order book slightly away from the touch, submitting an order to the other side of the order book (which reflects the true intention to trade) and, following the execution of the latter, rapidly removing the multiple initial orders from the book" (European Securities & Markets Authority, 2011, p. 27).

The Financial Industry Regulatory Authority (FINRA, 2012, para. 5) generally describes spoofing as a form of market manipulation intended for "triggering another market participant(s) to join or improve the NBBO, followed by cancelling the nonbonafide order and entering an order on the opposite side of the market." Section 747, Antidisruptive Practices Authority, of the Dodd-Frank Wall Street Reform and Consumer Protection Act (2010, p. 124, Stat. 1739), however, outlines a broader definition of spoofing, defining it as a disruptive practice that involves "bidding or offering with the intent to cancel the bid or offer before execution," which makes it unlawful to practice such a strategy.

Spoofing is executed with the intention of attracting liquidity using fake market or limit orders by forming the illusion that the market is moving soon due to greater demand in the order book. This strategy can be accomplished using algorithms designed to analyze liquidity information in the order book to predict incoming market activity and deliberately use the information to mislead other investors or algorithms (Serbera & Paumard, 2016). For example, HFTs can create such a situation by posting large displayed limit orders just below the best bid price, giving others the impression that the price will soon move upward. This situation encourages other traders to quickly buy the stock, by quoting the stock at a higher bid price, or even to execute market orders. In the meantime, HFTs might already own the stock beforehand and can now sell at a higher price in a bigger volume, thanks to the artificially inflated price that was driven by the fake limit buy orders.

Layering is a form of spoofing that involves the placement of a large number of fake orders at several different price limits on one side of the order book (NAFM, 2010). This creates the appearance of changing levels of supply and demand in the affected securities (FINRA, 2012). Others could erroneously interpret this pattern as a signal of increasing directional pressure on the price and act accordingly. HFTs will then profit from the price move they have initiated and cancel the fake limit orders before they are executed. Both spoofing and layering convey the impression that a security is more liquid than it actually is, or even suggest that the security is currently under- or overpriced (Harris, 2015). Cooper et al. (2016), however, claim that spoofing and layering are just other forms of bluffing, and, just as in poker, bluffing should be allowed. The authors conclude that the regulators should not treat all deception in the financial market as misconduct, and they propose a set of criteria for deciding which trading strategies should be regulated and which should not. They argue that an acceptable trading strategy (1) should be prudent, (2) should not block price discovery, and (3) should not circumvent transparent price discovery. Since spoofing works within the outlined criteria, it should not be prohibited.

Aspris et al. (2015) examine the effect of switching the matching algorithms adopted by the London International Financial Futures Exchange in 2007 for order submission strategies. The event involved the introduction of a "time pro rata" matching algorithm to replace the older "pure pro rata" mechanism. The mechanics of the former matching algorithm are found to incentivise traders to flood the order book with a much larger quantity than they truly intend to execute, a situation comparable to the spoofing and layering problems. Following the microstructure change, Aspris et al. (2015) find significant changes in market participant behaviour, evidenced by the sizeable decline in market depth, as well as a substantial increase in the numbers of small order entries and cancellations. The new matching mechanism is found to eliminate "false liquidity" from the market, thus, giving the participants a more reliable representation of the actual liquidity level in the market. Indirectly, the findings suggest that regulators indeed have ultimate power to ensure a level playing field that is fair for all; however, they should be meticulous in doing so, to avoid unintended adverse effects on the market.

2.3.2.3 Quote stuffing

Quote stuffing is another form of market manipulation strategy that utilises HFTs' ability to rapidly send and cancel orders. Easley et al. (2012, p. 228) describe quote stuffing as a strategy that "involves sending and cancelling massive numbers of orders with the intent of taking all available bandwidth and thereby preventing other traders from being able to submit orders." Similarly, the U.K. Government Office for Science (2012, p. 168) defines quote stuffing as "entering large numbers of orders and/or cancellations/updates to orders so as to create uncertainty for other participants, slowing down their process and to camouflage the manipulator's own strategy." The high rate of entered and cancelled orders involved in quote stuffing is viewed as a way to manipulate markets and to lure other traders into making mistakes (Narang, 2013).

Unlike spoofing and layering, which use limit orders near the best bid and ask prices, quote stuffing involves placing large amounts of nonexecutable orders, that is, limit orders that are far from the best quote, aimed to congest the market and slow down competitors (Lhabitant & Gregoriou, 2015). An exchange's network bandwidth can become congested from receiving unusually large numbers of trade messages (e.g., rapid orders and cancellations), thus, impairing other traders' access to the market (Angel & McCabe, 2013). The impairment leaves slower traders with an unclear picture of the actual market situation and affects their ability to execute trades. Faster traders, on the other hand, are able to gain a better understanding of what is happening in the market, allowing them to profit at the expense of slower traders (Biais & Woolley, 2011). Since a quote-stuffing strategy seeks to make a profit by preventing others from adding their private information to the market, it should be prohibited, based on the acceptable trading strategy criteria outlined by Cooper et al. (2016).

Nonetheless, as Egginton et al. (2016) note, sudden outbursts or episodic spikes in quoting activity could be the result of interactions between two or more algorithms that fail to converge. In this case, quote stuffing can be viewed as a side-effect of using robots in trading, rather than being part of a scheme to strategically manipulate the market. Either way, quote stuffing is still linked to market degradation. Egginton et al. (2016) analyse intense episodic spikes in quoting activity in the U.S. stock markets.[3] Their findings suggest that, during quote-stuffing events, affected stocks experience liquidity deterioration, higher trading costs, and greater short-term volatility. In addition, orders are more rapidly entered and cancelled, have shorter durations, have lower execution rates, and are smaller.

[3] Egginton et al. (2016, p. 588) define intense quoting episodes as "segments where the level of quoting activity exceeds the previous 20-day mean number of quotes per minute by at least 20 standard deviations. [They] also require that the average number of quotes for the entire trading day not exceed its previous 20-day rolling average by more than two standard deviations. The latter requirement is implemented to exclude trading days with an unusually high level of quoting activity."

Overall, the authors' findings are aligned with the notion that intense quoting periods are associated with the degradation of market quality.

Tick size reduction seems to be the simplest way to mitigate the order congestion problem. Theoretically, a finer tick size allows orders to be placed at more price points, which will give market participants greater freedom in deciding their entry/exit price, and essentially prevents quote stuffing Nonetheless, Dyhrberg et al. (2020) argue that a tick size that is too small would promote aggressive price undercutting by an economically nonsignificant amount. In a purely order-driven market, endogenous liquidity providers (ELPs) assume the role of market makers, since it is profitable to do so. A tick size that is too fine could disincentivise them from continuing to make the market, since this undercutting behaviour will expose them to the risk of losing execution priority and impede their ability to rapidly offload potential inventory. The absence of ELPs can significantly reduce liquidity supply in the market, which is detrimental to market quality (see Section 2.5.3 for a discussion on market-making obligations).

2.4 Effects on Market Quality

A large and growing body of literature has investigated the effect of HFT on market quality. The term *market quality* in itself is broadly defined, but commonly associated with price discovery and efficiency, liquidity, and volatility (e.g., Harris, 2003; U.K. Government Office for Science, 2012). Based on HFT characteristics, HFT can be thought of as a new breed of intermediary that can improve or harm the market. Whether HFT is beneficial or detrimental to the market is still a hot topic, among market participants, regulators, and the media, as well as academics (Menkveld, 2014). The many perspectives on HFT could have stemmed from the lack of consensus on its mechanics, where HFTs can act as market makers, arbitrageurs, predators, or some combination thereof (Carrion, 2013).

2.4.1 Price Discovery and Efficiency

Fama's (1970, p. 383) seminal article states that "a market in which prices always *fully reflect* available information is called *efficient*." Thus, in an efficient market, once information is publicly disclosed, it is quickly reflected in prices (Fox et al., 2017), and any mispricing and associated arbitrage opportunities should be rapidly eliminated (Goodhart & O'Hara, 1997). Nonetheless, in the era of HFT, the terms *immediately*, *rapidly*, and *current* need to be refined, since the HFT definition and perception of these terms are very different from those of ordinary human traders. Comparatively, it takes 400-500 milliseconds for a human being to blink, while HFTs can trade hundreds or thousands of times during a similar period (O'Hara, 2015).

As Aldridge (2013) notes, the process of impounding information from news into prices is not instantaneous. The price will first swing back and forth, due to implicit negotiations among the many buyers and sellers that can be seen in the order flow, before it eventually finds its optimal post-announcement price range. The price fluctuation gives HFTs an opportunity to profit from arbitraging surrounding news releases and to bring the market one step closer to its efficient state, following the efficient market hypothesis. Using directional event-based strategies, HFTs will place their trades based on forecasted market reactions to an event.

Hendershott et al. (2011) use the introduction of autoquotes on the NYSE, starting in 2003, as an exogenous event that increases the amount of AT in some stocks but not others. Before the introduction of autoquotes, market specialists in the NYSE had to manually disseminate the inside quotes whenever there was a relevant change in the NYSE limit order book. This would arise (1) with the arrival of a better-priced order, (2) when an order at the inside quote was cancelled, (3) when the inside quote was wholly or partially traded, or (4) when the size of the inside quote changed. The authors' findings show that AT increases quote informativeness and decreases trade-related price discovery, that is, AT activities discover efficient prices via quote updates rather than via trades. Hendershott et al. propose the ability of algorithms to respond quickly to information contained in order flows and adjust their trading and quoting activities accordingly as a plausible explanation for these findings. Brogaard et al. (2014) examine the role of HFT in the price discovery process using the NASDAQ HFT dataset and find that HFT generally plays a positive role in impounding information into stock prices. HFTs are found to trade in the same direction as permanent price changes and in the opposite direction of temporary pricing errors, which is consistent with the informed trading behaviour proposed by Kyle (1985).

Conrad et al. (2015) examine the full cross-section of securities in the U.S. equity markets from 2009 to 2011. They find that high-frequency quoting is associated with price series that more closely resemble random walks, which indicates greater efficiency in the price discovery process. In addition, they use data from the 300 largest stocks from the first section of the Tokyo Stock Exchange in an out-of-sample analysis. They use the introduction of the Arrowhead trading platform in January 2010 as a proxy for an exogenous shock that facilitates high-frequency quoting and trading on the Tokyo Stock Exchange. Before Arrowhead, the time between an order submission and posting to the order book or order execution ranged between 1 and 2 seconds. After Arrowhead's introduction, latency dropped to around 5 milliseconds. The findings confirm the authors' evidence from their US equity market study; that is, HFT activity has a positive impact on the price discovery process.

Boehmer et al. (2020) study the effect of AT on informational efficiency in 42 equity markets around the world between 2001 and 2011. They use the formal introduction of colocation services as an exogenous technological shock that allows high-speed traders to minimise their trading latency by locating their physical computer hardware close to the exchange. The event date is based on the actual introduction of colocation services made by the exchanges, which marks their commitment to provide low-latency infrastructure in their markets. *Ceteris paribus*, the faster trading infrastructure would be more appealing in AT and, therefore, should increase the level of AT in the post-colocation period. Their authors' findings show that stocks with greater AT intensity have intraday return autocorrelations with lower absolute values, which indicates more random prices. Overall, their results show that greater AT intensity leads to higher price efficiency.

Zhang (2010) investigates the role of HFT in incorporating fundamental information into asset prices by using all stocks covered by the Center for Research in Security Prices and Thomson Reuters Institutional Holdings databases between 1985 and 2009, with quarterly data on analyst forecast revisions and earnings surprises proxying for news about firm fundamentals. The lower-frequency dataset allows for the observation of a possibly longer-term impact of HFT, which is arguably more important from the perspective of market efficiency and resource allocation. Zhang suggests that HFTs' statistical arbitrage trading strategies fit the classical characteristics of short-horizon traders and are, therefore, likely to impact market efficiency. The author's findings show that HFT is negatively related to the market's ability to impound firms' fundamental information into prices. In addition, the market tends to overreact to a firm's fundamental news when HFT is at a high volume.

In short, greater HFT activity is found to have a positive association with price discovery, especially in research articles that utilise higher-frequency datasets. Regardless, as rebutted by Zhang (2010, p. 3), "it is unclear how a price discovery delayed by 50 milliseconds or 2 seconds would affect resource allocation efficiency in any meaningful way." Thus, to obtain a holistic picture of the effect of HFT on price discovery and efficiency future researchers should utilise datasets of various frequencies.

2.4.2 Liquidity

Theoretically, HFT could have both positive and negative effects on liquidity. The light-speed trading activity of HFTs is claimed to promote liquidity through rapid price adjustments, allowing for narrower bid-ask spreads within a market, strengthening intermarket linkages and activity (Goldstein et al., 2014), and lowering the cost of intermediation (Jones, 2013). However, the higher level of trading activity of HFTs cannot simply be an indicator of better liquidity in the market, since the HFTs can be on either side of the trades. Dominance in the supply side would lead to higher liquidity and narrower spreads, while greater trading activity on the demand side would remove liquidity from the market and widen spreads (Goldstein et al., 2014). For instance, the US Commodity Futures Trading Commission (CFTC) and SEC published a joint report (CFTC & SEC, 2010b) suggesting that, even though HFTs usually provide liquidity, during the flash crash of 2010, discussed later, they turned to consuming liquidity. Easley et al. (2011) suggest that their actions produce toxic order flow and can exacerbate any ongoing liquidity crisis. This behaviour of HFTs has led to calls for regulatory discussion and debate on whether to impose quotation obligations on HFTs and/or prevent them from high-speed quotation entries/deletions (Gomber et al., 2011).

Generally, market-making HFTs provide liquidity by matching buy and sell orders, or by buying and selling securities from their own inventories should they fail to immediately match buyers and sellers (Shorter & Miller, 2014). HFTs that engage as market makers use their speed advantage to quickly update quotes, and they profit from the difference between the price buyers are willing to pay and the ask price sellers are willing to accept for a security. Since this activity requires HFTs to maintain limit orders on both sides of the trades, it provides liquidity to the market (Chung & Lee, 2016). Riordan and Storkenmaier (2012) study the effect of a decrease in latency on market quality following the Deutsche Börse's release of Xetra 8.0 in 2007. The new trading platform was introduced solely to reduce system latency, with no other meaningful microstructure change. Following the introduction, system latency was reduced from 50 to 10 milliseconds. Riordan and Storkenmaier find significant reductions in spread measures, which indicate liquidity improvement in the market after the upgrade.

Even though the increasing competition in market making generally benefits the market, HFTs do not have an affirmative obligation to make the market like a traditional market maker or specialist. This raises concern that they could cause disruptions by fleeing the market at will (Carrion, 2013), for example, when it is no longer profitable (Anand & Venkataraman, 2013). The lack of constraining obligations also gives HFTs more flexibility to formulate market-making strategies beyond traditional means (Brogaard et al., 2014). To overcome this issue, certain trading venues have taken the initiative to offer liquidity rebates to attract market-making HFTs. This relation is mutually beneficial to both HFTs and the exchanges themselves. For rebate-paying exchanges, the rebate incentivises HFTs to route their orders to their exchanges, which translates into greater liquidity supply (Harris, 2015). To market-making HFTs, the rebate rewards them for their liquidity-supplying service (U.K. Government Office for Science, 2012). Studies find that HFT market makers would lose money in the absence of the rebate (Hendershott & Riordan, 2013), especially when transactions exhibit tighter spreads (Brogaard et al., 2014).

Goldstein et al. (2020) examine strategic order placement strategies employed by HFTs, using proprietary data on the Australian Securities Exchange. Their findings show that, on average, HFTs supply liquidity on the thick side of the order book, where depth is less needed, and demand liquidity on the thin side of the order book, where depth is much needed. Through the placement of strategic limit orders, HFTs initially submit their orders when a small order imbalance arises. If the order book imbalances continue to move in the same direction as the HFTs' initial orders, then the order would be left for execution. In the event of the order imbalances becoming less favourable, the HFTs will quickly cancel or amend their orders, which will exacerbate future order book imbalances. In short, while it is indeed true that HFTs supply liquidity to the market, they mostly do so when liquidity is less needed and shy away when liquidity is most needed. This behaviour is consistent with order anticipation strategies, and it is more evident during volatile periods and when trading is faster.

Aitken et al. (2018) highlight the importance of safeguarding not only market efficiency, but also market fairness, as part of the mandate by regulatory bodies such as ASIC (Australia), the SEC (United States), and the Financial Services Authority (United Kingdom). Using trade-to-trade data on all listed securities on the LSE and NYSE-Euronext Paris from 2003 to 2011, Aitken et al. (2018) find that higher levels of AT increases liquidity, as indicated by the smaller effective spreads across all stocks in London and top quantile stocks in Paris, all while maintaining the market fairness of either market. Higher levels of AT activity are also found to improve market fairness in top quintile stocks (by volume traded) in both markets, as evidenced by the decline in end-of-day price manipulation and information leakage.

2.4.3 Volatility

In a theoretical paper, Froot et al. (1992) show that short-term traders could demonstrate herding behaviour when reacting to one source of information, creating price dislocation and excess volatility. Their model shows that short-term traders could be relying too much on short-term information, even when it is not related to a firm's fundamentals at all, which, in turn, leads to price inefficiency. For example, technical analysts or chartists "use forecasting methods that appear, at best, tangentially related to fundamental values" (Froot et al., 1992, p. 1480), creating noise and hindering price discovery. Similarly, Jarrow and Protter (2012) theorise that HFTs' collective (but independent) reaction towards common signals could resemble the action of a large trader, which can create excessive price pressure and volatility.

Breckenfelder (2019) examines the effects of competition between HFTs on market quality using NOMX-St index stocks (OMX S30) as the sample, from June 2009 until January 2010. The author finds that HFTs' competition for trade increases intraday volatility but has no significant effect on interday volatilities, which is consistent with the typical behaviour of HFTs that close their positions at the end of each trading day, leaving no open position overnight. In addition, Breckenfelder shows that HFTs will behave more speculatively when an increase in their numbers in the market is accompanied by HFT competition, resulting in liquidity deterioration and higher short-term volatility. Similarly, Zhang (2010) finds that HFT is positively correlated with price volatility, even after controlling for stock fundamentals and explanatory variables for volatility, which could hinder the market's ability to impound firms' fundamentals into asset prices. The effect is stronger for the 3000 largest stocks by market capitalisation, for stocks with high institutional holdings, and during periods of high market uncertainty.

Shkilko and Sokolov (2020) investigate the effect of heavy precipitation shocks on HFTs' network speed. HFTs have been using microwave towers to gain a competitive edge over their rivals, since this technology is 30% faster than the nearest alternative, that is, fibre-optic cable. In addition, the microwave tower network is accessible to only a small group of trading firms (e.g. HFTs). Regardless, one major drawback of this network is that the speed is susceptible to precipitation, such as rain or snow, creating a speed differential between days with good and bad weather. Their results show that a higher level of fast trading (i.e. HFT) in the market is associated with greater volatility, as evidenced by their result showing lower volatility when precipitation is heavy.

Boehmer et al. (2018) show that HFTs do have highly correlated trading strategies. Coupled with their dominating presence, their actions can exacerbate price movements and increase short-term volatility. Using the S&P/TSX 60 Index stocks from June 2010 until March 2011 as the sample, Boehmer et al. investigate whether competition between HFTs affects the short-term volatility of individual stocks. Their results show that HFTs whose underlying common strategy is market making have a negative impact on short-term volatility. The authors find that HFT competition within this category reduces both the permanent and temporary price impact of trades, which explains the lower short-term volatility. These results are consistent with Hagströmer and Nordén (2013) finding that market-making HFTs are able to mitigate intraday volatility through their liquidity supplying activity.

2.4.4 Adverse Selection Costs

According to ASIC (2010, p. 15), in exchange market trading, there is a risk that the person you trade with is more informed than you are. If this is so, or you fear that this is so, you may respond by becoming more risk-averse, reducing the price at which you are willing to buy or increasing the price at which you are willing to sell. The consequence of such adverse selection is a widening of spreads. At an extreme, investors might decline to participate in trades or to not post limit orders. If many participants in a market act according to the principles of adverse selection, trading becomes encumbered and inefficient.

Some argue that the sheer speed of HFT causes slower investors to bear the cost of adverse selection (Jones, 2013). In a theoretical paper, Budish et al. (2015) develop a model in which market makers or traders that invest in speed will be the first to react and make profits from newly arrived public information. In the event of the traders receiving and reacting to news before the market makers do, the fast traders will trade with stale quotes, which imposes adverse selection costs on the market makers. This situation will discourage the provision of liquidity and, consequently, the market makers will include the cost of the adverse selection in their quotes, resulting in wider spreads and higher costs for slower investors.

Brogaard et al. (2014) argue that, should information eventually become public without the intermediation of HFTs, the adverse selection costs that slower traders have to bear could cause potential welfare gains from the faster price discovery to become trivial or even negative. Biais and Woolley (2011) also agree that, while the development of sophisticated and rapid trading algorithms can benefit the markets and investors through better price discovery and liquidity, they can be detrimental to slower traders, due to the adverse selection problem. In a similar vein, Biais et al. (2015) claim that, even though investment in fast trading does help address the issue of market fragmentation, it also comes with the risk of adverse selection to slow traders, decreasing social welfare. Scholtus et al. (2014) find evidence of deterioration of market quality around U.S. macroeconomic announcements. Using a 60-second event window around the release of news, they find that higher AT activity leads to lower depth and higher quoted spreads, adverse selection costs, and volatility measures.

It is also possible for the algorithm to be fed false information, either intentionally or accidentally. For instance, the price of United Airlines (UAL) stock suddenly crashed from US$12 to US$3 on September 8, 2008, for a 12-min period, during which shareholders lost approximately US$1 billion (Maynard, 2008). An investigation later revealed that the rapid drop was mainly due to the interplay between algorithms that reacted to a six-year-old headline that mistakenly hit a news feed. Human traders should not have been deceived by the headline blunder (Donefer, 2010). Similarly, two weeks prior to the UAL event, on August 27, 2008, Bloomberg News accidentally published an obituary for Steve Jobs, Apple's chief executive officer (Elmer-DeWitt, 2008). However, the blunder happened during off-trading hours and was quickly retracted (Donefer, 2010). These events do raise the question of whether the immediacy of information dissemination is always a good thing.

Shkilko and Sokolov (2020) show that, when network disruptions occur, the microwave towers used by HFTs lose their speed advantage, and adverse selection and trading costs decrease by up to 6.7 and 5.2%, respectively. These results hold even when tested using the long-term removal of speed differentials. In addition, the authors find higher trading volumes under such scenarios, consistent with the notion of greater gains from trades in the absence of ultra-fast traders. In a recent paper by Cartea et al. (2019) using NASDAQ's Historical TotalView-ITCH dataset, ultra-fast activity is associated with lower stock market quality as evidenced by higher quoted spreads, higher effective spreads, and lower limit order book depths. The results are also found to be economically significant and robust to different specifications, endogeneity tests, and alternative measures of ultra-fast activity.

In conclusion, scholars' understanding of the impact of HFT on market quality is still lacking, due to HFT's short time in operation and lack of high-quality data (Carrion, 2013). However, the empirical evidence on the impact of HFT on market quality is generally mixed. Despite many empirical studies finding positive effects of HFTs participation in the market, they cannot rule out the possibility that HFT could harm the market through predatory trading strategies (Manahov et al., 2014). Recent empirical evidence on HFT studies seems to be in favour of the latter view (e.g., Cartea et al., 2019; Goldstein et al., 2020; Shkilko & Sokolov, 2020). Regulatory bodies around the world either have implemented or are mulling over rules to contain and mitigate any HFT activity that has the potential to be detrimental to market quality (Benos & Sagade, 2016). It is generally agreed that any abusive or predatory trading activity, which goes against market integrity, should not be permitted. Nonetheless, regulators must be careful in formulating their regulations, to avoid any excessive regulations and constraints that could be counterproductive and have unanticipated effects on market quality. For example, any newly formulated regulation should not prevent beneficial HFT strategies that have positive effects on liquidity, such as market-making strategies, or price discovery and market efficiency such as arbitrage strategies (Gomber et al., 2011).

2.5 Controversies Relating to HFT

This section highlights the negative sentiment and controversies surrounding HFT. The identified controversies are (1) the flash crash of May 6, 2010, (2) the economic welfare of the arms race, and (3) HFTs' market-making obligations.

2.5.1 Flash Crash of May 6, 2010

On May 6, 2010, the U.S. financial markets were shocked with a short-lived yet severe drop in prices that happened within minutes. The sudden market crash of May 6, 2010, was later dubbed a flash crash, given its brief time frame. The CFTC and SEC released joint preliminary findings concerning the event on May 18, 2010 (CFTC & SEC, 2010a), and full findings were released later, on September 30, 2010 (CFTC & SEC, 2010b).

The U.S. financial markets opened on May 6, shrouded by negative market sentiment stemming mainly from the European debt crisis, causing the S&P 500 volatility index to rise by 22.5% from its opening level by around 2.30 p.m. Central Standard Time. This triggered investors to engage in a flight to quality, creating selling pressure that pushed the Dow Jones Industrial Average down by 2.5%. At 2.32 p.m., Waddell & Reed, a large fundamental trader, initiated a sell order algorithm to sell 75,000 E-mini (S&P 500 futures) contracts to hedge its existing equity position (CFTC & SEC, 2010a; Lash & Spicer, 2010). Initially, the selling pressure was absorbed by HFTs and other intermediaries in the futures market, followed by fundamental buyers and cross-market arbitrageurs, the latter transferring the selling pressure to the equities market.

From the Waddell & Reed Sell Algorithm order, HFTs accumulated a net long position in E-mini contracts, which led them to aggressively sell the contracts they held to reduce their inventories (CFTC & SEC, 2010b). Nearly 140,000 E-mini contracts (over 33% of the total trading volume) were traded by HFTs. The dramatic increase in trading volume raised the volatility in the market, which, in turn, scared long-term traders away. The lack of demand in the market caused HFTs to buy and sell from each other, generating a "hot potato" volume effect that drove the price of the E-mini down by 3% within a 4-min period. At the same time, cross-market arbitrageurs that bought the E-mini simultaneously sold equivalent amounts in the equity markets, driving the price of the S&P 500 SPDR (SPY) down by approximately 3% as well.

The combined selling pressure created a dramatic order imbalance in the market, pushing E-mini prices down by another 1.7% in a mere 15 seconds, to reach an intraday low of 1,056 points. At 2:45:28 p.m., the Chicago Mercantile Exchange's Stop Logic Functionality was triggered by the E-mini's rapid price decline, halting all E-mini trading for 5 seconds. After trading resumed at 2:45:33 p.m., the E-mini price stabilised and started to recover, thanks to opportunistic and longer-term traders that re-entered the market and rapidly accumulated long positions (Kirilenko et al., 2017). Subsequently, SPY also recovered.

Despite the E-mini's recovery, the prices of many other securities continued to show extreme volatility. Approximately 2 billion shares with a total value of more than US$ 56 billion traded between 2:40 p.m. and 3:00 p.m. on May 6. During this 20-min window, more than 98% of all shares were traded within 10% of their value at 2:40 p.m. However, some extreme trades were recorded. For example, Accenture plc (ACN) rapidly declined from about US$ 30 at 2:47:47 p.m. to US$ 0.01 by 2:47:54 p.m. and then recovered within a matter of a few more seconds (CFTC & SEC, 2010a). These extreme cases were caused by orders executed against stub quotes, which were triggered by the sudden loss of liquidity (Gomber et al., 2011). Stub quotes are quotes generated by market makers at levels far from the current market, to comply with the obligation to maintain continuous two-sided quoting. However, stub quotes are not intended to be executed (CFTC & SEC, 2010a).

Overall, over 20,000 trades (amounting to 5.5 million shares) across 300 different securities and exchange traded funds traded at prices 60% or more from their 2:40 p.m. prices. By 3:00 p.m., the prices of most securities had reverted to their rational values. After the market closed, the SEC and FINRA met and agreed to adopt the "clearly erroneous" trade rules, and thus, all trades classified as clearly erroneous were considered "broken trades." From the joint report, it is evident that HFTs did not trigger the flash crash. However, the repeated buying and selling of contracts executed by the automated systems created the hot-potato effect as HFTs competed for liquidity. Thus, their trading behaviour during a period of unusually high selling pressure on May 6 is perceived to have exacerbated the price declines and market volatility (Kirilenko et al., 2017). A study by Brogaard et al. (2018) supports the view that HFTs play a positive role in supplying liquidity in times of extreme price movements; however, when multiple extreme price movements occur simultaneously, such as with the flash crash, they can switch to being demanders of liquidity. Due to the May 2010 flash crash, HFT has received considerable critical attention from both the CFTC and the SEC (2010b) for creating excessive short-term volatility.

2.5.2 Information acquisition, social welfare issues, and the HFT arms race

HFTs' contribution to the process of price discovery can be beneficial, since more informative stock prices should lead to better resource allocation in the economy. However, some studies have questioned whether AT does, in fact, lead to more informative stock prices. Price informativeness relates to the degree to which firm-specific information is incorporated into prices. Weller (2017) shows that AT, which includes HFT, can reduce price informativeness, despite prior evidence of AT improving price efficiency. In measuring information content in prices, Weller examines the information content of stock quarter announcements using SEC data and shows that the information content in prices decreases by as much as 13% per standard deviation of AT activity. In other words, AT activity appears to detract from the information acquisition activities of other market players. Weller's (2017) work complements that of Baldauf and Mollner (2020). Baldauf and Mollner show that, while HFT leads to smaller spreads, it also leads to less intensive research and, therefore, less information production and less informative stock prices as informed traders are squeezed out, having less time to trade.

On a similar note, Menkveld (2014) agrees that the presence of market-making HFTs in electronic markets does improve welfare, by reducing informational frictions from nonsimultaneous order arrivals in the market. Another welfare benefit is proposed by Malceniece et al. (2019). Their study of Chi-X's entry into European equity markets shows HFT activity increases comovement in returns and liquidity. This improvement in comovement, or synchronicity, makes companies, particularly smaller ones, more attractive to large investors and, therefore, leads to more efficient pricing. However, the net welfare from HFT is questionable; the positive contribution from market-making activity can be negated when HFTs pick off investors' quotes at lightning speed on information that will surely reach marginally slower investors later.

HFTs acknowledge the importance of investing in hardware, software, and network capabilities to reduce latency in automated trading processes, motivated by the nature of the game where the winner takes all. The upgrades allow them to continuously refine their trading algorithms and win the arms race (Kauffman et al., 2015). Regardless of the fact that the technology arms race has significantly shortened transaction times the process does raise concerns about excessive spending without meaningful progress in market quality (Chung & Lee, 2016). The race among institutions to be the fastest is deemed unproductive, and the investment in the technological infrastructure required to reduce trading latency creates doubts as to whether HFT adds value overall (Chordia et al., 2013; Jones, 2013). In addition, Menkveld (2014) asserts that the technological investment itself could well be the source of a negative externality through the relative speed disadvantage it creates for others.

As Brogaard et al. (2015) note, not all HFTs choose to pay for colocation services, and there are many collocated non-HFTs. This suggests that not all HFTs have the need to be the fastest. The pursuit to be faster is relevant if and only if its benefits are greater than its costs. Baron et al. (2019) investigate the importance of superior relative latency on HFTs' performance on the NOMX-St. Their findings show that, by being among the fastest, HFTs with a passive (e.g., market-making) trading strategy experience lower adverse selection risk (i.e., have better risk management), and HFTs with an active trading strategy (e.g., news trading) are more responsive to new information. The authors also find high concentrations of trading volumes and trading revenues among the fastest HFTs, and these were nondeclining over their 5-year sample period.[4] Additionally, new HFT entrants are relatively slower, underperform, and are more likely to exit. These findings confirm that the small differences in latency have a substantial effect on HFTs' performance.

In a more recent study, Aquilina et al. (2020) use LSE message data to quantify the latency arbitrage race, allowing them to observe the details of the race between HFTs.[5] Their findings show that there is about one race per minute in every symbol traded on the FTSE 100; the winner is 5-10 milliseconds faster than the runner-up (i.e., the first loser); the races account for approximately 20% of the daily trading volume; the top six firms win about 82% of the races, but lose 87% of the

---

[4] The model of Baron et al. (2019) predicts that the average daily trading revenue of the five fastest HFT firms is SEK 15,451 higher than that of the other HFT firms. Being one of the top five fastest high-frequency traders is associated with earning an additional SEK 24,639, on top of their revenue.
[5] A limit order book provides a complete picture of all the messages that add liquidity to the order book, such as new limit orders, cancelled orders, and trades, time stamped with extreme precision. However, the message data record all failed attempts to trade or cancel, which is not captured by the limit order book because they failed to be submitted to it.

races; aggressive orders (e.g., quote sniping) win 90% of the races; the top six firms cumulatively supply about 42% of the liquidity in the races, while taking about 80%; and most of the liquidity taken by the winners is supplied by market participants other than the top six. In the aggregate, the small races collectively (i) make up a significant proportion of the price impact, (ii) create meaningful harm to liquidity, and (iii) add up to a substantial winning stake in the arms race, valued on the order of US$ 5 billion per annum in the global equity markets. Aquilina, Budish, and O'Neill also find that, by eliminating latency arbitrage, the cost of liquidity can be reduced by almost 17%.

Even without the issue of an arms race, HFTs still pose a threat to many, since they can use high-speed predatory trading strategies (see the harmful strategies discussed in Section 2.3.2), such as introducing "microstructure noise" that generates an unnecessary extra layer of intermediation between buyers and sellers, leading to higher price volatility and worse market quality (Cartea & Penalva, 2012).

2.5.3 Market-making obligations and excessive liquidity

Anand and Venkataraman (2013) study the trades of two types of market makers, designated market makers (DMMs) and ELPs. The main difference between DMMs and ELPs lies in their obligation to make the market. DMMs, or specialists, are bounded by specific obligations imposed by the exchange, that is, to maintain a market presence by continuously posting quotes with reasonable depth. ELPs, on the other hand, employ market-making strategies because of their profitability, with no affirmative obligations to maintain markets. Anand and Venkataraman (2013) state that HFTs are the most active market makers in financial markets today, where some position themselves as ELPs, meaning that they are likely to supply liquidity whenever it is profitable for them to do so. They will cease providing liquidity when facing large adverse selection risks (Chung & Chuwonganant, 2018) or whenever market conditions are unfavourable for them to make profits. This is more likely to happen in times of high market uncertainty (Zhang, 2010).

The lack of commitment to make the market, especially in times of market stress and in thinly traded securities, raises concerns among practitioners and regulators. HFTs' optional market making can exacerbate execution uncertainty, and, thus, the liquidity supplied by HFTs is deemed unreliable, which can reduce investors' confidence and participation. Liquidity withdrawals by HFTs can thin out the order book, which can induce extreme market movements (Gomber et al., 2011). Such a situation could also be the underlying reason for the heightened sensitivity of liquidity and returns to market volatility in the HFT era. Furthermore, non-HFTs are playing on an uneven playing field, because of their technological inferiority with respect to HFTs, and they could find that the market is unfair and, consequently, stop participating altogether (Anand & Venkataraman, 2013). In response to this potential problem, regulators considered imposing quotation obligations on HFTs and/or preventing them from engaging in high-speed order entries and cancellations (Gomber et al., 2011).

2.6 Responses to HFT

Due to the potential harm caused by the earnings model of predatory HFTs, regulatory bodies and scholars around the world have introduced or proposed various measures such as speed bumps, price improvement rules, and new trading mechanics to ensure a fair and orderly market.

In 2013, the Investors Exchange pioneered the use of speed bumps to slow down traffic by intentionally delaying order messages submitted to and from its trading platform. The Investors Exchange speed bump symmetrically delays all orders by 350 milliseconds, using a 61 kilometres fibre-optic cable near its trading engine. Nonetheless, this speed bump design affects not only liquidity takers (e.g. order snipers), but also liquidity providers (e.g. market makers). Therefore, several other exchanges have introduced variations in the mechanics of speed bumps, designed to asymmetrically affect predatory latency arbitrageurs.[6] In an experimental study, Khapko and Zoican (2020) show that asymmetric speed bumps reduce investment in the arms race by 20%, and, by increasing the lengths of the speed bumps by one standard deviation, the endowment is further reduced by 8.33%.[7]

[6] See Baldauf and Mollner (2020) for a list of exchanges worldwide that implemented or proposed the use of speed bumps.
[7] In Khapko and Zoican's study, one standard deviation of the speed bump corresponds to 2 seconds, or 40% of the unconditional exchange latency.

Their findings also suggest that symmetric speed bumps have no effect on reducing the arms race investment and are equivalent to having no speed bump at all.

Dark trading, which is conducted in dark pools as opposed to disclosed trading conducted in "lit" markets, is used by institutional investors to trade large positions that, if sent as a single order to the market, could spark large price movements. Dark trading also allows institutional investors to hide their large orders from the public, giving them a better chance to implement their trading strategy. However, by sending pinging orders, HFTs are able to detect hidden liquidity and take strategic positions against the large hidden orders, making a profit at the cost of institutional investors. In 2013, ASIC introduced a new market integrity rule that require below block size dark trades to be executed at an "improved price," a price at least one tick size better than the prevailing best bid or ask price, or the midquote on lit exchanges. The price improvement rule protects the interests of investors posting orders on the lit exchange and disincentivises predatory HFTs from conducting a latency arbitrage strategy, due to the higher spread in the dark pools. ASIC (2015) reports that, after the implementation of the new rule, the percentage of block trades against total turnover increased by 46%, while the percentage of trades below a block decreased by 22%. This development aligns with the original purpose of using dark trades, that is, to facilitate the trading of large orders.

Budish et al. (2015) claim that the arms race is socially wasteful, but its existence is actually a symptom, stemming from a flaw in the architecture of modern financial exchanges that use continuous-time trading, which also creates adverse selection rents that attract HFT. Budish et al. suggest that the problem can be addressed by using frequent batch auctions, which will create a discrete-time market to replace the current market design, which is based on the continuous limit order book. All orders received in the same batch (i.e., time interval) are treated equally, and that with the best price (i.e., highest bid or lowest ask) will be matched first. This encourages competition on price rather than speed, thus, reducing the incentive to place an order first. This approach will render the tiny speed advantage much less valuable, intuitively ending the arms race. However, Yao and Ye (2018) find evidence that, even with discrete timing, HFTs could continue to race against each other, this time competing for rents from the queuing channel, originated from yet another microstructure design element, the tick size.

At the opposite end of the spectrum, Kyle and Lee (2017) propose fully continuous exchange where buyers and sellers use a new type of order, called a continuous scaled limit order. The new type of order requires traders to supply five parameters: (i) a buy or sell indicator, (ii) the maximum quantity, (iii) the lowest price, (iv) the highest price, and (v) the maximum trading speed (shares per hour). For example, a buy order message is read as “buy up to the maximum quantity of shares, between the lowest and highest prices, at the maximum buying rate per hour.” The exchange would calculate the market clearing price (to the nearest one-tick price increment) that satisfy all flows of demand and supply submitted to the market. The trading mechanism slices the trading volumes and gradually spread them over time, allowing large orders to continuously flow into the market. This approach removes the need for large traders to self-determine their optimal trade size. In the event of changes in fundamentals, fast traders would still have the upper hand in updating their orders. This advantage, however, is limited by the flow rate of trade set by slow traders, which limits the quantity of shares fast traders can trade, hence, reducing slow traders’ adverse selection costs. Kyle and Lee (2017) suggest that a continuous scaled limit order would address the harmful incentives created by the discreteness in price, quantity, and time found in conventional limit orders.

2.7 Conclusions

Since the advent of the infamous flash crash of 2010, HFT has gained considerable attention from regulators, researchers, and others following or involved in stock markets. Even though almost a decade has passed since, there is still no standard or universal definition for HFT. The lack of a precise definition leads to other problems such as inaccurate estimations of HFTs’ market shares and influence. This also complicates the process of researching HFT, which leads to the various conclusions on the actual effect of HFT on the market. Nonetheless, five traits are commonly associated with HFT: (1) a specialised form of AT, (2) the use of high-speed, sophisticated computer programs and systems, (3) very high order-to-transaction ratios, (4) extremely short average holding periods, and (5) ending the trading day with flat positions. Using these unique characteristics, researchers have teamed up with regulators and exchanges to accurately identify HFT activity in the market, as depicted by the NASDAQ HFT dataset. Alternatively, researchers with access to order book-level information can use commonly used HFT proxies, such as the OTR, which measures quoting intensity, or even Hasbrouck and Saar's (2013) *RunsInProcess*, which is based on HFTs' dynamic and low-latency order placement strategies.

Using fully automated trading strategies, HFTs attempt to identify and profit from short-term irregularities and earn small amounts of money from every trade. The ability to trade at low latency allows HFTs to profit from the trading environment itself. HFTs exhibit variability in their trading strategies by documenting differences in liquidity provision, end-of-day and maximum intraday positions, and trading revenues, for example, Benos and Sagade (2016). The algorithms HFTs employ can determine their order execution style, such as being aggressive or passive, or sending orders as either one trade or split into smaller trades. Aldridge (2013) generally categorises HFT strategies into statistical arbitrage, directional strategies, and market making, where all three are considered beneficial strategies. Nonetheless, HFTs can also employ harmful strategies, such as front running, spoofing, and quote stuffing, utilising their superior speed to make a profit and prey on slower traders.

Generally, the scholarly evidence on the impact of HFT activity on market quality is mixed. For instance, Boehmer et al. (2020) and Hendershott and Riordan (2013) find that HFT participation leads to faster price discovery and makes pricing more informative. Market-making HFTs are found to provide liquidity by matching buyer and seller orders, which promotes liquidity in the market (Shorter & Miller, 2014). HFTs' speed is also found to reduce adverse selection costs in market making (Jovanovic & Menkveld, 2016). On the contrary, Zhang (2010) finds that HFT negatively affects the market's ability to incorporate firm's fundamental information into prices. The CFTC-SEC (2010b) joint report finds that, though HFTs usually provide liquidity, in periods of high uncertainty, they consume liquidity. Further, HFTs' speed-driven advanced access to value-relevant information can also incur adverse selection costs for slower traders in the market (Biais et al., 2015).

CHAPTER THREE:
ESSAY TWO
RELATIVE TICK SIZE AND HIGH-FREQUENCY TRADING

This chapter shows the effect of relative tick size on HFT activity. The chapter starts with the introduction of the essay, which covers the background of the study and research motivation. The chapter continues with literature review and hypotheses development, followed by methodology, findings, discussions, and conclusion.

3.1 Introduction

The tick size, also known as the minimum price variation, is defined as "the smallest amount by which share prices are permitted to fluctuate. It determines the prices at which orders may be entered. Orders may only be entered at prices that are evenly divisible by the minimum tick size" (ASIC, 2010, p. 84). Smaller tick sizes are clearly important in the HFTs technique because they result in lower bid-ask spreads, which directly affect minimum trading costs (Comerton-Forde, 2012; Harris, 1994). Regardless, this does not mean that smaller tick sizes are always beneficial – a tick size that is too small may negatively impact the interaction between different types of investors in the market. This may occur, for instance, when a trader obtains execution priority by placing a limit order with a trivially better price, allowing them to skip the order book queue.[8] This circumstance might hamper other investors' willingness to disclose their orders, hence impeding HFTs participation in the market and causing a reduction in market depth (Chordia et al., 2011; O'Hara, Saar, & Zhong, 2019; Yao & Ye, 2018).

Angel (1997, 2012) emphasises the importance of tick size in market regulation, and he explains why the optimal tick size is not zero: (1) a non-zero tick simplifies traders' information sets, (2) an economically significant (i.e. non-trivial) tick size preserves price and time priority in an order book, which incentivises

[8] Orders submitted to the market are queued based on price-time priority. This indicates that orders are executed based on the best price, and if several orders share the same price, the order with the earliest time is executed first.

traders to provide liquidity by posting limit orders, and, (3) tick size creates a floor for the quoted bid-ask spread, which works as an incentive for dealers to make markets. The narrowest bid-ask spread is one tick size; hence, a bigger tick size increases the minimum transaction costs for investors by widening the bid-ask gap. Furthermore, tick size restricts the number of possible price points and decimals that can be stated, making it easier for human traders to understand the actual market situation. This problem, on the other hand, does not affect algorithmic traders, as their trading bots should be able to comprehend complex numbering without difficulty.

3.2 HFT in Australia

In 2009, Recommendation 4.5 of the Johnson Report underlines the need to increase competition on exchange-traded markets which is expected to lower costs and offer more options for market players.[9] Subsequently, Chi-X Australia was launched as an alternative to the ASX, and since its inception, it has employed a maker-taker pricing model, charging a fee of 0.06 basis points for liquidity providers and 0.12 basis points for liquidity takers.[10,11] In response, ASX lowered its headline trade execution fee from 0.28 basis points to 0.15 basis points in June 2010 and established its own low-latency alternative trading venue, ASX PureMatch, in November 2011. The new trading platform directly competes with Chi-X Australia for HFTs' market share, and it aims to "meet the growing needs of the trading community for order books that offer the most liquid stocks across the fastest available platform" (ASX, 2011). Consequently, these innovations provide a trading environment with fragmented markets, low-latency trading platforms, and low explicit trading fees, which, together with the inherently small tick sizes used in Australia, may stimulate an increase in HFT activity (Comerton-Forde, 2012).

---

[9] The report was originally titled as "Australia as a Financial Centre – Building on Our Strengths," and it was released by the Australian Financial Centre Forum. Later on, the report became commonly known as "The Johnson Report" due to the name of its chairman, Mr. Mark Johnson, the former Deputy Chairman of Macquarie Bank.

[10] On October 25, 2011, Chi-X began operations with a "soft launch" in which only a few stocks were available for trading. Following the success of the launch and ASIC approval, Chi-X Australia fully operates on November 9, 2011, trading all S&P/ASX 200 constituent stocks and ASX-listed exchange traded funds (ETFs).

[11] A liquidity provider is a passive limit order placed on the market that increases the depth of the order book, whereas a liquidity taker is an aggressive market order that seeks to match against a passive limit order and thereby decreases the book's depth.

The maker-taker pricing model incentivises traders to provide liquidity, where the liquidity "maker" is compensated with a rebate (or charged a lower transaction fee) for the limit order they placed, whereas the liquidity "taker" is charged a higher transaction fee for the market order they submitted. The exchange's profit is the difference between the transaction fees collected and the rebates provided. Studies find that without a rebate, HFTs potentially lose money on their market-making operations, which might discourage them from providing liquidity (Brogaard et al., 2014; Hendershott & Riordan, 2013). In Australia, the ASX and CHIX have different pricing model, where the former charges a similar fee to both liquidity providers and takers, whereas the latter subsidised liquidity providers only. Therefore, market-making HFTs would naturally prefer trading on the CHIX since they would be more resistant to issues that may erode their profitability, such as tick size reduction, and thus able to continue providing liquidity on the CHIX due to the presence of a liquidity rebate.

Figures 3.1, 3.2, 3.3, and 3.4 depict the estimated level of HFT activity in Australia based on the message-to-trade ratio (MTR), the algorithmic trading ratio (ALGO), the total number of high-frequency order identifiers (HFO), and the HFO's message ratio (HFOR), which are the HFT proxies employed in this study.[12,13] A closer look at the HFT measures employed indicates that CHIX has greater HFT activity when estimated by MTR or ALGO, whereas HFO and HFOR suggest that ASX has consistently higher HFT activity. Trends analysis shows an increase in HFT activity on the ASX from 2008 to 2017, with the uptrend being most pronounced in 2010 and 2011, which may be attributable to the regulatory agencies' initiatives to promote HFT. The subsequent decline observed from 2012 to 2014 is presumably due to competition from CHIX for HFT's market share, resulting in some HFT activity shifting to the new trading venue. Since 2015, however, the contrasting trend between the ASX and CHIX markets has been more evident, with HFT activity rising in the former and declining in the latter, implying that the ASX has become the preferred platform for HFTs in Australia in recent years.

[12] In the latter section of this essay, the method used to derive these measures is described in detail.
[13] The figures adopt a distinct y-axis for the ASX and CHIX values due to the substantial disparities in their values; this enables the study to highlight the differences in trend between the two markets.

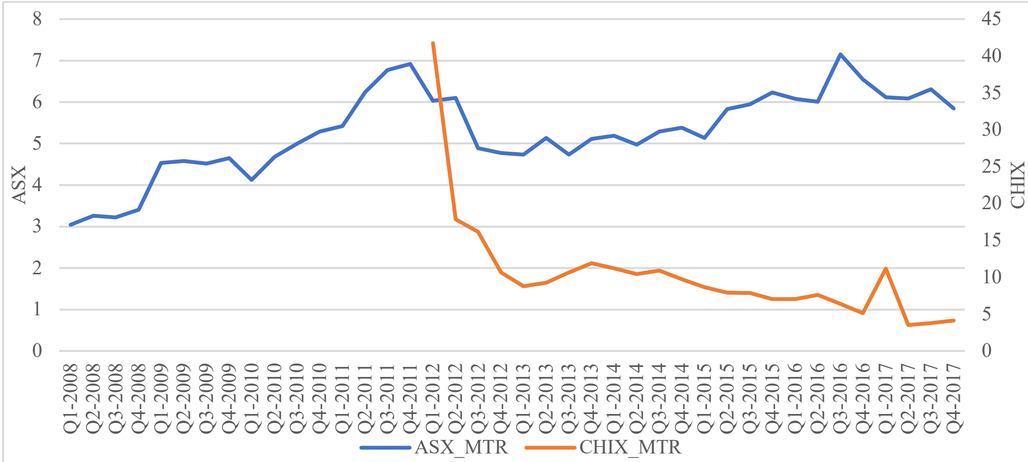

Figure 3.1: Quarterly average of message-to-trade ratio (MTR) in Australia

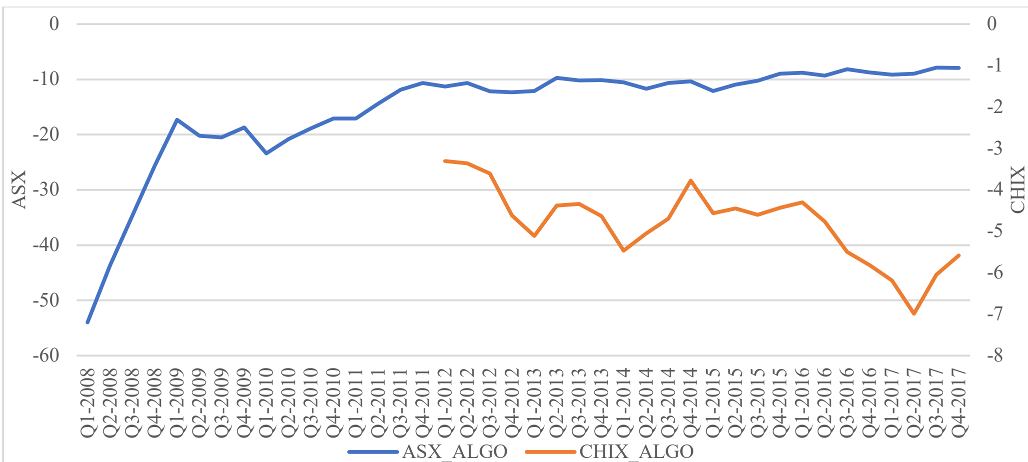

Figure 3.2: Quarterly average of algorithmic trading ratio (ALGO) in Australia

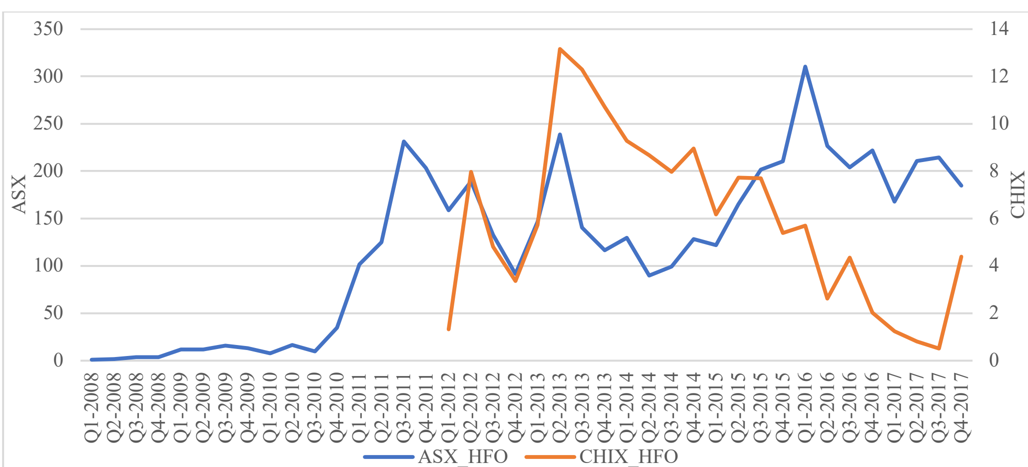

Figure 3.3: Quarterly average of high-frequency order ID (HFO) in Australia

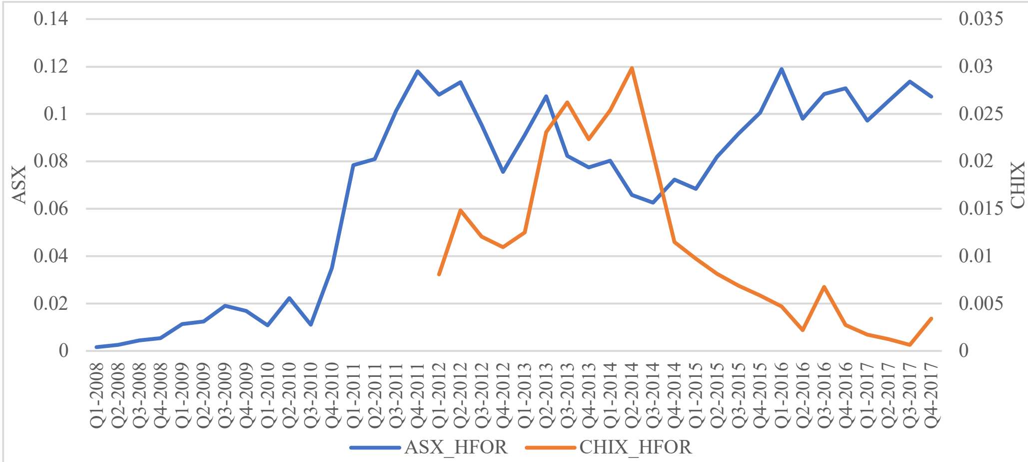

Figure 3.4: Quarterly average of HFO's message ratio (HFOR) in Australia

3.3 Tick size structure in Australia

In the Australian equity market, there are three nominal tick sizes: (i) A$0.001 (one-tenth of a cent) for stocks priced below A$0.10; (ii) A$0.005 (half-cent) for stocks priced between A$0.10 and A$1.995; and (iii) A$0.01 (one cent) for stocks priced at or above A$2.00. This structure generates two tick size borders at A$0.10 and $2.00. Relative tick size, which is defined as nominal tick size divided by stock prices, is the smallest price variation expressed as a percentage of a stock's price. Therefore, the presence of tick size borders results in a substantial disparity between the relative tick size of stocks priced on opposing sides of the border. O'Hara et al. (2019) assert that "a larger relative tick size benefits HFT firms that make markets on the NYSE: they leave orders in the book longer, trade more aggressively, and have higher profit margins", implying that a large relative tick size may incentivise liquidity-providing HFTs to participate. In other words, relative tick size can be perceived as the profit potential that HFTs can earn from a single tick of price change in a transaction.

The tick size borders in Australia results in stocks priced at A$0.099 and A$0.10 will have relative tick sizes of 1.01% and 5.00%, whereas those priced at A$1.995 and A$2.00 would have relative tick sizes of 0.25% and 0.50%, respectively. The discontinuity in the relative tick size values observed at the A$0.10 and A$2.00 borders is presented in Figure 3.5, which shows a significantly different profit potential for HFTs' limit orders placed near the borders, which might influence their trading strategy. Figures 3.6 and 3.7 provide a closer look at the dynamics between relative tick size and stock price around the respective borders.[14]

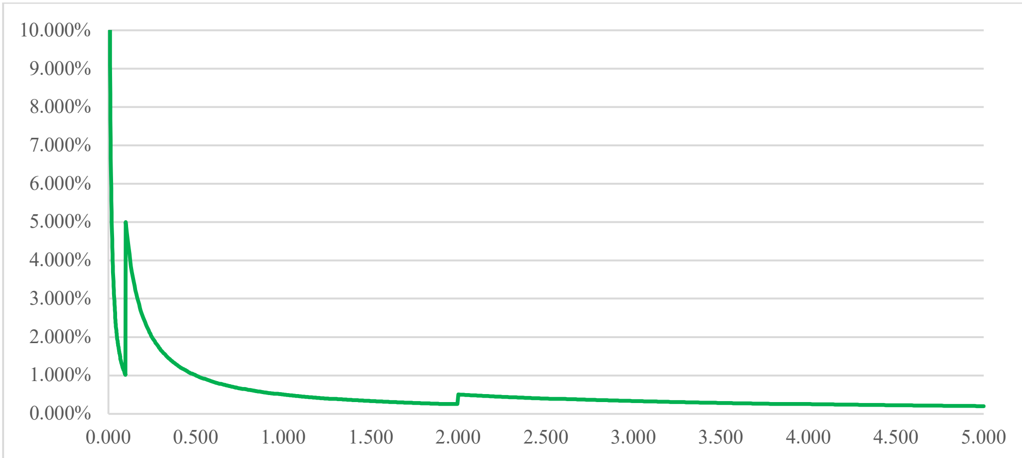

Figure 3.5: Relative tick size for stock prices ranging from A$0.01 to A$5.00

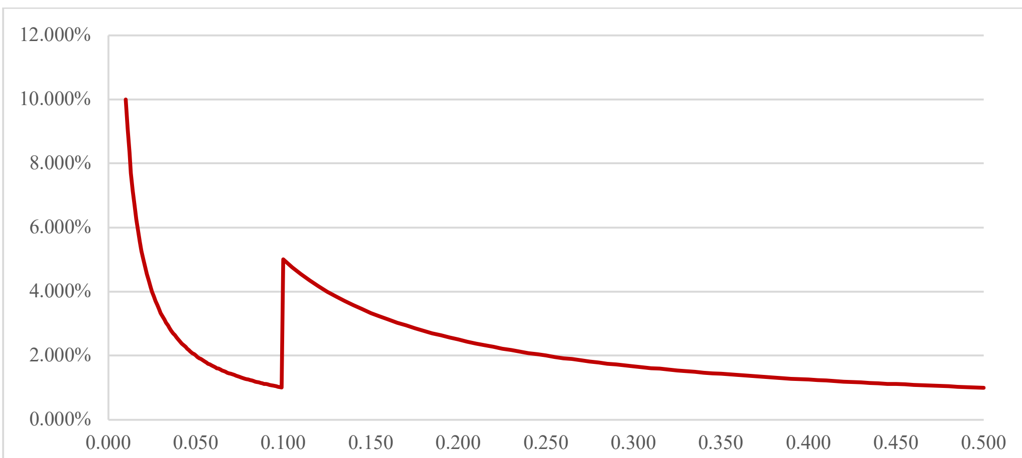

Figure 3.6: Relative tick size for stock prices surrounding the A$0.10 border

[14] The scale used for the Y-axis in Figure 3.6 is ten times larger than the scale used in Figure 3.7.

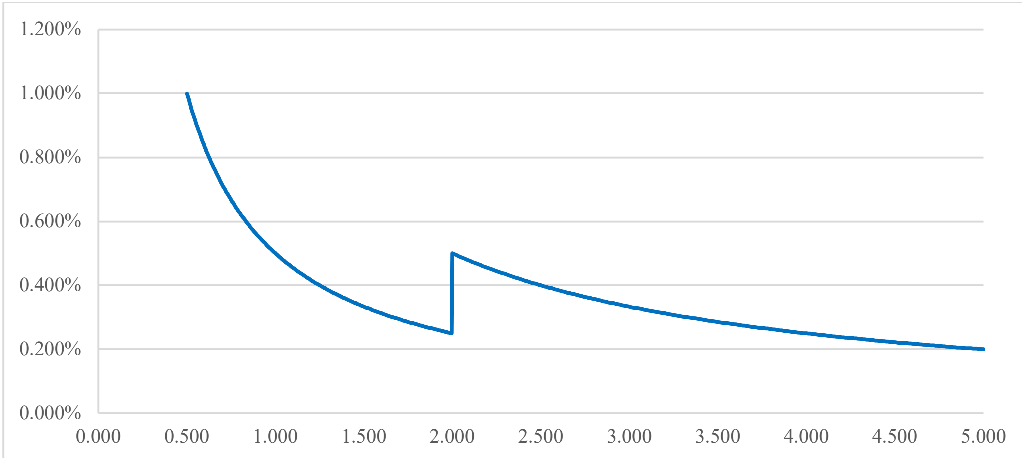

Figure 3.7: Relative tick size for stock prices surrounding the A$2.00 border

Table 3.1 shows the differences in tick size structures and relative tick size values between the Australian and American markets. For all stocks traded on the U.S. equity market, there are only two nominal tick sizes: US$0.0001 (one-hundredth of a cent) for stocks valued less than US$1.00, and US$0.01 (one cent) for stocks priced more than or equal to US$1.00. The tick size structure of the U.S. market results in a substantial disparity between the relative tick size values of stocks priced near the border. For instance, a stock priced at US$0.9999 and US$1.00 will have a relative tick size value of 0.01% and 1.00%, respectively, signifying an almost 100-fold increase while being separated by just one tick. In comparison, the largest relative tick size increase in Australia is fivefold, which is only one-twentieth of what observed in the U.S. market. Therefore, the variations in tick size structure employed in these two markets may necessitate HFTs to use a different trading approach to make profit, which could affect their overall presence and influence on the market they operate in.

In addition, stocks in the Australian market inherently have no designated market-maker, which presents an opportunity for HFTs to voluntarily undertake this role by leveraging their speed advantage. From this perspective, Australia appears to offer a more fertile ground for HFTs to succeed as a liquidity provider than the U.S., where there are already market-makers and market specialists, and thus greater competition for providing liquidity. Therefore, HFTs in Australia may be less likely to employ an aggressive, liquidity-taking trading approach that is detrimental to other market players, and may instead allocate more resources towards market-making activities.

Table 3.1. Tick size structure in the Australian and U.S. equity markets

This table compares the tick size structures applied in the Australian and U.S. equity markets. Tick size refers to the nominal tick size used in each market. The relative tick size is calculated by dividing the nominal tick size by the price.

Australia (A$)			
Price Range	\$0.001 - \$0.099	\$0.100 - \$1.995	\$2.00 - \$99,999,990
Tick Size	\$0.001	\$0.005	\$0.01
Highest relative tick size	100.00%	5.00%	0.50%
Lowest relative tick size	≈1.01%	0.25%	≈0.00%
United States (US$)			
Price Range	p < \$1.000	p ≥ \$1.000	
Tick Size	\$0.0001	\$0.01	
Highest relative tick size	100.00%	1.00%	
Lowest relative tick size	≈0.01%	≈0.00%	

Furthermore, the minimum trading unit in Australia also differs from that in the U.S., where all equities in the latter market must be traded at a minimum of 100 units per board lot, and trading with odd lots results in a higher trading cost. On the contrary, the mandated minimum trading unit in Australia is one unit, which gives all traders, including HFTs, the opportunity to trade at any unique combination with no additional cost.[15] Trading in Australia gives HFTs more flexibility in formulating their strategy because they are not bound by the minimum trading unit. Due to the smaller minimum trading unit, large institutional traders in Australia may have a better opportunity to hide their huge orders among retail orders in the market by "re-packaging" their single large orders into multiple smaller orders, as opposed to those in the U.S. market. This trait may impair HFTs' ability to detect approaching large orders, making it more difficult for them to "ride the wind".

Empirical studies on tick size are mainly centred in the U.S. financial markets (see for example Angel, 1997; Bessembinder, 2003; Gibson, Singh, & Yerramilli, 2003; Goldstein & Kavajecz, 2000; Jones & Lipson, 2001; Lipson & Mortal, 2006; O'Hara et al., 2019; Schultz, 2000; Yao & Ye, 2018). However, the aforementioned

[15] This is compared to the higher fees charged for odd-lot trading in markets with a minimum trading unit of greater than one.

argument suggests that the differences in the underlying architecture of the Australian and American markets may influence HFTs' strategy, activity, and behaviour, pushing them to operate differently in each market. In summary, factors such as a distinct tick size structure, the absence of a designated market-maker, and a more flexible minimum trading unit policy, provide a unique trading environment for HFTs in Australia. Therefore, the results of this research, which utilises the Australian dataset, contribute to a better understanding of HFT, notably on the influence of tick size on their behaviour and strategy in a pure order-driven market.

3.4 Literature review and hypotheses development

3.4.1 Nominal and relative tick sizes

In a frictionless market, the bid-ask spread, which is simply the difference between the lowest ask price and the highest bid price, would theoretically settle at a level that compensates liquidity providers exactly for the value received by liquidity takers (Linton et al., 2013). In practise, however, markets do have frictions due to factors such as information asymmetry, illiquidity issues, and costs deriving from the market's architecture, such as nominal tick size (see e.g.: Amihud et al., 2005; Biais et al., 2005; Fama, 1970). As a result, these frictions ensure that the bid-ask spread is always greater than zero.

Tick size is the minimum price increment or pricing grid that constraints market participants from submitting quotes in increments smaller than the mandated tick size value. Most stock exchanges around the world operate under a fixed tick size regime, wherein the regulator nominates a tick size value that is applied to all stocks. As shown in the previous section, it is not uncommon for different nominal tick sizes to be assigned to distinct, non-overlapping price ranges; however, the nominated value will remain constant within its specified range. On the other hand, the relative tick size is dynamic and sensitive to stock price movements and changes in nominal tick size. A relative tick size may be shocked when: (i) a regulatory body revises an existing tick size value; (ii) a stock price naturally crosses a tick size border; and (iii) a corporate action or informative event causes a substantial shift in stock price. O'Hara et al. (2019) propose that relative tick size provides fund managers with a clearer understanding of the transaction costs incurred when trading a certain dollar amount of fund compared to nominal tick size, which simply displays the quoted cost in cents.

A number of studies have shown that the size of a nominal tick or relative tick may have a substantial impact on the profits and decisions made by liquidity providers and liquidity takers (e.g., Angel, 1997; Foley et al., 2019; Foley et al., 2022; Glosten, 1994; Li et al., 2021; Mahmoodzadeh & Gençay, 2017; O'Hara et al., 2019; Werner et al., 2019; Yao & Ye, 2018). A liquidity provider is, by definition, a trader who posts a limit order at a specified price and quantity on the market and then waits for a trade to occur; hence, they are considered passive or patient traders. A liquidity taker, on the other hand, is a trader who submits a market order to accept a posted limit order, resulting in an immediate trade. Therefore, liquidity takers are regarded as aggressive or impatient traders (Li et al., 2021; Yao & Ye, 2018). In most markets, orders are executed based on price-time priority, where a limit order with the best price is given execution priority, and for the same price, an order with the earliest submission time is at the head of the queue (O'Hara, 2015; Parlour & Seppi, 2008). To obtain execution priority over an existing limit order on the market, a liquidity provider must improve the current price by submitting a limit order with a better price that is at least one tick above the highest bid price or one tick below the lowest ask price.

Predominantly, a trade will occur when a limit order placed by a liquidity provider is matched with a market order sent by a liquidity taker (Li et al., 2021). Therefore, it is imperative that market conditions are favourable for both parties, which can be estimated by the bid-ask spread. The limit orders that liquidity providers place to make market allow them to purchase at the bid price and sell at the ask price. Given that the bid price is always lower than the ask price, the spread represents their potential profit and incentive to engage in market-making. In contrast, the market orders that liquidity takers use to match against existing limit orders would prompt them to purchase at the ask price and sell at the bid price. Since their purchase price is higher than their selling price, the spread is treated as a transaction cost. For this reason, although a larger tick size offers greater trading incentives that may encourage more engagement from liquidity providers, it also reflects higher transaction costs that may discourage liquidity takers from participating, resulting in no trades. Therefore, establishing an optimal tick size requires a trade-off between the trading incentive for liquidity providers and the transaction costs for liquidity takers (Bacidore, 1997; Bourghelle & Declerck, 2004; Cordella & Foucault, 1999; Goldstein & Kavajecz, 2000; Harris, 1991, 1996; Werner et al., 2019).

3.4.2 HFTs as market-makers

In modern stock markets, designated market makers with contractual obligations to provide liquidity have almost disappeared in modern electronic markets (Clark-Joseph et al., 2017). With the advent of electronic limit order books, any participant can provide liquidity through limit order placements, thereby lowering the entry barrier into the market-making business. This has fostered market-making competition, resulting in the traditional market makers being overtaken by voluntary market makers (Foley et al., 2019). Theoretically, voluntary market makers compete primarily on price and speed (Glosten, 1994; Aït-Sahalia & Sağlam, 2017; Li et al., 2021). However, in situation when the bid-ask spread is precisely equal to one tick, there is no price level at which a liquidity provider may obtain execution priority in the market through price improvement.[16] Therefore, the nominal tick size is argued to be constraining price competition among liquidity providers, forcing them to compete solely on the basis of the time priority rule.

This market setting, which rewards execution priority to the fastest trader, incentivises competing participants to engage in a technological arms race to lower latency (Budish, Cramton & Shim, 2015; Foley, Gorbenko & Ruf, 2019; Yao & Ye, 2018). In addition, studies suggest that the speed advantage of HFTs allows them to cancel their limit order once it becomes obsolete due to the arrival of new information, hence avoiding their orders from being adversely selected (Jones, 2013; Menkveld, 2016). Therefore, HFTs would naturally assume the role of market-makers due to their reduced operating costs, adverse selection costs, and inventory costs. When paired with their superior speed, these lower costs should provide them with a competitive edge in the provision of liquidity for stocks with a greater adverse

[16] Using high-frequency data from the Australian stock market, Foley et al. (2019) discover that most stocks in their sample had bid-ask spreads of exactly one tick, with the average and median stocks being tick-constrained 85.30% and 92.41% of the time, respectively.

selection risk (see, e.g., Aït-Sahalia & Saglam, 2017; Brogaard et al., 2015; Carrion, 2013; Hagströmer & Nordén, 2013; Han et al., 2014; Hoffmann, 2014; Menkveld, 2013).

3.4.2.1 Large tick size and order-queuing activity

A one-tick spread between the bid and ask prices reflects the smallest profit that liquidity providers could earn by disclosing their private information through limit orders placement. Thus, a larger relative tick size would correspond to a larger profit from market-making activity, resulting in an increase in the number of limit orders placed on the market (Angel, 1997). In a recent study by O'Hara et al. (2019), a larger relative tick size is found to incentivise HFT market makers to be more aggressive, such that they would leave limit orders in the book longer and post a better price than the resting limit orders, resulting in improved prices. Nonetheless, they also show that this effect varies substantially depending on whether the bid-ask spread is equal to one tick (i.e. constrained) or multiple ticks (i.e. unconstrained). In tick-constrained stocks, a larger relative tick size would lead to more depth in the limit-order book due to order-queuing activity; in tick-unconstrained stocks, it would result in less depth since the HFTs may undercut the existing queue through price improvement. This suggests that HFT activity could impose adverse selection costs on less informed traders, and that they are more inclined to do so when the financial benefit is larger.

Yao and Ye (2018) show that tick size creates rents for liquidity provision, and the revenue margins for liquidity provision are higher for stocks with larger relative tick sizes. Higher rents incentivise HFTs to place more limit orders, which lengthens the queue to provide liquidity at the best bid and ask prices. This circumstance discourages market-making HFTs from cancelling limit orders once they have reached the front of the queue. When the nominal bid-ask spread is constrained to one tick, non-HFT liquidity providers will have no opportunity to improve prices, and since they cannot compete with HFTs' speed, they will be forced to use market orders, even when doing so is more costly. In short, a large relative tick size would crowd out the liquidity-providing activities of non-HFT participants. Hasbrouck and Saar (2013) argue that even though the algorithms deployed by non-HFTs entailed the use of limit orders, their objective was not to make profits from liquidity provision, but instead to minimise their transaction costs through, for example, splitting up large orders into smaller fragments and submitting them to multiple exchanges. Hence, the differing motivations allow non-HFTs to quote tighter bid-ask spreads than HFTs, since they suffer lower opportunity costs for placing limit orders (Li et al., 2021).

In addition, Foley et al. (2019) suggest that stocks with a large relative tick size are likely to be tick-constrained, forcing limit orders to queue at the best bid and ask prices and resulting in substantial depth at these levels. This discourages HFT market-makers from cancelling their limit orders, as resubmission would place them at the end of the queue. As a result, HFTs must accept greater adverse selection risks to maintain their execution priority, preventing these risks from being transferred to slower non-HFT market-makers and allowing them to provide liquidity. In summary, a coarser pricing grid or larger relative tick size creates a more favourable environment for market-making HFTs to provide liquidity and reduces their adverse selection costs due to restrictions on price competition and enforcement of time priority, particularly in tick-constrained stocks.

3.4.2.2 Small tick size and order-undercutting activity

A smaller tick size results in a finer pricing grid, which reduces the cost to undercut a standing limit order. Chordia et al. (2013) raise concern that HFTs might exploit this condition by using their superior speed to crowd out liquidity provision from slower participants. Non-HFT investors may witness a narrower spread due to HFTs' competition for liquidity provision, however the lower probability of their limit orders being executed raises questions about whether HFT is actually beneficial to the market. In reality, non-HFT investors may be forced to take liquidity to execute their strategy, which unnecessarily increases their overall transaction costs. Consequently, the general welfare may decline if the benefits of faster speeds are outweighed by the potential increase in aggregate costs. In a similar vein, O'Hara et al. (2019) suggest that theoretically, a smaller tick size allows HFT market makers to impose adverse selection costs on other traders by engaging in order-undercutting activities. The capacity of HFTs to swiftly monitor price-sensitive public information enables them to make informed decisions by deliberately undercut the best bid (ask) limit order if incoming news is anticipated to be positive (negative) for stock prices.

This scheme reduces (increases) the likelihood that non-HFT liquidity providers' resting limit orders will be executed when the change in stock price is favourable (unfavourable), hence unnecessarily increasing their exposure to adverse selection risk.

In contrast, Yao and Ye (2018) discover that a smaller tick size encourages non-HFTs to provide liquidity since they have a greater opportunity to establish price priority by undercutting HFTs' existing limit orders. As a consequence of the competition posed by non-HFTs, Yao and Ye (2019) argue that market-making HFTs would be exposed to a larger risk of adverse selection, hence reducing their ability to provide liquidity. Similarly, O'Hara et al. (2019) note that the market-making HFTs would be forced to cancel their orders more often, resulting in "fleeting" market liquidity. Moreover, Dyhrberg et al. (2020) suggest that the order-undercutting behaviour of non-HFTs would pose significant concerns for electronic market-makers, as their execution priority would be compromised and their ability to rapidly offload potential inventories would be impeded. As a result, the market-makers may choose to withdraw from the market, therefore diminishing liquidity and negatively affecting market quality.

Werner et al. (2019) demonstrate that after a tick size reduction, the limit orders that had been clustered together at the previous price levels become more dispersed due to the increased number of price levels. For liquid stocks with tick-constrained spread, this situation results in in a shorter queue at all price levels, which in turn encourages investors to provide liquidity rather than taking it. Nevertheless, in less liquid stocks with tick-unconstrained spreads, a finer pricing grid might promote aggressive order-undercutting to outbid existing limit orders with better prices that are economically insignificant. Similarly, Angel et al. (2011) propose that smaller tick sizes discourage traders from revealing their positions, especially in the presence of informed or large-uninformed traders whose trading might impact prices, resulting in a smaller displayed order. In other words, it reduces the incentive to submit limit orders and makes it easier for traders to abuse standing limit orders using destructive quote-matching trading strategies.

3.4.2.3 Relative tick size trade-off

For liquidity providers, a larger relative tick size represents a higher profit margin from market-making spread and a greater adverse selection risk from limit order placements, and *vice versa* (see e.g.: Angel, 1997; O'Hara et al., 2019; Sandås, 2001). Consequently, the size of a nominal or relative tick would present liquidity providers with a choice between profit-maximisation, which favours a larger tick size, and risk-minimisation, which prefers a smaller tick size. This trade-off fundamentally depends on the risk appetite of the liquidity provider, i.e., whether they are willing to assume more risk for a higher return (profit maximisation) or are willing to accept a lower profit to ensure a lower risk exposure (risk minimisation). Therefore, liquidity-providing HFTs that employ order-queuing activity may be interpreted as profit-driven traders, while HFTs that prefer order-undercutting can be regarded as risk-averse traders.

3.4.3 Hypotheses development

The formula for calculating relative tick size relies on two parameters: the stock price and the nominal tick size. When the nominal tick size remains constant, stocks with lower prices have larger relative tick sizes, while stocks with higher prices have smaller relative tick sizes. For instance, in Australia, all stocks priced between A$0.100 and A$1.995 have a nominal tick size of A$0.005 (half-cent). Consequently, the relative tick size of stocks at the lowest and highest ends of the price range would be 5.000% and 0.251%, respectively. The literature suggests that relative tick size significantly impacts HFTs; more activity in stocks with large relative tick sizes implies greater order-queuing activity, while more activity in stocks with small relative tick sizes indicates greater order-undercutting activity. This study examines whether the substantial disparity in relative tick size at opposite ends of a price band results in significantly different levels of HFT activity. Therefore, the study proposes the following hypothesis:

H1: *Stocks with larger relative tick sizes will have significantly higher levels of HFT activity due to greater order-queuing activity compared to stocks with smaller relative tick sizes.*

The current tick size structure in the Australian equity market creates two tick size borders at A$0.10 and A$2.00, with nominal tick size values of A$0.005 (half-cent) and A$0.01 (one-cent), respectively. These borders represent the lowest price that can be reached within the same nominal tick size; therefore, stocks priced at these borders would also have the highest relative tick size value within their respective group, which is 5.000% and 0.500%, respectively. In contrast, a stock priced at A$1.995, precisely one tick below the A$2.00 border, would have a relative tick size value of 0.251%, which is the smallest value attainable for stocks within the A$0.005 nominal tick size group. As a result, stocks priced just above the border would have large relative tick sizes, while those priced just below the border would have small relative tick sizes. This study examines whether the contrast in relative tick size between stocks priced slightly above and slightly below the A$2.00 tick size border corresponds to significantly different levels of HFT activity. Based on these arguments, the study proposes the following hypothesis:

H2: *Stocks priced slightly above the A$2.00 tick size border will have significantly higher levels of HFT activity due to their larger relative tick sizes compared to stocks priced slightly below the A$2.00 tick size border.*

Despite the common perception that stock prices are continuous, they are in fact discrete due to tick sizes, which form a pricing grid in the market. For instance, stocks priced above the A$2.00 tick size border would have a pricing grid of A$0.01 (one cent), whereas stocks priced below the border would have a pricing grid of A$0.005 (half-cent). Stock prices are susceptible to demand and supply forces, which may cause a stock's price to fluctuate to the point where it crosses the tick size border, resulting in a substantial disparity in the crossed stock's relative tick size value before and after the crossing occurred. If the stock crossed the border in an upward direction, the relative tick size would substantially increase; however, if the stock crossed the border in a downward direction, the relative tick size would substantially decrease (see Figure 3.5 – 3.7). Therefore, this study examines whether there is a statistically significant difference in the level of HFT activity before and after a stock crossed a tick size border in either an upward or downward direction and posits the following research hypothesis:

H3: *Crossing a tick size border in an upward (downward) direction results in a statistically significant increase (decrease) in the level of HFT activity for the affected stock.*

3.5 Methodology

3.5.1 Data description

This research employs order book data starting from January 2008 and ending in December 2017 for the ASX, and from December 2011 to December 2017 for the Chi-X Australia, using datasets supplied by the Securities Industry Research Centre of Asia-Pacific (SIRCA). ASX order book data was derived from the Australian Equities Tick History (AETH) database prior to May 31, 2016. On June 1, 2016, it was replaced with ASX ITCH datasets. Chi-X Australia order book information is provided by the Australian Chi-X Exchange (CHIX). The constituents of the S&P/ASX 100 (ASX: XTO) index, which includes both large and medium-cap firms, are used to ensure that the stocks included are sufficiently large and liquid. This generates almost 9.5 billion rows of order book data over the study period.[17] Due to its magnitude, RStudio is used to extract and aggregate relevant information from the raw dataset in order to create a daily-level dataset. Table 3.2 provides a summary of the data extracted from the three datasets (AETH, ITCH and CHIX) used to estimate the key variables in this study, as well as a brief description of the raw datasets.

[17] The list of constituent stocks is based on the information provided by Thomson Reuters Datastream and updated on a monthly basis.

Table 3.2. Relevant information from the datasets

This table presents relevant information on the datasets used in this study, which are provided by SIRCA. Columns *AETH*, *ITCH*, and *CHIX* present the information sourced from the Australian Equities Tick History, ASX ITCH, and Australian Chi-X Exchange databases, respectively. *Period* refers to the date range of which the data of the study is retrieved from. *Firms* refer to the number of unique firms. *Observations* refers to the number of firm-day observations. *Timestamp* refers to the smallest precision unit for time used to record the messages in the order book. *Rows* refers to the number of lines in the order book for the specified time period. *Size on disc* refers to the size of the dataset used in this study as recorded on the hard drive. *Order book messages* refers to the information provided in each dataset and how it is defined.

	AETH	ITCH	CHIX
Period	1/1/2008 – 31/5/2016 (1887 days)	1/6/2016 – 31/12/2017 (657 days)	25/10/2011 – 31/12/2017 (1559 days)
Firms	171	113	145
Observations	209,644	39,806	150,673
Timestamp	Millisecond (one-thousandth of a second)	Nanosecond (one-billionth of a second)	Millisecond (one-thousandth of a second)
Rows	5,550,425,473	1,783,656,562	2,237,353,517
Size on disc	739 GB (794,503,270,400 bytes)	217 GB (233,758,228,480 bytes)	232 GB (249,538,936,832 bytes)
Order book messages	Record type: ▪ **ENTER**: Entry of a new order into the order book. ▪ **DELETE**: Deletion of an order from the order book. ▪ **AMEND**: Modification of existing order. ▪ **TRADE**: A trade between two orders. Prices (daily): ▪ **Open**: The first message recorded as "TRADE". ▪ **Close**: The last message recorded as "TRADE". ▪ **High**: The highest price of message recorded as "TRADE". ▪ **Low**: The lowest price of message recorded as "TRADE". Other information: ▪ **BuyID**: A unique order identification assigned to buy-side messages. ▪ **AskID**: A unique order identification assigned to sell-side messages. ▪ **OrderID**: A combination of BuyID and AskID. ▪ **Volume**: The quantity of shares in an order. ▪ **Value**: The dollar value of an order.	Message type: ▪ **A**: Add order message. ▪ **D**: Order delete message. ▪ **U**: Order replace message. ▪ **E**: Order executed message. ▪ **C**: Order executed message (with price). Prices (daily): ▪ **Open**: The first message recorded as "C". ▪ **Close**: The last message recorded as "C". ▪ **High**: The highest price of message recorded as "E" or "C". ▪ **Low**: The lowest price of message recorded as "E" or "C". Other information: ▪ **OrderID**: The identifier assigned to the new order. The number is only unique per order book and side. ▪ **Quantity**: The visible quantity of shares placed in an order, i.e. volume. ▪ **Value**: Price × Quantity	Message type: ▪ **A**: Add order message. ▪ **E**: Order execution message. Prices (daily): ▪ **Open**: The first message recorded as "E". ▪ **Close**: The last message recorded as "E". ▪ **High**: The highest price of message recorded as "E". ▪ **Low**: The lowest price of message recorded as "E". Other information: ▪ **Order Reference**: Unique order reference number of the day. ▪ **Quantity**: The visible quantity of shares placed in an order, i.e. volume. ▪ **Value**: Price × Quantity

3.5.2 Sample selection

The first hypothesis states that "*stocks with larger relative tick sizes will have significantly higher levels of HFT activity due to greater order-queuing activity compared to stocks with smaller relative tick sizes.*" To verify this claim, samples are categorised according to their nominal tick sizes, which are either A\$0.005 (half-cent) or A\$0.01 (one-cent).[18] Observations in the first category will have prices between A\$0.10 and A\$1.995, while observations in the second category will have prices of A\$2.00 or greater. This sample excludes any observations that crossed any tick size border. This is achieved by ensuring that a stock's daily low and high prices fall within the price range applicable to each nominal tick size category. The closing prices of the stocks in each category are then used to split them into five quintiles, resulting in groupings with extreme values of relative tick sizes clustered at opposite extremes of the spectrum. Stocks in the first quintile have the largest relative tick size (RTS_{LARGE}), whilst the fifth quintile have the smallest relative tick size (RTS_{SMALL}). In total, four RTS groups and two pairs are defined based on the nominal and relative tick sizes, which are (i) $RTS_{SMALL\_0.005}$ and $RTS_{LARGE\_0.005}$, and (ii) $RTS_{SMALL\_0.01}$ and $RTS_{LARGE\_0.01}$. Table 3.3 summarises the data utilised to test the first hypothesis, categorised by tick size.

Table 3.3. Data description for the samples used to test the first hypothesis

This table describes the data used to test the first hypothesis. *Panels A* and *B* show the information obtained from the ASX and CHIX datasets, respectively. The top and bottom sections of the table display the data for the A\$0.005 and A\$0.01 tick size categories, accordingly. RTS_{SMALL} and RTS_{LARGE} denotes the group of observations with low and high relative tick size values, respectively. *Observations*, *Highest price,* and *Lowest price* refer to the number of observations, the highest and lowest closing prices for each RTS group, accordingly.

	Panel A: ASX		**Panel B: CHIX**	
	RTS_{SMALL}	**RTS_{LARGE}**	**RTS_{SMALL}**	**RTS_{LARGE}**
Tick size: A\$0.005				
Observations	6,022	6,041	2,655	2,669
Highest price (A\$)	1.995	0.880	1.995	0.975
Lowest price (A\$)	1.510	0.100	1.640	0.240
Tick size: A\$0.01				
Observations	43,596	43,526	27,383	27,346
Highest price (A\$)	199.700	4.400	186.720	4.170
Lowest price (A\$)	22.050	2.000	24.400	2.000

[18] Due to inadequate sample size, stocks with prices below \$0.100 are omitted from all tests performed in this study.

The second hypothesis states that "*stocks priced slightly above the A$2.00 tick size border will have significantly higher levels of HFT activity due to their larger relative tick sizes compared to stocks priced slightly below the A$2.00 tick size border.*" To evaluate this premise, the study divides stock prices into three categories based on their distance from the tick size border: "FAR," "MID," and "NEAR," allowing the researcher to examine the level of HFT activity in stocks trading above and below the tick size border. The first category, "FAR", contains the most distant data, with prices ranging from A$1.70 to A$1.795 in the low relative tick size group (RTS_{SMALL}), and from A$2.21 to A$2.30 in the high relative tick size group (RTS_{LARGE}). The second category, "MID", includes observations that sit between the first and third categories, with prices ranging from A$1.80 to A$1.895 in the RTS_{SMALL} group, and from A$2.11 to A$2.20 in the RTS_{LARGE} group. The third category, "NEAR", comprises of observations closest to the tick size border, with prices ranging from A$1.90 to A$1.995 for the RTS_{SMALL} group, and from A$2.00 to A$2.10 for the RTS_{LARGE} group. There are a total of three pairs of RTS groups based on the price ranges categories: (i) RTS_{SMALL_FAR} and RTS_{LARGE_FAR}, (ii) RTS_{SMALL_MID} and RTS_{LARGE_MID}, and (iii) RTS_{SMALL_NEAR} and RTS_{LARGE_NEAR}. Table 3.4 presents a summary of the data used to test the second hypothesis for each price distance category.

Table 3.4. Data description for the samples used to test the second hypothesis

This table describes the data used to test the second hypothesis. *Panels A* and *B* show the information obtained from the ASX and CHIX datasets, respectively. The top, mid, and bottom sections of the table display the data for *FAR*, *MID*, and *NEAR* categories, respectively. RTS_{SMALL} (RTS_{LARGE}) denotes the group of observations with low (high) relative tick size values. *Observations*, *Highest price,* and *Lowest price* refer to the number of observations, the highest and lowest closing prices for each RTS group, respectively.

	Panel A: ASX		**Panel B: CHIX**	
	RTS_{SMALL}	**RTS_{LARGE}**	**RTS_{SMALL}**	**RTS_{LARGE}**
Distance: FAR				
Observations	1,251	777	713	629
Highest price (A$)	1.795	2.300	1.795	2.300
Lowest price (A$)	1.700	2.210	1.700	2.210
Distance: MID				
Observations	1,017	788	574	614
Highest price (A$)	1.895	2.200	1.895	2.200
Lowest price (A$)	1.800	2.110	1.800	2.110
Distance: NEAR				
Observations	1,013	984	526	639
Highest price (A$)	1.995	2.100	1.995	2.100
Lowest price (A$)	1.900	2.000	1.900	2.000

The third hypothesis argue that "*crossing a tick size border in an upward (downward) direction results in a statistically significant increase (decrease) in the level of HFT activity for the affected stock.*" To test this hypothesis, the study first identifies which observations experience tick size crossing events by comparing the daily low and high prices of each stock to the A$2.00 tick size border. This assessment will produce one of the following outcomes: (i) both the low and high prices are less than A$2.00 but greater than or equal to A$0.10; (ii) both the low and high prices are greater than or equal to A$2.00; or (iii) the low price is less than A$2.00 but greater than or equal to A$0.10, while the high price is greater than or equal to A$2.00. All observations that fit the description of the first, second, and third outcomes are labelled as "small relative tick size" (RTS_{SMALL}), "large relative tick size" (RTS_{LARGE}), and "tick size crossing event" (CROSS), respectively. Subsequently, all observations identified as CROSS are screened based on their price positions relative to the A$2.00 tick border on the day before and after the crossing events, denoted as PRE_CROSS and POST_CROSS, respectively. Table 3.5 outlines the process of identifying and evaluating CROSS events to determine whether they are accepted or rejected.

Table 3.5. Identification and classification of crossing events

This table presents the potential scenarios for tick size crossing events and how they are classified. *CROSS* denotes the day on which a crossing event occurred; hence, their relative tick size values are recorded as '*Nil*'. *PRE_CROSS* and *POST_CROSS* refer to the immediate trading days before and after the occurrence of either a single-day or multiple-day CROSS event. RTS_{SMALL} and RTS_{LARGE} signify the relative tick size position during PRE_CROSS and POST_CROSS days. Event classification refers to the decision to classify whether an event is accepted or rejected. An *UPWARDS* event starts with RTS_{SMALL} on the PRE_CROSS day and ends with RTS_{LARGE} on the POST_CROSS day, whereas a *DOWNWARDS* event starts with RTS_{LARGE} on the PRE_CROSS day and ends with RTS_{SMALL} on the POST_CROSS day. Events with any combination other than the aforementioned scenarios are classified as *Rejected*. Panel A shows the possible combinations involving a single-day crossing event, while Panel B depicts potential scenarios involving multiple days of crossing events in a row.

Panel A: Single-day crossing

PRE_CROSS	*CROSS*	*POST_CROSS*	*Event classification*
RTS_{SMALL}	Nil	RTS_{LARGE}	UPWARDS
RTS_{SMALL}	Nil	RTS_{SMALL}	Rejected
RTS_{LARGE}	Nil	RTS_{SMALL}	DOWNWARDS
RTS_{LARGE}	Nil	RTS_{LARGE}	Rejected

Panel B: Multiple-days crossing

PRE_CROSS	*CROSS*	*CROSS*	*POST_CROSS*	*Event classification*
RTS_{SMALL}	Nil	Nil	RTS_{LARGE}	UPWARDS
RTS_{SMALL}	Nil	Nil	RTS_{SMALL}	Rejected
RTS_{LARGE}	Nil	Nil	RTS_{SMALL}	DOWNWARDS
RTS_{LARGE}	Nil	Nil	RTS_{LARGE}	Rejected

Accepted events are further categorised by their crossing direction, which is either UPWARDS or DOWNWARDS, depending on their relative tick size's position during PRE_CROSS and POST_CROSS days. Table 3.6 summarises the data selected to test the third hypothesis for each tick size crossing category.

Table 3.6. Data description of the crossing events selected to test the third hypothesis

This table describes the data of the tick size crossing events selected to test the third hypothesis. *Panels A* and *B* show the information obtained from the ASX and CHIX datasets, respectively. *UPWARDS* and *DOWNWARDS* reflect the category of tick size crossing events, as detailed in the preceding table. *Average*, *Highest*, and *Lowest prices* reflect the mean, maximum, and minimum closing prices for the PRE_CROSS and POST_CROSS groups, while *Average*, *Highest*, and *Lowest differences* represent the mean, maximum, and minimum closing prices differences between the POST_CROSS and PRE_CROSS periods, respectively. *Accepted* and *Rejected events* indicate the number of tick size crossing events that were accepted and rejected in the final sample, respectively. *Total observations* shows the number of firm-day observations resulting in tick-size border crossings.

	Panel A: ASX		Panel B: CHIX	
	UPWARDS	DOWNWARDS	UPWARDS	DOWNWARDS
PRE_CROSS				
Average price (A$)	1.931	2.093	1.960	2.052
Highest price (A$)	1.995	3.740	1.995	2.270
Lowest price (A$)	1.495	2.000	1.865	2.000
POST_CROSS				
Average price (A$)	2.085	1.884	2.055	1.902
Highest price (A$)	2.500	1.990	2.210	1.995
Lowest price (A$)	2.000	0.940	2.000	0.980
Difference (POST – PRE)				
Average difference (A$)	0.154	-0.210	0.095	-0.150
Highest difference (A$)	0.755	-0.015	0.305	-0.020
Lowest difference (A$)	0.025	-2.270	0.015	-1.170
Duration (POST – PRE)				
Average duration	4.309 days	4.617 days	3.459 days	4.333 days
Longest duration	14 days	15 days	7 days	14 days
Shortest duration	2 days	2 days	2 days	2 days
Accepted events	95	111	37	42
Rejected events	370	399	136	155
Total observations	1072		326	

3.5.3 Measurement of variables

3.5.3.1 HFT activity measures

Numerous HFT-related research make use of trade-level datasets, such as the NASDAQ HFT, NASDAQ OMX-St, and TSX trade-level datasets, which offer some form of identification for each order submitted to the market. In this study's datasets, however, such information is not available. Due to this constraint, this research uses the general characteristics of HFT as outlined by various regulatory agencies and academics to proxy for HFT activity at daily level. The message-to-trade ratio, the algorithmic trading ratio, the total number of high-frequency orders (HFO), and the HFO message ratio are selected as proxies because they utilise information that is commonly available on order-book data. This methodology enhances the reproducibility of the research, allowing it to be replicated on other markets and analysed over longer time periods. However, one drawback of this indirect approach is that the proxies utilised may also capture the activity of other types of market players who use similar low-latency trading strategies as full-fledged HFT firms, and thus may not accurately reflect the activity of the latter. Therefore, any results on "HFT activity" in this research should be taken as reflecting the activity of "low-latency traders" and not "high-frequency trading firms" per se.

1. Message-to-trade ratio

The message-to-trade ratio (MTR) is calculated by dividing the total number of *ENTER*, *AMEND*, or *DELETE* order-book messages recorded on a given day by the total number of trades executed on that day.[19] HFTs often places a large number of limit orders at multiple price levels and revises them whenever new information becomes available; hence, stocks with a high MTR are commonly linked with a high level of HFT activity. In addition, a high MTR indicates intensive quotation activity, a high degree of agility, and a low tolerance for adverse selection risk, all of which are consistent with the strategy and risk appetite of HFTs. MTR is widely used by practitioners, regulators, and researchers as a proxy for HFTs' liquidity providing activities (see e.g. Aquilina & Ysusi, 2016; ASIC, 2013, 2015; Brogaard et al., 2015; Friederich & Payne, 2015; Frino et al., 2015; Hagstromer & Norden, 2013).[20] The formula for calculating MTR is shown in Equation 3.1. A higher (lower) MTR value suggests a higher (lower) degree of HFT activity in stock *i* on day *t*, whereas a ratio of one implies that all orders submitted to the market are traded.

---

[19] "Order-to-trade ratio" (OTR) is a more widely used term than "message-to-trade ratio" (MTR). In the first essay, the former term is used to reflect this knowledge. However, to be consistent with the relevant terms found in the study's datasets, the term MTR is used in the second and third essays of this study (see Table 3.2).

[20] Yao and Ye (2018), on the other hand, argue that the MTR is a poor cross-sectional proxy for HFT activity. In contrast to popular belief, they discovered that the presence of HFTs has a negative relationship with MTR values.

$$MTR_{i,t} = \frac{\sum_1^{i,t} Message_{i,t}}{\sum_1^{i,t} Trade_{i,t}}$$

(Equation 3.1)

Where $\sum_1^{i,t} Message_{i,t}$ is the total number of *ENTER*, *AMEND*, and *DELETE* messages recorded on stock i on day t,[21] and $\sum_1^{i,t} Trade_{i,t}$ is the total number of *TRADE* messages recorded on stock i on day t.[22] For the sake of brevity, the in-text explanation is based solely on information from the AETH dataset.

2. Algorithmic trading ratio

The datasets used for this study do not disclose whether an order was placed by a trading bot or a human. Consequently, it is impossible to monitor algorithmic trading activities directly through the order book. Hendershott et al. (2011) use the rate of electronic message traffic as a proxy for the amount of algorithmic trading (AT), and asserted that its variations are predominantly driven by the variations of limit order submissions and cancellations; therefore, the measure should primarily capture algorithmic liquidity provision. This also suggests that AT is less likely to reflect algorithmic arbitrage activity, since this liquidity-taking action uses market orders and not limit orders. Even though AT cannot accurately quantify HFT activity, HFT remains a subset of AT, therefore it can still be employed to represent HFT's general attributes. Following the approach of Hendershott et al. (2011), this study utilises algorithmic trading ratio (ALGO) as a proxy for HFT activity, defined as the sum of daily trading value (in dollars) normalised by the total number of messages recorded as *ENTER*, *AMEND*, or *DELETE*, multiplied by negative one. Higher (lower) ALGO values suggest more (less) algorithmic trading activity. Equation 3.2 is the formula used to calculate ALGO.

$$ATR_{i,t} = \frac{\sum Trading\ Value_{i,t}}{\sum_1^{i,t} Message_{i,t}} \times (-1)$$

(Equation 3.2)

---

[21] Message: AETH = *ENTER*, *AMEND*, *DELETE*; ITCH = *A*, *U*, *D*; CHIX = *A*

[22] Trade: AETH = *TRADE*; ITCH = *E*, *C*; CHIX = *E*

Where $\sum Trading\ Value_{i,t}$ is the sum of all trading value on stock *i* on day *t*, and $\sum_{1}^{i,t} Message_{i,t}$ is the total number of messages recorded as *ENTER*, *AMEND*, and *DELETE* on stock *i* on day *t*.[23]

3. High-frequency orders

HFT is distinguishable from other algorithmic trading activities and the rest of the market mostly by its speed, making it a unique form of market participant. The primary activity of HFTs is market-making, which involves rapid quote updates in response to new market information, resulting in a large number of linked messages. Hasbrouck and Saar (2013) and Boehmer, Li, and Saar (2018) utilise extended strategic runs of at least ten linked messages to quantify HFT activity, and such runs are often seen in dynamic algorithmic strategies that often contain several limit order amendments and resubmissions. As noted by Hasbrouck and Saar (2013), "While the 10-message cut off is somewhat arbitrary, these runs represent more than half of the total number of messages that are linked to runs in each sample period… Such longer runs characterise much low-latency activity" (p. 659).

Additionally, if HFTs' algorithm detects the threat of being adversely selected or attempts to capitalise on profitable yet transitory trading opportunities, it will withdraw or rapidly update its existing limit orders, resulting in a short order resting time. Due to their speed, HFTs should naturally have a shorter average order resting time than non-HFTs. Subrahmanyam and Zheng (2016) discover that for large, medium, and small-cap firms, the average survival times of HFTs' orders (i.e., order duration) inside the top three price levels of the limit order book are 28.74, 33.03, and 51.89 seconds, respectively. Therefore, a limit order sent by HFTs that consists of 10 messages should have a duration of 30 seconds or less, which is equivalent to an average order resting time of three seconds.[24]

---

[23] Trading value: AETH = *Value* when *Record Type* is equal to *TRADE*; ITCH = (*Price* × *Quantity*) when *Message Type* is equal to *E* or *C*; CHIX = (*Price* × *Quantity*) when *Message Type* is equal to *E*.
[24] This is due to the fact that only large and medium-sized firms were included in the study's sample.

The datasets used in this study include a unique order identification (OrderID) for every order submitted to the market (see Table 3.2).[25] This allows the researcher to monitor the entire history of each OrderID from the moment it enters the market until it is withdrawn from the order book by cancellation or execution.[26] Based on the aforementioned criteria, OrderIDs submitting at least 10 messages with an average order resting time of less than three seconds are most likely generated by HFTs.[27] The formula used to identify the high-frequency order (HFO) is shown in Equation 3.3.

$$OrderDuration_{j,i,t} = OrderID_{j,i,t,\max(d)} - OrderID_{j,i,t,\min(d)}$$

$$ORT_{j,i,t} = \frac{OrderDuration_{j,i,t}}{\sum_{1}^{j,i,t} Messages_{j,i,t}}$$

$$\sum_{1}^{i,t} HFO_{i,t} = \sum_{1}^{j,i,t}\left[\left(ORT_{j,i,t} \leq 3 \text{ seconds}\right) \,\&\, \left(\sum_{1}^{j,i,t} Message_{j,i,t} \geq 10 \text{ messages}\right)\right]$$

(Equation 3.3)

Where $OrderID_{j,i,t,\max(d)}$ is the OrderID *j* on stock *i* on day *t* with the highest timestamp (*d*); $OrderID_{j,i,t,\min(d)}$ is the OrderID *j* on stock *i* on day *t* with the lowest timestamp (*d*); $OrderDuration_{j,i,t}$ is the difference between the highest and lowest timestamps of OrderID *j* on stock *i* on day *t*; $\sum_{1}^{j,i,t} Message_{j,i,t}$ is the total number of messages generated by OrderID *j* on stock *i* on day *t*; $ORT_{j,i,t}$ is the order resting time of OrderID *j* on stock *i* on day *t*; and $\sum_{1}^{i,t} HFO_{i,t}$ is the total number of OrderID on stock *i* on day *t* that satisfy the following criteria: (i) order resting time $(ORT_{j,i,t})$ of less than or equal to 3 seconds, and (ii) number of messages

[25] Order identification: AETH = *OrderID*; ITCH = *OrderID*; CHIX = *Order Reference*

[26] This includes everything in between, such as order modification and/or incomplete execution (if any). When an order is modified, it may lose its queue position in the limit order book if: (1) its price is changed; and (2) its modified quantity is greater than the original amount. In these cases, the order is pushed to the back of the queue.

[27] This study removes any HFO with an average order resting time of less than five milliseconds. Despite the fact that this number is arbitrary, it is necessary to include a minimum limit in the HFO calculation to prevent misidentification due to the order book's underlying mechanics. For example, when a large limit order to buy is placed in the market and then traded against many small market orders to sell, several AMEND messages are sent to reflect the remaining balance of the large order based on the number of transactions that had occurred. Consequently, the total number of messages recorded in the order book is overstated, resulting in an inaccurate estimation of HFT activity using the HFO method.

$\left(\sum_{1}^{j,i,t} Message_{j,i,t}\right)$ of more than or equal to 10. All of the parameters in Equation 3.3 are derived from messages recorded as *ENTER*, *AMEND*, and *DELETE*.

4. HFO message ratio

The identification of HFO allows the study to estimate the daily total number of messages produced by this type of OrderID. With this information, it is possible to determine the high-frequency order ratio (HFOR), which represents the proportion of messages generated by HFO in the market. The formula to calculate HFOR is expressed by Equation 3.4.

$$HFOR_{i,t} = \frac{\sum_{1}^{HFO,i,t} Message_{HFO,i,t}}{\sum_{1}^{i,t} Message_{i,t}}$$

(Equation 3.4)

Where $\sum_{1}^{HFO,i,t} Message_{HFO,i,t}$ is the total number of messages generated by OrderID identified as HFO on stock *i* on day *t*; and $\sum_{1}^{i,t} Message_{i,t}$ is the total number of all messages generated on stock *i* on day *t*.

3.5.3.2 Explanatory variables

1. Independent variable

The main purpose of this research is to determine whether relative tick size has an effect on HFT activity. Relative tick size is calculated as nominal tick size $\left(Tick\ Size_{i,t}\right)$ divided by closing price $\left(Close_{i,t}\right)$, as shown in Equation 3.5. As explained in the previous sections, specific sample groups are selected to represent observations with differing relative tick size values, namely RTS_{SMALL} and RTS_{LARGE}. To capture this effect, a dummy variable with the value one is assigned to observations in the RTS_{SMALL} group, and zero otherwise.

$$RTS_{i,t} = \frac{Tick\ Size_{i,t}}{Close_{i,t}}$$

(Equation 3.5)

2. Control variables

The study controls for several characteristics identified in the literature as having a significant effect on HFT activity, including volatility, liquidity, and firm size. Studies show that stocks with greater volatility have higher HFT activity; hence, HFT activity is expected to have a positive association with volatility, which is proxied in this study by the daily trading range (see e.g., Boehmer et al., 2020; Ersan & Ekinci, 2016; Hasbrouck & Saar, 2013; Lee, 2015; Manahov, 2016; Yilmaz et al., 2015). As shown in Equation 3.6, the volatility measure is calculated by dividing the difference between the daily high $(High_{i,t})$ and low $(Low_{i,t})$ prices by their average.

$$VOLATILITY_{i,t} = \frac{High_{i,t} - Low_{i,t}}{\left(\frac{High_{i,t} + Low_{i,t}}{2}\right)}$$

(Equation 3.6)

In addition, research shows that HFT activity is more prevalent in stocks that are highly liquid and have a large market capitalisation (Brogaard, Hendershott & Riordan, 2014; Bhattacharya et al., 2020; Ersan & Ekinci, 2016). Therefore, HFT activity should be positively related to both liquidity and firm size. The spread measure developed by Corwin and Schultz (2012) is used as a proxy for liquidity in this study, and its formula is shown in Equation 3.7. According to the formula, negative spread values are conceivable; hence, the authors recommend substituting these values with zero. The size effect is proxied by the natural logarithm of a firm's market capitalisation, as depicted by Equation 3.8.

$$LIQUIDITY_{i,t} = \frac{2(e^{\alpha_{i,t}} - 1)}{1 + e^{\alpha_{i,t}}}$$

$$\alpha_{i,t} = \frac{\sqrt{2\beta_{i,t}} - \sqrt{\beta_{i,t}}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma_{i,t}}{3 - 2\sqrt{2}}}$$

$$\beta_{i,t} = \left(\ln\frac{High_{i,t-1}}{Low_{i,t-1}}\right)^2 + \left(\ln\frac{High_{i,t}}{Low_{i,t}}\right)^2$$

$$\gamma_{i,t} = \left(\ln\frac{max\{High_{i,t-1}, High_{i,t}\}}{min\{Low_{i,t-1}, Low_{i,t}\}}\right)^2$$

(Equation 3.7)

$$SIZE_{i,t} = \ln\left(Market\ Capitalisation_{i,t}\right)$$

(Equation 3.8)

3.5.4 Model specification

The first and second hypotheses are examined using univariate analysis, which compares the mean HFT activity between the RTS_{SMALL} and RTS_{LARGE} groups using a parametric test (t-test). Literature indicates that other variables may potentially influence HFT activity, and a simple univariate test cannot account for these additional factors. Consequently, the study employs multiple regression analysis to provide evidence about the effect of relative tick size on HFT activity, while also controlling for other firm-specific factors such as volatility, liquidity, and firm size. The model used to evaluate the first and second hypotheses is represented by Equation 3.9.

$$HFT_{i,t} = \beta_0 + \beta_1\left(DSMALL_{i,t}\right) + \beta_2\left(CONTROL_{i,t-1}\right) + \varepsilon_{i,t}$$

(Equation 3.9)

DSMALL is a dummy variable that equals one if the observation of firm *i* on day *t* belongs to the RTS_{SMALL} group and zero otherwise.[28] The regression analysis would yield one of the following results: (i) not significant – HFT activity is unaffected by relative tick size; (ii) significantly positive – HFT executed more order-undercutting activity when the tick size is small; or (iii) significantly negative – HFTs' engagement is reduced when the tick size is small. $CONTROL_{i,t-1}$ represents the three control variables used in the model, namely VOLATILITY, LIQUIDITY and SIZE of firm *i* on day *t*-1, as proxied by the daily trading range, the Corwin-Schultz spread, and the natural logarithm of market capitalisation, respectively. Lagged values are applied to the control variables to avoid the potential of having reverse causality issue. In addition, firms (cross-sectional unit) and day (time unit) fixed effects are used to account for omitted variables bias, which may result from unobservable factors that vary across firms and time.

[28] As described in the preceding section, the first and second hypotheses are distinguished by their methods for defining the RTS_{SMALL} and RTS_{LARGE} groups, resulting in a unique set of samples for each hypothesis. However, they analyse their respective samples using similar univariate and multivariate tests.

To test the third hypothesis, the study employs univariate and multivariate difference-in-difference techniques. The tick size crossing event is identified as the event that would cause an exogenous shock to relative tick size values while having no direct impact on HFT activity. Therefore, any differences in HFT activity seen on the days before (PRE_CROSS) and after (POST_CROSS) a crossing event should be related to the relative tick size shift that occurred as a result of the crossing event. A tick size crossing event, as defined in Table 3.5, is classified as either UPWARDS or DOWNWARDS based on its RTS position before and after the event. Due to the contradiction between these two categories, it would be inappropriate to include all tick crossing size events in a single analysis, as doing so would obscure the actual effects of relative tick size on HFT activity, leading to a false conclusion. Thus, the UPWARDS and DOWNWARDS events are analysed independently.

In addition, the difference-in-difference method requires the construction of two sample groups, named “TREATMENT” and “CONTROL”. TREATMENT comprises of all tick size crossing events accepted based on the procedure outlined in Table 3.5, which will belong to either UPWARDS or DOWNWARDS category. CONTROL, on the other hand, consists of samples that are matched against each event identified in the TREATMENT group. To be selected, the following conditions must be satisfied: (i) the matched sample does not belong to the TREATMENT group; and (ii) on both PRE_CROSS and POST_CROSS days, the daily low and high prices of the matched sample must lie between A$1.00 and A$1.995 for the UPWARDS category, and between A$2.00 and A$3.99 for the DOWNWARDS category.[29] The observations of each sample in the TREATMENT and CONTROL groups are further separated into the PRE_CROSS or POST_CROSS groups, depending on their timing relative to the event. The research designs for the UPWARDS and DOWNWARDS groups are illustrated in Figures 3.8 and 3.9, respectively.

---

[29] The highest relative tick size value for stocks with a nominal tick size of A$0.01 is 0.50% at A$2.00, which is the same as stocks priced at A$1.00 with a nominal tick size of A$0.005. Similarly, the lowest relative tick size value for stocks with a nominal tick size of A$0.005 is 0.2506% at A$1.995, which is the same as stocks priced at A$3.99 with a nominal tick size of A$0.01. The price ranges stated in the main text for RTS_{SMALL} and RTS_{LARGE} are decided based on these price and relative tick size limits.

	PRE_CROSS	POST_CROSS
CONTROL	(1) $\text{CONTROL}_{\text{PRE\_CROSS}}$ $\text{RTS}_{\text{CONTROL}} = \text{RTS}_{\text{LOW}}$	(3) $\text{CONTROL}_{\text{POST\_CROSS}}$ $\text{RTS}_{\text{CONTROL}} = \text{RTS}_{\text{LOW}}$
TREATMENT	(2) $\text{TREATMENT}_{\text{PRE\_CROSS}}$ $\text{RTS}_{\text{TREATMENT}} = \text{RTS}_{\text{LOW}}$	(4) $\text{TREATMENT}_{\text{POST\_CROSS}}$ $\text{RTS}_{\text{TREATMENT}} = \text{RTS}_{\text{HIGH}}$

Figure 3.8: Illustration of the research design used to test the third hypothesis (UPWARDS)

	PRE_CROSS	POST_CROSS
CONTROL	(1) $\text{CONTROL}_{\text{PRE\_CROSS}}$ $\text{RTS}_{\text{CONTROL}} = \text{RTS}_{\text{HIGH}}$	(3) $\text{CONTROL}_{\text{POST\_CROSS}}$ $\text{RTS}_{\text{CONTROL}} = \text{RTS}_{\text{HIGH}}$
TREATMENT	(2) $\text{TREATMENT}_{\text{PRE\_CROSS}}$ $\text{RTS}_{\text{TREATMENT}} = \text{RTS}_{\text{HIGH}}$	(4) $\text{TREATMENT}_{\text{POST\_CROSS}}$ $\text{RTS}_{\text{TREATMENT}} = \text{RTS}_{\text{LOW}}$

Figure 3.9: Illustration of the research design used to test the third hypothesis (DOWNWARDS)

The top and bottom sections of the figures represent the CONTROL and TREATMENT groups, whereas the left and right panels reflecting the PRE_CROSS and POST_CROSS days, respectively. Quadrants (1) and (2) reflect the data for CONTROL and TREATMENT data before the crossing event, while Quadrants (3) and (4) indicate the data for CONTROL and TREATMENT after the crossing event, respectively. The subsequent steps are performed to evaluate whether HFT activity differs across different levels of RTS:

i. (2) – (1) = Difference between TREATMENT and CONTROL before the tick size crossing event occurred ($DIFF_{PRE\_CROSS}$)
ii. (4) – (3) = Difference between TREATMENT and CONTROL after the tick size crossing event occurred ($DIFF_{POST\_CROSS}$)
iii. ($DIFF_{POST\_CROSS}$) – ($DIFF_{PRE\_CROSS}$) = Difference due to RTS change ($DIFF_{POST\text{-}PRE}$)

The multivariate regression model used in the difference-in-difference analysis are shown in Equation 3.10.

$$HFT_{i,t} = \beta_0 + \beta_1\left(DTREATMENT_{i,t}\right) + \beta_2\left(DPOST_{i,t}\right) + \beta_3\left(DTREATMENT_{i,t} \times DPOST_{i,t}\right) + \beta_4\left(CONTROL_{i,t-1}\right) + \varepsilon_{i,t}$$

(Equation 3.10)

$DTREATMENT_{i,t}$ represents a dummy variable that equals one if the observation of firm *i* on day *t* belongs to the Treatment group, and zero otherwise; $DPOST_{i,t}$ is a dummy variable that equals one if the observation of firm *i* on day *t* belongs to the POST_CROSS group, and zero otherwise; and $DTREATMENT_{i,t} \times DPOST_{i,t}$ estimates the interaction term between dummy variable for POST_CROSS and TREATMENT groups. The interpretation of the control variables is the same as in Equation 3.9. The model also incorporates the firms and time (day) fixed-effects to account for any bias caused by omitted variables.

3.6 Results, analyses, and discussions

This section presents the study's findings and analysis in accordance with the sequence of the hypotheses. To summarise, the first hypothesis examines HFT activity among opposing RTS groups that have the same nominal tick size. The second hypothesis compares HFT activity in stocks priced just above and below the A$2.00 tick size border. The third hypothesis explores the impact of crossing a tick size border that results in substantial changes in relative tick size on HFT activity.

This section concludes with a discussion of the outcomes obtained from the testing the three hypotheses.

3.6.1 HFT activity across different RTS groups categorised by nominal tick sizes

3.6.1.1 Descriptive statistics

Table 3.7 describes the dataset used to test the first hypothesis, which examines the impact of relative tick size on HFT activity, categorised by nominal tick size of either half-cent (Panel I) or one-cent (Panel II).[30] This is performed by grouping observations inside each nominal tick size category according to their relative tick size values, resulting in four subgroups, namely $RTS_{SMALL\_0.005}$, $RTS_{LARGE\_0.005}$, $RTS_{SMALL\_0.01}$, and $RTS_{LARGE\_0.01}$. The table displays a greater number of observations for the ASX and the one-cent category than for the CHIX and the half-cent category, respectively. These figures reflect the fact that the ASX has greater trading activity than the CHIX, and that more stocks are traded using a one-cent nominal tick size than a half-cent nominal tick size. The PRICE and RTS values shown for each subgroup on both marketplaces reflect the conditions specified when the groups are constructed, as outlined in Section 3.5.2.

The table depicts that, on average, the samples in the $RTS_{SMALL\_0.005}$ and $RTS_{SMALL\_0.01}$ groups have a lower VOLATILITY than their RTS_{LARGE} counterparts, and that the ASX are more volatile than the CHIX. Similar trend is seen in LIQUIDITY, where samples from RTS_{SMALL} groups have, on average, wider spreads than those from RTS_{LARGE} groups, and the ASX's spread is consistently wider than the CHIX's. In terms of SIZE, the sample in the RTS_{SMALL} groups has a significantly greater market capitalisation than the sample in the RTS_{LARGE} groups. In the half-cent tick size category, the average firm size of RTS_{SMALL}'s sample is almost twice that of RTS_{LARGE}, and in the one-cent tick size category, it is nearly seven times greater. In addition, the data shows that the average market capitalisation of the ASX and CHIX markets across all subgroups examined is comparable.

[30] As noted in Section 3.2.2, it is not possible to test stocks with $0.001 (one-tenth of once-cent) due to the limited number of observations available at this nominal tick size group.

Table 3.7. Descriptive statistics of the data used to test Hypothesis 1

This table describes the data employed to test the first hypothesis, which are categorised by nominal tick sizes of either A\$0.005 (*Panel I*) or A\$0.01 (*Panel II*). *Panels A* and *B* represent the ASX and CHIX datasets, while RTS_{SMALL} and RTS_{LARGE} refer to the observations in the fifth and first percentile based on their relative tick size values, respectively. *N*, *Mean*, *Std. Dev.*, *Minimum*, and *Maximum refer* to the number of observations, average, standard deviation, lowest value, and highest value, accordingly. *PRICE* refer to the closing price; *RTS* indicates the relative tick size, which is calculated by dividing nominal tick size by closing price (Equation 3.5); *VOLATILITY* is measured by difference between the highest and lowest price of the day, divided their average prices (Equation 3.6); *LIQUIDITY* is measured using the Corwin and Schultz (2012) high-low spread (Equation 3.7); and *SIZE* is the actual dollar value of market capitalisation.

	Panel A: ASX					Panel B: CHIX				
	N	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**	**N**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
	Panel I: Tick size = A\$0.005 (half-cent)									
RTS_{SMALL} (5th quintile)										
PRICE (\$)	6,022	1.822	0.086	1.510	1.995	2,655	1.834	0.080	1.640	1.995
RTS (%)	6,022	0.275	0.013	0.251	0.331	2,655	0.273	0.012	0.251	0.305
VOLATILITY (%)	6,022	2.627	1.917	0.289	32.749	2,655	2.084	1.305	0.000	14.934
LIQUIDITY (%)	6,012	0.626	0.892	0.000	9.845	2,645	0.426	0.641	0.000	7.630
SIZE (\$ billion)	6,022	3.817	1.915	0.339	10.590	2,655	3.953	2.288	0.779	10.590
RTS_{LARGE} (1st quintile)										
PRICE (\$)	6,041	0.558	0.172	0.100	0.880	2,669	0.712	0.190	0.240	0.975
RTS (%)	6,041	1.041	0.553	0.568	5.000	2,669	0.776	0.290	0.513	2.083
VOLATILITY (%)	6,041	5.232	5.109	0.612	73.684	2,669	3.068	2.359	0.000	50.932
LIQUIDITY (%)	6,020	1.205	1.902	0.000	26.430	2,651	0.606	0.967	0.000	8.142
SIZE (\$ billion)	6,041	1.893	1.381	0.056	6.355	2,669	1.830	1.062	0.243	5.570
	Panel II: Tick size = A\$0.01 (one-cent)									
RTS_{SMALL} (5th quintile)										
PRICE (\$)	43,596	45.555	23.137	22.050	199.700	27,383	48.625	23.948	24.400	186.720
RTS (%)	43,596	0.026	0.009	0.005	0.045	27,383	0.024	0.009	0.005	0.041
VOLATILITY (%)	43,596	2.050	2.076	0.000	162.557	27,383	1.543	0.906	0.000	24.063
LIQUIDITY (%)	43,545	0.412	0.632	0.000	14.485	27,171	0.293	0.449	0.000	6.480
SIZE (\$ billion)	43,596	34.530	36.530	1.035	166.000	27,383	37.120	38.440	1.454	156.000

Table 3.7 (continue)

RTS$_{LARGE}$ (1st quintile)										
PRICE ($)	43,526	3.007	0.528	2.000	4.400	27,346	3.085	0.569	2.000	4.170
RTS (%)	43,526	0.344	0.064	0.227	0.500	27,346	0.336	0.066	0.240	0.500
VOLATILITY (%)	43,526	2.760	1.914	0.277	67.410	27,346	2.037	1.340	0.000	31.237
LIQUIDITY (%)	43,460	0.634	0.892	0.000	24.975	27,180	0.427	0.630	0.000	10.422
SIZE ($ billion)	43,526	5.103	6.219	0.393	50.150	27,346	5.116	5.529	0.757	50.640

Overall, these values indicate that stocks with higher prices (i.e., RTS_{SMALL}) have smaller intraday price ranges, narrower spreads, and larger market capitalisation than those with lower prices (i.e., RTS_{LARGE}). The figures also imply that the activity of ASX market participants resulted in greater price fluctuations (VOLATILITY) and wider spreads (LIQUIDITY) than those exhibited on CHIX, which is likely due to the presence of noise traders (i.e., retail investors) on the former and their absence on the latter. This argument is plausible considering that CHIX is regarded as a trading venue specifically designed to meet HFTs' technological requirements, which demands a low-latency trading environment (Chordia et al., 2013; Menkveld, 2013). Moreover, Malceniece et al. (2019) portray CHIX's entry to a new market as an exogenous instrument which reflects the onset of HFT in a market, whereas Foley et al. (2019) characterise slow and fast brokers based on their participation on the CHIX. For these reasons, it is apparent that the CHIX is not a trading platform where retail traders and unsophisticated investors would participate.

3.6.1.2 Univariate analysis

Table 3.8 illustrates the results of univariate tests performed to compare HFT activity, as proxied by MTR, ALGO, HFO, and HFOR, between two opposing relative tick size groups (RTS_{SMALL} and RTS_{LARGE}), for each nominal tick size category of either half-cent (Panel I) or one-cent (Panel II). The mean values of HFT proxies are contrasted between the RTS_{SMALL} and RTS_{LARGE} groups for each tick size category using a two-sample t-test. The table depicts that there is a statistically significant difference between the RTS_{SMALL} and RTS_{LARGE} groups with regards to HFT activity, with the former exhibiting greater MTR, ALGO, HFO, and HFOR values. The exception to this is ALGO in the ASX market's one-cent category, which has a positive but insignificant result. This evidence suggests that HFT activity is more prevalent in stocks with smaller relative tick sizes, with the one-cent tick size category showing the largest disparity.

Furthermore, the mean values show that the CHIX has more intensive order quotation activity (i.e., MTR) and algorithmic liquidity provision (i.e., ALGO) than the ASX. This behaviour is also shown in the average differences between RTS_{SMALL} and RTS_{LARGE} for those variables, with the CHIX exhibiting larger disparities than the ASX. The statistics for HFO and HFOR, however, suggest the contrary; the ASX has a greater number of fast OrderIDs (i.e., HFO) and a larger order-book presence (i.e., HFOR) than the CHIX. This pattern is also evident in the size of the average differences between RTS_{SMALL} and RTS_{LARGE} for HFO and HFOR, with the ASX showing more pronounced differences than the CHIX.

Table 3.8. Mean comparison of HFT activity categorised by nominal tick sizes

This table displays the results of a univariate analysis using observations classified by their nominal tick sizes to test the first hypothesis. The findings from the A$0.005 and A$0.01 categories are shown in *Panels I* and *II*, respectively. The results for ASX and CHIX are shown in the upper and lower portions of each panel, correspondingly. *Obs*. and *Mean* refers to the number of observations and the average values of each HFT measure, accordingly. *Difference* represents the difference between the mean values of RTS_{SMALL} and RTS_{LARGE}. Message-to-trade ratio (MTR), average trade size (ALGO), high-frequency orders (HFO), and HFO-contributed message ratio (HFOR) are the variables used as proxies for measuring HFT activity. The formula are illustrated in Equations 3.1, 3.2, 3.3, and 3.4, respectively. Data are winsorised at three standard deviations (3-sigma) from their respective means.

Panel I:	**RTS_{SMALL} (5th quintile)**		**RTS_{LARGE} (1st quintile)**		**Difference**
(TS = A$0.005)	**Obs.**	**Mean**	**Obs.**	**Mean**	**(RTS_{SMALL} – RTS_{LARGE})**
ASX					
MTR (%)	6,022	503.189	6,041	449.623	53.566***
ALGO	6,022	-13.770	6,041	-17.300	3.531***
HFO (Ln)	6,022	2.323	6,041	1.404	0.919***
HFOR (%)	6,022	3.269	6,041	2.439	0.83***
CHIX					
MTR (%)	2,655	746.922	2,669	651.099	95.823***
ALGO	2,655	-4.775	2,669	-5.785	1.01***
HFO (Ln)	2,655	0.136	2,669	0.049	0.087***
HFOR (%)	2,655	0.169	2,669	0.123	0.046**

Panel II:	**RTS_{SMALL} (5th quintile)**		**RTS_{LARGE} (1st quintile)**		**Difference**
(TS = A$0.01)	**Obs.**	**Mean**	**Obs.**	**Mean**	**(RTS_{SMALL} – RTS_{LARGE})**
ASX					
MTR (%)	43,596	612.243	43,526	511.546	100.697***
ALGO	43,596	-16.362	43,526	-16.389	0.028
HFO (Ln)	43,596	5.129	43,526	2.450	2.679***
HFOR (%)	43,596	17.179	43,526	3.532	13.647***
CHIX					
MTR (%)	27,383	1733.621	27,346	773.160	960.46***
ALGO	27,383	-2.719	27,346	-6.576	3.857***
HFO (Ln)	27,383	2.120	27,346	0.163	1.959***
HFOR (%)	27,383	2.488	27,346	0.267	2.221***

*** p<0.01, ** p<0.05, * p<0.10

Nevertheless, it is possible that the reported findings from the univariate test are influenced by the differences found at firm level characteristics between stock composing the RTS_{SMALL} and RTS_{LARGE} groups (see Table 3.7), rather than explicitly driven by the small relative tick size factor. For this reason, a multivariate regression model is used to further analyse the data before any definitive conclusions are drawn.

3.6.1.3 Multivariate analysis

Table 3.9 displays the results of a multiple regression analysis to examine the influence of a small relative tick size value on HFT activity, categorised by nominal tick size value of either half-cent or one-cent. In Panel I, the regression outcomes for the half-cent tick size category indicate that stocks with a small relative tick size result in a significantly more HFO (β = 0.484) on the ASX, but it has no explanatory power on other HFT measures. On the other hand, the results for CHIX show that relative tick size has no significant effect on all HFT measures employed. These findings suggest that the significant differences in HFT activity between the RTS_{SMALL} and RTS_{LARGE} groups observed in the preceding univariate tests are most probably due to other factors, and not the relative tick size itself. With the exception of the MTR on the CHIX, which contains no significant explanatory variable, all HFT measures on the ASX and CHIX are found to be significantly influenced by at least one of the control variables employed.

Panel II exhibits the regression results for the one-cent tick size category. The findings show that stocks with a small relative tick size have significantly higher HFT activity across all measures analysed on the ASX (MTR: β = 135.552; ALGO: β = 11.870; HFO: β = 1.802; HFOR: β = 6.815), whereas for the CHIX, it leads to significantly higher MTR (β = 2956.856) and HFO (β = 1.158) only. These results imply that the significant difference in HFT activity between the RTS_{SMALL} and RTS_{LARGE} groups observed in the earlier univariate tests is indeed driven by relative tick size values, and this holds true even after adjusting for other factors including volatility, liquidity, size, and cross-sectional (firm) and time (day) fixed effects, lending credence to the reported findings.

The results of the regression analysis corroborate the undercutting hypothesis, which proposes that HFTs are more engaged in stocks with a smaller relative tick size, since they may use their speed advantage to obtain execution priority. This is clearly apparent in the one cent tick size category, but almost entirely insignificant in the half cent tick size category. This situation may be better explained by examining the relative tick size values shown in Table 3.7, which describes the dataset used for the regression models.

Table 3.9. Regression analysis on HFT activity categorised by nominal tick sizes

This table shows the results of multivariate regression analysis using observations categorised by their nominal tick sizes to test the first hypothesis. The findings from the A\$0.005 and A\$0.01 categories are shown in *Panels I* and *II*, respectively. *Panels A* and *B* illustrate the findings using the ASX and CHIX datasets respectively. Dependent variables are the HFT activity measures, namely message-to-trade ratio (*MTR*), average trade size (*ALGO*), high-frequency orders (*HFO*), and HFO-contributed message ratio (*HFOR*). The formula are shown in Equations 3.1, 3.2, 3.3, and 3.4, respectively. The independent variable is *DSMALL*, which is a dummy variable assigned with a value of one if the observation belongs to the group with low relative tick size (RTS_{SMALL}), and zero otherwise. The control variables are the one-day lagged (t – 1) values of *VOLATILITY*, *LIQUIDITY*, and *SIZE*. *VOLATILITY* is measured by difference between the highest and lowest price of the day, divided their average prices (Equation 3.6); *LIQUIDITY* is measured using the Corwin and Schultz (2012) high-low spread (Equation 3.7); and *SIZE* is the natural log of market capitalisation, respectively. All models are controlled for firm and day fixed-effects. Data are winsorised at three standard deviations (3-sigma) from their respective means. The standard errors are calculated using the Huber/White/sandwich estimator of variance method.

	Panel A: ASX				**Panel B: CHIX**			
	MTR	**ALGO**	**HFO**	**HFOR**	**MTR**	**ALGO**	**HFO**	**HFOR**
	Panel I: Tick size = A\$0.005 (half-cent)							
DSMALL	-9.296	2.514	0.484***	0.134	94.927	-0.780	0.016	-0.102
	(18.474)	(2.463)	(0.144)	(0.427)	(147.373)	(0.940)	(0.035)	(0.098)
VOLATILITY	-2.496*	-0.243**	0.039***	0.064***	-10.525	-0.115***	0.005	-0.008
	(1.343)	(0.112)	(0.007)	(0.019)	(10.574)	(0.041)	(0.004)	(0.007)
LIQUIDITY	1.372	0.386***	-0.018***	-0.043*	10.950	0.302**	0.002	0.013
	(1.098)	(0.103)	(0.005)	(0.024)	(12.106)	(0.116)	(0.006)	(0.017)
SIZE	-8.725	-4.341***	0.254***	0.355	38.909	1.529**	0.134***	0.354***
	(14.439)	(1.286)	(0.077)	(0.243)	(172.848)	(0.573)	(0.042)	(0.124)
Constant	577.616*	72.096**	-6.024***	-8.082	1288.212	-34.890***	-2.857***	-7.515***
	(322.408)	(27.801)	(1.708)	(5.298)	(3924.394)	(12.593)	(0.898)	(2.666)
Observations	12,047	12,047	12,047	12,047	5,300	5,300	5,300	5,300
R-squared	0.463	0.344	0.6634	0.3617	0.370	0.390	0.354	0.239
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Panel II: Tick size = A\$0.01 (one-cent)							
DSMALL	135.552***	11.870***	1.802***	6.815**	2956.856***	1.603	1.158*	2.647
	(33.918)	(2.612)	(0.165)	(3.233)	(701.792)	(1.429)	(0.599)	(1.711)
VOLATILITY	-6.336***	-0.235**	0.079***	0.488***	-18.067	-0.056	0.053***	0.099***
	(0.879)	(0.103)	(0.007)	(0.106)	(17.663)	(0.041)	(0.010)	(0.032)
LIQUIDITY	8.658***	1.026***	-0.009**	-0.025	-12.189	0.252***	0.002	0.009
	(0.823)	(0.087)	(0.004)	(0.042)	(14.449)	(0.035)	(0.009)	(0.023)

Table 3.9 (continue)

SIZE	35.744*	-5.531***	0.649***	6.153**	94.417	-1.150	0.713***	1.006
	(18.557)	(2.000)	(0.138)	(2.643)	(261.661)	(1.040)	(0.233)	(0.622)
Constant	-611.204	62.196	-16.419***	-149.395**	8417.129	24.716	-13.588***	-11.276
	(422.390)	(45.126)	(3.142)	(59.909)	(6380.220)	(22.917)	(5.141)	(13.707)
Observations	86,994	86,994	86,994	86,994	54,329	54,329	54,329	54,329
R-squared	0.492	0.561	0.799	0.471	0.416	0.155	0.333	0.195
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10

The average values of relative tick size for the $RTS_{SMALL\_0.005}$ group are 0.275% for the ASX and 0.273% for the CHIX. These figures are not markedly different from the values reported for the $RTS_{LARGE\_0.01}$ group, which are 0.344% for the ASX and 0.336% for the CHIX. These figures suggest that stocks defined as having a *small relative tick size* in the half-cent category are virtually identical to stocks labelled as having a *large relative tick size* in the one-cent category. Therefore, the relative tick size of the RTS_{SMALL} group in the half-cent category is just not small enough to attract HFTs.

The $RTS_{SMALL\_0.01}$ group is arguably the best depiction of a setting with a very small relative tick size. The group's average relative tick size for the ASX and CHIX is just 0.026% and 0.024%, respectively, which are roughly equivalent to one-tenth of the values shown in the $RTS_{SMALL\_0.005}$ and $RTS_{LARGE\_0.01}$ groups. This setting makes the relative tick size of the $RTS_{SMALL\_0.01}$ group extremely small, allowing fast traders like HFTs to have their limit orders filled first by quoting slightly better prices (Werner et al., 2011). In turn, this would make it less attractive for non-HFTs to establish price-priority on the order book through limit order placements, resulting in shorter queues across all price levels (Angel, 2011). This also enables HFTs to regularly update or cancel their limit orders without fear of being unable to quote a better price, or having their new orders placed at the end of a lengthy queue. Overall, these findings imply that HFTs would only engage in order-undercutting when the relative tick size is sufficiently small.

3.6.2 HFT activity surrounding a tick size border

3.6.2.1 Descriptive statistics

Table 3.10 describes the dataset used to test the second hypothesis; it is divided into three categories representing different price distance from the A$2.00 tick size border, namely FAR (Panel I), MID (Panel II), and NEAR (Panel III). Stocks with the farthest price distance (FAR) have a price range of A$1.70 – A$1.795 (RTS_{SMALL}) and A$2.21 – A$2.30 (RTS_{LARGE}), while stocks with a medium price distance (MID) have a price range of A$1.80 – A$1.895 (RTS_{SMALL}) and A$2.11 – A$2.20 (RTS_{LARGE}), and stocks with the shortest price distance (NEAR) have a price range of A$1.90 – A$1.995 (RTS_{SMALL}) and A$2.00 – A$2.10 (RTS_{LARGE}).

Table 3.10. Descriptive statistics of the data used to test Hypothesis 2

This table describes the data used to test the second hypothesis, categorised as either "*FAR*" (*Panel I*), "*MID*" (*Panel II*), or "*NEAR*" (*Panel III*), based on their respective price distance from the A$2.00 tick size border. Panels *A* and *B* describe the data of observations representing the ASX and CHIX datasets, while RTS_{SMALL} and RTS_{LARGE} refer to the observations priced below and above the tick size border, respectively. *N*, *Mean*, *Std. Dev.*, *Minimum*, and *Maximum refer* to the number of observations, average, standard deviation, lowest value, and highest value, accordingly. *PRICE* refer to the closing price; *RTS* indicates the relative tick size, which is calculated by dividing nominal tick size by closing price (Equation 3.5); *VOLATILITY* is measured by difference between the highest and lowest price of the day, divided their average prices (Equation 3.6); *LIQUIDITY* is measured using the Corwin and Schultz (2012) high-low spread (Equation 3.7); and *SIZE* is the actual dollar value of market capitalisation.

	Panel A: ASX					**Panel B: CHIX**				
	N	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**	**N**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Panel I: Distance = FAR										
RTS_{SMALL} (1.70 – 1.795)										
PRICE ($)	1,251	1.746	0.022	1.700	1.795	713	1.747	0.023	1.700	1.795
RTS (%)	1,251	0.286	0.004	0.279	0.294	713	0.286	0.004	0.279	0.294
VOLATILITY (%)	1,251	1.996	0.835	0.289	5.436	713	1.719	0.850	0.000	5.436
LIQUIDITY (%)	1,249	0.509	0.627	0.000	4.187	712	0.390	0.555	0.000	3.476
SIZE ($ billion)	1,251	4.054	1.908	0.647	9.503	713	4.461	2.156	0.813	9.503
RTS_{LARGE} (2.21 – 2.30)										
PRICE ($)	777	2.256	0.022	2.210	2.300	629	2.256	0.023	2.210	2.300
RTS (%)	777	0.443	0.004	0.435	0.453	629	0.443	0.004	0.435	0.453
VOLATILITY (%)	777	1.944	0.728	0.436	3.991	629	1.636	0.746	0.000	3.991
LIQUIDITY (%)	777	0.529	0.653	0.000	3.556	624	0.420	0.563	0.000	2.811
SIZE ($ billion)	777	3.797	2.002	0.841	11.980	629	3.903	2.167	1.017	11.980
Panel II: Distance = MID										
RTS_{SMALL} (1.80 – 1.895)										
PRICE ($)	1,017	1.845	0.023	1.800	1.895	574	1.844	0.023	1.800	1.895
RTS (%)	1,017	0.271	0.003	0.264	0.278	574	0.271	0.003	0.264	0.278
VOLATILITY (%)	1,017	1.945	0.883	0.532	5.142	574	1.657	0.800	0.000	4.878
LIQUIDITY (%)	1,015	0.528	0.662	0.000	4.697	572	0.366	0.537	0.000	3.879
SIZE ($ billion)	1,017	3.891	1.986	0.680	9.982	574	3.846	2.346	0.822	9.982
RTS_{LARGE} (2.11 – 2.20)										
PRICE ($)	788	2.157	0.022	2.110	2.200	614	2.157	0.022	2.110	2.200
RTS (%)	788	0.464	0.005	0.455	0.474	614	0.464	0.005	0.455	0.474

Table 3.10 (continue)

VOLATILITY (%)	788	1.997	0.718	0.464	4.176	614	1.607	0.725	0.000	3.721
LIQUIDITY (%)	787	0.551	0.644	0.000	3.140	609	0.445	0.592	0.000	3.248
SIZE ($ billion)	788	4.034	2.178	0.806	11.660	614	3.950	2.339	0.966	11.660
Panel III: Distance = NEAR										
RTS_{SMALL} (1.90 – 1.995)										
PRICE ($)	1,013	1.946	0.022	1.900	1.995	526	1.946	0.023	1.900	1.995
RTS (%)	1,013	0.257	0.003	0.251	0.263	526	0.257	0.003	0.251	0.263
VOLATILITY (%)	1,013	1.900	0.820	0.509	4.878	526	1.671	0.776	0.000	4.627
LIQUIDITY (%)	1,010	0.487	0.633	0.000	4.124	522	0.330	0.498	0.000	2.795
SIZE ($ billion)	1,013	4.083	1.897	0.736	10.590	526	3.443	2.233	0.882	10.590
RTS_{LARGE} (2.00 – 2.10)										
PRICE ($)	984	2.049	0.024	2.000	2.100	639	2.050	0.025	2.000	2.100
RTS (%)	984	0.488	0.006	0.476	0.500	639	0.488	0.006	0.476	0.500
VOLATILITY (%)	984	2.121	0.852	0.482	4.878	639	1.683	0.825	0.000	4.401
LIQUIDITY (%)	983	0.645	0.741	0.000	4.085	637	0.429	0.570	0.000	2.787
SIZE ($ billion)	984	3.907	2.092	0.747	11.070	639	3.567	2.309	0.934	11.070

The table indicates that a large number of ASX stocks are priced below and far from the border (RTS_{SMALL_FAR}), whereas in the CHIX, the figures are nearly similar across all categories. On average, ASX dataset is shown to exhibit a higher intraday price movement (VOLATILITY) than the CHIX across all groups (RTS_{SMALL} and RTS_{LARGE}) and categories (FAR, MID, and NEAR). In ASX, RTS_{SMALL_NEAR} and RTS_{LARGE_NEAR} show the lowest and highest volatility, respectively, whereas in CHIX, RTS_{LARGE_MID} and RTS_{SMALL_FAR} represent the lowest and highest volatility, respectively. In addition, stocks with a smaller relative tick size tend to be less volatile on the ASX, but the opposite is true on the CHIX. Nevertheless, the difference in volatility between the RTS_{SMALL} and RTS_{LARGE} groups is generally small.

In terms of LIQUIDITY, the ASX exhibits wider spreads than the CHIX across all examined groups, indicating that the former is less liquid. Stocks classified as RTS_{SMALL} are consistently shown to have larger spreads than those identified as RTS_{LARGE} in both markets. Furthermore, the RTS_{SMALL_NEAR} is shown to have the highest liquidity on both markets, whilst the RTS_{LARGE_NEAR} and RTS_{LARGE_MID} have the lowest liquidity on the ASX and CHIX, respectively. In general, stocks with a small relative tick size would be more liquid on both exchanges. As for SIZE, the statistics presented in the table show that the market capitalisations across all relative tick size groups and price distance categories are somewhat comparable. It is shown that the average market capitalisation in both markets is around A$4 billion, and that stocks with smaller relative tick sizes have a higher firm size. Overall, stocks trading at prices below the A$2.00 tick size border (i.e., RTS_{SMALL}) are more liquid and have a larger market capitalisation than those trading at prices above the border (i.e., RTS_{LARGE}) in both markets, while showing a similar intraday volatility.

3.6.2.2 Univariate analysis

Table 3.11 shows the results of univariate analysis using a two-sample t-test to compare HFT activity, as proxied by MTR, ALGO, HFO, and HFOR, across two relative tick size groups (RTS_{SMALL} and RTS_{LARGE}), which is classified based on different price distance of either FAR (Panel I), MID (Panel II), or NEAR (Panel III). The table indicates that there is a statistically significant difference in HFT activity between the RTS_{SMALL} and RTS_{LARGE} groups.

Table 3.11. Mean comparison of HFT activity near the A$2.00 tick size border

This table shows the results from univariate analysis using stocks near the A$2.00 tick size border to test the second hypothesis. The data is categorised as either "*FAR*" (*Panel I*), "*MID*" (*Panel II*), or "*NEAR*" (*Panel III*), based on their respective price distance from the A$2.00 tick size border. The results for ASX and CHIX are shown in the upper and lower portions of each panel, correspondingly. *Obs*. and *Mean* refers to the number of observations and the average values of each HFT measure, accordingly. *Difference* represents the difference between the mean values of RTS_{SMALL} and RTS_{LARGE}. Message-to-trade ratio (MTR), average trade size (ALGO), high-frequency orders (HFO), and HFO-contributed message ratio (HFOR) are the variables used as proxies for measuring HFT activity. The formula are illustrated in Equations 3.1, 3.2, 3.3, and 3.4, respectively. Data are winsorised at three standard deviations (3-sigma) from their respective means.

Panel I:	**RTS_{SMALL} (1.70 – 1.795)**		**RTS_{LARGE} (2.21 – 2.30)**		**Difference**
(Dist. = FAR)	**Obs.**	**Mean**	**Obs.**	**Mean**	**(RTS_{SMALL} – RTS_{LARGE})**
ASX					
MTR (%)	1,251	523.720	777	557.603	-33.884***
ALGO	1,251	-12.496	777	-11.876	-0.620
HFO (Ln)	1,251	2.384	777	2.532	-0.148***
HFOR (%)	1,251	3.185	777	3.535	-0.351**
CHIX					
MTR (%)	713	750.430	629	758.185	-7.755
ALGO	713	-5.223	629	-7.472	2.249***
HFO (Ln)	713	0.134	629	0.102	0.032**
HFOR (%)	713	0.173	629	0.149	0.024

Panel II:	**RTS_{SMALL} (1.80 – 1.895)**		**RTS_{LARGE} (2.11 – 2.20)**		**Difference**
(Dist. = MID)	**Obs.**	**Mean**	**Obs.**	**Mean**	**(RTS_{SMALL} – RTS_{LARGE})**
ASX					
MTR (%)	1,017	524.675	788	548.935	-24.261***
ALGO	1,017	-12.736	788	-13.827	1.091**
HFO (Ln)	1,017	2.388	788	2.360	0.028
HFOR (%)	1,017	3.226	788	3.106	0.120
CHIX					
MTR (%)	574	804.149	614	949.663	-145.514
ALGO	574	-4.433	614	-7.244	2.812***
HFO (Ln)	574	0.110	614	0.060	0.051***
HFOR (%)	574	0.128	614	0.087	0.041*

Panel III:	**RTS_{SMALL} (1.90 – 1.995)**		**RTS_{LARGE} (2.00 – 2.10)**		**Difference**
(Dist. = NEAR)	**Obs.**	**Mean**	**Obs.**	**Mean**	**(RTS_{SMALL} – RTS_{LARGE})**
ASX					
MTR (%)	1,013	508.102	984	507.390	0.712
ALGO	1,013	-12.701	984	-13.672	0.972**
HFO (Ln)	1,013	2.521	984	2.287	0.234**
HFOR (%)	1,013	3.684	984	3.220	0.465***
CHIX					
MTR (%)	526	872.144	639	738.080	134.064*
ALGO	526	-4.209	639	-6.573	2.364***
HFO (Ln)	526	0.102	639	0.060	0.043***
HFOR (%)	526	0.133	639	0.082	0.051*

*** p<0.01, ** p<0.05, * p<0.10

However, the findings for ASX and CHIX across the various HFT proxies and price distance categories examined are inconsistent. In the FAR category of the ASX, stocks in the RTS_{SMALL} group have MTR, HFO, and HFOR values that are substantially lower than those in the RTS_{LARGE} group. In the MID category, the results are contradictory: MTR is shown to be significantly lower in the RTS_{SMALL} group than in the RTS_{LARGE} group; ALGO is shown to be significantly higher in the RTS_{SMALL} group; and HFO and HFOR values are shown to be not statistically different between the two groups.

On the other hand, the NEAR category shows that RTS_{SMALL} have significantly higher ALGO, HFO, and HFOR values than RTS_{LARGE}. For the CHIX dataset, the findings are more uniform; HFT activity is significantly greater among stocks in the RTS_{SMALL} group compared to the RTS_{LARGE} group. Three of the four HFT measures (ALGO, HFO, and HFOR) are substantially larger in RTS_{SMALL} than in RTS_{LARGE} in the FAR and MID categories. In the NEAR category, the results are even more conclusive; all four HFT measures tested are significantly higher in the RTS_{SMALL} group.

Overall, the results of the univariate tests indicate that when the relative tick size values are substantially different, as represented by the NEAR category, it becomes evident that HFT activity is greater in the stocks with a smaller relative tick size, which suggest more order-undercutting activity. However, when the discrepancy in relative tick size is less pronounced, as indicated by the FAR category, HFT activity is found to be more prevalent in stocks with large relative tick size, which suggest more order-queuing activity. Nonetheless, as shown in the descriptive statistics in Table 3.10, other firm-specific factors such as volatility, liquidity and size might influence the level of HFT activity observed. Therefore, a multivariate analysis is required to isolate and control for these other influences.

3.6.2.3 Multivariate analysis

Table 3.12 shows the results of a multiple regression study to assess the influence of a small relative tick size value on HFT activity, classified as FAR (Panel I), MID (Panel II), or NEAR (Panel III) based on their respective price distances from the A$2.00 tick size border. The regression findings show that on the ASX, stocks in the

FAR category with a small relative tick size exhibit significantly lower MTR (β = -97.413) and higher HFO (β = 0.512) values, while having no influence on ALGO or HFOR. For the MID and NEAR categories, stocks with a small relative tick size on the ASX is shown to have higher HFO (MID: β = 0.415; NEAR: β = 0.393) and HFOR (MID: β = 1.041; NEAR: β = 1.138) values, but it has no influence on either MTR or ALGO. The control variables employed are found to be significant in some of the models presented in the table, especially in the FAR category and when HFT is measured by MTR or ALGO.

For CHIX, the regression results of the FAR category demonstrate that none of the HFT measures investigated are substantially influenced by relative tick size or any of the control variables utilised. However, the high R-squared values (MTR: R^2 = 0.724; ALGO: R^2 = 0.864; HFO: R^2 = 0.778; HFOR: R^2 = 0.802) suggest that some of the variance in the HFT measures may have been explained by cross-sectional (firm) or time (day) factors that were not explicitly specified in the model used in this study. For the MID category, stocks with a small relative tick size would have a higher MTR (β = 332.009) and ALGO (β = 1.672), while in the NEAR category, it is shown to be positively affecting ALGO (β = 2.080) and HFO (β = 0.091). Notably, all of the control variables are shown to have no impact on any of the analysed HFT measures across all three price distance categories, but this is with the exception to LIQUIDITY, which is observed to affect ALGO in the MID category.

The differences between ASX and CHIX results may be attributable to the characteristics of their respective markets. The ASX is naturally comprised of a diverse spectrum of participants, including fast and slow traders, informed and uninformed investors, and institutional and retail players. This demography provides HFTs with greater opportunities to trade against uninformed traders, hence reducing their adverse selection risk associated with market-making. In contrast, the CHIX is typically used by sophisticated traders that require a low-latency trading environment, such as the HFTs. Therefore, it is conceivable that uninformed investors would not participate in the CHIX market, which would force market-making HFTs to trade against other informed traders, therefore increasing their adverse selection risk.

Table 3.12. Regression analysis on HFT activity near the A$2.00 tick size border

This table shows the results from multivariate regression analysis using stocks near the A$2.00 tick size border to test the second hypothesis. The data is categorised as either "*FAR*" (*Panel I*), "*MID*" (*Panel II*), or "*NEAR*" (*Panel III*), based on their respective price distance from the border. *Panels A* and *B* illustrate the findings using the ASX and CHIX datasets respectively. Dependent variables are the HFT activity measures, namely message-to-trade ratio (*MTR*), average trade size (*ALGO*), high-frequency orders (*HFO*), and HFO-contributed message ratio (*HFOR*). The formula are shown in Equations 3.1, 3.2, 3.3, and 3.4, respectively. The independent variable is *DSMALL*, which is a dummy variable assigned with a value of one if the observation belongs to the group with low relative tick size (RTS_{SMALL}), and zero otherwise. The control variables are the one-day lagged (t – 1) values of *VOLATILITY*, *LIQUIDITY*, and *SIZE*. *VOLATILITY* is measured by difference between the highest and lowest price of the day, divided their average prices (Equation 3.6); *LIQUIDITY* is measured using the Corwin and Schultz (2012) high-low spread (Equation 3.7); and *SIZE* is the natural log of market capitalisation, respectively. All models are controlled for firm and day fixed-effects. Data are winsorised at three standard deviations (3-sigma) from their respective means. The standard errors are calculated using the Huber/White/sandwich estimator of variance method.

	Panel A: ASX				**Panel B: CHIX**			
	MTR	**ALGO**	**HFO**	**HFOR**	**MTR**	**ALGO**	**HFO**	**HFOR**
Panel I: Distance = FAR (1.70 – 1.795; 2.21 – 2.30)								
DSMALL	-97.413***	-0.308	0.512**	1.099	296.631	1.140	0.059	-0.027
	(34.131)	(1.854)	(0.196)	(0.748)	(224.875)	(1.300)	(0.109)	(0.106)
VOLATILITY	-6.348	-0.356	-0.002	-0.086	95.148	-0.264	0.035	-0.009
	(8.965)	(0.501)	(0.032)	(0.152)	(118.283)	(0.179)	(0.024)	(0.048)
LIQUIDITY	15.344*	0.992**	-0.027	-0.052	131.557	0.254	-0.039	-0.063
	(8.748)	(0.389)	(0.046)	(0.225)	(154.838)	(0.307)	(0.029)	(0.053)
SIZE	-138.206**	-9.549**	0.672**	2.163**	1783.433	-2.155	-0.005	-0.326
	(55.270)	(4.623)	(0.257)	(0.936)	(1412.506)	(3.178)	(0.221)	(0.318)
Constant	3683.323***	205.038**	-12.695**	-46.862**	-26306.658	46.532	-0.035	6.934
	(1213.484)	(101.215)	(5.766)	(20.954)	(30226.670)	(69.576)	(4.852)	(6.866)
Observations	2,024	2,024	2,024	2,024	1,337	1,337	1,337	1,337
R-squared	0.826	0.815	0.882	0.754	0.724	0.864	0.778	0.802
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel II: Distance = MID (1.80 – 1.895; 2.11 – 2.20)								
DSMALL	-7.210	2.663	0.415***	1.041**	332.009*	1.672*	0.078	0.078
	(14.908)	(1.725)	(0.131)	(0.417)	(183.128)	(0.959)	(0.090)	(0.126)
VOLATILITY	-9.506	-0.575	0.0633**	0.113	357.576	0.058	0.021	0.002
	(6.883)	(0.417)	(0.030)	(0.157)	(318.237)	(0.302)	(0.025)	(0.050)
LIQUIDITY	20.730	1.393*	-0.023	0.132	134.848	0.522*	0.017	0.050
	(14.499)	(0.704)	(0.065)	(0.268)	(134.410)	(0.271)	(0.040)	(0.072)

Table 3.12 (continue)

SIZE	-83.029*	-8.934	0.415	0.481	-527.547	-3.625	0.218	0.358
	(47.417)	(5.714)	(0.390)	(0.953)	(1091.001)	(3.156)	(0.320)	(0.389)
Constant	2116.780**	165.788	-9.313	-10.547	18930.403	78.708	-4.725	-7.699
	(1040.483)	(124.312)	(8.543)	(20.710)	(23570.691)	(68.490)	(6.931)	(8.372)
Observations	1,799	1,799	1,799	1,799	1,177	1,177	1,177	1,177
R-squared	0.885	0.826	0.893	0.812	0.833	0.859	0.763	0.821
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Panel III: Distance = NEAR (1.90 – 1.995; 2.00 – 2.10)							
DSMALL	-12.730	0.675	0.393***	1.138**	-45.490	2.080**	0.091*	0.166
	(11.092)	(0.865)	(0.106)	(0.493)	(563.525)	(0.989)	(0.049)	(0.141)
VOLATILITY	0.603	-0.077	0.050	0.201	-48.188	-0.339	-0.011	-0.111
	(7.142)	(0.514)	(0.031)	(0.259)	(77.015)	(0.401)	(0.022)	(0.075)
LIQUIDITY	-2.468	1.056	0.075	0.405	-27.356	0.006	-0.011	-0.104
	(7.495)	(0.651)	(0.063)	(0.266)	(75.727)	(0.295)	(0.029)	(0.127)
SIZE	-110.607**	-5.501*	0.724	1.252	-5522.185	-0.154	0.321	0.520
	(43.524)	(3.005)	(0.462)	(1.638)	(9254.173)	(13.702)	(0.488)	(1.445)
Constant	2584.583***	68.725	-15.956	-26.948	121172.230	3.592	-6.760	-10.522
	(942.596)	(66.508)	(10.293)	(36.455)	(198311.640)	(292.241)	(10.452)	(31.073)
Observations	1,994	1,994	1,994	1,994	1,156	1,156	1,156	1,156
R-squared	0.891	0.879	0.912	0.778	0.650	0.856	0.845	0.715
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10

In stocks that are priced relatively closer to the tick size border as represented by the MID and NEAR categories, the disparity in relative tick size between RTS_{SMALL} and RTS_{LARGE} becomes more distinct. In these price ranges, stocks priced below the A$2.00 tick size border ($RTS_{SMALL}$) would have small relative tick sizes, which correspond to a low adverse selection risk for market-making HFTs, thereby enticing them to undercut orders through marginal price improvements. In contrast, stocks priced above the border (RTS_{LARGE}) would have large relative tick sizes, which translate to a large profit from market-making and thus encourage limit order placements using order-queuing. In this setting, RTS_{SMALL} is found to have a higher HFT activity on both the ASX and CHIX markets, suggesting that the HFTs are predominantly risk-averse traders, as they choose to minimise their adverse selection risk through order-undercutting rather than attempting to maximise their profits through order-queuing.

On the contrary, when stocks are priced further from the tick size border, as represented by the FAR category, the relative tick size difference between RTS_{SMALL} and RTS_{LARGE} reduces. This setting implies that the relative tick size is neither too small nor too large, which signifies an adverse selection risk that is not too low and a market-making profit that is not too high, hence reducing the incentive for HFTs to participate in either order-undercutting or order-queuing activities. On the ASX, this situation yields conflicting findings, with RTS_{SMALL} exhibiting significantly lower MTR but higher HFO. Due to the presence of uninformed traders on the ASX market, the adverse selection risk from order-queuing is reduced, which cause some HFTs to prefer stocks with large relative tick size (RTS_{LARGE}).[31] Nonetheless, other HFTs may choose to perform order-undercutting in order to minimise their adverse selection risk. In contrast, the demographics of the CHIX market compel HFTs to constantly choose stocks with a small relative tick size (RTS_{SMALL}) in order to minimise their adverse selection risk, given that other market participants are primarily informed traders. Therefore, when a stock's relative tick size value is neither too small nor too large, it will be ignored by HFTs' trading algorithm, which will instead utilise information from other parameters. This may explain why none of

[31] As indicated by the significant negative relationship between DSMALL and MTR shown in Table 3.12 (Panel I).

the examined HFT measures in the FAR category of the CHIX show a significant effect on relative tick size.

Overall, these findings indicate that HFT activity could indeed be affected by relative tick size values. HFTs would almost always prefer stocks with a smaller relative tick size, if the relative tick size is sufficiently small. In addition, other factors, such as the proportion of informed and uninformed market participants, would affect HFTs' attitude and, therefore, their activity level. The majority of the findings indicate that HFTs would use their speed to establish price priority through undercutting activity. In addition, given that HFTs would have spent extensively to be faster than their competitors, it is plausible that they would leverage on their speed superiority whenever feasible, especially in minimising their adverse selection risk. Consequently, should market authorities seek to modify an existing nominal tick size to influence HFT activity, the new tick size must be sufficiently small or large; otherwise, it would be counterproductive, since it would have negligible effect on HFTs and may potentially harm other participants.

3.6.3 HFT activity surrounding tick size crossing events

3.6.3.1 Descriptive statistics

Table 3.13 displays the data used to test the third hypothesis, which assessed the impact of relative tick size change due to crossing the tick size border on HFT activity. The dataset is divided into two types of tick size crossing, either UPWARDS or DOWNWARDS, and further segregated based on the timing of the observation, which is either before (PRE-EVENT) or after (POST-EVENT) the occurrence of a crossing event. This categorisation generates four sample groups, namely PRE-EVENT$_{\text{UPWARDS}}$ POST-EVENT$_{\text{UPWARDS}}$, PRE-EVENT$_{\text{DOWNWARDS}}$, and POST-EVENT$_{\text{DOWNWARDS}}$, which are shown in Panel I (a), Panel I (b), Panel II (a), and Panel II (b), respectively.

Table 3.13. Descriptive statistics of the data used to test Hypothesis 3

This table describes the data used to test the third hypothesis, which are organised by the direction of the tick size crossing events. *Panels I (a)* and *(b)* represent the data for the PRE-EVENT$_{UPWARDS}$ and POST-EVENT$_{UPWARDS}$, whereas *Panels II (a)* and *(b)* refer to the PRE-EVENT$_{DOWNWARDS}$ and POST-EVENT$_{DOWNWARDS}$, respectively. *PRE-EVENT* and *POST-EVENT* refer to the values in the period before and after a tick size crossing event occurrence, accordingly. *Panels A* and *B* show the values from the ASX and CHIX datasets. *Treatment* refers to all observations classified as accepted tick size crossing events, while *Control* refers to non-crossing observations that fulfil the criteria outlined in Section 3.5.4 (Model specification). *N*, *Mean*, *Std. Dev.*, *Minimum*, and *Maximum refer* to the number of observations, average, standard deviation, lowest value, and highest value, accordingly. *PRICE* refer to the closing price; *RTS* indicates the relative tick size, which is calculated by dividing nominal tick size by closing price (Equation 3.5); *VOLATILITY* is measured by difference between the highest and lowest price of the day, divided their average prices (Equation 3.6); *LIQUIDITY* is measured using the Corwin and Schultz (2012) high-low spread (Equation 3.7); and *SIZE* is the actual dollar value of market capitalisation.

	Panel A: ASX					Panel B: CHIX				
	N	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**	**N**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Panel I (a): PRE-EVENT$_{UPWARDS}$										
Treatment										
PRICE ($)	95	1.933	0.070	1.495	1.995	37	1.960	0.028	1.865	1.995
RTS (%)	95	0.259	0.011	0.251	0.334	37	0.255	0.004	0.251	0.268
VOLATILITY (%)	95	3.839	3.903	0.855	27.429	37	2.098	1.384	0.503	6.897
LIQUIDITY (%)	94	0.226	0.797	0.000	6.744	37	0.079	0.277	0.000	1.435
SIZE ($ billion)	95	3.383	2.064	0.3572	10.51	37	4.003	2.546	1.149	10.51
Control										
PRICE ($)	691	1.455	0.257	1.005	1.975	210	1.439	0.281	1.010	1.940
RTS (%)	691	0.355	0.065	0.253	0.498	210	0.361	0.072	0.258	0.495
VOLATILITY (%)	691	3.618	2.554	0.607	20.921	210	2.246	1.406	0.257	11.411
LIQUIDITY (%)	686	0.853	1.196	0.000	8.440	210	0.600	0.812	0.000	3.879
SIZE ($ billion)	691	2.86	1.529	0.1917	8.039	210	3.113	1.772	0.6137	8.039
Panel I (b): POST-EVENT$_{UPWARDS}$										
Treatment										
PRICE ($)	95	2.080	0.070	2.000	2.310	37	2.055	0.052	2.000	2.210
RTS (%)	95	0.481	0.015	0.433	0.500	37	0.487	0.012	0.453	0.500
VOLATILITY (%)	95	3.987	3.600	0.499	30.769	37	2.506	1.671	0.976	7.092
LIQUIDITY (%)	95	0.942	1.280	0.000	5.548	37	0.391	0.596	0.000	2.374
SIZE ($ billion)	95	3.614	2.178	0.4287	11.23	37	4.203	2.688	1.184	11.23

Table 3.13 (continue)

Control										
PRICE ($)	691	1.472	0.257	1.010	1.985	210	1.459	0.282	1.015	1.995
RTS (%)	691	0.351	0.063	0.252	0.495	210	0.356	0.071	0.251	0.493
VOLATILITY (%)	691	3.511	2.370	0.557	19.380	210	2.229	1.432	0.416	8.237
LIQUIDITY (%)	690	0.776	1.223	0.000	9.855	209	0.459	0.725	0.000	5.370
SIZE ($ billion)	691	2.9	1.553	0.1981	8.465	210	3.152	1.788	0.6595	8.465
Panel II (a): PRE-EVENT$_{DOWNWARDS}$										
Treatment										
PRICE ($)	111	2.093	0.177	2.000	3.740	42	2.052	0.054	2.000	2.270
RTS (%)	111	0.480	0.027	0.267	0.500	42	0.488	0.012	0.441	0.500
VOLATILITY (%)	111	4.380	3.075	0.990	20.833	42	3.430	3.398	0.000	20.833
LIQUIDITY (%)	111	0.227	0.569	0.000	3.417	42	0.181	0.537	0.000	2.787
SIZE ($ billion)	111	3.339	2.069	0.4117	10.91	42	3.059	2.643	0.7573	10.91
Control										
PRICE ($)	1,689	3.027	0.506	2.020	3.970	753	3.047	0.509	2.020	3.970
RTS (%)	1,689	0.340	0.060	0.252	0.495	753	0.338	0.060	0.252	0.495
VOLATILITY (%)	1,689	3.231	2.454	0.254	41.745	753	1.955	1.280	0.000	12.522
LIQUIDITY (%)	1,689	0.692	1.044	0.000	9.683	749	0.368	0.565	0.000	3.585
SIZE ($ billion)	1,689	4.981	6.459	0.4042	48.28	753	4.969	6.287	0.9594	48.28
Panel II (b): POST-EVENT$_{DOWNWARDS}$										
Treatment										
PRICE ($)	111	1.886	0.140	0.940	1.990	42	1.902	0.167	0.980	1.995
RTS (%)	111	0.267	0.031	0.251	0.532	42	0.266	0.040	0.251	0.510
VOLATILITY (%)	111	5.383	7.709	0.757	73.498	42	4.497	11.091	0.505	72.857
LIQUIDITY (%)	111	1.091	2.237	0.000	16.830	41	0.353	0.615	0.000	2.672
SIZE ($ billion)	111	3.08	1.977	0.3312	10.49	42	2.874	2.511	0.3312	10.49
Control										
PRICE ($)	1,654	2.969	0.506	2.010	3.960	752	3.025	0.509	2.000	3.970
RTS (%)	1,654	0.347	0.062	0.253	0.498	752	0.341	0.061	0.252	0.500
VOLATILITY (%)	1,654	3.338	2.463	0.281	1,654	752	2.011	1.345	0.000	11.111
LIQUIDITY (%)	1,654	0.764	1.153	0.000	1,654	750	0.405	0.672	0.000	5.385
SIZE ($ billion)	1,654	4.872	6.336	0.4117	1654	752	4.927	6.261	0.9384	48.03

The table illustrates that, across all groups, the number of Treatment observations is consistently lower than the number of matching Control observations, and there are higher numbers of tick size crossing events recorded on the ASX than on the CHIX. This is because the study period using the ASX dataset began in January 2008, whereas for the CHIX dataset, it does not begin until November 2011. Moreover, there are cases in which a tick size crossing event recorded on the ASX does not appear on the CHIX dataset because no trading transpired on the CHIX for that specific stock on that day, thereby reducing the number of accepted tick size crossing events recorded on the CHIX dataset.[32]

The statistics for UPWARDS events indicate that for the ASX, the Treatment sample in general has a larger intraday price range (VOLATILITY), a smaller bid-ask spread (LIQUIDITY), and a larger market capitalisation (SIZE) than their corresponding Control sample, both before and after the event. In the post-event period, the Treatment's average intraday price range increased by only 0.1486%, whereas its bid-ask spread widened by 0.716%, and firm size increased by A$0.231 billion. In comparison, the exhibited changes for the Control are weaker, as the intraday price range reduced by 0.107%, the bid-ask spread shrank by 0.077%, and the firm size increased by only A$0.04 billion. For CHIX, in the pre-event period, stocks in the Treatment group exhibit lower volatility, narrower spread, and greater market capitalisation than those in the Control group. Compared to the pre-event period, the Treatment's volatility increased by 0.408%, the bid-ask spread widened by 0.312%, and the size of the firms grew by A$0.200 billion after crossing the tick size border. In contrast, the Control group only saw moderate changes, with volatility decreased by 0.017%, spreads tightened by 0.141%, and market capitalisation rose by only A$0.039 billion.

According to the statistics for DOWNWARDS events on the ASX, the Treatment group displays a larger intraday price range, a narrower bid-ask spread, and a smaller market capitalisation than its Control sample prior to the event. After the event, the Treatment's average intraday price range surged by 1.003%, while the

[32] On February 25, 2016, for instance, Spark Infrastructure Group (ASX:SKI) stock prices fluctuated from A$1.98 to A$2.05, indicating that the stock price had crossed the A$2.00 tick size border. However, no SKI trades were completed on the CHIX on that day.

bid-ask spread markedly widened by 0.864%, and the firm size fell by A$0.259 billion. Comparatively, the post-event figures for Control are only slightly different, with the intraday price range rising by 0.107%, the bid-ask spread expanding by 0.072%, and the firm size reducing by just A$0.109 billion. For CHIX, in the pre-event period, stocks in the Treatment group are shown to be more volatile, have a narrower spread, and have a smaller market capitalisation than their counterparts in the Control group. Following the tick size crossing event, the Treatment's stock volatility is shown to be 1.067% larger, the bid-ask spread is 0.172% wider, and the firm size is reduced by A$0.185 billion. Comparatively, the Control group experienced minimal changes, with volatility and spreads rising by just 0.056% and 0.037%, respectively, and market capitalisation falling by only A$0.042 billion.

In summary, apart from the market capitalisation of the stocks in the Treatment group, which is expected to increase in the UPWARDS event and decrease in the DOWNWARDS event, volatility and liquidity are shown to be considerably different after a tick size crossing event. Changes in volatility are found to be stronger in DOWNWARDS events, which increase volatility by 1.003% on the ASX and 1.067% on the CHIX, whereas UPWARDS events increase volatility by just 0.1486% on the ASX and 0.408% on the CHIX. For liquidity, the UPWARDS and DOWNWARDS events expanded the spreads on the ASX's Treatment group by 0.716% and 0.864%, respectively, whilst on the CHIX, the spreads are only 0.332% and 0.172% wider, respectively. In addition, the small changes detected in the Control group are consistent with expectations, implying that the samples are unaffected by the changes in tick size occurred on the Treatment stocks.

3.6.3.2 Univariate analysis

Table 3.14 presents the results of a univariate difference-in-difference analysis of the tick size crossing events. For the UPWARDS events shown in Panel I, the ASX dataset demonstrates that: (i) in the pre-event period, Treatment has more HFT activity than the Control, as indicated by the significantly higher HFO and HFOR values; (ii) in the post-event period, Treatment has less HFT activity, as indicated by the significantly lower ALGO value; and (iii) difference-difference analysis shows that an instant upsurge in relative tick size value is accompanied by a significant decrease in ALGO, thus implying a reduction in HFT activity.

Table 3.14. Univariate difference-in-difference analysis of HFT activity measures for tick size crossing events

This table presents the results of univariate difference-in-difference analysis to test the third hypothesis. *Panels I* and *II* represent the UPWARDS and DOWNWARDS tick size crossing events, respectively. *Panels A* and *B* show the information obtained from the ASX and CHIX datasets, accordingly. *Treatment* refers to all observations classified as accepted tick size crossing events, while *Control* refers to non-crossing observations that fulfil the criteria outlined in Section 3.5.4. $DIFF_{PRE}$ and $DIFF_{POST}$ refers to the difference between the values observed in Treatment and Control in the period before and after the crossing events, respectively. *DIFF-IN-DIFF* refers to the difference-in-difference values produced by subtracting the $\mathrm{DIFF}_{\mathrm{POST}}$ with $\mathrm{DIFF}_{\mathrm{PRE}}$. Message-to-trade ratio (MTR), average trade size (ALGO), high-frequency orders (HFO), and HFO-contributed message ratio (HFOR) are the variables used as proxies for measuring HFT activity. The formula are illustrated in Equations 3.1, 3.2, 3.3, and 3.4, respectively. Data are winsorised at three standard deviations (3-sigma) from their respective means. The standard errors are calculated using the Huber/White/sandwich estimator of variance method.

	Panel A: ASX				Panel B: CHIX			
	MTR	**ALGO**	**HFO**	**HFOR**	**MTR**	**ALGO**	**HFO**	**HFOR**
				Panel I: $\mathrm{RTS}_{\mathrm{UPWARDS}}$				
Pre-event								
Treatment (T)	481.13	-14.92	2.32	3.23	674.00	-4.77	0.06	0.02
Control (C)	459.25	-13.96	1.93	2.68	698.60	-4.47	0.11	0.21
$\mathrm{DIFF}_{\mathrm{PRE}}$ (T – C)	21.88	-0.95	0.39**	0.55*	-24.61	-0.30	-0.05	-0.19**
	(19.00)	(1.34)	(0.18)	(0.33)	(80.36)	(0.70)	(0.04)	(0.08)
Post-event								
Treatment (T)	467.91	-19.10	2.11	2.78	483.90	-6.48	0.12	0.06
Control (C)	459.15	-14.60	1.89	2.73	675.27	-4.97	0.09	0.25
$\mathrm{DIFF}_{\mathrm{POST}}$ (T – C)	8.76	-4.49***	0.22	0.05	-191.37**	-1.51**	0.03	-0.19**
	(19.98)	(1.63)	(0.17)	(0.36)	(75.56)	(0.71)	(0.05)	(0.09)
DIFF-IN-DIFF								
$\mathrm{DIFF}_{\mathrm{POST}} - \mathrm{DIFF}_{\mathrm{PRE}}$	-13.12	-3.54*	-0.17	-0.50	-166.76	-1.21	0.07	0.00
	(27.57)	(2.11)	(0.25)	(0.48)	(110.30)	(1.00)	(0.07)	(0.12)
				Panel II: $\mathrm{RTS}_{\mathrm{DOWNWARDS}}$				
Pre-event								
Treatment (T)	435.63	-19.51	1.68	2.28	939.21	-4.85	0.12	0.24
Control (C)	475.21	-19.94	2.11	2.89	1,035.11	-5.09	0.19	0.29
$\mathrm{DIFF}_{\mathrm{PRE}}$ (T – C)	-39.58***	0.43	-0.43***	-0.61**	-95.90	0.24	-0.07	-0.05
	(13.78)	(1.48)	(0.15)	(0.29)	(277.60)	(0.62)	(0.05)	(0.17)
Post-event								
Treatment (T)	426.45	-16.96	2.21	3.27	1,365.06	-3.65	0.38	0.27
Control (C)	476.64	-18.24	2.16	2.95	1,139.41	-5.43	0.17	0.29
$\mathrm{DIFF}_{\mathrm{POST}}$ (T – C)	-50.18***	1.28	0.05	0.32	225.66	1.78***	0.20**	-0.02
	(14.25)	(1.42)	(0.17)	(0.36)	(316.17)	(0.64)	(0.09)	(0.09)
DIFF-IN-DIFF								
$\mathrm{DIFF}_{\mathrm{POST}} - \mathrm{DIFF}_{\mathrm{PRE}}$	-10.61	0.85	0.48**	0.93**	321.56	1.55*	0.28***	0.04
	(19.82)	(2.05)	(0.22)	(0.46)	(420.75)	(0.89)	(0.10)	(0.19)

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Furthermore, the results for the CHIX dataset illustrate that: (i) in the pre-event period, Treatment has less HFT activity than Control, as indicated by the significantly lower HFOR values; (ii) in the post-event period, Treatment has less HFT activity, as indicated by the significantly lower MTR, ALGO, and HFOR values; and (iii) difference-difference analysis shows that the hike in relative tick size value has no significant effect on any HFT measures employed. In general, evidence from UPWARDS events implies that the sudden increase in relative tick size after a tick size crossing event may reduce HFT activity, as shown by the significantly lower algorithmic liquidity provision (ALGO); however, this outcome is exclusive to the ASX and absent from the CHIX.

Panel II displays the results of the DOWNWARDS events. The ASX dataset illustrates that: (i) in the pre-event period, Treatment has less HFT activity than the Control, as indicated by the significantly lower MTR, HFO, and HFOR values; (ii) in the post-event period, Treatment has less HFT activity, as indicated by the significantly lower MTR value; and (iii) difference-difference analysis shows that the instant reduction in relative tick size value results in a significant increase in HFO and HFOR. In addition, the findings for the CHIX dataset signify that: (i) in the pre-event period, the level of HFT activity in Treatment and Control is similar, as none of the HFT proxies are significant; (ii) in the post-event period, Treatment has more HFT activity, as shown by the significantly higher ALGO and HFO values; and (iii) difference-difference analysis revealed that the decline in relative tick size value leads to greater HFT activity, as evidenced by the significantly higher ALGO and HFO values. In general, evidence from DOWNWARDS events shows that the sudden reduction in relative tick size after a tick size crossing event resulted in significantly higher HFT activity.

Overall, the results indicate that HFT activity is asymmetrically affected by sudden changes in relative tick sizes triggered by tick size border crossings. The smaller pricing grid resulting from a relative tick size reduction stimulates HFT activity on both exchanges; however, when the situation is reversed, the coarser pricing grid suppresses HFT activity on the ASX while having no impact on the CHIX. This suggests that HFT is more sensitive when relative tick size is reduced, as this motivates them to use their speed to engage in order-undercutting activity; conversely, when relative tick size is increased, they do not use the order-queuing approach to make profit, suggesting that they are more incentivised to profit from order-undercutting than order-queuing strategies. Moreover, despite the fact that this technique used matching Control samples, it is plausible that the observed variations in HFT activity were also influenced by factors other than the relative tick size changes, thus, prompting the use of multivariate regression analysis.

3.6.3.3 Difference-in-difference multivariate analysis

Table 3.15 displays the results of a multivariate regression analysis conducted to analyse the impact of a sudden change in relative tick size due to tick size border crossing on HFT activity. When the stock prices of Treatment stocks crossed the A$2.00 tick size border, the relative tick size values would jump drastically in the UPWARDS event (Panel I) and fall substantially in the DOWNWARDS event (Panel II). For Control stocks, their prices would stay on the same side of the border; hence, there would be no substantial change in their relative tick size values.

The coefficients of DTREATMENT reflect the aggregate impact of Treatment stocks on HFT activity, which includes the influence observed in the period before and after their relative tick size experiences a dramatic change due to tick size border crossing. Similarly, the coefficients of DPOST represent the aggregate influence of the post-event day on HFT activity, which combines the impacts of stocks with (Treatment) and without (Control) substantial relative tick size change on HFT activity. Therefore, DTREATMENT and DPOST would be less informative in explaining the variation of the HFT measures when viewed in isolation. By interacting these dummy variables, it is possible to distinguish the impact of relative tick size changes on HFT activity from any influence that may have emerged from the Treatment or post-event day's inherent effect. Therefore, the coefficients of DPOST×DTREATMENT are utilised to highlight whether changes in relative tick size would influence HFT activity.

Panel I exhibits the findings for the UPWARDS scenario, which represents the event in which relative tick size increased drastically due to tick size crossings. Using the ASX dataset, the coefficients for DPOST×DTREATMENT are shown to be significantly negative in ALGO (β = -2,946), HFO (β = -0.201), and HFOR (β = -0.569), however using the CHIX dataset, only ALGO (β = -1.579) is significantly negative. Furthermore, it is shown that these HFT measures are negatively associated with DTREATMENT; although this relationship is not statistically significant, it does imply that Treatment stocks generally exhibit lower levels of HFT activity than Control stocks.

Table 3.15. Regression analysis on HFT activity using tick size crossing events

This table presents the results of multivariate regression analysis using tick size crossing events to test the third hypothesis. *Panels I* and *II* represent the *UPWARDS* and *DOWNWARDS* tick size crossing events, respectively. *Panels A* and *B* show the information obtained from the ASX and CHIX datasets, accordingly. Dependent variables are the HFT activity measures, namely message-to-trade ratio (*MTR*), average trade size (*ALGO*), high-frequency orders (*HFO*), and HFO-contributed message ratio (*HFOR*). The formula are shown in Equations 3.1, 3.2, 3.3, and 3.4, respectively. The independent variables are *DTREATMENT*, *DPOST*, and *DTREATMENT×DPOST*, where *DTREATMENT* is a dummy variable that equals to one if the observation is identified as a tick size crossing event (see Section 3.5.4: Model specification), and zero otherwise; *DPOST* is a dummy variable assigned with a value of one if the observation belongs to the post-event period, and zero otherwise; and the interaction term, *DTREATMENT×DPOST*, estimates the effect of changes in relative tick size due to tick size crossing event on HFT activity. The control variables are the one-day lagged (*t* – 1) values of *VOLATILITY*, *LIQUIDITY*, and *SIZE*. *VOLATILITY* is measured by difference between the highest and lowest price of the day, divided their average prices (Equation 3.6); *LIQUIDITY* is measured using the Corwin and Schultz (2012) high-low spread (Equation 3.7); and *SIZE* is the natural log of market capitalisation, respectively. All models are controlled for firm and day fixed-effects. Data are winsorised at three standard deviations (3-sigma) from their respective means. The standard errors are calculated using the Huber/White/sandwich estimator of variance method.

	Panel A: ASX				**Panel B: CHIX**			
	MTR	**ALGO**	**HFO**	**HFOR**	**MTR**	**ALGO**	**HFO**	**HFOR**
	Panel I: UPWARDS ($RTS_{SMALL} \rightarrow RTS_{LARGE}$)							
DTREATMENT	9.327	-1.319	-0.029	-0.190	44.759	-0.630**	-0.068	0.070
	(15.256)	(1.370)	(0.054)	(0.250)	(69.166)	(0.257)	(0.058)	(0.169)
DPOST	4.813	6.061***	0.185	-1.579***	-439.900*	-1.322	-0.070	-0.659***
	(25.301)	(1.245)	(0.239)	(0.451)	(233.366)	(1.136)	(0.072)	(0.187)
DTREATMENT×DPOST	-6.129	-2.946**	-0.201***	-0.569**	-163.069	-1.579***	0.050	0.057
	(17.982)	(1.172)	(0.064)	(0.243)	(115.916)	(0.565)	(0.075)	(0.120)
VOLATILITY	-5.195***	-0.3128***	0.019	0.088*	-41.173	-0.126	-0.004	-0.076
	(1.680)	(0.109)	(0.015)	(0.050)	(25.737)	(0.106)	(0.013)	(0.055)
LIQUIDITY	4.148*	0.642***	-0.011	0.002	38.191	0.107	-0.015	0.008
	(2.095)	(0.224)	(0.012)	(0.056)	(47.034)	(0.179)	(0.022)	(0.045)
SIZE	4.977	-6.643***	0.578***	1.293***	543.569**	-0.327	0.028	-0.047
	(17.156)	(0.990)	(0.126)	(0.440)	(243.933)	(1.161)	(0.093)	(0.319)
Constant	176.045	117.477***	-12.532***	-28.391***	-11230.266**	2.741	-0.579	1.301
	(373.188)	(22.129)	(2.707)	(9.565)	(5231.015)	(24.937)	(1.984)	(6.947)
Observations	1,559	1,559	1,559	1,559	494	494	494	494
R-squared	0.538	0.463	0.770	0.364	0.279	0.320	0.233	0.130
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.15 (continue)

	Panel II: DOWNWARDS (RTS$_{LARGE}$ → RTS$_{SMALL}$)							
DTREATMENT	-1.532	0.480	-0.156**	-0.280	104.810	-0.804	-0.045	-0.021
	(11.112)	(1.081)	(0.075)	(0.253)	(187.926)	(0.664)	(0.052)	(0.160)
DPOST	0.629	2.169	-0.376	-0.416	-3036.036***	-6.187***	-0.024	-0.074
	(19.113)	(4.157)	(0.254)	(0.363)	(695.777)	(1.561)	(0.093)	(0.120)
DTREATMENT×DPOST	-3.379	0.634	0.476***	0.902***	527.724	1.653***	0.290**	0.129
	(8.547)	(1.153)	(0.063)	(0.234)	(335.389)	(0.425)	(0.115)	(0.182)
VOLATILITY	-4.009***	-0.110	0.055***	0.098***	-74.585***	-0.155	-0.007	-0.058***
	(1.217)	(0.215)	(0.008)	(0.024)	(22.830)	(0.113)	(0.010)	(0.019)
LIQUIDITY	3.212*	0.409	-0.004	-0.071	-69.729	0.193	0.014	0.071
	(1.845)	(0.261)	(0.013)	(0.046)	(43.028)	(0.121)	(0.022)	(0.053)
SIZE	12.202	-5.031***	0.317***	0.646	708.912*	-2.758*	0.066	0.072
	(13.140)	(1.741)	(0.089)	(0.406)	(377.149)	(1.469)	(0.075)	(0.123)
Constant	16.310	49.289	-7.293***	-14.650	-12183.111	57.997*	-1.373	-1.370
	(292.432)	(39.032)	(2.003)	(9.065)	(7996.006)	(32.197)	(1.655)	(2.691)
Observations	3,563	3,563	3,563	3,563	1,581	1,581	1,581	1,581
R-squared	0.561	0.452	0.768	0.347	0.211	0.226	0.189	0.101
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Therefore, the UPWARDS event is considered as the catalyst that causes a further decline in the HFT activity of Treatment stocks, which widened the gap in HFT activity between the Treatment and Control groups. Overall, the results confirm that a steep increase in relative tick size would substantially impede HFT activity on both the ASX and CHIX markets.

Panel II provides the outcomes for the DOWNWARDS scenario, which illustrates the event where relative tick size decreased substantially as a result of tick size crossings. The coefficients for DPOST×DTREATMENT are found to be significantly positive in HFO ($\beta = 0.476$) and HFOR ($\beta = 0.902$) using the ASX dataset, and in ALGO ($\beta = 1.653$) and HFO ($\beta = 0.290$) using the CHIX dataset. In addition, these HFT measures are shown to be negatively related with DTREATMENT, suggesting that Treatment stocks have less HFT activity than Control stocks in the DOWNWARDS event as well. Therefore, the positive coefficients in the interaction term imply that the DOWNWARDS event *is* the turning point that leads the Treatment stocks to exhibit greater HFT activity than the Control stocks. Essentially, these findings reveal that a considerable reduction in relative tick size would greatly stimulate HFT activity in the Australian equity market.

Using the ASX dataset, the regression results of the control variables show that: (i) stocks with higher volatility would have significantly lower MTR and ALGO, but higher HFO and HFOR; (ii) stocks with wider spread would have significantly higher MTR and ALGO; and (iii) stocks with larger capitalisation would have significantly lower ALGO, but higher HFO and HFOR. The findings for the CHIX dataset indicate that: (i) more volatile stocks would have lower MTR and HFOR; (ii) the bid-ask spread has no significant influence on any of the HFT measures used; and (iii) larger stocks would have higher MTR but lower ALGO.

In conclusion, the findings indicate that there is an inverse relationship between HFT activity and relative tick size, and this is evident on both the ASX and CHIX datasets. The findings indicate that HFTs prefer the order-undercutting strategy, which enables them to capitalise on their speed while mitigating adverse selection risk; hence, a finer pricing grid is always desired. Market-makers would generate a higher return with a coarser pricing grid; however, this is only attainable with the order-queuing approach, which HFTs generally avoid since it negates their speed advantage and increases their risk exposure. These results also suggest that HFT activity can be influenced through regulatory intervention by adjusting nominal tick size values, or through corporate actions by artificially altering stock prices using forward or reverse splits.

3.7 Conclusion

Using data from the Australian equity markets, this research investigates the impact of relative tick size on HFT activity as measured by MTR (quoting intensity), ALGO (algorithmic liquidity provision), HFO (high-speed OrderIDs), and HFOR (HFO-contributed message). In this study, HFT activity in stocks with relative tick sizes classified as small (RTS_{SMALL}) or large (RTS_{LARGE}) was compared. The relative tick size values are directly influenced by nominal tick size and stock price; thus, these parameters are used to identify three distinct scenarios, which serve as the foundation to verify the hypotheses proposed in this study.

The first hypothesis postulates that, "*stocks with larger relative tick sizes will have significantly higher levels of HFT activity due to greater order-queuing activity compared to stocks with smaller relative tick sizes.*" Nonetheless, the study shows that smaller relative tick sizes result in greater HFT activity on both ASX and CHIX markets. Even though this is evident in the one-cent tick size category, however, the effect on most HFT measures in the half-cent tick size category is insignificant. This is because stocks in the RTS_{SMALL} group of the half-cent category have an almost identical relative tick size to stocks in the RTS_{LARGE} group of the one-cent category. Therefore, their relative tick size is not small enough to attract HFTs. From the literature, HFTs prefer stocks with a very small relative tick size for three reasons: (i) the availability of many price levels allows HFTs to undercut existing limit orders by posting slightly better prices (Werner et al., 2019); (ii) slower traders hesitate to place limit orders for fear of being undercut, resulting in a shorter order queue (Angel, 2011); and (iii) the speed of HFTs enables them to enter and exit the market rapidly as required, without worrying about getting stuck in a lengthy order queue upon re-entry. Overall, the findings of the study contradict the first hypothesis as the results show that HFTs favour stocks with very small relative tick sizes, suggesting a preference for an undercutting strategy.

The second hypothesis states that "*stocks priced slightly above the A$2.00 tick size border will have significantly higher levels of HFT activity due to their larger relative tick sizes compared to stocks priced slightly below the A$2.00 tick size border*." As stock prices approach the A$2.00 tick size border, the relative tick size disparity between RTS_{SMALL} and RTS_{LARGE} widens, signifying a greater incentive for order-undercutting (minimising risk) and order-queuing (maximising profit) activities. This scenario leads to greater HFT activity in the RTS_{SMALL} group on both the ASX and CHIX markets. However, when prices move farther away from the tick size border, the disparity between RTS_{SMALL} and RTS_{LARGE} lessens, hence reduces the incentive for HFTs to participate. On the ASX, this situation yields conflicting results. It implies that some HFTs still choose the order undercutting approach, while others take advantage of the ASX' demographics by trading with uninformed traders. This benefits them from a reduced adverse selection risk. In contrast, due to CHIX's demographics, market-making HFTs face a greater adverse selection risk. This forces them to constantly choose stocks with a small relative tick size. In the absence of such stocks, market-making HFTs stop using relative tick size as a parameter in their trading algorithms. Overall, the findings are in contrast to the proposed hypothesis, and show that HFTs favour order undercutting over order-queuing, especially when informed traders are present in large numbers and the relative tick size is sufficiently small. This suggests that HFTs are risk-averse and prioritise risk reduction over profit maximisation.

The third hypothesis suggests "*crossing a tick size border in an upward (downward) direction results in a statistically significant increase (decrease) in the level of HFT activity for the affected stock.*" The analysis shows that when relative tick size crosses the A$2.00 tick size border in an upward direction, HFT activity declines substantially. Conversely, when relative tick size plunges due to a downward crossing direction, HFT activity increases significantly. These results are consistent across the ASX and CHIX markets. It indicates that HFTs prefer stocks with fine pricing grids and would forsake them if their grids become coarse. The inverse relationship between HFT activity and relative tick size demonstrates the risk-averse character of market-making HFTs. This evidence also highlights the importance of order-undercutting techniques for market-making HFTs, which is attributable to their extremely low tolerance for adverse selection risks.

In conclusion, this study's results challenge the idea that stocks with large relative tick sizes have greater HFT activity. Instead, the findings support the view that stocks with small relative tick sizes have higher HFT activity. While previous studies, primarily focused on the U.S. markets (e.g., O'Hara et al., 2019; Yao & Ye, 2018), suggested otherwise, differences between the Australian and American markets' architecture may explain the inconsistent findings. In Australia, market-making HFTs incur lower costs due to less market fragmentation and more effective risk management when choosing stocks with smaller relative tick size. In addition, the lack of designated market makers reduces competition for liquidity provision, allowing HFTs to capture a larger share of revenue from such activities. This is most evident in high-priced stocks since their relative tick size is extremely small and thus more attractive to market-making HFTs. On the CHIX market, where informed traders are more present, HFTs face increased pressure to monitor their risk exposure closely, and are compelled to consistently employs order undercutting strategies. Moreover, the study shows that when a stock's relative tick size decreases, HFT activity increases while it decreases when a stock's relative tick size increases.

CHAPTER FOUR:
ESSAY THREE
EXPECTED VOLATILITY, HIGH-FREQUENCY TRADING, AND LIQUIDITY

This chapter demonstrates how expected volatility influences HFT activity, and how the resulting shift in HFT activity impacts liquidity. The chapter starts with the introduction of the essay, which covers the background of the study and research motivation. The chapter continues with a literature review and hypotheses development, followed by methodology, findings, discussions, and conclusion.

4.1 Introduction

The CBOE Volatility Index (VIX), commonly known as the "fear gauge" or "fear factor", is a forward-looking index that represents the unforeseen future market fluctuations that investors anticipate (Hull, 2018). The original VIX was developed by Whaley in 1993 for the Chicago Board Options Exchange (CBOE) to measure the expected volatility of the S&P 100 Index (OEX) using 30-day at-the-money options, and this characteristic distinguishes the VIX from other stock market indices that monitor prices. In 2003, the CBOE revised the definition and computation of the VIX and replaced the OEX with the S&P 500 Index (SPX) as its underlying index. The new VIX is calculated using a weighted average of SPX puts and calls with a broad range of strike prices over the next 30 days.[33] Several stock exchanges across the world have adopted a similar methodology to track near-term expected volatility in their respective markets, including the VSTOXX in Eurozone, AXVI in Australia, VHSI in Hong Kong, and INVIXN in India, underlined by the EURO STOXX 50, S&P/ASX 200, Hang Seng Index, and NIFTY 50, respectively.

The concept of implied volatility, which forms the basis of the VIX index, reflects investors' expectations of near-term future volatility in the stock market, with higher levels of the index suggesting greater investor concern over future economic prospects. Consequently, the indicator can also measure stock market

[33] The formula for calculating the VIX is detailed in https://cdn.cboe.com/resources/vix/vixwhite.pdf.

sentiment (Reilly & Brown, 2012). Whaley (2009) notes that the rates of change in the VIX and the SPX are asymmetric and observes that investors' fear of a bearish market dominates their excitement (or greed) in a bullish market. This behaviour also suggests that a high VIX reflects a heightened degree of fear over the possibility of a market crash, while a low VIX indicates higher investor confidence.

Similarly, Ang, Chen, and Xing (2006) find that the behaviour of investors towards upside potential and downside risk is asymmetrical, where the latter is shown to have a relatively greater influence on stock prices. This pattern suggests that investors are more sensitive to downside risks than upside opportunities; therefore, the magnitude of market reactions is expected to be greater when the VIX is high (pessimistic) than when it is low (optimistic). In addition, Savor (2012) shows that when the VIX is high, the ratio of no-information to information-based price shocks is greater. His finding suggests that news concerning firm fundamentals has a lower impact on stock prices during periods of high uncertainty and that no-information price shocks are more frequent during such times. Savor (2012) posits that stock prices might be more sensitive to investor sentiments and liquidity shocks during pessimistic periods. For the reasons mentioned above, it is prudent for investors to take precautionary measures to safeguard the value of their assets whenever the VIX signals high market uncertainty. This purpose may be attained by purchasing options contracts or engaging in short selling to take advantage of the elevated fear sentiment, which serves as an insurance policy to protect the portfolio's value.

On the other hand, investors may choose the flight-to-quality strategy, in which their high-risk market positions are liquidated, and the proceeds are invested in relatively safer financial instruments[34] (see, e.g., Amihud & Mendelson, 2012; Sarwar, 2017; Troster, Bouri & Roubaud, 2019). In a radical approach, pessimistic investors may liquidate their financial assets and abandon the market until the situation improves. A herding behaviour from such action might create excessive selling pressure in the market, which consequently would cause the stock market

[34] For instance, blue-chip stocks, futures contracts for precious metals such as gold and silver, and Treasury bills.

index to plummet. Furthermore, the decision to remain on the sidelines would immediately diminish market liquidity, exacerbating an already fragile market. In theory, the VIX should have no direct effect on the liquidity of a stock market. Regardless, the arguments mentioned above imply that the fear index may substantially influence market participants' expectations and behaviours, mainly when sentiment is negative (i.e., when the VIX is high), which results in the deterioration of market liquidity.

4.1.1 Volatility index in Australia

In Australia, the ASX introduced its volatility index, the S&P/ASX 200 VIX (AXVI), on September 23, 2010. The end-of-day index tracks the settlement prices of S&P/ASX 200 index's (AXJO) put and call options to calculate a weighted average of the implied volatility of the options.[35] Similar to the original VIX, the AXVI captures the sentiment of market participants on the expected level of volatility in the Australian equity market in the near future. Higher values suggest that the market anticipates substantial changes in the underlying index over the next 30 days, whereas lower values imply greater market confidence. Figure 4.1 shows the weekly average of AXJO and AXVI values since the latter's inception in September 2010. The graph demonstrates that the two indices appear to be negatively correlated, with high AXVI values corresponding to low AXJO levels and *vice versa*. This inverse relationship suggests that when market sentiment is negative (positive), selling pressure outweighs buying pressure, resulting in lower (higher) AXJO values.

In addition, Edwards and Preston (2017) propose that even a straightforward interpretation of the VIX may help forecast future volatility, such as defining a VIX level below 12 as "low", above 20 as "high", and values in between as "normal". Based on these threshold levels, it is expected that the underlying index would fluctuate by either ±3.5% (low VIX) or ±5.8% (high VIX) after one month.[36] Figure

---

[35] The following link provides further information on the AXVI computation: www.spglobal.com/spdji/en/documents/methodologies/methodology-sp-asx-200-vix.pdf.

[36] This value is calculated using the following formula: $\overline{S\&P500}_{t+30} = VIX_t \div \sqrt{12}$

4.2 illustrates the distribution of AXJO price changes over the next 21-day trading period, classified by the previously specified threshold values.[37]

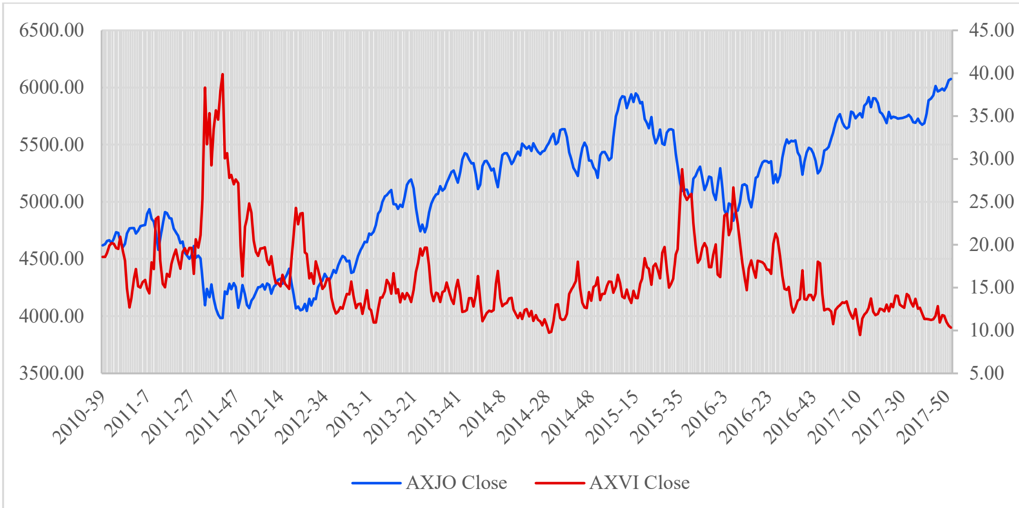

Figure 4.1: Weekly average of S&P/ASX 200 index (AXJO) and S&P/ASX 200 VIX index (AXVI)

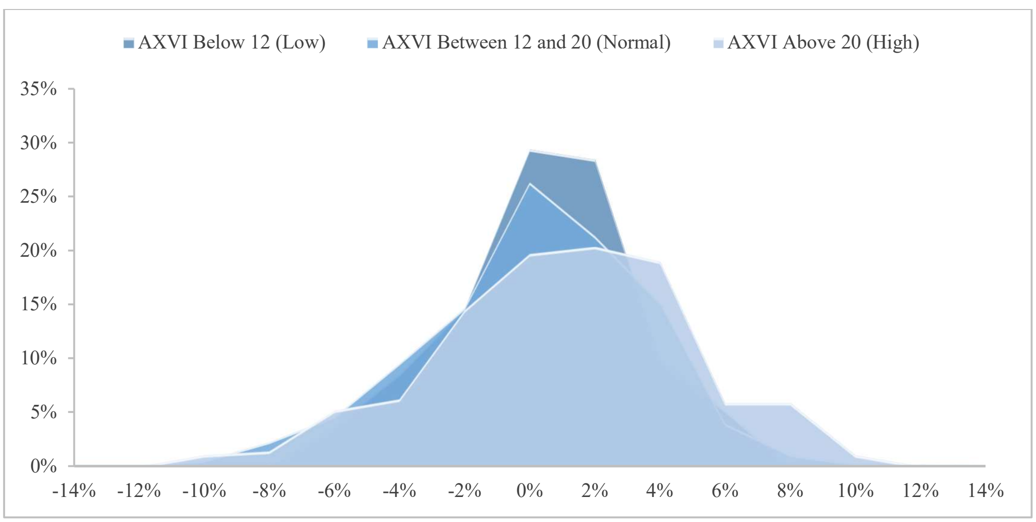

Figure 4.2: Variation in the AXJO's price over the next 21 trading days (to the nearest 2%)

[37] The duration of 21 trading days corresponds to approximately 30 calendar days, which is also the projected horizon for the VIX index.

The diagram indicates that observations from the group with a high VIX have a thicker tail, implying a larger likelihood of large price swings (6% or more) than when the VIX is normal or low. Assuming the current value of AXJO is 5,000 points, the index will change by at least 300 points in either direction over the next 21 trading days, with a probability of 20%, 13%, and 9%, respectively, when the VIX is high, normal, and low.[38] Therefore, although the AXVI may not accurately predict the direction of future changes in the AXJO, it may be possible to forecast the magnitude of future changes in its underlying index. This information may help investors time their market entry and exit, allowing them to make better investment decisions.

On February 28, 2013, the AXVI was made available in real-time due to the rise of volatility as an asset class in response to the global economic uncertainties. This action allows the ASX to issue a range of financial instruments, providing market players with greater opportunities to trade, diversify, and hedge their portfolios against volatility. Moreover, the real-time AXVI supplies the Australian equity market with continuous information on expected stock market volatility, thereby increasing the informativeness of the stock market. The new feature is expected to be well-received by HFTs and other market players who depend heavily on real-time, short-lived information. In addition, the real-time AXVI would allow investors to develop trading strategies based on market sentiment, which may be especially relevant on volatile days due to the increased amount of information.

4.2 Literature review and hypotheses development

4.2.1 Liquidity

Liquidity is defined as the ability to trade a stock quickly and at a low cost; hence, price movement and market viability rely on sellers' and buyers' ability to satisfy their trading desires (O'Hara, 1995). Similarly, Sundaresan and Wang (2009) describe liquidity as the easiness with which a substantial amount of a security may be exchanged in the market in a short period of time without triggering an adverse price reaction. Liquidity is regarded as an important trait of capital assets and has a significant impact on their pricing, and studies find that it is priced in the cross-

[38] See Table A1 in the Appendix for further information on the data used to construct the graph shown in Figure 4.2.

section of stock returns (Acharya & Pedersen, 2005; Amihud & Mendelson, 1991). Despite its importance, "liquidity" is difficult to define and cannot be directly observed owing to its multifaceted nature; hence, it cannot be represented by a single measure (Amihud, 2002). There are three widely recognised dimensions of market liquidity: depth, resilience, and tightness (see, e.g.: Duan & Zou, 2014; Kyle, 1985). However, as noted by Sar and Lybek (2002), these attributes may overlap to some extent. In empirical research, liquidity measures are often employed as proxy for transaction cost, price impact, and trading activity, which may represent one or more of the aforementioned dimensions.

Transaction costs are the costs associated with the execution of a trade. Some of the costs, such as taxes and commission fees, are known in advance (i.e., explicit costs), but others, such as the bid-ask spread, price impact and opportunity cost, may be less apparent (i.e., implicit costs) yet account for a significant portion of the overall transaction cost. Therefore, liquidity measures such as the high-low spread of Corwin-Schultz (2012) and the illiquidity ratio of Amihud (2002) are often used to reflect a different aspect of transaction costs, which are bid-ask spread and price impact, respectively. Madhavan (2000) suggests that the bid-ask spread may also represent the cost of immediacy paid by traders to market makers in order to have their orders executed quickly. Volume-based liquidity measures used the volume of transactions to measure liquidity and capture the breadth and depth of a market or securities (Sarr & Lybek, 2002). Since a transaction occurs when the bid and ask prices are matched, a tighter (wider) spread would signify a higher (lower) trading volume, and this relationship suggests that spreads and volume are negatively linked. In contrast, Easley and O'Hara (1992) argue that there would be no trade if there were no information event, either good or bad. This scenario represents a "safer" trading environment, allowing market makers to post a tighter spread. In contrast, the greater the volume, the greater the probability that the market maker assumes an information event has happened, and consequently, they post a wider spread. In any case, these arguments show a positive relationship between volume and spreads, with higher volume being associated with wider spreads and *vice versa*.

Market makers act as liquidity providers due to their role in facilitating immediate trade execution by matching buy and sell orders, which is performed through frequent limit orders posts. Due to this operating mechanism, market makers may suffer loss when trading with investors who possess price-sensitive private information, exposing them to adverse selection risks. In addition, market makers must maintain a certain level of stock inventories in order to quickly match the standing limit orders in the market. This factor exposed them to the risk of unanticipated future changes, such as the direction of stock prices and the time required to have their limit orders executed. Consequently, the bid-ask spread posted by market makers should reflect the risks they must assume to make the market in addition to the profits earned by such activity. During periods of heightened uncertainty (e.g., high VIX), investors may choose to leave the market *en masse* or refrain from trading, both of which diminish market liquidity. The importance of having market makers increases during such periods, but so does the risk they must assume, which results in wider bid-ask spreads. The scenario may be seen as the fear index's indirect influence on liquidity, which is channelled through the index's influence on market participants' expectations and behaviours, particularly when sentiment is negative.

4.2.2 High-frequency trading strategies

The evolution of technology transforms how information is transmitted, allowing "hard" information such as stock market data and corporate financial statements to be received and processed faster.[39] The extensive use of high-speed computers, massive database programmes, and low-latency networking have amplified trading activities reliant on hard information, such as those practised by the HFTs (Liberti & Petersen, 2019). HFTs are notably distinct from other types of investors due to their lightning-fast operations, making it impossible for other players to replicate their trading strategies (Harris, 2013).

[39] This also includes data obtained from publicly available indexes, such as the volatility indices stated previously.

Menkveld (2014) asserts that HFTs have a competitive advantage over human traders due to the following factors: (1) the ability to identify profitable trading opportunities instantly; (2) the capacity to process newly arrived information and execute the necessary actions rapidly; and (3) the ability to evaluate textual context from machine-readable news. Scholtus, van Dijk, and Frijns (2014) investigate the importance of speed to the profitability of news-based trading strategies using U.S. datasets. According to their findings, a delay of 300 milliseconds or more severely impairs the returns of such a strategy, with the reduction being more pronounced on days with high-impact news and high volatility. Their results demonstrate how crucial speed is to the profitability of short-term traders such as the HFTs, and how its importance escalates during periods of high uncertainty. For these reasons, HFTs spend a fortune on technological infrastructures that minimise latency and hire quantitative analysts ("quants") to develop trading algorithms for their automated trading operations.[40] Due to this high entry barrier, sophisticated market players such as full-fledged HFT firms, proprietary trading desks, and hedge funds are the predominant users of HFT strategies (Goldstein et al., 2014).[41]

In theory, HFT strategies may have both beneficial and detrimental effects on liquidity due to their trading flexibility – a stronger presence on the supply side would increase the order book's depth, resulting in more liquidity and narrower spreads, whereas a stronger presence on the demand side would rapidly deplete standing limit orders, thereby draining liquidity from the market and widening spreads. In general, HFTs provide liquidity when they assume the role of market maker, using their speed advantage to swiftly update quotes and profiting from the spread between the bid and ask prices. This method requires HFTs to place limit orders on both sides of the book, therefore supplying liquidity to the market (Chung & Lee, 2016). Their market-making activities also contribute to market efficiency and stability; they sell when others prefer to buy and purchase when others wish to

[40] Since the nature of the game is winner-take-all, HFTs continuously upgrade their technologies to remain competitive (Kauffman et al., 2015; NAFM, 2010). This aspect leads to an arms race between HFTs, which is criticised for wasting resources without meaningful improvements to market quality. The race is seen as counterproductive, and it is debatable whether HFTs add value to the broader market (Chordia et al., 2013; Jones, 2013).
[41] Full-fledged HFT firms in Australia include Citadel Securities, Jump Trading, Liquid Capital, Susquehanna International Group, and Virtu Financial.

sell (Angel, 2014). Moreover, Boehmer et al. (2018) demonstrate that the competition between market-making HFTs lowers both the permanent and temporary price impact of trades, resulting in reduced short-term volatility. Similar results are reported by Hagstromer and Nordén (2013), who find that market-making HFTs decrease intraday volatility by providing liquidity.

In addition, Benos and Sagade (2016) find that passive HFTs are liquidity suppliers while aggressive HFTs are liquidity takers, and that their liquidity taking/making behaviour does not change substantially over time. This distinction results in a wide variety of HFT strategies, which translates to varying sensitivity towards recent order book and inventory level changes. On the other hand, Aldridge (2013) asserts that the order execution algorithms employed by HFTs determine whether their strategy is aggressive or passive – an order placed at or near the current market price is perceived as aggressive, whereas a limit order placed far away is regarded as passive.[42] Some exchanges even employ the maker/taker pricing model, in which passive orders are subsidised with "rebates" and aggressive orders are charged "fees".[43,44] Studies find that the absence of rebate might put market-making HFTs in a loss position, notably when spreads are narrower. Consequently, HFTs may be discouraged from engaging in market-making activities (Brogaard et al., 2014; Hendershott & Riordan, 2013).

Although HFTs' market-making is generally beneficial to the market, their reliability as a liquidity source is debated, particularly during times of stress, since they are not obligated to make the market like a traditional market maker. This absence of responsibility raises concerns that HFTs might leave the market at their convenience, for instance, when participation is no longer profitable (Anand & Venkataraman, 2013; Carrion, 2013). According to O'Hara (2014), spreads are narrower as a result of HFTs' intermarket arbitrage, which moves liquidity from a market with a surplus of liquidity to a market with a shortage of liquidity.

---

[42] A market order, also known as a marketable order, is an order placed at the current market price. This order gives the sender price-priority, allowing it to be executed as quickly as possible; hence, it is sent when a trader requires an immediate order match.
[43] Electronic limit order books depend on the voluntary supply of liquidity; thus, exchanges must incentivise traders to place limit orders, resulting in the adoption of the maker-taker pricing model.
[44] Alternatively, the maker-taker pricing model may offer asymmetric trading fees, with lower transaction costs for liquidity suppliers and higher trading fees for liquidity takers (see Durbin, 2010).

Nevertheless, HFTs may use illegal yet difficult to detect predatory algorithms. VanKervel and Menkveld (2019) observe that although retail investors may benefit from a narrower bid-ask spread, institutional investors complain that the presence of HFTs increases their execution costs.[45] Their research shows that when HFTs initially enter the market, they operate as a liquidity provider by trading against (*against-wind*) large institutional orders. However, they rapidly switch roles and become liquidity demanders by trading with (*with-wind*) the large orders. As a result, the strategic exploitation of HFTs increased the execution costs for institutional traders supplying liquidity, making it costly for the latter and profitable for the former.

VanKervel and Menkveld (2019) claim that despite the fact that HFTs' with-wind trading may make prices more efficient in the short term, it may cause prices to be less efficient in the long run. The greater execution costs inflicted on institutional investors may discourage them from conducting costly analyst research, since the informational rents generated from such effort are forcibly shared with others, thus reducing the information trader's profits. Overall, the practise of order anticipation by HFTs is considered parasitic because it neither contributes to price discovery nor liquidity, while unnecessarily increasing the execution costs of large liquidity providers and negatively impacting their trading strategy. Furthermore, it may reduce the incentive for large traders to acquire information (Agarwal, 2012; Grossman & Stiglitz 1980, Harris, 2015; Stiglitz 2014, Weller 2018).

Goldstein et al. (2020) show that HFTs, on average, supply depth on the thick side of the order book, but demand depth from the thin side of the order book. This behaviour suggests that HFTs provide liquidity when it is less necessary and abstain from doing so when it is critical. Goldstein et al. (2020) argue that HFTs' order placement is more consistent with order anticipation strategies, and this is more apparent during volatile periods and when trading is faster.[46] Hirschey (2020)

[45] Institutional investors use algorithms to split their bulk orders into multiple small orders and feed them to the market sequentially. This is done to conceal their originally large transactions from other traders, hence lowering their trade's price impact and execution costs.
[46] Order anticipation is regarded as a "very harmful" trading strategy and a form of front-running (Harris, 2013, 2015). This strategy operates by monitoring trades and quotes to identify algorithms

reported findings suggesting that HFTs could trade ahead of non-HFT order flow, which is made possible because, (i) HFTs may identify the persistent order flow of informed non-HFTs, and (ii) liquidity providers are slow to update their quotes. Therefore, liquidity providers are forced to trade fewer shares than desired, or have their orders fulfilled at a worse price.

Zhang (2017) shows that HFTs can react more quickly and aggressively than non-HFTs to hard information shocks, allowing them to take strategic positions and profit from the shock. Her finding implies that HFTs play a vital role in short-term price discovery, especially on days with an incredible amount of hard information, such as when the market is volatile. Similarly, Brogaard, Hendershott, and Riordan (2014) demonstrate that the trading direction of HFTs is correlated with publicly available information such as macroeconomic news releases, market-wide price fluctuations, and limit order book imbalances. Riordan and Storkenmaier (2012) investigate the 2007 upgrade of Deutsche Boerse's Xetra systems, which reduced the latency of the trading system from 50 milliseconds to 10 milliseconds. The decreased latency should be irrelevant to human traders as it transcends their time perception; however, HFTs may benefit since their strategies are time-sensitive, and the exchange's infrastructure upgrade would offer a faster trading environment for HFTs' algorithms to prosper. They observe that both the quoted and effective spreads decreased in the post-upgrade period, which is probably attributable to HFTs' activity. Similarly, the 2013 launch of the real-time AXVI index may have a stronger impact on HFTs and other traders with a short trading horizon. The new index would feed the market with real-time, publicly accessible information, allowing HFTs to take strategic positions and profit from any opportunities resulting from the market's immediate response towards fluctuations in the VIX levels.

Furthermore, even though HFTs are emotionless and do not experience "anxiety" or "fear," and can only execute the algorithm they were programmed, their trading decisions are susceptible to order-book information. Consequently, the fear-

---

deployed by large traders, then trading ahead of them to profit from the anticipated direction of price movements.

driven activities of other investors amidst periods of high uncertainty may substantially influence the behaviour of HFTs. In situations such as the Flash Crash, which sees an extreme fluctuation of the VIX index, some HFTs are reported to cease trading to avoid the risk of enormous losses, leaving other investors with fewer players to take the opposite side of their orders (Patterson, 2010). Moreover, unlike designated market makers (DMMs), HFTs operating as electronic liquidity providers (ELPs) have neither the responsibility nor the commitment to remain within an unfavourable market. This factor makes them a less credible source for liquidity, which may aggravate execution uncertainty (Anand & Venkataraman, 2013; Chung & Chuwonganant, 2018; Zhang, 2010). Furthermore, in markets where they play a critical role in supplying liquidity, their sudden absence during volatile times might result in a severe liquidity shortage, leading to extreme market movements similar to the Flash Crash (Gomber et al., 2011).

Therefore, the positive effect from HFTs' activity may not persist during fearful periods, and the pessimism of other investors may adversely impact HFTs' influence on the market, driving them to switch from being liquidity suppliers to liquidity takers. In addition, the absence of a need to make market enables HFTs to adopt a range of strategies; hence, their role in the stability and pricing efficiency of markets, particularly during periods of heightened uncertainty, is regarded with scepticism (Brogaard, Hendershott and Riordan, 2014). Regardless, *everyone has the right to be presumed innocent until proved guilty*, which motivated the researcher to conduct further investigation into the allegations made against HFTs, particularly concerning their influence on market liquidity during periods of negative sentiment.[47]

4.2.3 Hypotheses development

According to Liberti and Petersen (2019), the emergence of high-speed computers, high-quality databases, and low-latency networking has led to trading activity that largely depends on hard information, such as the strategies used by HFTs. Zhang (2017) shows that HFTs play an important role in short-term price discovery,

[47] This statement is based on the presumption of innocence outlined in article 14(2) of the International Covenant on Civil and Political Rights (ICCPR), which was retrieved from www.austlii.edu.au/au/other/dfat/treaties/ATS/1980/23.html.

particularly on days with an enormous amount of hard information. For example, when the market is volatile, HFTs can rapidly update quotes and earn from the difference between the bid and ask prices (Chung & Lee, 2016). This promotes liquidity and improves market efficiency and stability (Angel, 2014). In Australia, stock market participants have continuous access to information about expected volatility due to the availability of real-time AXVI. Adding real-time features to the AXVI is crucial for HFTs and other fast market players with a short trading horizon. It enables them to formulate trading strategies based on market sentiment and profit from any opportunities resulting from fluctuations in the VIX levels (Brogaard et al., 2014). This innovation should have a substantial influence on HFTs on the Australian market as they would have more alternatives for their trading strategy. While the real-time AXVI introduction event (VIX_{RT}) would have no direct impact on liquidity, it may indirectly affect liquidity via its relationship with HFTs. Consequently, the effect of the VIX_{RT} event on HFTs' influence on liquidity may be amplified or diminished. Based on the argument, the following hypothesis is proposed:

H1: *The introduction of real-time AXVI (VIX_{RT}) have a positive impact on HFT activity and indirectly increase liquidity through its relationship with HFTs.*

Although HFTs lack emotions, their trading decisions are driven by order-book data and may be indirectly affected by negative sentiment through the trading activity of emotional traders. For instance, on days when the VIX is extremely high and widespread intraday price swings emerge, some investors may leave the market in a panic or refuse to participate at all. This can influence HFTs' trading strategies. Moreover, market-making HFTs are not legally required to maintain liquidity at all times and may also leave the market if the situation is undesirable. This opportunistic behaviour may exacerbate the already fragile liquidity situation in the market during such times (Anand & Venkataraman, 2013; Carrion, 2013), calling into question the credibility of HFTs as liquidity providers. In periods of high volatility and rapid trading, HFTs' order placement behaviour aligns more closely with order anticipation strategies (Goldstein et al., 2020). This approach preys on other players, particularly large traders whose execution costs would be unnecessarily inflated (Agarwal, 2012; Harris, 2015), and does not contribute to price discovery or liquidity. As a result, HFTs' strategies may change on high VIX days, affecting the market's liquidity. This research makes the following hypothesis founded on these arguments:

H2: *As VIX levels increase, HFT activity changes in a way that exacerbates the already fragile liquidity situation in the market, calling into question the credibility of HFTs as liquidity providers.*

4.3 Methodology

4.3.1 Data description

This research employs order book information supplied by the Securities Industry Research Centre of Asia-Pacific (SIRCA). Only S&P/ASX 100 (ASX: XTO) constituents are sampled to ensure that the selected stocks are reasonably large and liquid.[48] The list of XTO's constituent stocks is retrieved from Thomson Reuters Datastream and is reviewed on a monthly basis.

4.3.2 Sample selection

The first hypothesis suggests that the introduction of real-time AXVI (VIX_{RT}) on February 28, 2013, have a significant effect on HFT activity, and influence the relationship between HFT activity and liquidity. To verify this hypothesis, the study examines observations that occur one year before and one year after the VIX_{RT} event day; thus, only data from firms that consistently appear on the XTO constituent list during this time period are selected. Throughout this 24-month period, there are a total of 114 unique firms; however, 34 firms were excluded due to incomplete data issue, leaving the final sample with only 80 firms.[49] The selected observations are subsequently categorised as "Pre-event" or "Post-event".

---

[48] The XTO index consists of the 100 largest firms listed on the ASX by float-adjusted capitalisation, all of which are large and medium-sized corporations.

[49] A stock is considered to have incomplete data if it meets the following criteria: (i) it does not consistently appear in the XTO's constituent list throughout the 24-month period surrounding the VIX_{RT} event; and (ii) it has too many missing data in either the ASX dataset only, the CHIX dataset only, or both datasets.

The study further evaluates whether the observed difference (if any) persists in the short-term (1 month), medium-term (6 months), and long-term (12 months) following the VIX_{RT} event. For this purpose, three different datasets covering the aforementioned date ranges surrounding the VIX_{RT} event are utilised, with each dataset comprising the same number of cross-sectional units. The reason for employing different observation lengths is to determine whether the effects (if any) are: (i) evident only in the periods close to the event date, indicating a temporary effect; (ii) evident across all tested periods, indicating a permanent effect; and (iii) evident only in the extended period and not in the immediate period, suggesting a slow adoption of the new features offered by the VIX_{RT}.

Table 4.1 summarises the data used to test the first hypothesis. The table shows that the average value of VIX in the post-event period of the 6 months dataset is higher than it was prior to the event. In contrast, the 12 months dataset indicates the opposite; the average pre-event VIX values are higher. This pattern implies that sentiment in the first half of 2012 was relatively more pessimistic, which is evident by the greater maximum VIX value of the pre-event period shown in Panel C of Table 4.1.

Table 4.1. Data description for the samples used to test the first hypothesis

This table briefly describes the dataset used to test the first hypothesis. *Pre-VIX_{RT}* and *Post-VIX_{RT}* denote the groups of observations that occurred before and after the VIX_{RT}'s introduction, respectively. Panel A, Panel B, and Panel C represent the short-term, medium-term, and long-term datasets, which span from February 1, 2013, through March 28, 2013, September 3, 2012, through August 30, 2013, and March 1, 2012, through February 28, 2014, respectively. *Observations*, *Mean VIX*, *Maximum VIX*, and *Minimum VIX* refer to the number of firm-day observations, and the average, the highest, and the lowest VIX values, in the pre and post VIX_{RT} periods, correspondingly.

	Observations	Mean VIX	Maximum VIX	Minimum VIX
Panel A: (1 month)				
Pre-VIX_{RT}	1,520	14.372	16.987	13.244
Post-VIX_{RT}	1,680	15.231	18.303	13.669
Panel B: (6 months)				
Pre-VIX_{RT}	9,896	13.264	17.089	10.536
Post-VIX_{RT}	10,230	15.454	21.675	12.476
Panel C: (12 months)				
Pre-VIX_{RT}	19,960	15.512	26.639	10.536
Post-VIX_{RT}	20,272	14.578	21.675	10.689

This is also corroborated by the line chart of AXVI illustrated in Figure 4.1, which show higher VIX values recorded during that period. Nevertheless, the average values of VIX before and after the VIX_{RT} event across all three datasets are comparable, as their differences are small and within the "normal VIX" range described in Edwards and Preston (2017). Therefore, it may be inferred that market sentiment is less likely to influence the outcomes generated by these datasets, and that any observable results are more likely to be driven by the additional features available post-VIX_{RT}.

The second hypothesis is formed on the premise that the levels of VIX and HFT activity influence liquidity. This hypothesis is tested using data from all available trading days since the introduction of the VIX_{RT}, wherein all observations possess similar real-time market information. The sample period extends until the last trading day of December 2017, a total of 1,225 distinct observation days. This approach retains the time-series characteristics of the original data and preserve the continuity of observations within the dataset, resulting in a high number of firm-day observations.[50] Employing a large sample size reduces the margin of error and increases the confidence level and power of the statistical tests used to confirm the hypothesis, leading to more accurate conclusions. The trading days are then divided into smaller groups according to their respective end-of-day VIX readings and HFT activity levels. Based on the threshold value suggested by Edwards and Preston (2017), all days with VIX values equal to or greater than 20 are labelled as "High VIX" (VIX_H), or "Event", whilst all other days are classified as "Non-high VIX" (VIX_{NH}), or "Non-event".[51, 52]

Moreover, two additional categories are formed based on their HFT activity level, as measured by the total number of high-frequency orders ID (HFO).[53] Observations with HFO values in the 90th percentile are classified as "High HFT" (HFT_H), or "Treatment", whereas all other observations are designated as "Non-high HFT" (HFT_{NH}), or "Control". The selected percentile values for VIX and HFO are shown in Table 4.2.

---

[50] This is in contrast to when samples consist of data from days with a high VIX and a low VIX only, and exclude any observations that do not belong to either category.
[51] This figure corresponds to the 91st percentile of the VIX.
[52] Investors' fear of a bearish market outweighs their greed in a bullish market (Whaley, 2009). Therefore, this study considered "low VIX" days to be less important, and they were pooled with other observations that also did not satisfy the threshold for "high VIX". In the final sample, these observations are designated as "non-high VIX".
[53] The following section provides details on the definition and method used to determine HFO.

Table 4.2. Percentile values for VIX_{CLOSE} and HFO[54]

This table displays the selected percentile values of the VIX_{CLOSE} and *HFO* used to test the second hypothesis. The reported figures are based on the longest study period used in this research, which began on February 28, 2013, and concludes in December 2017 (1,225 trading days). The variables VIX_{CLOSE}, HFO_{ASX} and HFO_{CHIX}, respectively, represent the end-of-day VIX value, and HFO values generated from the ASX and CHIX datasets. For the VIX_{CLOSE}, *Observations* refers to the number of daily observations, whereas for the HFO_{ASX} and HFO_{CHIX}, it refers to the number of firm-day observations.

	Observations	Percentile						
		5%	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**
VIX_{CLOSE}	1,225	10.953	11.378	12.466	13.995	16.688	19.566	21.984
HFO_{ASX}	121,777	9	14	26	56	162	493	805
HFO_{CHIX}	119,090	0	0	0	0	2	15	34

Next, four subsample groups are formed to capture the possible combinations of VIX and HFT, which are: (i) $Control_{Non\text{-}event}$ (VIX_{NH}-HFT_{NH}); (ii) $Treatment_{Non\text{-}event}$ (VIX_{NH}-HFT_{H}); (iii) $Control_{Event}$ (VIX_{H}-HFT_{NH}); and (iv) $Treatment_{Event}$ (VIX_{H}-HFT_{H}). The information relevant to these groups is summarised in Table 4.3.

Table 4.3. Description of the datasets used to test the second hypothesis

The table presents the data used to test the second hypothesis. Panel I describes the datasets for the sample in the Main groups, which is formed based on the values of VIX_{CLOSE} (end-of-day VIX), HFO_{ASX} (HFO derived from the ASX dataset), and HFO_{CHIX} (HFO derived from the CHIX dataset). For the VIX_{CLOSE}, days with VIX readings equal to or greater than 20 are labelled as VIX_H (Event), otherwise VIX_{NH} (Non-event). For both HFO_{ASX}, and HFO_{CHIX}, observations with HFO values in the 90th percentile are labelled as HFT_H (Treatment), otherwise HFT_{NH} (Control). The VIX_H and VIX_{NH} are then paired with HFT_H and HFT_{NH}, creating four subgroups for each dataset, as shown in Panel II. The subgroups are: (i) $Control_{Non\text{-}event}$ (VIX_{NH}-HFT_{NH}); (ii) $Treatment_{Non\text{-}event}$ (VIX_{NH}-HFT_{H}); (iii) $Control_{Event}$ (VIX_{H}-HFT_{NH}); and (iv) $Treatment_{Event}$ (VIX_{H}-HFT_{H}). *Observations* refer to the number of firm-day observations for their respective groups. *Weight* refers to the proportion of the total observations that are attributable to the observations of a certain group. *Mean* VIX_{CLOSE}, *Mean* HFO_{ASX}, and Mean HFO_{CHIX} are the average values for the end-of-day VIX, and the HFO values of the ASX and CHIX datasets, respectively.

Panel I: Main groups	**VIX_{CLOSE}**		**HFO_{ASX}**		**HFO_{CHIX}**	
	VIX_{NH} (Non-event)	**VIX_H (Event)**	**HFT_{NH} (Control)**	**HFT_H (Treatment)**	**HFT_{NH} (Control)**	**HFT_H (Treatment)**
Observations	111,098	10,683	109,581	12,196	106,948	12,142
Weight	91.23%	8.77%	89.98%	10.02%	89.80%	10.20%
Mean VIX_{CLOSE}	14.16	23.31	14.87	15.82	14.92	15.2
Mean HFO_{ASX}	166.87	292.11	89.23	974.17	Nil	Nil
Mean HFO_{CHIX}	6.18	8.08	Nil	Nil	1.33	50.55

Panel II: Subgroups	**VIX_{NH} (Non-event)**		**VIX_H (Event)**	
	HFT_{NH} (Control)	**HFT_H (Treatment)**	**HFT_{NH} (Control)**	**HFT_H (Treatment)**
	VIX_{NH}-HFT_{NH}	**VIX_{NH}-HFT_H**	**VIX_H-HFT_{NH}**	**VIX_H-HFT_H**
<u>ASX</u> (Obs. = 121,777)				
Observations	100,558	10,536	9,023	1,660
Weight	82.58%	8.65%	7.41%	1.36%
Mean HFO_{ASX}	87.35	925.80	110.15	1,281.19
Mean VIX_{CLOSE}	14.11	14.64	23.32	23.27

[54] Details regarding HFO are provided in Section 3.5.3.1 (Essay Two) or Section 4.3.3.2. (Essay 3).

Table 4.3 (continue)

CHIX (Obs. = 119,090)				
Observations	97,552	11,085	9,396	1,057
Weight	81.91%	9.31%	7.89%	0.89%
Mean HFO_{CHIX}	1.33	48.84	1.29	68.44
Mean VIX_{CLOSE}	14.11	14.42	23.31	23.43

These segmentations allow the researcher to determine whether: (i) the liquidity of stocks during high VIX days (Event) significantly differs from stocks during non-high VIX days (Non-event); (ii) the liquidity of stocks with high HFT activity (Treatment) significantly differs from stocks with non-high HFT activity (Control); (iii) the liquidity of stocks amongst the subgroups are significantly different ($Control_{Non\text{-}event}$, $Treatment_{Non\text{-}event}$, $Control_{Event}$, and $Treatment_{Event}$); and (iv) the influence of high VIX days (Event) on the effect of high HFT activity (Treatment) on liquidity.

4.3.3 Measurement of variables

4.3.3.1 Liquidity measures

This study seeks to determine whether HFT activity affects liquidity and whether high VIX days influence HFT's effect on liquidity. Due to the multidimensional nature of liquidity, the study employs several measures to gain a comprehensive understanding of the impact of VIX and HFT on liquidity. Accordingly, three different liquidity measures, namely the Corwin and Schultz (2012) High-Low Spread, the Amihud (2002) Illiquidity Ratio, and the Volume Turnover, are employed to capture the transaction cost, price impact, and volume dimensions of liquidity, respectively. This study employs liquidity proxies derived using daily data (i.e., low frequency) since such data are often widely available. As a result, the methodology used in this study may be more reproducible and applicable to a range of international markets over extended time periods.

1. Corwin-Schultz High-Low spread

The conventional bid-ask spread calculation requires bid and ask quotes data, which are more difficult to obtain than the high and low prices utilised in the calculation of the High-Low Spread (CSHL) measure developed by Corwin and Schultz in 2012. Such data is typically accessible on the majority of stock exchanges, making this new measure highly replicable. The CSHL formula, which is shown in Equation 4.1, made it possible to obtain negative spread values, especially during volatile days or when there was a significant overnight price change. In accordance with the authors' suggestion, the negative values are replaced with zero. Corwin and Schultz (2012) assert that the daily price range reflects the stock's volatility and bid-ask spread since the high (low) prices are almost always buyer (seller) initiated. Thus, CSHL is advocated as a measure of stock liquidity, with a high value indicating lower liquidity and a low value suggesting higher liquidity.

$$CSHL_{i,t} = \frac{2(e^{\alpha_{i,t}} - 1)}{1 + e^{\alpha_{i,t}}}$$

$$\alpha_{i,t} = \frac{\sqrt{2\beta_{i,t}} - \sqrt{\beta_{i,t}}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma_{i,t}}{3 - 2\sqrt{2}}}$$

$$\beta_{i,t} = \left[\ln\left(\frac{high_{i,t+1}}{low_{i,t+1}}\right)\right]^2 + \left[\ln\left(\frac{high_{i,t}}{low_{i,t}}\right)\right]^2$$

$$\gamma_{i,t} = \left[\ln\left(\frac{max\{high_{i,t+1}, high_{i,t}\}}{min\{low_{i,t+1}, low_{i,t}\}}\right)\right]^2$$

(Equation 4.1)

Where $CSHL_{i,t}$ is the High-Low Spread of stock *i* on day *t*; $high_{i,t}$ and $low_{i,t}$ represent the high and low prices of stock *i* on day *t*, respectively, while $high_{i,t+1}$ and $low_{i,t+1}$ represent the values obtained on day *t+1*.

2. Amihud Illiquidity ratio

The illiquidity measure proposed by Amihud (2002) in his seminal article is the most widely employed low-frequency price impact ratio in finance literature (Le & Gregoriou, 2020). The illiquidity ratio represents the magnitude of absolute price change for each dollar of volume traded on a stock, hence quantifying the impact of a trade on the stock's price. Since the measure is calculated daily, it reflects the day-long impact on prices. For a given degree of price fluctuation, a greater trading volume results in a lower illiquidity ratio, and *vice versa*. Thus, a larger Amihud illiquidity ratio indicates a lower liquidity, whilst a smaller ratio would reflect a higher liquidity.

$$ILLIQ_{i,t} = \frac{|R_{i,t}|}{DVOL_{i,t}}$$

(Equation 4.2)

Where, $ILLIQ_{i,t}$ represents the Amihud Illiquidiy Ratio of firm i on day t; $DVOL_{i,t}$ represents the daily volume traded (in A$) of firm i on day t; and $|R_{i,t}|$ represents the absolute value of return of firm i on day t.

3. Volume Turnover

Volume, which is directly expressed by the number of volumes traded, is one of the dimensions of liquidity. Regardless, it may be argued that directly citing volume could result in a size bias, as larger firms would naturally have more volume. To address this issue, the study uses volume turnover ratio, which is the number of daily volumes traded (in units) divided by the number of outstanding shares (see Equation 4.3). The ratio indicates that a higher volume turnover corresponds to a higher liquidity level, and *vice versa*.

$$VOLTO_{i,t} = \frac{DVOL_{i,t}}{SO_{i,t}}$$

(Equation 4.3)

Where, $VOLTO_{i,t}$ represents the volume turnover of firm i on day t; $DVOL_{i,t}$ represents the daily volume traded (in unit) of firm i on day t; and $SO_{i,t}$ represents the number of shares outstanding of firm i on day t.

4.3.3.2 HFT activity measures

Numerous HFT-related research have used proprietary datasets that accurately identify the sender for each order submitted to the market; the datasets utilised in this study, however, lack this feature. This study uses widely established HFT criteria as a basis for assessing HFT activity to ensure that the chosen proxies are appropriate for estimating the actual activity of HFT. For the purpose of this essay, only one proxy for HFT activity is used, which is the high-frequency orders (HFO), which is meant to measure the activity of low-latency traders, such as HFTs.[55] However, the use of this measure could also include the activities of non-HFTs operating in the sub-second trading environment. Therefore, any findings concerning "HFT activity" drawn from this study should be understood as reflecting the activity of "low-latency traders" as a whole, and not purely "full-fledged HFT firms".

Under the premise that an order will either be fully executed or fully cancelled, any order placed to the market may see the following message combinations:

(i) submission → executed
(ii) submission → cancelled
(iii) submission → amendment → executed
(iv) submission → amendment → cancelled
(v) submission → amendment → amendment → executed
(vi) submission → amendment → amendment → cancelled
(vii) and so forth (with more messages recorded as amendment in between).

The message chain may be shorter for human traders who submit their orders manually, since they are less likely to modify their orders frequently due to the tedious and time-consuming nature of the process. For traders of all sizes who utilise trading bots (i.e. algorithm-based trading), their orders may comprise a lengthy chain of messages that might span the whole trading day. However, the rate at which their quotes are updated is limited by the speed of their trading infrastructures. In contrast, low-latency algorithmic traders, such as HFTs, have access to cutting-edge technology and high-speed trading infrastructures, allowing them to update their quotations at a faster pace than other traders, resulting in a shorter order resting

[55] Although the message-to-trade ratio (MTR) and algorithmic trading ratio (ALGO) are often used as proxies for high-frequency trading (HFT) activity, they are less effective at capturing activity that is primarily driven by HFT activity and not by other market players. The formula used to calculate the MTR and ALGO provides a more broad estimate of HFT activity on a daily basis. In stock markets like as Australia, where HFT involvement is estimated to be around 20%, the figures provided by MTR and ALGO may not be effective measures of HFT activity given that the great majority of market activity is still produced by non-HFTs.

time.[56] In essence, speed is the element that distinguishes HFTs from other algorithm-based trading; without a speed advantage, HFTs are no different from other algorithm-based traders.

HFTs employing a market-making strategy are forced to constantly update their quotes in reaction to new market information, resulting in a large number of message submission. In addition, their limit orders will be immediately cancelled or amended if they are at risk of being adversely selected, or if they are attempting to profit from transitory trading opportunities – both of which result in a lengthy message chain and a short order resting period. Hasbrouck and Saar (2013) and Boehmer, Li, and Saar (2018) estimate HFT presence using strategic runs comprising a minimum of 10 linked-messages, asserting that frequent order modifications are often used in dynamic algorithmic strategies. In addition, Subrahmanyam and Zheng (2016) find that the average HFT order duration inside the top three price levels of the limit order book is 28.74 seconds for large firms and 33.74 seconds for medium-sized firms. Assuming an HFTs-submitted order contains at least 10 linked-messages, their results equate to an average order resting time of around 3 seconds. In summary, the abovementioned studies suggest that orders placed by HFTs should satisfy the following criteria: (i) have a lengthy message chain consisting of at least 10 messages; and (ii) have a short order resting time.

The datasets for this study include a unique order identification (OrderID) that allows the researcher to follow the chronology of all orders placed in the market, from the time they are originally submitted until they are removed through self-cancellation or traded by the opposite party.[57] Based on the previously established HFT criteria, the following formula presented in Equation 4.4 is used to identify high-frequency orders (HFO), which, theoretically, are sent by HFTs.

[56] Low-latency trading infrastructures consist of trade-related proprietary services (such as networking, co-location, sponsored access, and direct market access) and state-of-the-art computer hardware (such as high-speed CPUs, GPUs, and FPGAs).
[57] The second essay of this thesis provides additional information on OrderID, the dataset used, and relevant trading mechanisms. The author omitted certain sections to avoid repetition in the thesis.

$$OrderDuration_{j,i,t} = OrderID_{j,i,t,\max(d)} - OrderID_{j,i,t,\min(d)}$$

$$ORT_{j,i,t} = \frac{OrderDuration_{j,i,t}}{\sum_{1}^{j,i,t} Messages_{j,i,t}}$$

$$HFO_{i,t} = \left(ORT_{j,i,t} \leq 3 \text{ seconds}\right) \,\&\, \left(\sum_{1}^{j,i,t} Message_{j,i,t} \geq 10 \text{ messages}\right)$$

(Equation 4.4)

Where $OrderID_{j,i,t,\max(d)}$ represents the OrderID *j* on stock *i* on day *t* with the highest timestamp (*d*); $OrderID_{j,i,t,\min(d)}$ represents the OrderID *j* on stock *i* on day *t* with the lowest timestamp (*d*); $OrderDuration_{j,i,t}$ represents the difference between the highest and lowest timestamps of OrderID *j* on stock *i* on day *t*; $\sum_{1}^{j,i,t} Message_{j,i,t}$ represents the total number of messages generated by OrderID *j* on stock *i* on day *t*; $ORT_{j,i,t}$ represents the order resting time of OrderID *j* on stock *i* on day *t*; and $HFO_{i,t}$ represents the OrderID on stock *i* on day *t* that meet the following criteria: (i) order resting time $\left(ORT_{j,i,t}\right)$ of less than or equal to 3 seconds, and (ii) number of messages $\left(\sum_{1}^{j,i,t} Message_{j,i,t}\right)$ of more than or equal to 10.

4.3.3.3 Other variables

The main objective of the research is to determine whether negative sentiment influences the impact of HFT activity on liquidity. To capture this effect, a dummy variable is used, with the value 1 assigned to observations during high VIX day and 0 otherwise. In addition to the above-mentioned measures of HFT activity, the study also controls for volatility, relative tick size, and firm size, which are known to have an effect on liquidity (see e.g., Madhavan, 2002).

The study uses daily trading range to proxy for a firm's intraday price volatility, which is calculated as the difference between the highest $\left(high_{i,t}\right)$ and lowest prices $\left(low_{i,t}\right)$ of firm *i* on day *t*, divided their average prices. Relative tick size is used to represent the lowest possible spread achievable at a given price, which is derived by dividing the tick size value $\left(TickSize_{i,t}\right)$ by the closing price $\left(Price_{i,t}\right)$ of firm *i* on day *t*. Size on the other hand, is proxied by the natural log of market capitalisation of firm i on day t. The respective formulas for volatility, relative tick size, and size are shown in Equations 4.5, 4.6, and 4.7.

$$VOLATILITY_{i,t} = \frac{high_{i,t} - low_{i,t}}{\left(\frac{high_{i,t} + low_{i,t}}{2}\right)}$$

(Equation 4.5)

$$RTS_{i,t} = \frac{TickSize_{i,t}}{Price_{i,t}}$$

(Equation 4.6)

$$SIZE_{i,t} = \ln\left(Market\ Capitalization_{i,t}\right)$$

(Equation 4.7)

4.3.4 Model specification

To test the first hypothesis, this study utilises the groups outlined in Table 4.1, which consist of three study periods of varying lengths, namely short-term (1 month), medium-term (6 months), and long-term (12 months), around the event date. Observations for each group are categorised as either ”Pre-event” or “Post-event”. The study uses two-sample t-test to assess whether the differences between the liquidity level (as measured by CSHL, ILLIQ, and VOLTO) and HFT activity (as measured by HFO) in the Pre-event and Post-event groups are statistically significant. Subsequently, multivariate regression analysis is performed to evaluate whether the VIX_{RT} introduction influences the relationship between HFT activity and liquidity. Equation 4.8 represents the model employed for this purpose:

$$\begin{aligned} LIQUIDITY_{i,t} = \beta_0 + \beta_1\left(DPOST_{i,t}\right) + \beta_2\left(HFT_{i,t-1}\right) + \beta_3\left(DPOST_{i,t} \times HFT_{i,t-1}\right) \\ + \beta_4\left(CONTROL_{i,t-1}\right) + \varepsilon_{i,t} \end{aligned}$$

(Equation 4.8)

Where $LIQUIDITY_{i,t}$ is alternately proxied by CSHL, ILLIQ, and VOLTO of firm i on day t; $DPOST_{i,t}$ represents a dummy variable that equals one if the observation of firm i on day t belongs to the post-VIX_{RT} period, and zero otherwise; $HFT_{i,t-1}$ is proxied by HFO of firm i on day t-1; $DPOST_{i,t} \times HFT_{i,t-1}$ is the interaction term which represent the values of lagged HFT measures in the post-VIX_{RT} period; and $CONTROL_{i,t-1}$ represents the three control variables used in the model, namely VOLATILITY, RTS and SIZE of firm i on day t-1. Variables on the right-hand side are assigned with lagged values to minimise the potential of having a reverse causality issue. Firms (cross-sectional unit) and day (time unit) fixed effects are used to control for omitted variables bias, enabling the model to account for any impacts caused by unobservable factors that vary across firms and across time.

To test the second hypothesis, this study employs all post-VIX_{RT} data and uses a comparison approach based on the difference-in-difference method to evaluate whether the liquidity between the studied groups is statistically different. For this purpose, the study uses the subgroups listed in Panel B of Table 4.3. This research design is illustrated in Figure 4.3, where top and bottom halves represent the Control and Treatment groups, while the left and right panels represent the Non-event and Event days, respectively. Quadrants (1) and (2) represent the data for Control and Treatment during Non-event, whereas Quadrants (3) and (4) represent the data for Control and Treatment during Event, respectively.

	Non-event (VIX_{NH})	**Event (VIX_H)**
Control (HFT_{NH})	**(1)** **$Control_{Non\text{-}event}$** **($VIX_{NH}$-$HFT_{NH}$)**	**(3)** **$Control_{Event}$** **(VIX_H-HFT_{NH})**
Treatment (HFT_H)	**(2)** **$Treatment_{Non\text{-}event}$** **($VIX_{NH}$-$HFT_H$)**	**(4)** **$Treatment_{Event}$** **(VIX_H-HFT_H)**

Figure 4.3: Illustration of the research design used to test the second hypothesis.

The following steps are then taken to determine whether liquidity varies across different levels of VIX (event impact) and HFT activity (treatment effect):

i. [(3) and (4)] – [(1) and (2)] = Difference caused by Event ($DIFF_{VIX}$)
ii. [(2) and (4)] – [(1) and (3)] = Difference caused by Treatment ($DIFF_{HFT}$)
iii. (2) – (1) = Difference caused by Treatment during Non-event day ($DIFF_{VIX\_NH}$)
iv. (4) – (3) = Difference caused by Treatment during Event day ($DIFF_{VIX\_H}$)
v. ($DIFF_{VIX\_H}$) – ($DIFF_{VIX\_NH}$)= Difference caused by Event and Treatment ($DIFF_{VIX,HFT}$)

Subsequently, the study employs multivariate regression analysis using all data in the post-VIX_{RT} period to further test the second hypothesis. For the groups in Panel A of Table 4.3, the sample is tested using the model shown in Equation 4.9 to capture the interaction effect between VIX and HFT activity:

$$LIQUIDITY_{i,t} = \beta_0 + \beta_1(DHHFT_{i,t}) + \beta_2(DHVIX_{i,t}) + \beta_3(DHHFT_{i,t} \times DHVIX_{i,t}) + \beta_4(CONTROL_{i,t-1}) + \varepsilon_{i,t}$$

(Equation 4.9)

Where $DHHFT_{i,t}$ represents a dummy variable that equals one if the observation of firm *i* on day *t* belongs to the high HFT group, and zero otherwise; $DHVIX_{i,t}$ represents a dummy variable that equals one if the observation of firm *i* on day *t* belongs to the high VIX days, and zero otherwise; and $DHHFT_{i,t} \times DHVIX_{i,t}$ represents the interaction term between dummy variable for high VIX days and high HFT group. The other variables are interpreted in the same manner as the variables in Equation 4.8. This model also employs firm and day fixed effects to account for omitted variables bias.

4.4 Results, analyses, and discussions

This section presents the results and analysis of the study, which are organised in accordance with the hypotheses. In summary, the hypothesis states that "*the introduction of real-time AXVI (VIX_{RT}) have a positive impact on HFT activity and indirectly increase liquidity through its relationship with HFTs.*" The second hypothesis on the other hand postulates that "*as VIX levels increase, HFT activity* *changes in a way that exacerbates the already fragile liquidity situation in the market, calling into question the credibility of HFTs as liquidity providers.*" This section concludes with a discussion of the findings from testing the two hypotheses.

4.4.1 HFT activity and liquidity surrounding the VIX_{RT} introduction event

4.4.1.1 Descriptive statistics

Table 4.4 outlines the datasets used to test the first hypothesis, which employs three date ranges to analyse HFT activity and liquidity surrounding the VIX_{RT} introduction event: 1 month, 6 months, and 12 months. For conciseness, only the 12 months date range is described in the table, since it covers the broadest date range for the first objective, thus effectively including all observations contained in the two smaller date range groups. The data supplied for descriptive statistics are not adjusted for outliers in order to portray the original attributes of the data employed. The table indicates that, on average, the number of observations in the pre-event and post-event periods are about the same, totalling approximately 20,000 firm-day observations. For VIX, its average pre-event value is greater than its average post-event value, which is due to the former having more days with high VIX readings.

Table 4.4. Descriptive statistics of the data used to test Hypothesis 1

This table describes the data employed to test the first hypothesis. *Pre-VIX_{RT}* and *Post-VIX_{RT}* refer to the group of observations in the period before and after the introduction of *VIX_{RT}* event on February 28, 2013, respectively. *N*, *Mean*, *Std. Dev.*, *Minimum*, and *Maximum* signify the number of observations, average, standard deviation, lowest and highest values, respectively. *VIX* represents the closing value of VIX index; *SIZE* is the dollar value of market capitalisation (Equation 4.7); *VOLATILITY* is computed by dividing the difference between the day's highest and lowest prices by their average values (Equation 4.5); *RTS* indicates the relative tick size, which is calculated by dividing tick size by closing price (Equation 4.6); and the ASX and CHIX subscripts denote the datasets used to estimate the variables.

	N	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Pre-VIX_{RT}					
VIX	20,087	15.512	3.242	10.536	26.639
SIZE (million)	20,087	\$12,340	\$19,840	\$821	\$125,000
$VOLATILITY_{ASX}$ (%)	19,960	1.985	1.965	0.162	199.994
$VOLATILITY_{CHIX}$ (%)	20,016	1.652	1.022	0.000	20.690
RTS_{ASX} (%)	19,960	0.193	0.181	0.012	2.041
RTS_{CHIX} (%)	20,016	0.194	0.182	0.012	2.000
Post-VIX_{RT}					
VIX_{CLOSE}	20,273	14.578	2.130	10.689	21.675
SIZE (million)	20,273	\$14,670	\$24,090	\$804	\$128,000
$VOLATILITY_{ASX}$ (%)	20,272	2.147	2.420	0.156	199.982
$VOLATILITY_{CHIX}$ (%)	20,270	1.921	1.089	0.000	31.237
RTS_{ASX} (%)	20,272	0.165	0.125	0.013	0.553
RTS_{CHIX} (%)	20,270	0.165	0.125	0.013	0.556

This fact is illustrated in Figure 4.1, which shows that the VIX readings are generally high from early May 2012 to late June 2012, whereas no such pattern appears at any time during the one-year period after the VIX_{RT} event. The average market capitalisation before the event is lower than its average value after the event despite having minimum and maximum values that are closely comparable. As illustrated by the AXJO graph in Figure 4.1, this suggests an upward trend in the aggregate value of ASX-listed stocks in the post-event period.

The intraday volatility estimates calculated from the ASX and CHIX datasets are substantially different. During the pre-event and post-event periods, the highest VOLATILITY values for the ASX are 199.994% and 199.982%, while for the CHIX, they are only 20.69% and 31.237%, respectively. The exceedingly high VOLATILITY values in the ASX dataset were produced by the prices of Rio Tinto Limited (RIO) on March 5, 2012 (Pre-VIX_{RT}), and Newcrest Mining Limited on March 22, 2013 (Post-VIX_{RT}). For RIO, its highest and lowest trading prices on the ASX market were A$65.84 and A$0.001, while on the CHIX market, they were A$65.59 and A$64.87, yielding intraday volatility values of 199.994% and 1.104%, respectively. Similarly, the figures observed for NCM on the ASX market were A$22.50 and A$0.001, and on the CHIX market, they were A$22.50 and A$22.20, which correspond to intraday volatility rates of 199.982% and 1.342%, respectively.[58] These figures are reflected in the average values of VOLATILITY, where ASX has higher intraday volatility (Pre-VIX_{RT} = 1.985%; Post-VIX_{RT} = 2.147%) than CHIX (Pre-VIX_{RT} = 1.652%; Post-VIX_{RT} = 1.921%) during both time periods.

In contrast, during the period either before or after the event, the RTS values for ASX and CHIX are nearly equal, suggesting that the closing prices recorded on both exchanges during the observation period were, for the most part, identical. The average RTS value prior to the event (0.194%) is greater than its value after the event (0.165%). This is consistent with the previously established premise that prices are generally higher in the latter period, and *ceteris paribus*, this essentially

---

[58] This behaviour is comparable to the extreme price movements witnessed on the U.S. stock market during the 2010 Flash Crash, which was driven by fast algorithms that traded rapidly against a thin order book. This situation leads to a liquidity dry up across all price levels and forces the trading algorithm to strike the furthest price in the limit order book by accident. These extreme prices were deemed to be the outcome of a trading error and were subsequently nullified.

translates to lower RTS values. Overall, based on the data observed between March 2012 and February 2014 (24 months), the differences between the pre and post VIX_{RT} event values can be attributed to an overall bullish market movement, and are less likely to be influenced by negative market sentiment (i.e., high VIX).

4.4.1.2 Univariate analysis

Table 4.5 displays the results of univariate analysis comparing liquidity and HFT activity before and after the real-time AXVI is made available on the Australian stock market, as indicated by CSHL, ILLIQ, VOLTO (for liquidity), and HFO (for HFT). This is accomplished by applying a two-sample t-test to compare the means of the variables observed from the Pre-VIX_{RT} and Post-VIX_{RT} groups. In addition, the study utilises observations from several date ranges to evaluate the impact of the event across different time horizons.

An analysis of the ASX and CHIX datasets reveals that CSHL and HFO consistently exhibit statistically significant positive difference values (i.e., Post-VIX_{RT} – Pre-VIX_{RT}), regardless of the period range used. Additionally, a significant increase in trading activity (VOLTO) is observed on both markets during the Post-VIX_{RT} period, particularly in the first six months following the event date. However, when the observation period is extended to 12 months, the findings suggest that VOLTO is significantly lower on the ASX but remains higher on the CHIX. The results for ILLIQ indicate a significantly greater level of illiquidity on the ASX market only when using the 6-month range. However, the results are not significant for the 1-month and 12-month ranges. In contrast, illiquidity levels in the CHIX market for the 6-month and 12-month ranges are found to be significantly lower than their respective Pre-VIX_{RT} values, while the 1-month range shows no notable difference.

In summary, these findings suggest an asymmetry in liquidity levels across different trading venues in Australia before and after the adoption of the real-time AXVI index. For ASX, it is shown that the post-VIX_{RT} period has: (i) significantly wider spreads; (ii) a statistically indifferent level of illiquidity; and (iii) significantly higher volume turnover only in the periods immediately following the event (1-month and 6-month). In contrast, results for CHIX suggest that although spreads are wider in the post-VIX_{RT} period, price impact is smaller and trading activity is higher, indicating a generally higher level of liquidity.

Table 4.5. Mean comparison of liquidity measures and HFT activity in the periods surrounding the VIX_{RT} event

This table displays the results of univariate tests performed on data collected before and after the VIX_{RT} event to evaluate the first hypothesis. *Panel A* and *Panel B* present the results using the ASX and CHIX datasets, respectively. *Range*, which can be either 1, 6, or 12 months, refers to the time periods used to sample data before (*Pre-VIX_{RT}*) and after (*Post-VIX_{RT}*) the event day. *N* and *Mean* represent the number of observations and the average values, respectively. *Diff.* $_{Post\text{-}Pre}$ is the difference between the mean values of the Post-VIX_{RT} and Pre-VIX_{RT} groups. The tested variables include three liquidity measures, namely Corwin-Schultz High-Low spread (*CSHL*), Amihud Illiquidity ratio (*ILLIQ*), and volume turnover (*VOLTO*), and one HFT measure that is proxied by high-frequency orders (*HFO*). The formula are illustrated in Equations 4.1, 4.2, 4.3, and 4.4, respectively. All data are winsorised at three standard deviations (3-sigma) from their respective means.

Panel A: ASX	**Pre-VIX_{RT}**		**Post-VIX_{RT}**		**Diff.** $_{Post\text{-}Pre}$
	N	**Mean**	**N**	**Mean**	
Range: 1 month					
CSHL	1,520	0.498	1,680	0.556	0.059***
ILLIQ	1,520	0.072	1,680	0.070	-0.002
VOLTO	1,520	0.365	1,680	0.382	0.017**
HFO	1,520	4.305	1,680	4.429	0.124***
Range: 6 months					
CSHL	9,894	0.445	10,230	0.546	0.101***
ILLIQ	9,894	0.080	10,230	0.085	0.005***
VOLTO	9,896	0.325	10,230	0.352	0.027***
HFO	9,896	3.978	10,230	4.525	0.547***
Range: 12 months					
CSHL	19,833	0.467	20,270	0.503	0.036***
ILLIQ	19,832	0.085	20,271	0.085	0.000
VOLTO	19,960	0.345	20,272	0.318	-0.028***
HFO	19,960	4.112	20,272	4.338	0.226***

Panel B: CHIX	**Pre-VIX_{RT}**		**Post-VIX_{RT}**		**Diff.** $_{Post\text{-}Pre}$
	N	**Mean**	**N**	**Mean**	
Range: 1 month					
CSHL	1,520	0.382	1,680	0.467	0.085***
ILLIQ	1,520	1.625	1,680	1.461	-0.165
VOLTO	1,520	0.024	1,680	0.026	0.003***
HFO	1,520	1.003	1,680	1.257	0.254***
Range: 6 months					
CSHL	9,886	0.331	10,228	0.441	0.11***
ILLIQ	9,886	3.600	10,228	1.711	-1.889***
VOLTO	9,890	0.016	10,229	0.029	0.013***
HFO	9,892	0.866	10,229	1.558	0.692***
Range: 12 months					
CSHL	19,971	0.329	20,266	0.403	0.074***
ILLIQ	19,967	11.162	20,267	1.645	-9.518***
VOLTO	19,889	0.013	20,269	0.030	0.017***
HFO	20,016	0.874	20,270	1.506	0.632***

*** p<0.01, ** p<0.05, * p<0.1

Concerning HFT activity, the conclusions are unanimous: the total number of high-frequency Order IDs has grown significantly since the availability of real-time AXVI data, which is consistent with the views of Liberti and Petersen (2019), who emphasise the importance of supplying hard information to this class of trader. In summary, these results suggest that there are a significantly greater number of HFT activity after the introduction of VIX_{RT} in both markets; however, in terms of liquidity, the level is significantly higher in the post-event period in the CHIX market, whereas in the ASX market, the results suggest otherwise.

4.4.1.3 Multivariate analysis

Table 4.6 presents the results of multivariate regression analysis using the VIX_{RT} event to test the first hypothesis. Panel A exhibits the regression results using the ASX dataset. The findings suggest that the VIX_{RT} event has a significant negative relationship with ILLIQ and CSHL only in the short and medium terms, respectively. For VOLTO, The event significantly increased trading activity in both the short and medium terms. On a long-term basis, the event is shown to have no significant effect on any of the examined liquidity measures.

Table 4.6. Regression analysis on liquidity measures following the VIX_{RT} event

This table shows the results from multivariate regression analysis using stocks around the real-time AXVI introduction event (VIX_{RT}) to test the first hypothesis. *Panel A* and *Panel B* represent the findings using the ASX and CHIX datasets, respectively. Each panel is further divided into three groups based on its *Range*, which can be either 1, 6, or 12 months. *Range* refers to the time periods used to sample data before and after the event day. Dependent variables (*DV*) are the liquidity measures, namely Corwin-Schultz high-low spread (*CSHL*), Amihud illiquidity ratio (*ILLIQ*), and volume turnover (*VOLTO*). The formula are illustrated in Equations 4.1, 4.2, and 4.3, respectively. The independent variables are *HFO*, *DPOST*, and *HFO×DPOST*. *DPOST* is a dummy variable assigned with a value of one if the observation belongs to the post-VIX_{RT} period, and zero otherwise. *HFO* is the natural logarithm of high-frequency orders (Equation 4.4), lagged by one day (*t*-1). The interaction term, *DPOST×HFO*, estimates the effect of HFO on liquidity measures, after the VIX_{RT} event. The control variables are the one-day lagged (*t*-1) values of *VOLATILITY*, *RTS*, and *SIZE*. *VOLATILITY* is measured by difference between the highest and lowest price of the day, divided their average prices (Equation 4.5). *RTS* indicates the relative tick size, which is calculated by dividing tick size by closing price (Equation 4.6). *SIZE* is the natural log of market capitalisation (Equation 4.7). All models are controlled for firm and day fixed-effects. Data are winsorised at three standard deviations (3-sigma) from their respective means. The standard errors are calculated using the Huber/White/sandwich estimator of variance method.

Panel A: ASX	**A1: Range = 1 month**			**A2: Range = 6 months**			**A3: Range = 12 months**		
	CSHL	**ILLIQ**	**VOLTO**	**CSHL**	**ILLIQ**	**VOLTO**	**CSHL**	**ILLIQ**	**VOLTO**
DPOST	-0.0878	-0.0472***	0.1358***	-0.325***	0.0132	0.0916***	0.007	-0.0059	0.022
	(0.1278)	(0.0147)	(0.0399)	(0.0834)	(0.0132)	(0.0279)	(0.0908)	(0.016)	(0.0356)
HFO	-0.0054	-0.004	0.066***	0.0157*	-0.0043**	0.0597***	0.0196***	-0.0065***	0.0552***
	(0.0281)	(0.0024)	(0.0083)	(0.0086)	(0.0021)	(0.0061)	(0.0058)	(0.0017)	(0.006)
DPOST×HFO	0.0255*	0.0035*	-0.0118*	-0.0073	-0.0017	-0.0003	-0.0091**	-0.0013	0.0061
	(0.0151)	(0.0021)	(0.0062)	(0.0059)	(0.0015)	(0.0037)	(0.0041)	(0.0022)	(0.0053)
VOLATILITY	0.0431***	-0.0028	0.0336***	0.0391***	0.0005	0.0253***	0.0382***	0.0026**	0.0267***
	(0.0137)	(0.0018)	(0.0045)	(0.0063)	(0.0009)	(0.0022)	(0.0039)	(0.001)	(0.0026)
RTS	1.6455	0.1056	-0.7697	0.4604***	0.2547***	-0.1599**	0.3987***	0.1435**	-0.0101
	(1.6033)	(0.4316)	(0.9393)	(0.1572)	(0.0466)	(0.0708)	(0.108)	(0.0572)	(0.0652)
SIZE	0.676*	-0.0123	-0.5049***	-0.0077	-0.0462***	-0.2819***	-0.0716**	-0.0628***	-0.1566***
	(0.4045)	(0.083)	(0.1846)	(0.0592)	(0.0165)	(0.0385)	(0.0278)	(0.0153)	(0.0288)
Constant	-15.0765	0.3705	11.5189***	0.5014	1.1038***	6.3687***	1.8976***	1.4911***	3.6243***
	(9.2655)	(1.945)	(4.3054)	(1.3725)	(0.3755)	(0.8613)	(0.6483)	(0.3489)	(0.6532)
Observations	3,200	3,200	3,200	20,122	20,124	20,124	39,974	40,103	40,103
R-squared	0.0538	0.0588	0.2079	0.0565	0.0868	0.248	0.0609	0.0974	0.251
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4.6 (continue)

Panel B: CHIX	B1: Range = 1 month			B2: Range = 6 months			B3: Range = 12 months		
	CSHL	**ILLIQ**	**VOLTO**	**CSHL**	**ILLIQ**	**VOLTO**	**CSHL**	**ILLIQ**	**VOLTO**
DPOST	-0.0163	-0.0413	0.0063***	-0.1885***	-1.482	0.0253***	0.0713	-288.2196**	0.0341***
	(0.0836)	(0.3838)	(0.002)	(0.07)	(1.3907)	(0.0024)	(0.07)	(112.094)	(0.0029)
HFO	-0.011	-0.2604*	0.0016***	0.0077	-0.7867*	0.0027***	0.0086**	-2.5065**	0.0031***
	(0.0166)	(0.1496)	(0.0005)	(0.0063)	(0.4368)	(0.0004)	(0.0042)	(1.0845)	(0.0004)
DPOST×HFO	0.0119	-0.0897	-0.0006	-0.0142***	0.0818	-0.0024***	-0.0134***	1.1057	-0.0032***
	(0.0138)	(0.1137)	(0.0004)	(0.0051)	(0.2411)	(0.0004)	(0.0035)	(0.6712)	(0.0005)
VOLATILITY	0.0446***	0.1638	0.0022***	0.0458***	-0.9896	0.002***	0.0456***	-4.3892***	0.002***
	(0.0132)	(0.1598)	(0.0003)	(0.0058)	(0.6062)	(0.0002)	(0.0037)	(1.1142)	(0.0002)
RTS	1.828	8.6769	-0.0986*	0.3238**	101.3407*	-0.0443*	0.1983**	66.999	-0.0294
	(1.4717)	(6.3937)	(0.0572)	(0.1249)	(53.8157)	(0.0223)	(0.0914)	(54.1237)	(0.0212)
SIZE	0.698*	-0.1647	-0.0452***	0.03	0.9571	-0.0251***	-0.0375	2.9655	-0.0213***
	(0.3614)	(2.4554)	(0.0142)	(0.0505)	(5.8034)	(0.0075)	(0.0267)	(16.3048)	(0.0057)
Constant	-15.6802*	3.7518	1.0566***	-0.4576	-33.0862	0.5767***	1.0386*	219.5805	0.4832***
	(8.3285)	(56.3278)	(0.3279)	(1.1621)	(135.3512)	(0.1697)	(0.6123)	(407.2862)	(0.1306)
Observations	3,200	3,200	3,200	20,107	20,114	20,112	40,198	40,234	40,108
R-squared	0.0528	0.0219	0.1178	0.0575	0.0205	0.3407	0.0616	0.0517	0.4303
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

These findings demonstrated that the event promotes liquidity on the ASX market; however, the effect is only temporarily evident in the short to medium term, and is no longer present in the long term. Higher HFO leads to significantly higher CSHL and lower ILLIQ over the medium and long terms, whereas for VOLTO, higher HFO results in greater trading activity throughout all date ranges examined. These results imply that high HFT activity is detrimental to liquidity as it widens the spread, but it also promotes liquidity by reducing price impact and increasing trading activity. The interaction term, DPOST×HFO, shows that the VIX_{RT} event influences the relationship between HFO and all liquidity measures in the short term, but only the relationship between HFO and spread in the long term. The findings suggest that the VIX_{RT} reverses the beneficial effect of HFT activity on liquidity in the ASX market in short-term.

Panel B of Table 4.6 shows the regression results using the CHIX dataset. The findings suggest that the VIX_{RT} has a significant negative impact on CSHL and ILLIQ only in the medium and long-term, respectively. In addition, the event causes VOLTO to be significantly greater across all examined date ranges. These results suggest that the new feature introduced by the VIX_{RT} gradually enhances the overall liquidity of the CHIX market. Specifically, the improvement in trading activity is immediately apparent following the occurrence of the event, and this positive effect is shown to be long-lasting. For HFO, the findings suggest that in CHIX, a higher HFT activity consistently leads to a lower price impact and higher trading activity (improved liquidity) across all date ranges, and in long term, it is also found to result in significantly wider spread (reduced liquidity). The results of the interaction variable DPOST×HFO suggest that the influence of VIX_{RT} exists only in the medium and long term, but in the short term, it has no significant effect. The event is shown to weaken the impact that HFO has on CSHL and VOLTO, where it lowers the detrimental effect of HFT activity on spread (improved liquidity), and dampens the beneficial effect of HFT activity on trading volume (reduced liquidity). Nevertheless, the VIX_{RT} is shown to have no influence on the relationship of HFT activity and price impact in the CHIX market.

Overall, even after controlling for volatility, tick size, firm size, firm fixed effects, and day fixed effects, the regression results indicate that both markets have shown improvements in liquidity since the introduction of real-time AXVI, with the effect being more immediate for the ASX, and more gradual for the CHIX. In addition, the findings show that an increase in HFT activity generally results in wider spreads, smaller price impacts, and higher trading activity on both markets, which suggests an overall favourable impact on liquidity. The results also imply that the event influences the relationship between HFT activity and liquidity measures, where it is shown to weaken the effect of HFT on liquidity in both the ASX (in the short-term only) and the CHIX (in the medium and long-terms) markets.

The VIX_{RT} event has enhanced the amount of publicly available hard information in real-time, which continuously supplies the market with the most recent VIX values, representing the current market sentiment. This new feature may be less essential for slow traders unless there is a substantial intraday VIX movement, as they can always make educated assumptions about market sentiment by referring to the previous day's VIX level. In contrast, the event presents an opportunity for fast traders such as the HFTs to take strategic positions in the market, since they are naturally able to respond more swiftly and aggressively than non-HFTs to hard information shocks (Zhang, 2017), such as the one produced by the real-time AXVI data. Hence, it is plausible to infer that HFTs' strategies are influenced by the VIX_{RT} event, and their trading algorithms should have accounted for the real-time AXVI data. Furthermore, HFTs might shift from being a liquidity provider to a liquidity taker by deploying aggressive trading algorithms to capitalise on the new features. For example, HFTs may profit from a transitory arbitrage opportunity that exists due to lagging price adjustments to the most recent VIX readings posted on the market, which imposes adverse selection costs on market makers. Therefore, the observed reversal in the effects of HFT activity on liquidity in the period immediately following the VIX_{RT} is likely attributable to the increased presence of liquidity-taking HFTs relative to liquidity-providing HFTs on the ASX market.

4.4.2 Liquidity, VIX and HFT activity

4.4.2.1 Descriptive statistics

Table 4.7 describes the datasets used to test the second hypothesis, which employs all observations in the post-VIX_{RT} period to analyse HFT activity and liquidity during days with heightened negative market sentiment. Panel I presents the "Main groups", which is formed based on the non-high and high values of VIX and HFT, resulting in four groups of sample: Non-high VIX (VIX_{NH}, i.e., Non-event), High VIX (VIX_{H}, i.e., Event), Non-high HFT (HFT_{NH}, i.e., Control), and High HFT (HFT_{H}, i.e., Treatment), for each dataset employed. The table also shows that the ASX dataset has a higher number of observations compared to the CHIX (N_{ASX} = 121,777; N_{CHIX} = 119,090), which is due to the former having lower number of missing data.[59] The data provided for descriptive statistics are not adjusted for outliers to represent the original characteristics of the data.

In both datasets, VOLATILITY is the found to be around 0.8% higher on both markets during Event compared to Non-event, which reflects the heightened level of uncertainty over the near-term direction of the market, indicated by the higher VIX readings in the former period. This situation might lead to a greater selling pressure in the market, leading to lower stock prices. This notion is consistent with the behaviour shown by RTS and SIZE, in which the relative tick size is around 3% higher, while the average market capitalisation is around one billion dollars lower during Event. For the groups defined by HFT activity, the average VIX values are found to be higher in Treatment, suggesting that a higher VIX is associated with an increase in HFT activity. The descriptive statistics of the variables used in this study show that HFT activity is higher in stocks with smaller RTS, lower intraday volatility, and larger market capitalisation.[60] The minimum and maximum values displayed in Panel I are the most extreme datapoints from the ASX and CHIX datasets used for this research. For VIX, the maximum value in Non-event and the minimum value in Event represent the employed cut-off point. For Control and Treatment, the highest and lowest VIX values are the same, which are 8.825 (March 10, 2017) and 31.185 (August 25, 2015), respectively.

---

[59] If there are no missing data, the highest number of firm-day observations is 121,781.

[60] See Tables A2 and A3 in the Appendix for further information about the characteristics of firms with high HFT activity, for the ASX and CHIX datasets, respectively.

Table 4.7 Descriptive statistics of the data used to test Hypothesis 2

This table describes the data employed to test the second hypothesis. Panels I and II refer to the classification of sample as either belong to the Main groups or Subgroups, respectively. All data are drawn from the post-VIX_{RT} period. Panels A1 and A2 (B1 and B2) describe the data of observations derived from the ASX (CHIX) dataset under the Main groups and Subgroups, respectively. Days with VIX readings equal to or greater than 20 are labelled as High VIX (VIX_H, i.e. Event), otherwise Non-high VIX (VIX_{NH}, i.e. Non-event). For both HFO_{ASX} and HFO_{CHIX}, observations with HFO values in the 90th percentile are labelled as High HFT (HFT_H, i.e. Treatment), otherwise Non-high HFT (HFT_{NH}, i.e. Control). The VIX_H and VIX_{NH} are then paired with HFT_H and HFT_{NH}, creating four subgroups for each dataset, which are: (i) $Control_{Non\text{-}event}$ (VIX_{NH}-HFT_{NH}); (ii) $Treatment_{Non\text{-}event}$ (VIX_{NH}-HFT_H); (iii) $Control_{Event}$ (VIX_H-HFT_{NH}); and (iv) $Treatment_{Event}$ (VIX_H-HFT_H). *N*, *Mean*, *Std. Dev.*, *Minimum*, and *Maximum* signify the number of observations, average, standard deviation, lowest and highest values, respectively. *VIX* represents the closing value of VIX index; *SIZE* is the dollar value of market capitalisation (Equation 4.7); *VOLATILITY* is computed by dividing the difference between the day's highest and lowest prices by their average values (Equation 4.5); and *RTS* indicates the relative tick size, which is calculated by dividing tick size by closing price (Equation 4.6).

Panel I: Main groups	**Panel A1: ASX**					**Panel B1: CHIX**				
	N	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**	**N**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
(1) Non-high VIX (Non-event)										
VIX	111,094	14.158	2.408	8.825	19.998	108,637	14.145	2.401	8.825	19.998
RTS (%)	111,094	0.163	0.137	0.005	2.083	108,637	0.160	0.134	0.005	2.083
VOLATILITY (%)	111,094	2.031	1.529	0.110	199.982	108,637	1.845	1.145	0.000	72.857
SIZE (million)	111,094	13,740	22,550	243	156,000	108,637	13,870	22,710	243	156,000
(2) High VIX (Event)										
VIX	10,683	23.312	2.692	20.011	31.185	10,453	23.318	2.704	20.011	31.185
RTS (%)	10,683	0.167	0.137	0.007	1.333	10,453	0.167	0.136	0.007	1.351
VOLATILITY (%)	10,683	2.802	2.411	0.222	181.372	10,453	2.564	1.575	0.000	20.990
SIZE (million)	10,683	12,770	20,460	628	140,000	10,453	12,860	20,580	628	140,000
(1) Non-high HFT (Control)										
VIX	109,581	14.866	3.502	8.825	31.185	106,948	14.921	3.560	8.825	31.185
RTS (%)	109,581	0.178	0.135	0.006	2.083	106,948	0.175	0.135	0.005	2.083
VOLATILITY (%)	109,581	2.102	1.564	0.110	199.982	106,948	1.927	1.222	0.000	72.857
SIZE (million)	109,581	9,753	14,660	243	148,000	106,948	10,510	16,290	243	153,000
(2) High HFT (Treatment)										
VIX	12,196	15.815	3.886	8.825	31.185	12,142	15.203	3.503	8.825	31.185
RTS (%)	12,196	0.025	0.021	0.005	0.532	12,142	0.037	0.032	0.005	0.457
VOLATILITY (%)	12,196	2.067	2.210	0.298	162.884	12,142	1.741	1.046	0.217	16.561
SIZE (million)	12,196	48,700	41,270	331	156,000	12,142	42,610	41,450	1,151	156,000

Table 4.7 (continue)

Panel II: Subgroups	Panel A2: ASX					Panel B2: CHIX				
	N	Mean	Std. Dev.	Minimum	Maximum	N	Mean	Std. Dev.	Minimum	Maximum
(1) Control$_{\text{Non-event}}$										
VIX	100,558	14.107	2.394	8.825	19.998	97,552	14.114	2.404	8.825	19.998
RTS (%)	100,558	0.177	0.136	0.006	2.083	97,552	0.174	0.134	0.005	2.083
VOLATILITY (%)	100,558	2.040	1.435	0.110	199.982	97,552	1.866	1.160	0.000	72.857
SIZE (million)	100,558	9,932	15,030	243	148,000	97,552	10,620	16,530	243	153,000
(2) Treatment$_{\text{Non-event}}$										
VIX	10,536	14.641	2.485	8.825	19.998	11,085	14.419	2.354	8.825	19.998
RTS (%)	10,536	0.024	0.021	0.005	0.532	11,085	0.037	0.032	0.005	0.457
VOLATILITY (%)	10,536	1.946	2.234	0.298	162.884	11,085	1.663	0.979	0.217	16.561
SIZE (million)	10,536	50,060	41,800	331	156,000	11,085	42,510	41,680	1,151	156,000
(3) Control$_{\text{Event}}$										
VIX	9,023	23.321	2.684	20.011	31.185	9,396	23.306	2.673	20.011	31.185
RTS (%)	9,023	0.193	0.134	0.007	1.333	9,396	0.181	0.136	0.007	1.351
VOLATILITY (%)	9,023	2.796	2.496	0.222	181.372	9,396	2.565	1.600	0.000	20.990
SIZE (million)	9,023	7,762	9,353	628	90,130	9,396	9,398	13,510	628	135,000
(4) Treatment$_{\text{Event}}$										
VIX	1,660	23.266	2.737	20.011	31.185	1,057	23.425	2.965	20.011	31.185
RTS (%)	1,660	0.030	0.022	0.007	0.376	1,057	0.038	0.030	0.009	0.227
VOLATILITY (%)	1,660	2.835	1.882	0.358	22.785	1,057	2.554	1.335	0.535	10.885
SIZE (million)	1,660	40,020	36,620	1,326	140,000	1,057	43,610	38,930	1,482	140,000

These figures imply that high HFT activity may occur even on days when the VIX is extraordinarily high or low, and *vice versa*. The lowest RTS value is 0.005% on November 28, 2017 (Cochlear Limited (COH)), while the highest RTS value is 2.083% on November 21, 2014 (Arrium Limited (ARI)). These values correspond to the highest (A$186.72; COH) and lowest stock prices (A$0.24; ARI) recorded throughout the study period, respectively. The lowest recorded value for VOLATILITY is 0.000%, which represents stocks that are traded at a single price throughout the trading day, resulting in the same value for its opening, highest, lowest, and closing prices. On the opposite extreme, Newcrest Mining Limited (NCM) on March 22, 2013, had the highest VOLATILITY at 199.982%.[61] For SIZE, the highest market capitalisation recorded was A$156.165 billion on March 20, 2015, by Commonwealth Bank of Australia (CBA), and the lowest was A$0.243 billion on November 27, 2015, by Slater & Gordon Limited (SGH).

Panel II displays the "Subgroups" derived from the unique combinations of the VIX and HFT groups, yielding four subgroups for each dataset: (i) $\text{Control}_{\text{Non-event}}$ (VIX_{NH}-HFT_{NH}); (ii) $\text{Treatment}_{\text{Non-event}}$ (VIX_{NH}-HFT_{H}); (iii) $\text{Control}_{\text{Event}}$ (VIX_{H}-HFT_{NH}); and (iv) $\text{Treatment}_{\text{Event}}$ (VIX_{H}-HFT_{H}). This segregation makes it possible to examine whether the event significantly modifies the effect of treatment on liquidity measures. During Non-event day, the Treatment group displayed smaller RTS and VOLATILITY and greater SIZE than the Control group. Moreover, the magnitude of these differences varies between the ASX and CHIX markets, with the Treatment group exhibiting RTS values that are 0.153% and 0.137% smaller, VOLATILITY values that are 0.094% and 0.203% lower, and SIZE values that are 4.04 times and 3.00 times greater, respectively. During Event day, the differences for RTS are found to be roughly similar, where the RTS values for the Treatment group are 0.163% and 0.143% smaller in the ASX and CHIX markets, respectively. For VOLATILITY, the magnitude of the difference between the Treatment and Control groups is smaller, suggesting that the average stock-level volatility on both markets during high VIX days (i.e., Event) is strikingly similar regardless of the level of HFT's presence in any given stock. As for SIZE, the differences are more pronounced during Event,

[61] This issue has been discussed in detail in Section 4.4.2.1.

where the Treatment is found to be 4.16 times and 3.64 times greater than the Control in the ASX and CHIX markets respectively.

These statistics indicate that stocks with low RTS values are more likely to attract a larger HFT presence regardless of market volatility, implying that within a similar tick size structure, stocks with a higher price will always have a greater HFT activity. Correspondingly, stocks with a larger market capitalisation have more HFT activity, and during highly volatile days, this phenomenon becomes more apparent, particularly in the CHIX market. This situation can be explained by the fact that only 10% of the trading volume for Australia's 100 largest stocks took place on the CHIX market.[62] As a result, HFT would be more prevalent on stocks with larger market capitalisations due to their relatively higher liquidity and lower risk compared to smaller firms, and the need to prioritise size would increase during high volatility days. In addition, the statistic shows that stocks with substantial intraday price fluctuations have, on average, less HFT activity during Non-event days. This behaviour is likely attributable to both the RTS and SIZE factors – firms with a larger market capitalisation tend to have a higher stock price, which corresponds to a lower RTS, and are generally highly liquid, making them less prone to experiencing large price swings.

During the Event, however, intraday volatility appears to be of less interest to HFT; stocks with either high or low HFT activity appear to be indifferent in terms of their volatility. In contrast to SIZE and RTS, which are relatively stable over time, VOLATILITY is a parameter that may vary drastically from day to day and is highly sensitive to the breadth and depth of the market. During high VIX days, most stocks are adversely affected, resulting in substantial intraday price swings across the market. Therefore, selecting a firm only on the basis of its low volatility during such days might provide HFT with a very limited number of options, making VOLATILITY a less important consideration for HFT during uncertain and volatile days.

[62] In 2013, the CHIX accounted for only 8.62% of the trading volume of the top 100 largest equities in Australia. The CHIX's influence steadily grows over the years, and by 2017, they are responsible for 13.05% of all trading volume for the S&P/ASX100 constituents.

4.4.2.2 Univariate analysis

Table 4.8 displays the results of univariate analyses to assess whether high VIX days result in significantly different levels of liquidity while controlling for HFT activity. In order to investigate this issue, the study first compares the levels of liquidity on high VIX and non-high VIX days, as well as the levels of liquidity in groups with high HFT activity and groups with low HFT activity, in two separate analyses. This separation enables the study to determine the specific (Panel I: Main groups) and combined (Panel II: Subgroups) effects of the event of interest (high VIX) and the treatment group (high HFT activity) on liquidity.

The results in Panel I indicate that on days with negative market sentiment, spreads are significantly wider, price impacts are significantly greater, and trading activities are significantly higher than on other days. These findings suggest that, on average, liquidity is generally hampered when the VIX is high, and this effect is consistent on both the ASX and CHIX markets. The results also indicate that when HFT activity is high, spreads are significantly tighter and price impacts are significantly smaller on both markets. High HFT activity is only associated with substantially lower trading activity on the CHIX market, but not on the ASX market. Overall, these findings imply that observations with high HFT activity have, on average, a higher level of liquidity than those with low HFT activity, and this conclusion holds true for both the ASX and CHIX markets.

The results in Panel II show that, during Non-event days, firms in the Treatment groups have a significantly narrower bid-ask spread, a smaller illiquidity ratio, and a lower volume turnover than firms in the Control group, on both the ASX and CHIX markets. Identical results are also reported during Event days; although, the magnitude of differences in liquidity measures between the Treatment and Control groups is not similar. These findings suggest that regardless of market sentiment, firms with substantial HFT activity are generally more liquid in terms of lower transaction costs and smaller price impact; however, they also suffer from a lower of trading activity.

Table 4.8. Mean comparison of liquidity measures during Event (VIX_H) and Non-event (VIX_{NH}) days between Treatment (HFT_H) and Control (HFT_{NH}) groups

This table displays the results of univariate tests performed on data collected in the period after the VIX_{RT} event to evaluate the second hypothesis. *Panels A1* and *A2* and *Panels B1* and *B2* represent the results derived from the ASX and CHIX datasets, respectively. *Panel I* show the results for univariate test of the sample in the Main groups, which is formed based on the values of VIX and HFO. For *VIX*, days with VIX readings equal to or greater than 20 are labelled as VIX_H and represent the "Event" sample, while other VIX values are labelled as VIX_{NH} and represent the "Non-event" sample. For *HFT*, observations with HFO values in the 90th percentile are labelled as HFT_H and represent the "Treatment" group, while other HFO values are labelled as HFT_{NH} and represent the "Control" group. $DIFF_{VIX\ (H\text{-}NH)}$ and $DIFF_{HFT\ (H\text{-}NH)}$ represent the difference between the means of Event and Non-event, and the means of Treatment and Control, respectively. Panel II displays the univariate analysis utilising the subgroups produced by pairing the "Event" and "Non-event" groups with the "Treatment" and "Control" groups. $DIFF_{Non\text{-}event\ (HFTH\ -\ HFTNH)}$ and $DIFF_{Event\ (HFTH\ -\ HFTNH)}$ indicate the difference between the means of "Treatment" and "Control" during the "Non-event" and "Event" days, respectively. *DIFF-IN-DIFF* refers to the difference-in-difference values produced by subtracting the $DIFF_{EVENT}$ with $DIFF_{NON\text{-}EVENT}$. The tested variables include three liquidity measures, namely Corwin-Schultz High-Low spread (*CSHL*), Amihud Illiquidity ratio (*ILLIQ*), and volume turnover (*VOLTO*), and the formula are illustrated in Equations 4.1, 4.2, and 4.3, respectively. All data are winsorised at three standard deviations (3-sigma) from their respective means. The standard errors are calculated using the Huber/White/sandwich estimator of variance method.

Panel I: Main groups	**Panel A1: ASX**			**Panel B1: CHIX**		
	CSHL	**ILLIQ**	**VOLTO**	**CSHL**	**ILLIQ**	**VOLTO**
VIX						
Event (VIX_H)	0.558	0.100	0.374	0.463	2.022	0.039
Non-event (VIX_{NH})	0.460	0.087	0.294	0.374	1.426	0.033
$DIFF_{VIX\ (H-NH)}$	0.098***	0.013***	0.08***	0.089***	0.596***	0.006***
	(0.007)	(0.001)	(0.002)	(0.007)	(0.103)	(0.001)
HFT						
Treatment (HFT_H)	0.390	0.026	0.299	0.322	0.549	0.023
Control (HFT_{NH})	0.477	0.095	0.301	0.390	1.584	0.035
$DIFF_{HFT\ (H-NH)}$	-0.087***	-0.069***	-0.002	-0.068***	-1.035***	-0.012***
	(0.005)	(0.001)	(0.002)	(0.005)	(0.026)	(0.000)

Panel II: Subgroups	**Panel A2: ASX**			**Panel B2: CHIX**		
	CSHL	**ILLIQ**	**VOLTO**	**CSHL**	**ILLIQ**	**VOLTO**
Non-event (VIX_{NH})						
Treatment (HFT_H)	0.375	0.024	0.29	0.308	0.559	0.022
Control (HFT_{NH})	0.469	0.093	0.294	0.382	1.525	0.034
$DIFF_{Non\text{-}event\ (HFTH\ -\ HFTNH)}$	-0.094***	-0.069***	-0.004*	-0.074***	-0.966***	-0.012***
	(0.005)	(0.001)	(0.002)	(0.005)	(0.027)	(0.000)
Event (VIX_H)						
Treatment (HFT_H)	0.489	0.037	0.352	0.466	0.442	0.032
Control (HFT_{NH})	0.571	0.112	0.379	0.463	2.201	0.04
$DIFF_{Event\ (HFTH\ -\ HFTNH)}$	-0.082***	-0.075***	-0.027***	0.004	-1.759***	-0.008***
	(0.018)	(0.002)	(0.005)	(0.021)	(0.115)	(0.001)
DIFF-IN-DIFF						
$DIFF_{Event} - DIFF_{Non\text{-}event}$	0.012	-0.006***	-0.023***	0.078***	-0.793***	0.004***
	(0.019)	(0.002)	(0.006)	(0.021)	(0.118)	(0.001)

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Nevertheless, it is plausible that the lower volume turnover is not a result of having high HFT presence, but rather an unintended effect of HFTs' penchant for firms with large capitalisation, which often have a great number of shares outstanding and, hence, a low volume turnover value.[63]

Using a technique similar to the difference-in-difference method, this study examines whether the event may substantially change the effect of HFT activity on liquidity measures. The univariate test indicates that market sentiment may have a significant influence on the HFT activity – liquidity relationship; however, the effect is inconsistent across the ASX and CHIX markets and varies amongst the examined liquidity measures. On the ASX, the results suggest that high VIX readings do not diminish the favourable effect that HFT has on spread, and in fact, it amplifies the positive influence that HFT has on lowering the illiquidity ratio. Nonetheless, firms with a high level of HFT activity during pessimistic times may have even lower trading activity on the ASX market. Findings from the CHIX market reveal that high VIX days weakened HFT's initially positive influence on spread, resulting in a wider gap between bid and ask prices. On the other hand, it also enhances the positive effect that HFT has on lowering illiquidity and significantly reduces the negative impact that HFT activity has on trading volume.

Based on the aforementioned findings, the study concludes that HFT plays an important role in lowering spreads, and that days with pessimistic sentiment have no impact on HFT's positive role on the ASX, but do cause wider spreads on the CHIX. Historically, only around one-tenth of total trading activity for S&P/ASX100 components took place on the CHIX.[64] Due to the additional risk of inadequate transactions, HFT must increase their market-making spread on the CHIX market by a bigger margin than on the ASX market. As noted by Brogaard et al. (2014) and Hendershott and Riordan (2009), this measure is necessary to guarantee that HFT continues to benefit from market-making operations. Failure to charge a wider spread might discourage HFT from participating entirely, and their absence on days

[63] This argument is supported by the descriptive statistics presented in Table 4.7 (Panel II), which demonstrate that the average firm size of stocks in the Treatment group is three times greater than those in the Control group.
[64] See footnote 63.

of extreme volatility would exacerbate the already deteriorating market liquidity. Moreover, the data indicate that HFT plays a crucial role in reducing price impact on both markets, a quality that is further highlighted during stressful periods. This is likely attributable to competition amongst market-making HFTs (see Boehmer et al., 2018), which strive to actively feed the market with attractive limit orders on both sides of the book, hence preserving its breadth and depth.

The research also reveals that an increase in HFT activity does not result in higher volume turnover; rather, it is the opposite. Furthermore, the data show that during volatile times, high HFT activity exacerbates the detrimental effect of HFT on volume turnover on the ASX, whereas on the CHIX, it helps to mitigate the effect. The findings of ASX are compatible with the argument of Easley and O'Hara (1992), which posits that if there is no information event, there will be no transaction, and the market maker will choose to post a tighter spread, resulting in a positive relationship between spread and trading volume. This action may also be interpreted as a market-making HFTs' effort to attract investors to trade in a market suffering from reduced trading volume due to pessimistic sentiment. On the other hand, the increased volume turnover observed on the CHIX during high uncertainty days is likely due to the greater number of HFTs' market-making activity, particularly in firms with larger market capitalisation. This is shown by the fact that the average size of stocks with high HFT activity on the CHIX increased by 2.59% during high VIX days, while the average size of other groups decreased due to generally lower stock prices.[65] The study posits that this scenario is likely a result of the maker-taker fee structure used in the CHIX, which may incentivise HFT to make market on the CHIX, particularly on days with a high VIX.

4.4.2.3 Multivariate analysis

Table 4.9 presents the results of multivariate regression analysis using high HFT activity and high VIX days to further test the second hypothesis. In the ASX dataset, DHHFT (Treatment) has significant positive relationships with CSHL and VOLTO, while DHVIX (Event) shows a significant positive relationship only with ILLIQ.

[65] Comparatively, the average market capitalisation of firms in the $\text{Control}_{\text{ASX}}$, $\text{Treatment}_{\text{ASX}}$, and $\text{Control}_{\text{CHIX}}$ during Event is lower by 21.85%, 20.06%, and 11.51%, respectively, than during Non-event.

These results indicate that high HFT activity results in significantly wider spreads and increased trading activity, but has no discernible influence on price impacts. On the other hand, days with a high VIX lead to significantly larger price impacts, but have no effect on spreads or trading volume. In the CHIX dataset, the observed results are slightly different; both DHHFT and DHVIX have a significant negative effect on ILLIQ and a significant positive effect on VOLTO. These findings indicate that high HFT activity and high VIX days both result in a smaller price impact and increased trading activity. The results suggest that the Treatment and Event caused a deterioration in liquidity on the ASX market, but an improvement in liquidity on the CHIX market.

Table 4.9. Regression analysis on liquidity measures while controlling for the effect of high VIX days and high HFT activity

This table shows the results from multivariate regression analysis using observations in the post-VIX_{RT} period to test the second hypothesis. *Panel A* and *Panel B* represent the findings using the ASX and CHIX datasets, respectively. Dependent variables (*DV*) are the liquidity measures, namely Corwin-Schultz high-low spread (*CSHL*), Amihud illiquidity ratio (*ILLIQ*), and volume turnover (*VOLTO*). The formula are illustrated in Equations 4.1, 4.2, and 4.3, respectively. The independent variables are *DHHFT*, *DHVIX*, and *DHHFT×DHVIX*. *DHHFT* is a dummy variable assigned with a value of one if the observation belongs to the high HFT group (Treatment), and zero otherwise (Control). *DHVIX* is a dummy variable assigned with a value of one if the observation belongs to the high VIX days (Event), and zero otherwise (Non-event). The interaction term, *DHHFT×DHVIX*, estimates the effect of HFT activity on liquidity measures during high VIX days. The control variables are the one-day lagged (*t*-1) values of *VOLATILITY*, *RTS*, and *SIZE*. *VOLATILITY* is measured by difference between the highest and lowest price of the day, divided their average prices (Equation 4.5). *RTS* indicates the relative tick size, which is calculated by dividing tick size by closing price (Equation 4.6). *SIZE* is the natural log of market capitalisation (Equation 4.7). All models are controlled for firm and day fixed-effects. Data are winsorised at three standard deviations (3-sigma) from their respective means. The standard errors are calculated using the Huber/White/sandwich estimator of variance method.

	Panel A: ASX			Panel B: CHIX		
	CSHL	**ILLIQ**	**VOLTO**	**CSHL**	**ILLIQ**	**VOLTO**
DHHFT	0.0632***	0.0022	0.0841***	-0.0011	-0.7468***	0.0093***
	(0.0107)	(0.0021)	(0.0131)	(0.0065)	(0.211)	(0.0011)
DHVIX	0.1113	0.0638***	0.0299	0.0618	-1.8225***	0.039***
	(0.1011)	(0.0137)	(0.0275)	(0.0936)	(0.652)	(0.0035)
DHHFT×DHVIX	-0.0095	-0.0122***	-0.0351***	0.074***	-0.6014**	-0.0004
	(0.0184)	(0.0028)	(0.0087)	(0.0192)	(0.233)	(0.0012)
VOLATILITY	0.0442***	0.0005	0.0389***	0.0446***	-0.0863	0.0042***
	(0.0024)	(0.0006)	(0.0016)	(0.0024)	(0.0578)	(0.0003)
RTS	0.338***	0.1452***	-0.1127*	0.1677**	1.2939	0.0049
	(0.076)	(0.0492)	(0.0579)	(0.0727)	(0.8506)	(0.0109)
SIZE	-0.0452***	-0.0693***	-0.1036***	-0.0245**	-0.5635**	-0.0178***
	(0.0143)	(0.0086)	(0.0173)	(0.0119)	(0.2723)	(0.0027)
Constant	1.4126***	1.618***	2.7084***	0.9014***	15.3697**	0.04165***
	(0.3441)	(0.1981)	(0.3931)	(0.2883)	(6.304)	(0.0608)
Observations	121,601	121,740	121,740	117,558	118,321	118,317
R-squared	0.0731	0.122	0.2715	0.0679	0.0929	0.2167
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The DHVIX×DHHFT coefficient is the Treatment and Event interaction term and is used to test for the influence of high VIX days (Event) on the relationship between HFT activity and the liquidity measures examined in this study. On the ASX market, the results show that the event (DHVIX) significantly affects the association between DHHFT and ILLIQ and VOLTO, where stocks with high HFT activity are shown to substantially decreases their illiquidity ratio (improve liquidity) and volume turnover (reduce liquidity). For ILLIQ, the event reduces the coefficient for treatment, where the β_{Actual} is 1.6718, and the $\beta_{Counterfactual}$ is 1.6840.[66] The lower β_{Actual} value suggests that the high VIX days lessens the detrimental impact that HFT activity has on the illiquidity ratio. Similarly, the event is found to reduce the coefficient of DHHFT in VOLTO, where its β_{Actual} and $\beta_{Counterfactual}$ are 2.7873 and 2.8224, respectively. The relatively smaller β_{Actual} indicates that the event dampened the enhancing effect that HFT activity has on trading activity on days with normal or low expected volatility.

On the CHIX market, the findings indicate that the influence of high VIX days on HFT activity's effect on liquidity is significant when measured by CSHL and ILLIQ, where the event mitigates the effect of high HFT activity on spreads while amplifying its effect on the illiquidity ratio. For CSHL, the event increases the treatment coefficient, where β_{Actual} is 1.0361 and $\beta_{Counterfactual}$ is 0.9621. The greater value of β_{Actual} implies that the beneficial effect of high HFT activity in lowering spread is weakened on days with a high VIX. On the contrary, the event is shown to reduce the coefficient of DHHFT in ILLIQ, where the β_{Actual} and $\beta_{Counterfactual}$ are 12.1990 and 12.8004, respectively. The lower β_{Actual} value signifies that the event magnified the favourable impact that high HFT activity has in reducing illiquidity level.

Analysis of the control variables demonstrates that stocks with greater intraday volatility have not only significantly wider spreads, but also substantially greater trading activity in both datasets. These results indicate that volatility has a mixed impact on liquidity on the ASX and CHIX markets. In the ASX dataset, RTS exhibits a significantly positive effect on spreads and price impact, but a negative

[66] $\beta_{Actual} = \beta_0 + (\beta_1 \times 1) + (\beta_2 \times 1) + (\beta_3 \times 1)$; $\beta_{Counterfactual} = \beta_0 + (\beta_1 \times 1) + (\beta_2 \times 1) + (\beta_3 \times 0)$; where β_0, β_1, β_2, and β_3 represent the coefficient for the regression model's Constant value, dummy for high-HFT observations (DHHFT), dummy for high-VIX period (DHVIX), and the interaction term between DHHFT and DHVIX, respectively.

effect on trading activity. In the CHIX dataset, RTS displays a significant positive correlation with spread, but has no influence on the other liquidity proxies examined. These findings reveal that stocks with a higher RTS have a significantly lower amount of liquidity across all three analysed dimensions, notably on the ASX market. For SIZE, the results are consistent on both markets, demonstrating that stocks with greater market capitalisation result in significantly lower spreads and price impacts (improved liquidity), but at the same time suffer from significantly fewer trading activity (reduced liquidity). These results indicate that, on both the ASX and CHIX markets, larger firms in general have greater liquidity.

Overall, based on ILLIQ, the findings show that high HFT activity has a beneficial impact on liquidity when the expected volatility is high, even after controlling for volatility, tick size, firm size, firm fixed effects, and day fixed effects. Evidence suggests that the event mitigates the detrimental impact of high HFT activity on the ASX's illiquidity level, and enhances the beneficial impact of high HFT activity on the CHIX's illiquidity level. High HFT activity is also associated with greater trading activity on the ASX and a smaller bid-ask spread on the CHIX on days with a normal or low VIX. However, on days with high expected volatility, high HFT activity is shown to significantly reduce trading volume and widen spreads on the ASX and CHIX markets, respectively, thereby negating the beneficial impact it generally has on liquidity. The asymmetric effect observed in these markets is likely due to differences in the underlying mechanisms on each market, such as the maker-taker fee structure offered in the CHIX, which rewards market makers and other traders who post standing limit orders, whereas this feature is absent in the ASX market.

4.5 Conclusion

The study proposes two hypotheses to examine whether high AXVI values (high VIX) influence the impact of HFT activity on liquidity. In this study, high-speed OrderIDs (HFO) represent HFT activity, while the Corwin and Schultz High-Low Spread (CSHL), Amihud Illiquidity Ratio (ILLIQ), and Volume Turnover (VOLTO) represent the transaction cost, price impact, and volume dimensions of liquidity, respectively.

The first hypothesis postulates that "*the introduction of real-time AXVI (VIXRT) have a positive impact on HFT activity and indirectly increase liquidity through its relationship with HFTs.*" To test this hypothesis, the study uses observations from one, six, and twelve months before and after the introduction of the real-time AXVI event (VIX_{RT}) to represent the short, medium, and long date ranges, respectively. On the ASX market, univariate analysis reveals that post-event observations have a wider spread, higher volume turnover, and have no effect on the illiquidity ratio; however, the difference is only significant for the shortest range. On the CHIX market, the post-event period was characterised by a larger spread, a lower illiquidity ratio, and increased trading activity across all examined date ranges. In addition, the availability of VIX at real time shows significantly increased HFT activity across all date ranges on both the ASX and CHIX markets. The multivariate analysis indicates that the post-event period has significantly higher liquidity, with the effect being immediate for the ASX and gradual for the CHIX. On both markets, a surge in HFT activity is associated with a greater transaction cost (decreased liquidity), a reduction in price impact (increased liquidity), and more trading activity (increased liquidity). The findings also suggest that the event significantly reduces the impact of HFT activity on liquidity in the short-term for the ASX market and in the medium- and long-term for the CHIX market.

The second hypothesis states that "*as VIX levels increase, HFT activity changes in a way that exacerbates the already fragile liquidity situation in the market, calling into question the credibility of HFTs as liquidity providers.*" To examine this hypothesis, the study applies univariate analysis to compare the levels of liquidity on high VIX (Event) and non-high VIX (Non-event) days, as well as across groups with high HFT (Treatment) and non-high HFT (Control) activities. On both markets, the results demonstrate that transaction costs, price impact, and trading volume are much greater on days with a high VIX (Event), indicating that, on average, market liquidity is lower when sentiment is negative. In comparison to the Control group, the Treatment group is generally more liquid on both markets, as indicated by lower transaction costs and smaller price impacts. Subsequently, the study adopts an approach similar to the difference-in-difference method to see whether the level of liquidity during Non-event and Event days between the Control and Treatment groups are significantly different.

The results show that: (i) HFT plays a significant role in reducing spreads, and on the ASX, high-uncertainty days have no effect on this beneficial function. However, on the CHIX, more HFT is shown to result in wider spreads. This situation is likely due to the inherently low volume of trades on the CHIX market, which results in higher market-making costs for HFT. These costs are magnified during highly volatile days, and the bid-ask spread ultimately mirrors these costs; (ii) HFT greatly reduces the price impact on both markets, and this role is even more evident on days with negative sentiment. This is possibly due to HFTs' market-making activities, which promotes a robust order book even when sentiment is pessimistic; and (iii) more HFT activity does not increase volume turnover, but rather decreases it. On the ASX, high VIX days appear to exacerbate the negative effect of HFT on volume, whereas on the CHIX, such day appear to mitigate this adverse effect. This behaviour is likely attributed to HFTs' more intense market-making activity during highly volatile days on the CHIX, which is more concentrated in firms with large market capitalisation.

The second hypothesis is further tested using multiple regression analysis to establish whether high HFT activity (Treatment), high VIX days (Event), and their interaction term have a causal influence on liquidity. The results demonstrate that the Event influences the relationship between the Treatment and liquidity measures (ILLIQ and VOLTO on the ASX market and CSHL and VOLTO on the CHIX market), even after accounting for volatility, tick size, firm size, firm fixed effects, and day fixed effects. On the ASX, days with negative market sentiment lower the initially detrimental but insignificant influence that high HFT activity has on price impacts, as well as reducing the originally beneficial impact that high HFT activity has on trading activity. On the CHIX, high VIX days are shown to reduce the favourable but insignificant effect that high HFT activity has on reducing spreads, while enhancing the beneficial effect that high HFT activity has on reducing price impacts.

Overall, the findings show that high VIX days have a significant influence on the relationship between high HFT activity and liquidity, with varying impacts on liquidity in both the ASX and CHIX markets. Nevertheless, the data also suggest that the Event may increase the Treatment's beneficial effect in lowering the illiquidity ratio, indicating that high HFT activity might lead to a reduced price impact during days with negative market sentiment in both markets.

CHAPTER FIVE:
CONCLUSION

This chapter concludes the thesis by providing a summary of the key findings and implications for each of the three essays, presented in Section 5.1. Section 5.2 shows the limitations of this study and suggests potential directions for future research.

5.1 Major findings and implications

5.1.1 Essay One: High-frequency trading: Definition, Implications, and Controversies

The first essay of this thesis provides a comprehensive survey of the relevant literature on HFT, including regulatory reports, theoretical and empirical research. The research concludes that the lack of a universal definition for HFT leads to additional problems, such as the inaccurate estimation of the HFTs' market shares, and obscure their actual influence on market quality. This aspect further complicates attempts to comprehend HFT, which consequently leads to varying HFT-related conclusions. Nevertheless, from regulatory perspectives, five characteristics of HFT are frequently mentioned: (i) a specialised form of AT that requires a low-latency network; (ii) the use of high-speed, sophisticated computer programmes and systems; (iii) extremely high order-to-transaction ratios; (iv) extremely short average holding periods; and (v) ending the trading day with flat positions.

HFT operations are based on the execution of numerous transactions with very slim profit margins, magnified by large trading volume (NAFM, 2010; Zhang, 2010). HFTs analyse order book flow for short-term inefficiencies to execute latency arbitrage, benefitting from the trading environment as opposed to the fundamental value of financial assets (Hasbrouck & Saar, 2013). Annually, the estimated worldwide revenue from latency arbitrage is US$5 billion (Aquilina et al., 2020). HFT trading strategies may be beneficial or harmful to the market (Benos & Sagade, 2016); hence, HFT is a double-edged sword. Beneficial strategies include statistical arbitrage, directional trading, and market-making, whereas harmful strategies uses front running, spoofing and layering, and quote stuffing.

The essay also highlights HFT-related controversy. Perhaps the most infamous case is the flash crash of May 6, 2010, when HFTs were criticised for exacerbating price declines and market volatility in their competition for liquidity (Kirilenko et al., 2017). Moreover, the arms race among HFTs to be the fastest, fuelled by the winner-take-all nature of the game, is perceived as unproductive, socially wasteful, and the substantial money invested to minimise latency by a few milliseconds raises doubts about whether HFT provides value overall (Chordia et al., 2013; Budish et al., 2015; Jones, 2013). HFTs are also accused of supplying liquidity on the thick side of the order book and taking liquidity on the thin side, which resembles order-anticipation strategies (Goldstein, et al., 2020). HFTs' market-making activity is also feared to aggravate execution uncertainty, particularly in volatile markets and thinly traded securities, since they are not mandated to provide liquidity at all times and may withdraw whenever they please (Anand & Venkataraman, 2013; Chung & Chuwonganant, 2018; Zhang, 2010).

As HFT has become more pervasive in the last decade, regulatory agencies and scholars around the world have taken or proposed a number of measures to level the playing field. This includes (i) applying asymmetrical speed bumps to slow down message traffic incoming to and outgoing from an exchange (Khapko & Zoican, 2020); (ii) instituting a "price improvement rule" to reduce the incentive for predatory HFTs from using latency arbitrage to exploit the difference between the bid-ask spreads on the lit and dark markets (ASIC, 2015); (iii) using "frequent batch auctions" to promote price competition rather than speed competition, thereby lowering the incentive to be the fastest (Budish et al., 2015); and (iv) utilising "continuous scaled limit order" to slow down the inflow of large orders into the market, hence reducing the adverse selection costs for slower traders (Kyle & Lee, 2017). Nevertheless, Harris (2013) advises that financial authorities should be mindful in their regulatory oversight so as not to inadvertently impede beneficial HFT strategies.

5.1.2 Essay Two: Relative Tick Size and High-frequency Trading

The second essay investigates the influence of relative tick size on HFT activity. For the purpose of this study, four different measures of HFT activity are used: the message-to-trade ratio (MTR), the algorithmic trading ratio (ALGO), the high-frequency OrderID (HFO), and the HFO's message ratio (HFOR). The research also uses a study period from January 2008 to December 2017 for the ASX, and from December 2011 to December 2017 for the CHIX, to compare HFT activity in two groups with contrasting relative tick sizes (i.e., small and large relative tick size) in three scenarios: (i) stocks with similar nominal tick sizes; (ii) stocks priced near the A$2.00 tick size border; and (iii) stocks that crossed the A$2.00 tick size border in both upwards and downwards directions.

Overall, the results of the second essay indicate that HFTs favour stocks with small relative tick size, which suggests that they would choose order undercutting over order-queuing in both the ASX and CHIX markets. This behaviour is particularly evident when a large number of informed traders are present, and the relative tick size is sufficiently small. The findings further demonstrate that HFTs would abandon stocks with fine pricing grids once their pricing grids become coarse. The inverse relationship between HFT activity and relative tick size implies that market-making HFTs are risk-averse. This evidence also underlines the importance of order-undercutting approaches for market-making HFTs, due to their extremely low tolerance for adverse selection risks.

The findings of the second essay lend credence to the perception that the primary strategy of HFTs is to generate tiny profits (NAFM, 2010) while keeping their risk exposure to an absolute minimum. Due to the fact that market-making HFTs may execute the same strategy thousands of times each day, the little profits rapidly accumulate into substantial amounts (Zhang, 2010), yet the probability of losing a trade remains minimal. Overall, the outcomes of this research contradict the arguments that a small relative tick size would discourage the liquidity provision of market-making HFTs and that a large relative tick size would attract more market-making HFTs, as suggested by Angel (2011), O'Hara et al. (2019), Werner et al. (2019), and Yao and Ye (2018). This contradicting results are likely because of the difference in the market microstructure underlying the Australian and the U.S. markets. The findings of this study demonstrate that HFTs are exceptionally risk-averse traders that prioritise risk minimisation over profit maximisation.

Chordia et al. (2013) argues that the HFTs might compromise the welfare of non-HFT participants; this study provides evidence that policymakers may implement a dynamic tick size policy to allocate HFT activity into stocks where it is most required. For instance, stocks with a low liquidity issue may need the intervention of market-making HFTs to improve their liquidity level, which may be facilitated by assigning a very small nominal tick size to such stocks. In contrast, if the stocks are highly liquid and the presence of HFT activity is considered toxic, the regulator could increase the nominal tick size to enforce price-priority, hence compelling the use of the order-queuing strategy which would discourage HFTs from trading these stocks.

5.1.3 Essay Three: Expected Volatility, High-frequency Trading, and Liquidity

The third essay demonstrates how expected volatility influences HFT activity, and how the resulting change in HFT activity affects liquidity. The first part of the essay utilises observations from one (short-term), six (medium-term), and twelve months (long-term) around the day real-time AXVI are made available. On both markets, an increase in HFT activity corresponds with a rise in transaction costs (decreased liquidity), a reduction in price impact (increased liquidity), and an improvement in trading activity (increased liquidity). The findings also imply that the event significantly lowers the influence of HFT activity on liquidity in the short-term for the ASX, and medium- and long-term for the CHIX markets, respectively.

The findings implies that the introduction of real-time AXVI index has increased the amount of publicly available hard information in real-time, allowing HFTs to capitalise on the new feature and take strategic positions in the market. The real-time feature are also more valuable for HFTs as they are able to react more quickly and aggressively to the information generated by such data than non-HFTs. Moreover, the innovation could incentivise HFT to be more aggressive, which may impose adverse selection costs on market liquidity providers. The observed reversal on the ASX in the immediate period following the event might be caused by greater presence of liquidity-taking HFTs relative to liquidity-providing HFTs on the market. The absence of such impact on CHIX is likely attributable to the fact that most CHIX participants are professional traders who deploy trading bots, thus, are more resistant to the influence of the new feature.

The second part of the essay examines liquidity levels on days with negative market sentiment (high VIX) with days with normal sentiment (non-high VIX), as well as across stocks with differing amounts of HFT activity (i.e., high HFT activity or non-high HFT activity). On the ASX, negative sentiment erodes the favourable effect that high HFT activity usually has in promoting higher trading activity when the sentiment is normal. On the CHIX, negative sentiment hinders the positive influence that high HFT activity has in reducing spreads during normal market sentiment. On the other hand, high HFT activity has been proven to result in a lower illiquidity ratio on days with normal sentiment, and this positive impact is amplified on days with negative sentiment on both markets. This finding suggests that high HFT activity may result in a lower price impact when the market sentiment is negative. In addition, the data indicate that negative market sentiment has a significant influence on the effect of HFT activity on liquidity measures, with differing impacts on liquidity in the ASX and CHIX markets. Nonetheless, the findings signify that when the market sentiment is negative, stocks with high HFT activity are likely to experience a smaller price impact on either the ASX or CHIX markets, indicating that the presence of HFT may reduce excessive price impacts when the market is extremely fearful.

Overall, the findings of this study imply that a greater quantity of hard information and a negative market sentiment can significantly influence the effect of high-frequency trading (HFT) on liquidity. This study also demonstrates that more HFT activity is not always negative, since it promotes liquidity by reducing price impacts on days with high uncertainties. Therefore, any attempt to completely ban or restrict HFT in the market might be viewed as inappropriate, as such actions could accidentally eliminate valuable market participants.

5.2 Limitations of the study and suggestions for future research

As with any other research, this thesis has limitations. An important caveat for Essay One is that it is impossible to include all regulatory reports, practitioner papers, and academic publications related to HFT. In order to gain a better understanding of

HFT's impact on the market, the author made every effort to ensure that the literature included paints a clearer image of HFT. Moreover, given that HFTs are dynamic in nature, their current behaviour and strategies may have also progressed, resulting in outcomes that potentially differ from those mentioned in the survey.

All of the HFT measures used in Essays Two and Three are proxies, and therefore cannot be regarded as accurately reflecting the actions of high-frequency trading firms such as Citadel Securities, Jump Trading, Liquid Capital, Susquehanna International Group, and Virtu Financial. Instead, any conclusions on "HFT activity" generated from this research should be interpreted as representing the activity of "low-latency traders" as a whole, and not just "full-fledged HFT firms." Furthermore, the method in which they are calculated suggests that they can only estimate the liquidity-providing activity of HFT and not the liquidity-taking activity of HFT. In addition, to the best of the researcher's knowledge, the high-frequency OrderID (HFO) and the HFO's message ratio (HFOR) have never been used in any other study. The author would also like to emphasise that, although HFO reflects the total number of unique OrderIDs in a stock on a given day, the amount indicated might be the result of a single trading account using rapid order placement with multiple entry points on the same day. Consequently, HFO and HFOR may also be interpreted as signifying the presence of high-frequency (or low-latency) traders in a stock on a certain day.

From Essay One, future research might incorporate the most recent regulatory actions and HFT-related microstructure changes. In addition, the author urges market regulators around the world to collaborate with academic scholars to produce a higher quality dataset, which is vital to ensuring that the conclusions formed about HFT are accurate, so that they are not held accountable for something they did not do. From Essay Two, future studies could evaluate the presence of non-HFTs in stocks with large or small relative tick sizes to assess whether their willingness to trade in stocks with small relative tick sizes is impeded by the existence of HFTs, and *vice versa*. In addition, the samples may be segmented based on whether they are tick-constrained or tick-unconstrained, since the literature indicates that this factor may significantly affect market-making HFTs' approach in providing liquidity (see, e.g. Foley et al., 2019; O'Hara et al., 2019; Werner et al., 2019; Yao & Ye, 2018). From Essay Three, future research may conduct the following research based on the findings of the essay: (i) to investigate the influence of HFT activity during negative market sentiment periods on other market quality measures, including price discovery, volatility, and adverse selection costs; (ii) make use of data from the Covid-19 period to examine how HFT operates when the market is extremely volatile and fearful; and (iii) examine the behaviour and influence of HFT on the liquidity of stocks with extreme intraday price swings.

Furthermore, futures studies might also validate the accuracy of the newly proposed HFT measures (i.e., HFO and HFOR) using datasets that has correctly identified HFT activity in the market, such as the NASDAQ's HFT dataset. In addition, the versatility of the HFO and HFOR measures enables their use in intraday-level research, and the threshold values (i.e., order resting time and minimum number of linked messages) employed in this study may be adjusted according to the researcher's needs and preferences. Thus, these measurements could be used to analyse the behaviour of the trading algorithms employed by both slow and fast market participants.

REFERENCES

Acharya, V. V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, *77*(2), 375-410.

Agarwal, A. (2012). High-frequency trading: Evolution and the future. London, UK.

Aitken, M. J., Aspris, A., Foley, S., & Harris, F. H. D. B. (2018). Market fairness: The poor country cousin of market efficiency. *Journal of Business Ethics*, *147*, 5–23.

Aitken, M., Cumming, D., & Zhan, F. (2017). Trade size, high-frequency trading, and colocation around the world. *European Journal of Finance*, *23*, 781–801.

Ait-Sahalia, Y., & Sağlam, M. (2017). High frequency market making: Optimal quoting. *Available at SSRN 2331613*.

Aldridge, I. (2013). *High-frequency trading: A practical guide to algorithmic*. New Jersey: John Wiley & Sons, Inc.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31-56.

Amihud, Y., & Mendelson, H. (1991). Volatility, efficiency, and trading: Evidence from the Japanese stock market. *The Journal of Finance*, *46*(5), 1765-1789.

Amihud, Y., Mendelson, H., & Pedersen, L. H. (2006). Liquidity and asset prices. *Foundations and Trends® in Finance*, *1*(4), 269-364.

Amihud, Y., Mendelson, H., & Pedersen, L. H. (2012). *Market liquidity: asset pricing, risk, and crises*. Cambridge University Press.

Anand, A., & Venkataraman, K. (2013). *Should exchanges impose market maker obligations?*. *Working paper*. Syracuse University and Southern Methodist University.

Ang, A., Chen, J., & Xing, Y. (2006). Downside risk. *The Review of Financial Studies*, *19*(4), 1191-1239.

Angel, J. J. (1997). Tick size, share prices, and stock splits. *The Journal of Finance, 52*(2), 655-681.

Angel, J. J. (2012). Tick size regulation: costs, benefits, and risks. Foresight, the future of computerised trading in financial markets, Economic Impact Assessment EIA7 London, UK: UK Government Office for Science (c) Crown Copyright.

Angel, J. J. (2014). When finance meets physics: The impact of the speed of light on financial markets and their regulation. *Financial Review*, *49*, 271–281.

Angel, J. J., & McCabe, D. (2013). Fairness in financial markets: The case of high-frequency trading. *Journal of Business Ethics*, *112*, 585–595.

Angel, J. J., Harris, L. E., & Spatt, C. S. (2011). Equity trading in the 21st century. *The Quarterly Journal of Finance*, 1(01), 1-53.

Aquilina, M., & Ysusi, C. (2016). Are high-frequency traders anticipating the order flow? Cross-venue evidence from the UK market. *FCA Occasional Paper*, No.16.

Aquilina, M., Budish, E. B., & O'Neill, P. (2020). Quantifying the high-frequency trading "arms race": A simple new methodology and estimates. Chicago Booth Research Paper (2020-2086).

Aquilina, M., Foley, S., O'Neill, P., & Ruf, T. (2016). Asymmetries in dark pool reference prices. FCA Occasional Paper 21.

Aspris, A., Foley, S., Harris, D., & O'Neill, P. (2015). Time pro-rata matching: Evidence of a change in LIFFE STIR futures. *Journal of Futures Markets*, *35*, 522–541.

Australian Securities and Investments Commission. (2010). Australian equity market structure. Report 215.

Australian Securities and Investments Commission. (2013). Dark liquidity and high-frequency trading. Report 331.

Australian Securities and Investments Commission. (2015). Review of high-frequency trading and dark liquidity. Report 452.

Australian Securities Exchange (2011). *PureMatch to go-live 28 November*. Retrieved from: https://www.asx.com.au/documents/media/PureMatchLaunchandPricingFinal-AustralianSecuritesExchange-ASX.pdf

Avramovic, A., Lin, V., & Krishnan, M. (2017). We're all high-frequency traders now. Credit Suisse.

Bacidore, J. M. (1997). The impact of decimalization on market quality: An empirical investigation of the Toronto Stock Exchange. *Journal of Financial Intermediation*, *6*(2), 92-120.

Baldauf, M., & Mollner, J. (2020). High-frequency trading and market performance. *The Journal of Finance*, *75*, 1495– 1526.

Baron, M., Brogaard, J., Hagströmer, B., & Kirilenko, A. (2019). Risk and return in high-frequency trading. *Journal of Financial and Quantitative Analysis*, *54*, 993–1024.

Benos, E., & Sagade, S. (2016). Price discovery and the cross-section. *Journal of Financial Markets*, *30*, 54–77.

Bessembinder, H. (2003). Trade execution costs and market quality after decimalization. *Journal of Financial and Quantitative Analysis, 38*(4), 747-777.

Bhattacharya, N., Chakrabarty, B., & Wang, X. F. (2020). High-frequency traders and price informativeness during earnings announcements. *Review of Accounting Studies*, *25*(3), 1156-1199.

Biais, B., & Woolley, P. (2011). High-frequency trading. Working paper. Toulouse School of Economics.

Biais, B., Foucault, T., & Moinas, S. (2015). Equilibrium fast trading. *Journal of Financial Economics*, *116*, 292–313.

Biais, B., Glosten, L., & Spatt, C. (2005). Market microstructure: A survey of microfoundations, empirical results, and policy implications. *Journal of Financial Markets*, *8*(2), 217-264.

Boehmer, E., Fong, K., & Wu, J. (2020). Algorithmic trading and market quality: International evidence. *Journal of Financial and Quantitative Analysis*, 1–30.

Boehmer, E., Li, D., & Saar, G. (2018). The competitive landscape of high-frequency trading firms. *The Review of Financial Studies*, *31*, 2227–2276.

Bourghelle, D., & Declerck, F. (2004). Why markets should not necessarily reduce the tick size. *Journal of Banking and Finance*, *28*(2), 373-398

Breckenfelder, J. (2019). Competition among high-frequency traders, and market quality. ECB Working paper 2290.

Brogaard, J., & Garriott, C. (2019). High-frequency trading competition. *Journal of Financial and Quantitative Analysis*, *54*, 1469–1497.

Brogaard, J., Carrion, J., Moyaert, T., Riordan, R., Shkilko, A., & Sokolov, K. (2018). High frequency trading and extreme price movements. *Journal of Financial Economics*, *128*, 253–265.

Brogaard, J., Hagströmer, B., Nordén, L., & Riordan, R. (2015). Trading fast and slow: Colocation and liquidity. *The Review of Financial Studies*, *28*, 3407–3443.

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-frequency trading and price discovery. *The Review of Financial Studies*, *27*, 2267–2306.

Brogaard, J., Hendershott, T., & Riordan, R. (2019). Price discovery without trading: Evidence from limit orders. *The Journal of Finance*, *74*, 1621–1658.

Brunnermeier, M. K., & Pedersen, L. H. (2005). Predatory trading. *The Journal of Finance*, *60*, 1825–1863.

Budish, E., Cramton, P., & Shim, J. (2015). The high-frequency trading arms race: Frequent batch auctions as a market design response. *Quarterly Journal of Economics*, *130*, 1547–1621.

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

Cartea, A., & Penalva, J. (2012). Where is the value in high-frequency trading? *Quarterly Journal of Finance*, *2*, 1–46.

Cartea, Á., Payne, R., Penalva, J., & Tapia, M. (2019). Ultra-fast activity and intraday market quality. *Journal of Banking & Finance*, *99*, 157–181.

Chordia, T., Goyal, A., Lehmann, B. N., & Saar, G. (2013). High-frequency trading. *Journal of Financial Markets*, *16*, 637–645.

Chordia, T., Roll, R., & Subrahmanyam, A. (2011). Recent trends in trading activity and market quality. *Journal of Financial Economics, 101*(2), 243-263.

Chung, K. H., & Chuwonganant, C. (2018). Market volatility and stock returns: The role of liquidity providers. *Journal of Financial Markets*, *37*, 17–34.

Chung, K. H., & Lee, A. J. (2016). High-frequency trading: Review of the literature and regulatory initiatives around the world. *Asia-Pacific Journal of Financial Studies*, *45*, 7–33.

Clark-Joseph, A. D., Ye, M., & Zi, C. (2017). Designated market makers still matter: Evidence from two natural experiments. *Journal of Financial Economics*, *126*(3), 652-667.

Comerton-Forde, C. (2012). Is Australia HFT-friendly? *JASSA: The Finsia Journal of Applied Finance*, 3(3), pp. 12-14.

Comerton-Forde, C., Malinova, K., & Park, A. (2018). Regulation dark trading: Order flow segmentation and market quality. *Journal of Financial Economics*, *130*, 347–366.

Committee of European Securities Regulators. (2010). Call for evidence on micro-structural issues of the European equity markets. Paris.

Conrad, J., & Wahal, S. (2020). The term structure of liquidity provision. *Journal of Financial Economics*, *136*, 239– 259.

Conrad, J., Wahal, S., & Xiang, J. (2015). High-frequency quoting, trading, and the efficiency of prices. *Journal of Financial Economics*, *116*, 271–291.

Cooper, R., Davis, M., & Vliet, B. V. (2016). The mysterious ethics of high-frequency trading. *Business Ethics Quarterly*, *26*, 1–22.

Cordella, T., & Foucault, T. (1999). Minimum price variations, time priority, and quote dynamics. *Journal of Financial Intermediation*, *8*(3), 141-173

Corwin, S. A., & Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance*, *67*(2), 719-760.

Dodd-Frank Wall Street Reform and Consumer Protection Act, Sec. (2010). Retrieved from: https://www.govinfo.gov/content/pkg/PLAW-111publ203 /pdf/PLAW-111publ203.pdf

Donefer, B. S. (2010). Algos gone wild: Risk in the world of automated trading strategies. *Journal of Trading*, *5*, 31–34.

Duan, J. C., & Zou, Q. (2014). Liquidity and default. *Available at SSRN 2450890*.

Durbin, M. (2010). All about high-frequency trading: The easy way to get started. New York: McGraw-Hill Companies, Inc.

Dyhrberg, A. H., Foley, S., & Svec, J. (2020). When bigger is better: The impact of a tiny tick size on undercutting behavior. Retrieved from https://www.org/SSRN 3194932.

Easley, D., & O'hara, M. (1992). Time and the process of security price adjustment. *The Journal of Finance*, *47*(2), 577-605.

Easley, D., Prado, M. M., & O'Hara, M. (2011). The microstructure of the "Flash Crash": Flow toxicity, liquidity crashes, and the probability of informed trading. *Journal of Portfolio Management*, *37*, 119–128.

Easley, D., Prado, M. M., & O'Hara, M. (2012). The volume clock: Insights into the high-frequency paradigm. *Journal of Portfolio Management*, *39*, 19–29.

Edwards, T., & Preston, H. (2017). Reading VIX®: Does VIX Predict Future Volatility? *S&P Dow Jones Indices Research*. Retrieved from: https://www.spglobal.com/spdji/en/documents/research/research-reading-vix-does-vix-predictfuture-volatility.pdf

Egginton, J. F., Van Ness, B. F., & Van Ness, R. A. (2016). Quote stuffing. *Financial Management, Fall*, *45*, 583–608.

Elmer-DeWitt (2008). How Steve Jobs' obit got published. Retrieved from https://fortune.com/2008/08/28/how-steve-jobs-obit-got-published/

Ersan, O., & Ekinci, C. (2016). Algorithmic and high-frequency trading in Borsa Istanbul. *Borsa Istanbul Review*, *16*(4), 233-248.

European Securities and Markets Authority. (2011). Guidelines on systems and controls in a highly automated trading environment for trading platforms, investment firms and competent authorities. Paris.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417.

Financial Industry Regulatory Authority. (2012). FINRA joins exchanges and the SEC in fining Hold Brothers more than $5.9 million for manipulative trading, anti-money laundering, and other violations. Washington, D.C.

Foley, S., Dyhrberg, A., & Svec, J. (2022a). When bigger is better: the impact of a tiny tick size on undercutting behavior. *Journal of Financial and Quantitative Analysis*.

Foley, S., Gorbenko, A., & Ruf, T. (2019). Can fast and slow liquidity providers co-exist in modern equity markets.

Foley, S., Meling, T., & Ødegaard, B. A. (2022b). Tick size wars: The market quality effects of pricing grid competition. *Review of Finance, rfac32.*

Foucault, T., Hombert, J., & Rosu, I. (2016). News trading and speed. *The Journal of Finance*, *71*(1), 335–382.

Foucault, T., Kozhan, R., & Tham, W. W. (2017). Toxic arbitrage. *The Review of Financial Studies*, *30*, 1053–1094.

Fox, M. B., Glosten, L. R., & Rauterberg, G. V. (2017). Informed trading and its regulation. *Journal of Corporation Law*, *43*(4), 817–898.

Friederich, S., & Payne, R. (2015). Order-to-trade ratios and market liquidity. *Journal of Banking and Finance*, *50*, 214–223.

Frino, A., Mollica, V., & Zhang, S. (2015). The impact of tick size on high-frequency trading: The case for splits. Working paper.

Froot, K. A., Scharfstein, D. S., & Stein, J. C. (1992). Herd on the street: Informational inefficiencies in a market with short-term speculation. *The Journal of Finance*, *47*, 1461–1484.

Gibson, S., Singh, R., & Yerramilli, V. (2003). The effect of decimalization on the components of the bid-ask spread. *Journal of Financial Intermediation, 12*(2), 121-148.

Gider, J., Schmickler, S., & Westheide, C. (2019). High-frequency trading and price informativeness. SAFE Working Paper Series, 248.

Glosten, L. R. (1994). Is the electronic open limit order book inevitable?. *The Journal of Finance*, *49*(4), 1127-1161.

Goldstein, M. A., & Kavajecz, K. A. (2000). Eighths, sixteenths, and market depth: changes in tick size and liquidity provision on the NYSE. *Journal of Financial Economics, 56*(1), 125-149.

Goldstein, M. A., Kumar, P., & Graves, F. C. (2014). Computerized and high-frequency trading. *Financial Review*, *49*, 177–202.

Goldstein, M. A., Kwan, A., & Philip, R. (2020). High-frequency trading strategies. Retrieved from https://www. org/SSRN 2973019.

Golub, A., Dupuis, A., & Olsen, R. B. (2013). High-frequency trading in FX markets. In D. Easley, M. L. Prado, & M. O'Hara (eds.), *High-frequency trading new realities for traders, markets and regulators* (pp. 65–90). London: Risk Books.

Gomber, P., Arndt, B., Lutat, M., & Uhle, T. (2011). High-frequency trading. Retrieved from: http://doi.org/10.2139/ssrn.1858626

Goodhart, C. A., & O'Hara, M. (1997). High-frequency data in financial markets: Issues and applications. *Journal of Empirical Finance*, *4*, 73–114.

Gromb, D., & Vayanos, D. (2002). Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics*, *66*, 361–407.

Grossman, S. J., & Miller, M. H. (1988). Liquidity and market structure. *The Journal of Finance*, *43*, 617–633.

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

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

Hagströmer, B., Nordén, L., & Zhang, D. (2014). How aggressive are high-frequency traders? *Financial Review*, *49*, 395–419.

Han, J., Khapko, M., & Kyle, A. (2014). *Liquidity with high frequency market making*. Unpublished working paper. University of Maryland, College Park, MD.

Harris, L. (1991). Stock Price Clustering and Discreteness. *The Review of Financial Studies*, *4*(3), 389–415.

Harris, L. (1994). Minimum price variations, discrete bid-ask spreads, and quotation sizes. *The Review of Financial Studies, 7*(1), 149-178.

Harris, L. (1996). *Does a large minimum price variation encourage order exposure?* (Vol. 96, No. 5). New York Stock Exchange.

Harris, L. (2003). Trading and exchanges: Market microstructure for practitioners. New York: Oxford University Press.

Harris, L. (2013). What to do about high-frequency. *Financial Analysts Journal*, *69*, 6–9.

Harris, L. (2015). Trading and Electronic markets: What investment professionals need to know. VA: Research Foundation of CFA Institute.

Hasbrouck, J. (2019). Price discovery in high resolution. *Journal of Financial Econometrics*, nbz027.

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

Hendershott, T., & Riordan, R. (2009). Algorithmic trading and information. *Manuscript, University of California, Berkeley*.

Hendershott, T., & Riordan, R. (2013). Algorithmic trading and the market for liquidity. *Journal of Financial and Quantitative Analysis*, *48*, 1001–1024.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *The Journal of Finance*, *66*, 1–33.

Hirschey, N. (2021). Do high-frequency traders anticipate buying and selling pressure?. *Management Science*, *67*(6), 3321-3345.

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

Hull, J. C. (2003). *Options futures and other derivatives*. Pearson Education Limited

Jarnecic, E., & Snape, M. (2014). The provision of liquidity by high-frequency participants. *Financial Review*, *49*, 371–394.

Jarrow, R. A., & Protter, P. (2012). A dysfunctional role of high frequency trading in electronic markets. *International Journal of Theoretical and Applied Finance*, *15*, 1250022.

Jones, C. M. (2013). What do we know about high-frequency trading? Columbia Business School Research Paper No. 13-11.

Jones, C. M., & Lipson, M. L. (2001). Sixteenths: direct evidence on institutional execution costs. *Journal of Financial Economics*, *59*(2), 253-278.

Jovanovic, B., & Menkveld, A. J. (2016). Middlemen in limit order markets. Working paper. Retrieved from https://ssrn.com/abstract=1624329

Kauffman, R. J., Hu, Y., & Ma, D. (2015). Will high-frequency trading practices transform the financial markets in the Asia Pacific Region? *Financial Innovation*, *1*, 1–27.

Kauffman, R. J., Liu, J., & Ma, D. (2015). Innovations in financial IS and technology ecosystems: High-frequency trading in the equity market. *Technological Forecasting and Social Change*, *99*, 339–354.

Kaya, O. (2016). High-frequency trading reaching the limits. Deutsche Bank Research.

Khapko, M., & Zoican, M. (2020). Do speed bumps curb low-latency investment? Evidence from a laboratory mar ket. *Journal of Financial Markets*, 100601.

Kirilenko, A., Kyle, A. S., Samadi, M., & Tuzun, T. (2017). The flash crash: High-frequency trading. *The Journal of Finance*, *72*, 967–998.

Korajczyk, R., & Murphy, D. (2019). High-frequency market making to large institutional trades. *The Review of Financial Studies*, *32*, 1034–1067.

Kosinski, R. J. (2013). *A literature review on reaction time*. Working paper. Clemson University.

Kozhan, R., & Tham, W. W. (2012). Execution risk in high-frequency arbitrage. *Management Science*, *58*, 2131–2149.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica*, *53*, 1315–1335.

Kyle, A. S., & Lee, J. (2017). Toward a fully continuous exchange. *Oxford Review of Economic Policy*, *33*, 650–675.

Lash, H., & Spicer, J. (2010). Mystery trader in selloff was Waddell: Kansas-based manager sold large order of e-mini contracts during crucial time period, document shows. The Globe and Mail, May 14.

Le, H., & Gregoriou, A. (2020). How do you capture liquidity? A review of the literature on low-frequency stock liquidity. *Journal of Economic Surveys*, *34*(5), 1170-1186.

Lee, E. J. (2015). High frequency trading in the Korean index futures market. *Journal of Futures Markets*, *35*(1), 31-51.

Lhabitant, F.-S., & Gregoriou, G. N. (2015). High-frequency trading: Past, present and future. In G. N. Gregoriou (ed.), *Handbook of high-frequency trading* (pp. 155–165). Waltham, MA: Academic Press.

Li, S., Wang, X., & Ye, M. (2021). Who provides liquidity, and when?. *Journal of Financial Economics*, *141*(3), 968-980.

Liberti, J. M., & Petersen, M. A. (2019). Information: Hard and soft. *Review of Corporate Finance Studies*, *8*(1), 1-41.

Linton, O., O'Hara, M., & Zigrand, J. P. (2013). The regulatory challenge of high-frequency markets. *High-Frequency Trading*, 227.

Lipson, M. L., & Mortal, S. (2006). The effect of stock splits on clientele: Is tick size relevant?. *Journal of Corporate Finance,* 12(5), 878-896.

London Stock Exchange Group. (2010) Response to CESR call for evidence on micro-structural issues of the European Equity Markets.

MacKenzie, D. (2015). Mechanizing the merc: The Chicago Mercantile Exchange and the rise of high-frequency trading. *Technology and Culture*, *56*, 646–675.

Madhavan, A. (2000). Market microstructure: A survey. *Journal of Financial Markets*, *3*(3), 205-258.

Madhavan, A. (2002). Market microstructure: A practitioner's guide. *Financial Analysts Journal*, *58*(5), 28-42.

Mahmoodzadeh, S., & Gençay, R. (2017). Human vs. high-frequency traders, penny jumping, and tick size. *Journal of Banking & Finance*, *85*, 69-82.

Malceniece, L., Malcenieks, K., & Putniņš, T. J. (2019). High frequency trading and comovement in financial markets. *Journal of Financial Economics*, *134*, 381–399.

Malinova, K., & Park, A. (2020). "Sniping" in fragmented markets. McMaster University and University of Toronto working paper.

Manahov, V. (2016). A note on the relationship between high-frequency trading and latency arbitrage. *International Review of Financial Analysis*, *47*, 281–296.

Manahov, V., Hudson, R., & Viktor, B. G. (2014). Does high-frequency trading affect technical analysis and market efficiency? And if so, how? *Journal of International Financial Market, Institutions and Money*, *28*, 131–157.

Markham, J. W. (2002). A financial history of the United States. 1. From Christopher Columbus to the robber barons (1492-1900). New York: M. E. Sharpe.

Maynard, M. (2008). United Airlines shares fall on false report of bankruptcy. The New York Times. Retrieved from: https://www.nytimes.com/2008/09/09/business/worldbusiness/09iht-AIR.1.16001879.html

Menkveld, A. J. (2013). High-frequency trading and the new market makers. *Journal of Financial Markets*, *16*, 712– 740.

Menkveld, A. J. (2014). High-frequency traders and market structure. *Financial Review*, *49*, 333–344.

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

Moosa, I., & Ramiah, V. (2015). The profitability of high-frequency trading: is it for real? In *The handbook of high-frequency trading* (pp. 25–45). Waltham, MA: Academic Press.

Moriyasu, H., Wee, M., & Yu, J. (2018). The role of algorithmic trading in stock liquidity and commonality in electronic limit order markets. *Pacific-Basin Finance Journal*, *49*, 103–128.

Narang, R. K. (2013). *Inside the black box: A Simple Guide to Quantitative* (2nd ed.). New Jersey: John Wiley & Sons, Inc.

Netherlands Authority of Financial Markets. (2010). High-frequency trading: The application of advanced trading technology in the European marketplace, Amsterdam.

O'Hara, M. (2014). High-frequency trading and its impact on markets. *Financial Analysts Journal*, *70*(3), 18-27.

O'Hara, M. (2015). High-frequency market microstructure. *Journal of Financial Economics*, *116*, 257–270.

O'Hara, M., 1995. *Market microstructure theory*. Basil Blackwell, Cambridge, MA.

O'Hara, M., Saar, G., & Zhong, Z. (2019). Relative tick size and the trading environment. *Review of Asset Pricing Studies*, *9*, 47–90.

Parlour, C. A., and D. J. Seppi. 2008. Limit order markets: A survey. In A. Boot and A. Thakor, eds. *Handbook of financial intermediation and banking*. Amsterdam, the Netherlands: Elsevier.

Patterson, S. (2010). *Did shutdowns make plunge worse?* Retrieved from: https://www.wsj.com/articles/SB10001424052748703686304575228721439480374

Pirrong, C. (2014). Pick your poison – Fragmentation or market power? An analysis of RegNMS, high frequency trading, and securities market structure. *Journal of Applied Corporate Finance*, *26*, 8–14.

Putniņš, T. J., & Barbara, J. (2020). The good, the bad, and the ugly: How algorithmic traders impact institutional trading costs.

Reilly, F. K. & Brown, K. C. (2012). *Investment Analysis & Portfolio Management.* South-Western Cengage Learning.

Riordan, R., & Storkenmaier, A. (2012). Latency, liquidity and price discovery. *Journal of Financial Markets*, *15*, 416–437.

Sarr, A., & Lybek, T. (2002). Measuring liquidity in financial markets. *Available at SSRN 880932*.

Sarwar, G. (2017). Examining the flight-to-safety with the implied volatilities. *Finance Research Letters*, *20*, 118-124.

Savor, P. G. (2012). Stock returns after major price shocks: The impact of information. *Journal of financial Economics*, *106*(3), 635-659.

Scholtus, M., van Dijk, D., & Frijns, B. (2014). Speed, algorithmic trading, and market quality around macroeconomic news announcements. *Journal of Banking and Finance*, *38*, 89–105.

Schultz, P. (2000). Stock splits, tick size, and sponsorship. *The Journal of Finance*, *55*(1), 429-450.

Securities and Exchange Commission. (2005). Regulation NMS. Release no. 34–51808 (New York, NY, August 29).

Serbera, J.-P., & Paumard, P. (2016). The fall of high-frequency trading: A survey of competition and profits. *Research in International Business and Finance*, *36*, 271–287.

Shkilko, A., & Sokolov, K. (2020). Every cloud has a silver lining: Fast trading, microwave connectivity, and trading costs. *The Journal of Finance*, *75*, 2899–2927.

Shorter, G., & Miller, R. S. (2014). High-frequency trading: Background, concern and regulatory development. Congressional Research Service.

Steiner, C. (2010). Wall Street's speed war. Forbes Magazine, September 27.

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

Subrahmanyam, A., & Zheng, H. (2016). Limit order placement by high-frequency traders. *Borsa Istanbul Review*, *16*(4), 185-209.

Sundaresan, S., & Wang, Z. (2009). Y2K options and the liquidity premium in Treasury markets. *The Review of Financial Studies*, *22*(3), 1021-1056.

Troster, V., Bouri, E., & Roubaud, D. (2019). A quantile regression analysis of flights-to-safety with implied volatilities. *Resources Policy*, *62*, 482-495.

U.K. Government Office for Science. (2012). Foresight: The future of computer trading in financial markets – Final project report. London.

U.S. Commodity Futures Trading Commission (CFT) & U.S. Securities and Exchange Commission (SEC). (2010a). Preliminary findings regarding the market events of May 6, 2010. Washington, D.C.

U.S. Commodity Futures Trading Commission (CFT) & U.S. Securities and Exchange Commission (SEC). (2010b). Findings regarding the market events of May 6, 2010. Washington, D.C.

U.S. Securities and Exchange Commission (SEC). (2010). Concept release on equity market structure. *Federal Register*, *75*, 3594–3614.

U.S. Securities and Exchange Commission (SEC). (2014). Equity market structure literature review Part II: High-frequency trading. Staff of the Division of Trading and Markets.

Van Kervel, V., & Menkveld, A. J. (2019). High-frequency trading around large institutional orders. *The Journal of Finance*, *74*, 1091–1137.

Weller, B. M. (2017). Does algorithmic trading reduce information acquisition? *The Review of Financial Studies*, *31*, 2184– 2226.

Weller, B. M. (2018). Does algorithmic trading reduce information acquisition?. *The Review of Financial Studies*, *31*(6), 2184-2226.

Werner, I. M., Wen, Y., Rindi, B., Consonni, F., & Buti, S. (2019). Tick Size, Trading Strategies and Market Quality, Fisher College of Business Working Paper Series.

Whaley, R. E. (2009). Understanding the VIX. *The Journal of Portfolio Management*, *35*(3), 98-105.

Wissner-Gross, A. D., & Freer, C. E. (2010). Relativistic statistical arbitrage. *Physical Review*, *82*, 1–7.

Yang, L., & Zhu, H. (2017). Back-running: Seeking and hiding fundamental information in order flows. Working paper, Massachusetts Institute of Technology.

Yao, C., & Ye, M. (2018). Why trading speed matters: A tale of queue rationing under price controls. *The Review of Financial Studies*, *31*, 2157–2183.

Yılmaz, M. K., Erdem, O., Eraslan, V., & Arık, E. (2015). Technology upgrades in emerging equity markets: Effects on liquidity and trading activity. *Finance Research Letters*, *14*, 87-92.

Zaharudin, K. Z., Young, M. R., & Hsu, W. H. (2022). High-frequency trading: Definition, implications, and controversies. *Journal of Economic Surveys*, *36*(1), 75-107.

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

Zhang, X. F. (2010). High-frequency trading, stock volatility, and price discovery. Working paper. Yale School of Management. Retrieved from: https://ssrn.com/abstract=1691679

APPENDIX

Table A1: Distribution of returns on day *t*+21 based on the VIX value on day *t*

Actual return ($t + 21$)	Frequency	AXVI ≤ 12 (Low)	12 < AXVI < 20 (Normal)	AXVI ≥ 20 (High)
-14%	0.05%	0.00%	0.08%	0.00%
-12%	0.05%	0.00%	0.08%	0.00%
-10%	0.55%	0.00%	0.53%	1.03%
-8%	1.87%	0.00%	2.27%	1.38%
-6%	4.62%	3.79%	4.62%	5.17%
-4%	8.90%	8.53%	9.55%	6.21%
-2%	14.67%	14.69%	14.71%	14.48%
0%	25.60%	29.38%	26.31%	19.66%
+2%	21.98%	28.44%	21.30%	20.34%
+4%	15.16%	9.95%	15.16%	18.97%
+6%	4.40%	5.21%	3.94%	5.86%
+8%	1.70%	0.00%	1.06%	5.86%
+10%	0.33%	0.00%	0.23%	1.03%
+12%	0.11%	0.00%	0.15%	0.00%
+14%	0.00%	0.00%	0.00%	0.00%

Table A2: Heatmap analysis using data from the ASX market (sort by HFO)

The table presents the heatmap analysis which is based on percentile values for all stocks used in third essay, sorted by HFO, using ASX dataset. *SYMBOL* represents the stock ticker symbol; *HFO* represents high-frequency OrderID; *CSHL* is the Corwin-Schultz high-low spread; *ILLIQ* is the Amihud illiquidity ratio; *VOLTO* is the volume turnover; *RTS* is the relative tick size; *VOLATILITY* is the daily trading range ratio; *SIZE* is the market capitalisation; *PRICE* is the closing price; and *PERCENTILE* is the average percentile values across all parameters excluding PRICE. The percentile rank for each parameter is based on each stock's average value throughout the study period. The deepest shade of green (red) indicates the highest (lowest) rank of each parameter, where values with the most (least) desirable traits have the highest (lowest) rank. For HFO, VOLTO, RTS, SIZE, and PRICE, greater values are desirable, whereas lower values are preferred for CSHL, ILLIQ, and VOLATILITY.

SYMBOL	HFO	CSHL	ILLIQ	VOLTO	RTS	VOLATILITY	SIZE	PRICE	PERCENTILE
CBA*	1.000	0.956	1.000	0.022	0.978	0.971	1.000	0.977	0.847
CSL*	0.992	0.829	0.948	0.088	0.993	0.897	0.948	0.985	0.814
MQG*	0.985	0.881	0.918	0.488	0.971	0.845	0.911	0.970	0.857
RIO*	0.977	0.948	0.941	0.770	0.963	0.823	0.925	0.955	0.907
WBC*	0.970	0.926	0.993	0.029	0.882	0.934	0.992	0.881	0.818
NAB*	0.962	0.941	0.978	0.044	0.867	0.956	0.970	0.866	0.817
DMP	0.955	0.187	0.441	0.614	0.949	0.215	0.474	0.948	0.548
ANZ*	0.948	0.911	0.986	0.059	0.860	0.919	0.977	0.859	0.809
COH	0.940	0.739	0.650	0.651	0.986	0.652	0.548	0.992	0.738
WES*	0.933	0.933	0.956	0.037	0.919	0.963	0.955	0.911	0.814
BHP*	0.925	0.963	0.971	0.200	0.838	0.889	0.985	0.829	0.824
RHC	0.918	0.672	0.695	0.111	0.956	0.593	0.785	0.962	0.676
WPL*	0.911	0.866	0.926	0.318	0.889	0.638	0.933	0.888	0.783
REA	0.903	0.560	0.448	0.096	0.941	0.482	0.592	0.940	0.575
WOW*	0.896	0.896	0.933	0.148	0.852	0.860	0.940	0.851	0.789
CTX	0.888	0.478	0.635	0.555	0.845	0.452	0.651	0.844	0.643
BKL	0.881	0.090	0.224	0.874	1.000	0.126	0.192	1.000	0.484
FLT	0.874	0.426	0.500	0.733	0.904	0.341	0.407	0.903	0.598
NCM	0.866	0.583	0.792	0.800	0.749	0.193	0.800	0.755	0.683
ASX	0.859	0.844	0.784	0.251	0.912	0.949	0.688	0.918	0.755
NWS	0.851	0.971	0.851	0.777	0.875	0.815	0.807	0.874	0.850
CIM	0.844	0.374	0.426	0.118	0.823	0.304	0.703	0.822	0.513
SRX	0.837	0.135	0.217	0.940	0.830	0.178	0.103	0.837	0.463
PPT	0.829	0.821	0.254	0.607	0.926	0.630	0.200	0.925	0.610
JBH	0.822	0.389	0.478	0.962	0.808	0.349	0.214	0.807	0.575
ORI	0.814	0.568	0.657	0.622	0.786	0.445	0.600	0.785	0.642
SHL	0.807	0.784	0.709	0.311	0.793	0.719	0.666	0.792	0.684
FOX*	0.800	1.000	0.814	0.496	0.897	0.993	0.888	0.896	0.841
QBE*	0.792	0.747	0.874	0.540	0.712	0.534	0.866	0.703	0.724
AGL	0.785	0.627	0.821	0.288	0.778	0.793	0.770	0.777	0.695
MFG	0.777	0.351	0.299	0.325	0.815	0.363	0.385	0.814	0.474
ANN	0.770	0.433	0.433	0.681	0.800	0.475	0.325	0.800	0.560
WOR	0.762	0.209	0.292	0.896	0.667	0.112	0.355	0.733	0.470
JHX	0.755	0.515	0.553	0.362	0.771	0.415	0.622	0.770	0.570
SEK	0.748	0.657	0.515	0.562	0.756	0.489	0.503	0.748	0.604
AMC	0.740	0.724	0.866	0.296	0.719	0.645	0.844	0.711	0.691
SUN*	0.733	0.918	0.903	0.274	0.734	0.852	0.874	0.718	0.755
STO	0.725	0.523	0.724	0.762	0.475	0.245	0.718	0.562	0.596
ORG	0.718	0.680	0.732	0.407	0.600	0.326	0.829	0.622	0.613
ALL	0.711	0.232	0.411	0.400	0.563	0.312	0.585	0.659	0.459
BXB*	0.703	0.717	0.859	0.170	0.660	0.712	0.859	0.651	0.669
LLC	0.696	0.612	0.680	0.422	0.741	0.497	0.681	0.740	0.618
ILU	0.688	0.254	0.396	0.829	0.593	0.149	0.370	0.555	0.468
BSL	0.681	0.105	0.389	0.851	0.452	0.097	0.392	0.496	0.424
CWN	0.674	0.620	0.627	0.155	0.726	0.541	0.725	0.725	0.581
FMG	0.666	0.142	0.769	0.903	0.282	0.075	0.822	0.281	0.523
WDC*	0.659	0.814	0.911	0.266	0.675	0.904	0.918	0.666	0.735
OSH	0.651	0.702	0.762	0.414	0.549	0.460	0.762	0.518	0.614
WFD*	0.644	0.754	0.881	0.214	0.608	0.778	0.896	0.585	0.682
A2M	0.637	0.180	0.642	0.866	0.534	0.230	0.511	0.503	0.514
CPU	0.629	0.500	0.598	0.348	0.697	0.563	0.570	0.688	0.558
INM	0.622	0.978	0.023	0.007	0.934	0.800	0.792	0.933	0.594
SGM	0.614	0.284	0.150	0.748	0.652	0.252	0.162	0.644	0.409
BOQ	0.607	0.806	0.612	0.718	0.704	0.689	0.451	0.696	0.655
TWE	0.600	0.463	0.463	0.600	0.519	0.423	0.540	0.540	0.515
CGF	0.592	0.471	0.486	0.644	0.541	0.430	0.466	0.570	0.519

Table A2 (continue)

SYMBOL	HFO	CSHL	ILLIQ	VOLTO	RTS	VOLATILITY	SIZE	PRICE	PERCENTILE
MND	0.585	0.165	0.090	0.859	0.763	0.163	0.066	0.762	0.384
ALQ	0.577	0.068	0.165	0.688	0.504	0.082	0.303	0.481	0.341
CCL	0.570	0.792	0.717	0.333	0.645	0.838	0.644	0.637	0.648
TCL*	0.562	0.874	0.889	0.133	0.623	0.941	0.881	0.607	0.700
BEN	0.555	0.769	0.568	0.511	0.689	0.704	0.488	0.681	0.612
MIN	0.548	0.239	0.172	0.807	0.638	0.223	0.125	0.629	0.393
OZL	0.540	0.150	0.135	0.977	0.400	0.104	0.111	0.414	0.345
SGH	0.533	0.038	0.098	0.992	0.238	0.008	0.044	0.259	0.279
CAR	0.525	0.411	0.277	0.525	0.682	0.467	0.259	0.674	0.449
SPO	0.518	0.045	0.083	0.955	0.038	0.067	0.088	0.059	0.256
JHG	0.511	0.903	0.306	0.259	0.393	0.608	0.533	0.614	0.502
TPM	0.503	0.448	0.403	0.066	0.586	0.378	0.607	0.577	0.427
NST	0.496	0.403	0.374	0.933	0.363	0.186	0.288	0.348	0.435
UGL	0.488	0.112	0.127	0.911	0.556	0.171	0.022	0.525	0.341
S32	0.481	0.299	0.620	0.637	0.149	0.156	0.777	0.125	0.446
IAG	0.474	0.762	0.836	0.237	0.467	0.830	0.837	0.444	0.635
VOC	0.466	0.217	0.284	0.888	0.334	0.134	0.318	0.377	0.377
AMP	0.459	0.777	0.844	0.207	0.430	0.756	0.851	0.400	0.618
QAN	0.451	0.306	0.538	0.755	0.223	0.238	0.555	0.200	0.438
DXS	0.444	0.575	0.665	0.429	0.326	0.615	0.629	0.451	0.526
TLS*	0.437	0.889	0.963	0.051	0.408	0.978	0.962	0.385	0.670
HSO	0.429	0.224	0.381	0.474	0.097	0.400	0.459	0.170	0.352
APA	0.422	0.545	0.590	0.125	0.571	0.675	0.696	0.548	0.518
GMG	0.414	0.538	0.747	0.185	0.489	0.623	0.755	0.474	0.536
BLD	0.407	0.642	0.560	0.629	0.438	0.512	0.481	0.422	0.524
AIO	0.400	0.695	0.672	0.533	0.512	0.697	0.577	0.488	0.584
AGO	0.392	0.000	0.075	1.000	0.030	0.015	0.007	0.022	0.217
SCG*	0.385	0.732	0.896	0.103	0.297	0.726	0.903	0.288	0.577
DOW	0.377	0.120	0.187	0.740	0.378	0.200	0.222	0.370	0.318
RRL	0.370	0.098	0.038	0.822	0.208	0.052	0.081	0.229	0.238
IFL	0.362	0.851	0.359	0.592	0.630	0.786	0.266	0.592	0.549
AZJ	0.355	0.605	0.754	0.244	0.386	0.600	0.740	0.362	0.526
SYD	0.348	0.836	0.799	0.162	0.423	0.882	0.814	0.407	0.609
IPL	0.340	0.269	0.530	0.548	0.215	0.319	0.525	0.222	0.392
EVN	0.333	0.157	0.508	0.792	0.052	0.260	0.400	0.133	0.357
TOL	0.325	0.441	0.523	0.666	0.445	0.586	0.422	0.429	0.487
PNA	0.318	0.053	0.015	0.844	0.112	0.045	0.029	0.118	0.202
SGR	0.311	0.262	0.344	0.570	0.289	0.393	0.377	0.318	0.364
AWC	0.303	0.172	0.366	0.674	0.126	0.119	0.429	0.074	0.313
WHC	0.296	0.008	0.112	0.703	0.082	0.060	0.170	0.096	0.204
GPT	0.288	0.650	0.739	0.355	0.349	0.808	0.674	0.333	0.552
HVN	0.281	0.277	0.269	0.229	0.267	0.334	0.444	0.274	0.300
REC	0.274	0.381	0.060	0.392	0.482	0.386	0.140	0.459	0.302
GNC	0.266	0.709	0.202	0.503	0.615	0.734	0.177	0.600	0.458
DLX	0.259	0.687	0.314	0.459	0.497	0.771	0.244	0.466	0.462
CSR	0.251	0.314	0.209	0.814	0.260	0.289	0.133	0.251	0.324
PRY	0.244	0.329	0.232	0.725	0.312	0.356	0.207	0.311	0.344
RMD	0.237	0.993	0.605	0.074	0.526	0.986	0.748	0.511	0.596
SGP	0.229	0.635	0.806	0.370	0.319	0.763	0.733	0.303	0.551
LNK	0.222	0.665	0.351	0.281	0.578	0.749	0.340	0.533	0.455
TAH	0.214	0.590	0.418	0.585	0.304	0.549	0.362	0.296	0.432
MTS	0.207	0.127	0.321	0.925	0.186	0.275	0.229	0.177	0.324
PRU	0.200	0.075	0.000	0.881	0.163	0.023	0.000	0.066	0.192
WRT	0.192	0.598	0.829	0.518	0.200	0.867	0.711	0.214	0.559
MGR	0.185	0.344	0.687	0.437	0.178	0.519	0.614	0.088	0.423
ARI	0.177	0.023	0.068	0.985	0.008	0.038	0.059	0.029	0.194
SKI	0.170	0.359	0.336	0.303	0.171	0.578	0.333	0.103	0.321
CHC	0.162	0.859	0.456	0.466	0.460	0.912	0.274	0.437	0.513
ABC	0.155	0.486	0.195	0.222	0.341	0.526	0.311	0.340	0.319
TTS	0.148	0.553	0.493	0.177	0.252	0.667	0.518	0.244	0.401
ORA	0.140	0.202	0.180	0.444	0.134	0.297	0.296	0.140	0.242
BPT	0.125	0.060	0.105	0.785	0.119	0.141	0.118	0.044	0.208
NVT	0.118	0.321	0.045	0.140	0.415	0.371	0.148	0.392	0.223
MYR	0.111	0.247	0.262	0.970	0.089	0.267	0.051	0.162	0.285
VCX	0.103	0.336	0.583	0.385	0.141	0.556	0.659	0.192	0.395
MPL	0.096	0.366	0.702	0.451	0.104	0.571	0.637	0.185	0.418
NVN	0.088	0.418	0.575	0.192	0.075	0.682	0.562	0.111	0.370

Table A2 (continue)

SYMBOL	HFO	CSHL	ILLIQ	VOLTO	RTS	VOLATILITY	SIZE	PRICE	PERCENTILE
CYB	0.081	0.799	0.329	0.377	0.371	0.504	0.414	0.355	0.411
AUT	0.074	0.195	0.053	0.696	0.230	0.282	0.074	0.237	0.229
IOF	0.066	0.508	0.239	0.340	0.275	0.660	0.237	0.266	0.332
DJS	0.059	0.530	0.142	0.837	0.193	0.438	0.096	0.207	0.328
DUE	0.051	0.493	0.545	0.481	0.060	0.875	0.437	0.148	0.420
AST	0.044	0.456	0.247	0.014	0.156	0.741	0.496	0.051	0.308
FXJ	0.029	0.083	0.120	0.577	0.023	0.208	0.185	0.014	0.175
QUB	0.022	0.292	0.157	0.081	0.067	0.408	0.348	0.155	0.196
ALZ	0.014	0.986	0.777	0.948	0.356	1.000	0.251	0.325	0.619
CPA	0.007	0.396	0.471	0.711	0.045	0.926	0.281	0.037	0.405
LYC	0.000	0.015	0.008	0.918	0.000	0.030	0.014	0.000	0.141

* Top 20 stocks by market capitalisation (overall)

Table A3: Heatmap analysis using data from the CHIX market (sort by HFO)

The table presents the heatmap analysis which is based on percentile values for all stocks used in third essay, sorted by HFO, using CHIX dataset. *SYMBOL* represents the stock ticker symbol; *HFO* represents high-frequency OrderID; *CSHL* is the Corwin-Schultz high-low spread; *ILLIQ* is the Amihud illiquidity ratio; *VOLTO* is the volume turnover; *RTS* is the relative tick size; *VOLATILITY* is the daily trading range ratio; *SIZE* is the market capitalisation; *PRICE* is the closing price; and *PERCENTILE* is the average percentile values across all parameters excluding PRICE. The percentile rank for each parameter is based on each stock's average value throughout the study period. The deepest shade of green (red) indicates the highest (lowest) rank of each parameter, where values with the most (least) desirable traits have the highest (lowest) rank. For HFO, VOLTO, RTS, SIZE, and PRICE, greater values are desirable, whereas lower values are preferred for CSHL, ILLIQ, and VOLATILITY.

SYMBOL	HFO	CSHL	ILLIQ	VOLTO	RTS	VOLATILITY	SIZE	PRICE	PERCENTILE
CBA*	1.000	0.940	0.963	0.030	0.978	0.948	1.000	0.977	0.837
CSL*	0.992	0.835	0.813	0.037	0.993	0.850	0.948	0.984	0.781
RIO*	0.984	0.948	0.888	0.293	0.963	0.722	0.925	0.954	0.818
MQG*	0.977	0.910	0.068	0.097	0.970	0.797	0.911	0.969	0.676
ANZ*	0.969	0.888	0.993	0.255	0.850	0.903	0.977	0.849	0.834
WBC*	0.962	0.873	0.978	0.142	0.873	0.865	0.992	0.872	0.812
COH	0.954	0.790	0.316	0.172	0.985	0.692	0.548	0.992	0.637
NAB*	0.947	0.925	0.985	0.203	0.858	0.918	0.970	0.857	0.829
FLT	0.939	0.444	0.166	0.195	0.895	0.346	0.407	0.894	0.485
BHP*	0.932	0.955	0.970	0.338	0.828	0.813	0.985	0.819	0.832
RHC	0.924	0.685	0.294	0.052	0.955	0.579	0.785	0.962	0.611
WOW*	0.917	0.865	0.955	0.105	0.843	0.895	0.940	0.842	0.789
WPL*	0.909	0.828	0.880	0.135	0.880	0.700	0.933	0.879	0.752
WES*	0.902	0.933	0.850	0.060	0.910	0.933	0.955	0.902	0.792
REA	0.894	0.587	0.181	0.067	0.940	0.467	0.592	0.939	0.533
ASX	0.887	0.903	0.399	0.075	0.903	0.940	0.688	0.909	0.685
NCM	0.879	0.369	0.707	0.609	0.737	0.166	0.800	0.744	0.610
CTX	0.872	0.422	0.429	0.187	0.835	0.452	0.651	0.834	0.550
MND	0.864	0.286	0.031	0.263	0.752	0.204	0.066	0.751	0.352
DMP	0.857	0.256	0.113	0.150	0.948	0.226	0.474	0.947	0.432
QBE*	0.849	0.625	0.925	0.578	0.700	0.459	0.866	0.691	0.715
NWS	0.842	0.970	0.249	0.045	0.865	0.873	0.807	0.864	0.664
STO	0.834	0.339	0.797	0.894	0.467	0.188	0.718	0.556	0.605
SUN*	0.827	0.895	0.910	0.360	0.722	0.880	0.874	0.706	0.781
PPT	0.819	0.880	0.053	0.165	0.925	0.737	0.200	0.924	0.540
FOX*	0.812	0.993	0.527	0.285	0.888	0.993	0.888	0.887	0.769
ORG	0.804	0.512	0.752	0.624	0.587	0.271	0.829	0.609	0.626
SHL	0.796	0.722	0.610	0.233	0.782	0.632	0.666	0.781	0.634
AMC	0.789	0.647	0.828	0.345	0.707	0.677	0.844	0.699	0.691
WOR	0.781	0.166	0.219	0.691	0.655	0.091	0.355	0.721	0.423
CIM	0.774	0.527	0.076	0.022	0.813	0.369	0.703	0.812	0.469
BSL	0.766	0.068	0.497	0.849	0.437	0.076	0.392	0.488	0.441
WDC*	0.759	0.775	0.948	0.157	0.662	0.858	0.918	0.654	0.725
LLC	0.751	0.459	0.594	0.315	0.730	0.474	0.681	0.729	0.572
BEN	0.744	0.737	0.685	0.669	0.677	0.640	0.488	0.669	0.663
AGL	0.736	0.655	0.369	0.180	0.767	0.775	0.770	0.766	0.607
ORI	0.729	0.407	0.437	0.240	0.775	0.422	0.600	0.774	0.516
ILU	0.721	0.181	0.459	0.781	0.579	0.136	0.370	0.548	0.461
JHX	0.714	0.474	0.226	0.120	0.760	0.407	0.622	0.759	0.475
ANN	0.706	0.482	0.204	0.270	0.790	0.482	0.325	0.789	0.466
SGM	0.699	0.219	0.158	0.458	0.640	0.234	0.162	0.631	0.367
CWN	0.691	0.497	0.602	0.210	0.715	0.512	0.725	0.714	0.565
SEK	0.684	0.519	0.384	0.248	0.745	0.444	0.503	0.736	0.504
SRX	0.676	0.204	0.023	0.443	0.820	0.196	0.103	0.827	0.352
BOQ	0.669	0.767	0.655	0.766	0.692	0.617	0.451	0.684	0.660
BXB*	0.661	0.579	0.843	0.225	0.647	0.647	0.859	0.639	0.637
OSH	0.654	0.610	0.722	0.451	0.534	0.429	0.762	0.511	0.595
CPU	0.646	0.384	0.587	0.323	0.685	0.542	0.570	0.676	0.534
JBH	0.639	0.331	0.264	0.729	0.797	0.339	0.214	0.796	0.473
CCL	0.631	0.715	0.767	0.518	0.632	0.782	0.644	0.624	0.670
ALQ	0.624	0.106	0.196	0.593	0.489	0.098	0.303	0.481	0.344
MIN	0.616	0.391	0.121	0.398	0.625	0.241	0.125	0.616	0.360
CGF	0.609	0.414	0.549	0.714	0.527	0.376	0.466	0.563	0.522
RRL	0.601	0.053	0.143	0.774	0.204	0.038	0.081	0.218	0.271
UGL	0.593	0.173	0.083	0.646	0.542	0.219	0.022	0.518	0.325
BKL	0.586	0.707	0.008	0.015	1.000	0.324	0.192	1.000	0.405

Table A3 (continue)

SYMBOL	HFO	CSHL	ILLIQ	VOLTO	RTS	VOLATILITY	SIZE	PRICE	PERCENTILE
CAR	0.578	0.549	0.038	0.218	0.670	0.504	0.259	0.661	0.402
FMG	0.571	0.098	0.865	0.917	0.271	0.053	0.822	0.270	0.514
TCL*	0.563	0.858	0.918	0.330	0.610	0.910	0.881	0.601	0.724
TOL	0.556	0.354	0.670	0.751	0.429	0.557	0.422	0.421	0.534
OZL	0.548	0.136	0.331	0.939	0.384	0.083	0.111	0.406	0.362
MFG	0.541	0.467	0.098	0.127	0.805	0.384	0.385	0.804	0.401
APA	0.533	0.437	0.737	0.390	0.557	0.625	0.696	0.541	0.568
AIO	0.526	0.760	0.692	0.481	0.497	0.760	0.577	0.473	0.613
DOW	0.518	0.121	0.376	0.834	0.369	0.158	0.222	0.360	0.371
IAG	0.511	0.677	0.895	0.548	0.452	0.752	0.837	0.436	0.667
ALL	0.503	0.188	0.452	0.406	0.549	0.279	0.585	0.646	0.423
TWE	0.496	0.399	0.557	0.654	0.504	0.361	0.540	0.533	0.502
PNA	0.488	0.023	0.128	0.804	0.106	0.031	0.029	0.097	0.230
TPM	0.481	0.346	0.519	0.413	0.564	0.309	0.607	0.571	0.463
PRY	0.473	0.271	0.414	0.857	0.301	0.301	0.207	0.300	0.403
AUT	0.466	0.316	0.136	0.699	0.226	0.316	0.074	0.225	0.319
WHC	0.458	0.016	0.151	0.586	0.076	0.061	0.170	0.082	0.217
AMP	0.451	0.745	0.903	0.503	0.414	0.662	0.851	0.390	0.647
IFL	0.443	0.843	0.444	0.601	0.617	0.767	0.266	0.586	0.569
MTS	0.436	0.113	0.572	0.932	0.181	0.249	0.229	0.165	0.387
NST	0.428	0.264	0.512	0.977	0.354	0.106	0.288	0.338	0.418
QAN	0.421	0.211	0.700	0.887	0.219	0.173	0.555	0.187	0.452
GMG	0.413	0.452	0.745	0.368	0.474	0.587	0.755	0.466	0.542
AZJ	0.406	0.594	0.790	0.421	0.376	0.610	0.740	0.353	0.562
WFD*	0.398	0.692	0.820	0.375	0.594	0.685	0.896	0.578	0.637
REC	0.390	0.730	0.046	0.090	0.459	0.489	0.140	0.451	0.335
IPL	0.383	0.249	0.625	0.759	0.211	0.286	0.525	0.210	0.434
BLD	0.375	0.534	0.662	0.736	0.422	0.497	0.481	0.413	0.530
TLS*	0.368	0.918	1.000	0.466	0.391	0.963	0.962	0.375	0.724
GNC	0.360	0.805	0.061	0.383	0.602	0.820	0.177	0.593	0.458
VOC	0.353	0.151	0.564	0.954	0.324	0.113	0.318	0.368	0.397
RMD	0.345	0.963	0.715	0.353	0.512	0.970	0.748	0.503	0.658
ABC	0.338	0.557	0.391	0.556	0.331	0.534	0.311	0.330	0.431
TAH	0.330	0.489	0.617	0.812	0.294	0.519	0.362	0.285	0.489
MGR	0.323	0.376	0.211	0.631	0.166	0.527	0.614	0.075	0.407
DLX	0.315	0.632	0.482	0.706	0.482	0.707	0.244	0.458	0.510
S32	0.308	0.158	0.730	0.796	0.143	0.121	0.777	0.105	0.433
SGP	0.300	0.640	0.873	0.563	0.309	0.715	0.733	0.293	0.590
ARI	0.293	0.046	0.241	0.962	0.008	0.046	0.059	0.022	0.236
CSR	0.285	0.234	0.467	0.909	0.249	0.264	0.133	0.240	0.363
GPT	0.278	0.670	0.782	0.526	0.339	0.790	0.674	0.323	0.580
HVN	0.270	0.279	0.407	0.616	0.256	0.294	0.444	0.263	0.367
AGO	0.263	0.000	0.301	1.000	0.023	0.008	0.007	0.015	0.229
SKI	0.255	0.361	0.534	0.676	0.173	0.572	0.333	0.090	0.415
WRT	0.248	0.700	0.835	0.473	0.196	0.843	0.711	0.203	0.572
NVT	0.240	0.324	0.091	0.300	0.399	0.391	0.148	0.383	0.270
PRU	0.233	0.076	0.016	0.488	0.158	0.016	0.000	0.060	0.141
A2M	0.225	0.061	0.940	0.992	0.519	0.151	0.511	0.496	0.486
DXS	0.218	0.572	0.324	0.541	0.316	0.602	0.629	0.443	0.457
DJS	0.210	0.617	0.346	0.864	0.188	0.437	0.096	0.195	0.394
TTS	0.203	0.542	0.640	0.496	0.241	0.655	0.518	0.233	0.471
HSO	0.195	0.301	0.489	0.789	0.091	0.399	0.459	0.157	0.389
MYR	0.187	0.241	0.422	0.924	0.083	0.256	0.051	0.150	0.309
BPT	0.180	0.091	0.286	0.827	0.113	0.143	0.118	0.037	0.251
SGR	0.172	0.226	0.474	0.721	0.279	0.354	0.377	0.308	0.372
AWC	0.165	0.143	0.579	0.842	0.121	0.128	0.429	0.067	0.344
JHG	0.157	0.978	0.256	0.007	0.918	0.978	0.533	0.917	0.547
EVN	0.150	0.128	0.760	0.969	0.046	0.211	0.400	0.112	0.381
SCG*	0.142	0.662	0.933	0.278	0.286	0.670	0.903	0.278	0.553
SYD	0.135	0.797	0.858	0.428	0.407	0.828	0.814	0.398	0.610
SPO	0.127	0.031	0.271	0.902	0.031	0.068	0.088	0.052	0.217
SGH	0.120	0.038	0.188	0.984	0.234	0.000	0.044	0.248	0.230
CYB	0.112	0.850	0.279	0.308	0.361	0.549	0.414	0.345	0.410
VCX	0.105	0.429	0.647	0.511	0.136	0.594	0.659	0.180	0.440
DUE	0.097	0.752	0.632	0.571	0.061	0.925	0.437	0.127	0.496
INM	0.090	1.000	0.000	0.000	0.933	0.985	0.792	0.932	0.543
ORA	0.082	0.196	0.106	0.684	0.128	0.331	0.296	0.120	0.260

Table A3 (continue)

SYMBOL	HFO	CSHL	ILLIQ	VOLTO	RTS	VOLATILITY	SIZE	PRICE	PERCENTILE
IOF	0.075	0.504	0.339	0.533	0.264	0.745	0.237	0.255	0.385
CPA	0.067	0.782	0.542	0.661	0.038	0.955	0.281	0.030	0.475
AST	0.060	0.602	0.361	0.112	0.151	0.805	0.496	0.045	0.370
QUB	0.052	0.309	0.234	0.436	0.068	0.414	0.348	0.142	0.266
LNK	0.045	0.820	0.504	0.639	0.572	0.835	0.340	0.526	0.536
MPL	0.037	0.294	0.805	0.744	0.098	0.564	0.637	0.172	0.454
FXJ	0.030	0.083	0.354	0.819	0.016	0.181	0.185	0.007	0.238
NVN	0.022	0.564	0.309	0.082	0.053	0.730	0.562	0.135	0.332
LYC	0.015	0.008	0.173	0.947	0.000	0.023	0.014	0.000	0.169
ALZ	0.007	0.985	0.677	0.872	0.346	1.000	0.251	0.315	0.591
CHC	0.000	0.813	0.775	0.879	0.444	0.888	0.274	0.428	0.582

* Top 20 stocks by market capitalisation (overall)