High-frequency trading and layering manipulation practices : an empirical investigation of Australian market quality

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HIGH-FREQUENCY TRADING AND LAYERING MANIPULATION PRACTICES: AN EMPIRICAL INVESTIGATION OF AUSTRALIAN MARKET QUALITY

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Declaration

I certify that the work presented in this thesis is, to the best of my knowledge and belief, original, except as acknowledged in the text, and that the material has not been submitted, either in whole or in part, for a degree at this or any other university.

I acknowledge that I have read and understood the University's rules, requirements, procedures and policy relating to my higher degree research award and to my thesis. I certify that I have complied with the rules, requirements, procedures and policy of the University (as they may be from time to time).

Panha Heng

6 August 2018

Abstract

Recent advances in information and communication technology are making possible new approaches to securities market trading. Such advances are having a major impact on exchanges worldwide. It is now possible for market participants, using complex algorithms processed by powerful computers co-located near exchange servers, to analyse markets and execute orders in fractions of a second. The consequences of these developments for securities market quality are not yet fully understood, particularly in Australia. Drawing upon trading data obtained from the Australian Securities Exchange (ASX), this investigation examines: (1) the impact of co-location facilities and the capacity of the Australian market to absorb information via major news announcements into prices; and (2) the existence of market manipulation in the Australian market. Of specific interest is the effect of high-frequency trading (HFT) and layering manipulation on Australian market efficiency and integrity.

The findings of the research suggest that the ASX is informationally efficient enough to accommodate the rapidly growing presence of HFT. Findings concerning the impact of HFT on market integrity are less positive. Layering, a form of market price manipulation made possible by HFT, is both observable and profitable in the Australian data analysed. Layering involves the routine posting, at high speed, of buy-sell orders intended solely to raise or lower the market's best bid-ask price to generate profits for the trader concerned. Of particular importance is the strategy's potential to generate comparative trading advantages and profits, along with negative impacts for market quality; thus, eroding investor confidence in securities markets over time.

Automated forms of trading appear destined to become a fixed and important part of securities market trading. There seems little doubt that, by revolutionising the speed at which transactions occur, HFT is contributing enormously to the growth in the volume of securities being traded in the Australian market. At stake, though, is trust in the integrity of securities markets. There has been an extraordinary increase in the number of new financial products available as a consequence of HFT. The contribution these new products offer to market quality must be promptly appraised, with regulatory controls needing to be swiftly developed, particularly where the effects of such products are found to be adverse. This investigation has demonstrated the need for vigilance and proposes avenues for the development of effective regulatory controls.

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Table of Contents

Chapter 5. Commercial in Confidence

List of Tables

List of Figures

Abbreviations

Australian Securities and Investment Commission	ASIC
Adjusted Return	AR
American Dollar	USD
Australian Dollar	AUD
Australian Eastern Standard Time	AEST
Australian Securities Exchange	ASX
Average Adjusted Return	AAR
Capital Market CRC	CMCRC
Consumer Price Index	CPI
Cumulative Average Adjusted Return	CAR
Deutschmark	DM
Difference-In-Difference	DID
Efficient Market Hypothesis	EMH
European Securities and Markets Authority	ESMA
Exchange Traded Fund	ETF
Gross Domestic Product	GDP
High-Frequency Trading	HFT
Hong Kong Stock Exchange	HKSE
Identification	ID
Korea Exchange	KRX
Midpoint Price Volatility	MPV
Ordinary least squares	OLS
Random Walk Hypothesis	RWH
Reserve Bank of Australia	RBA
Securities Industry Research Centre of Asia-Pacific	SIRCA
Share Price Index 200	SPI200
Singapore Stock Exchange	SGX
SMARTS NASDAQ OMX	SMARTS
Standard Derivation	ST.DEV
Sydney Futures Exchange	SFE
Thomson Reuters Tick History	TRTH
Trade Price Volatility	TPV
Volume-Weighted Average Price	VWAP
Walrasian General Equilibrium	WGE

Chapter One

INTRODUCTION

1.1 Background

This investigation is concerned with the phenomenon of market quality. Traditionally, the quality of a securities market is viewed through the lens of efficiency. More recently, especially in response to the widespread adoption of high-frequency trading (HFT), market quality is also being viewed from the perspective of integrity. The effects of HFT, defined by Hendershott, Jones and Menkveld (2011) as the use of computer algorithms to execute price-changing orders at extremely short intervals, are far-reaching and dramatic. In particular, HFT has increased to the extent that it is challenging the speed with which securities may be bought and sold. Manahov (2016) explains, for example, that a sophisticated HFT algorithm can execute 40,000 back-to-back transactions in approximately 10 millionths of a second. The way in which this form of trading relates to market quality warrants further investigation, which to date has not adequately been undertaken.

1.2 Market Quality Framework

Efficiency and integrity are described by Aitken, Harris and Ji (2014) as being the two pillars of market quality. Not unexpectedly, mandatory requirements for securities exchanges focus strongly, therefore, upon the preservation of these two pillars. In the market quality framework developed by Aitken and Harris (2011), the focus of securities exchanges is portrayed as being concerned with having the appropriate combination of technology, regulation, information, participants and instruments to enhance efficiency and integrity (see Figure 1.1). It is by these means that individual securities exchanges seek to secure a competitive advantage.

Figure 1.1: Market quality framework

Source: Aitken and Harris (2011, p. 24)

The market quality framework advanced by Aitken and Harris (2011) makes certain assumptions about efficiency. It assumes, for example, that a perfectly efficient market will be one which keeps transaction costs down to a minimum, while at the same time maximising market participants' efforts regarding price discovery.[1] Empirical studies (see, for example, Berkman & Comerton-Forde, 2011; Bryant & Haigh, 2004; Campbell, Lo & MacKinlay, 1997; Chelley-Steeley & Park, 2012; Frino, Peng He & Lepone, 2014; Niarchos & Alexakis, 2003; Starks, 1994; Whitcomb, 2003) use bid-ask spreads, market depth and price impact to measure transaction costs. Price discovery has also been examined empirically, using the same four elements identified by Aitken and Harris (2011), namely: information share (Aitken & Harris, 2011), common factor share (Aitken, McInish & Wong, 2009), price discovery efficiency (Putniņš, 2013), and permanent information impounding (Yan & Zivot, 2010).

As shown in Figure 1.1, the framework also makes assumptions about integrity. It identifies market integrity as referring broadly to the extent to which market participants are dissuaded from engaging in three types of trading behaviour, namely: insider trading (i.e., using privileged and/or sensitive market information for personal gain)[2]; market manipulation (i.e., false financial reporting)[3]; and broker/client conflict (i.e., 'front-running'). Insider trading studies typically examine trading behaviour and market reaction to news announcements or

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[1] Frijns, Indriawan and Tourani-Rad (2015) indicate that price discovery plays an important role in studies of the effects of news reports on asset price volatility.
[2] Insider trading is defined as the exercise of the dissemination of non-public, 'price sensitive' information prior to being released to the public.
[3] Market manipulation is the creation of misleading or false representation of prices and/or volumes with the intention of impacting market prices.

private information released with a view to generating abnormal profits. These forms of information include, for example, takeover announcements (Aspris, Foley & Frino, 2012; Seyhun, 1986), bankruptcy announcements (Elliott, Morse & Richardson, 1984; Gosnell, Keown & Pinkerton, 1992; Stanley, Todd De Zoort & Taylor, 2009), and mergers and acquisitions (Hirschey & Zaima, 1989; Schwert, 1996). Regarding market manipulation, models employed to investigate abnormal behaviour have addressed misleading information (Bommel, 2003), the ramping up of market prices (Aggarwal & Wu, 2006), and brokers manipulating closing prices to influence their clients' perception of their execution ability (Hillion & Suominen, 2004). Despite the potential to adversely affect market quality, prohibited trading strategies are under-researched, as it is difficult to detect information leakage in market manipulation cases due to the sensitive nature of the data. Yet, a number of putative manipulation strategies exist.

1.2.1 Market efficiency

Efficiency is critical to the quality of securities markets. These markets play a vital economic function by encouraging savings and by making available the long-term capital required for investment and economic growth (Aitken, Harris & Ji, 2014). The efficient functioning of these markets is essential if they are to promote liquidity and channel resources to the most productive industries in an economy (Levine, 2002, 2005; Wurgler, 2000). Efficient functioning is also essential as a basis for perceived market fairness and public confidence in the role these markets play in contributing to economic advancement (see, for example, Arnoldi, 2016; Brogaard, Hendershott & Riordan, 2014; Chiyachantana, Jain, Jiang & Wood, 2004; Comerton-Forde & Rydge, 2006; Goldstein, Kumar & Graves, 2014; Liu, Lai, Yen & Zhu, 2015; Minenna, 2003). Policymakers must, therefore, be acutely concerned about the efficiency of securities markets (Arestis & Sawyer, 2011).

Notions about how securities markets should function efficiently have been strongly influenced by Fama's efficient market hypothesis (EMH). Fama (1970, 1991, 1998), in his seminal works, examined the role of information in setting security prices. He hypothesised that security prices will reflect the true value of assets when *all* relevant and available information is quickly and accurately impounded into the current financial price of the assets being traded in a securities market. This situation, he argued, was more likely to be achieved under conditions where: there are no trading costs; the accessibility and availability of market information is equally and efficiently distributed to market participants; the market is large and liquid; and market participants have sufficient financial knowledge, specifically in relation to tolerance of risk. Fama's view of market efficiency largely reflected Walrasian General Equilibrium (WGE) theory (Walras, 1954),[4] though he more pointedly accentuated the importance of market-based information being able to flow freely and quickly.

Financial markets cannot absolutely be efficient or inefficient, but instead fall somewhere along the continuum between these two extremes. Following the work of Fama (1970), there have been numerous attempts (see, for example, Barnes, 1986; Butler & Malaikah, 1992; Campbell, Lo & MacKinlay, 1997; Fama & French, 1988; Leland, 1980; Los, 1998; Ma, 1989; Martens, 1998; Rozeff & Zaman, 1988; Urrutia, 1995) to explain an idealisation of perfect efficiency in securities markets. The most enduring of these models is the random walk hypothesis (RWH) which, according to Campbell, Lo and MacKinlay (1997), states that market prices are consistent with a random walk (i.e., random price movements) and are unpredictable. Fama's (1970) EMH was ultimately inspired by the RWH, and on this basis he defined three classes of market efficiency, namely: weak-form, semi-strong form, and strong-form.

In a weak-form efficient market, according to Fama, only historical trading data may be incorporated into current asset prices, and so market participants cannot rely on historical patterns or trends to develop a trading strategy for predicting future price scenarios. In a semi-strong efficient market, all publicly available information (i.e., information available in a weak-form market, together with all information relevant to the pricing of a security that is in the public domain) may be incorporated quickly and without bias into current asset prices. If asset prices cannot react instantaneously to public information, then profitable arbitrage opportunities would emerge for market participants, as Campbell, Lo and MacKinlay (1997) show. In a strong-form efficient market, current asset prices reflect *all* available information, including historical, public and private information. Strong-form market efficiency assumes, however, that no individual may draw upon privileged information (i.e., information deemed to be private and sensitive) to outperform the market. If significant price movements were to be observed upon the release of new information to the market (e.g., by means of earnings reports, new resource discoveries, takeover bids, etc.), then strong-form efficiency could not be presumed to exist (Campbell, Lo & MacKinlay, 1997).

[4] WGE, which is constructed under a general model of market competitiveness, places emphasis on a set of prices in which supplies are determined by the maximised profit of all firms, and demands are determined by full consumption of all households, subject to a budget constraint based on the agreed value of their endowments, and excess demand for all goods is zero.

There is an abundance of research confirming the plausibility of Fama's model (see, for example, Dow & Gorton, 1997; Ederington & Lee, 1993; Kawakatsu & Morey, 1999). Recently, however, scholars have begun to raise questions about the extent to which technological developments, particularly in the form of HFT, may have given rise to a new set of conditions that potentially undermine the universal applicability of Fama's hypothesis. These questions need to be explored empirically.

1.2.2 High-frequency trading

In financial markets, having the ability to obtain quickly, and then react promptly, to information about market developments is vital. According to Brogaard, Hagströmer, Nordén and Riordan (2015), it was this need to have ready access to market information that gave rise to the traditional practice of market traders buying a seat on a stock exchange. Over recent years, however, developments in information and computing technology have transformed this traditional practice. Market traders now buy the right to co-locate their computer servers in securities exchanges. These servers are able to process market information at speeds that are challenging to imagine. With assistance from programmed algorithms, the servers co-located in securities exchanges may also issue bids intended to implement a trading strategy devised to make profits. These arrangements come under the general heading of HFT.

The impact of HFT on market efficiency is not yet well understood. Hendershott, Jones and Menkveld (2011) report mixed empirical evidence in this regard. Negative impacts are reported in studies by Brogaard, Hendershott and Riordan (2014) and Hendershott and Moulton (2011). It has been reported, for example, that large orders submitted by means of HFT tend to have a permanently higher price impact, which potentially leads to higher adverse selection costs. Concerns along these lines have also been expressed in studies by Aitken, Cumming and Zhan (2015), Egginton, Van Ness and Van Ness (2016), and Gerace, Chew, Whittaker and Mazzola (2014). Aitken, Cumming and Zhan (2015) report, for example, that there is a strong correlation between HFT and significant end-of-day price dislocation, also commonly known as end-of-day price manipulation. Egginton, Van Ness and Van Ness (2016) report that HFT contributes to 'quote stuffing', a practice whereby a number of large orders are submitted and then withdrawn almost immediately, with the aim being to profit from data inefficiencies regarding prices quoted between securities exchanges. However, studies, such as those by Brogaard, Hendershott and Riordan (2014), Frino, Mollica and Webb (2014), and Riordan and Storkenmaier (2012), provide a more benign perspective on the impact of HFT on market efficiency. In general, the relationship between HFT and market efficiency is a topic that requires further empirical research.

The relationship between HFT and market integrity also requires further research. A matter of concern here is that market manipulation strategies implemented by means of HFT are not obvious to detect; neither are they readily prosecutable. In the HFT environment, the trading activities of market manipulators are often indistinguishable from the trading behaviours of their law-abiding counterparts, as Fischel and Ross (1991) have observed. Kyle and Viswanathan (2008) also noted that a trading strategy cannot be classified as illegal unless it can be established that the trader's intent was to jeopardise market price signals for efficient resource allocation and to reduce market liquidity for risk transfer. This situation presents obvious challenges for policymakers and regulators, particularly in situations where traders employ high-speed, sophisticated and financially lucrative algorithms.

Automated market surveillance systems are being widely employed by securities exchanges in an effort to identify potential market abuse behaviour as it happens or shortly afterwards. One of these systems is NASDAQ SMARTS[5], which is currently the most highly regarded market surveillance system. SMARTS customises and develops market surveillance alerts in accordance with the specific requirements of securities exchanges and commissions around the world (Aitken, Harris & Ji, 2014). Some HFT-based manipulative strategies and techniques able to be detected by SMARTS technology include: wash sales; wash trades; painting the tape; marking the opening and/or closing price; trash and cash; cornering the market; short squeezing; front-running; pinging; phishing and quote stuffing; insider trading; spoofing; and layering – all of which are explained in depth in Chapter 2.

The layering and spoofing manipulation strategies are identified by NASDAQ (2018) as a particular concern. Both strategies involve entering multiple orders in an order book with the intention of interfering with accurate price signals about supply and demand, thereby influencing other participants' decisions in ways likely to result in a windfall profit for the manipulating entities. In *SEC vs Biremis* (2012, p. 3), the judge described layering as a practice where "a trader creates a false appearance of market activity by entering multiple non-bona fide orders on one side of the market, at generally increasing (or decreasing) prices, in order to

[5] SMARTS surveillance operating under NASDAQ OMX consists of two entities, namely: (1) SMARTS market surveillance proving service for market regulators/exchanges; and (2) SMART trade surveillance proving service for stockbrokers. Since 2013, SMARTS surveillance products have been voted by Waters Technology (2017) as the best sell-side surveillance product for five consecutive years.

move that stock's price in a direction whereby the trader intends to induce others to buy (or sell) at a price altered by the non-bona fide orders."[6] The difference between layering and spoofing is a matter of degree. Spoofing is similar in nature, but much more aggressive in terms of the way in which it is executed. Market manipulators implementing a spoofing strategy will generally place much larger orders across a limited number of price levels on one side of the market. Layering, by comparison, is more elusive, more complex and more long-term in its profit-making horizon. Layering, which is possibly less profitable in the short-term than spoofing, is a more recent phenomenon. As market regulators have become more successful in prosecuting trading entities engaging in spoofing, traders intent upon manipulating the market have turned their attention to layering. References to layering in the scholarly literature are, therefore, relatively recent. The practice appears not to have become widely observable until over the past five years or so. A more detailed comparison of layering and spoofing is explained in Chapter 2.

The infamous 'Flash Crash' incident on 6 May 2010, which resulted in one of the biggest one-day points declines in the recent history of the Dow Jones Industrial Average index, provides an insight into the risks associated with these trading practices (Dalko, 2016). Within a matter of five minutes (between 2:42 pm and 2:47 pm), the index dropped 998.5 points. By 3:07 pm, much of the loss (600 points) had been recovered. Dalko (2016) claims that the event was driven by the high speed and intensity of buy/sell activities during the five-minute period, creating a huge surge in market volatility. As Aldrich, Grundfest and Laughlin (2017) have recently observed, the most concerning aspect of this incident was that there was no indication or signal provided to investors which might have helped to mitigate the losses incurred by investors. The incident subsequently led to the arrest of Navinder Singh Sarao, a London-based futures trader, who was accused of instigating a spoofing event. Sarao's strategy involved placing multiple sell orders in E-mini contracts at different price steps, which ultimately triggered a highly panicked market response. After a trading halt was implemented by the Chicago Mercantile Exchange, Sarao and other HFTs executed large buy orders at favourable prices once the price of the E-mini contracts fell.

There have been numerous recent court cases involving allegations of market manipulation by means of either a layering or spoofing strategy. These include: *SEC v Biremis* (2012); *FSA*

[6] In practice, however, market manipulators may strategically position their orders to cover both sides of the market, with orders on one side being for the purposes of layering, while orders on the other side may be genuine.

v Select Vantage (2014), *FCA v Da Vinci* (2015); *US vs Nav Sarao* (2015); *US vs Aleksandr Milrud* (2015); *CFTC vs Igor B. Oystacher* (2015); *US vs Michael Coscia* (2015); and *FSA v Swift Trade* (2015). In addition, on 29 January 2018, the US Commodity Futures Trading Commission filed eight anti-spoofing enforcement actions against three major banks (Deutsche Bank, HSBC and UBS) and six individuals, accusing them of engaging in commodities fraud and spoofing schemes. The outcome of these allegations is, at the time of writing, yet to be announced.

The literature is also unclear in terms of the classification of automated liquidity trading. Gerig and Michayluk (2017), for example, attempt to distinguish between HFT and algorithmic trading by explaining that algorithmic trading is a general term covering all types of automated trading strategies, while HFT refers specifically to non-directional, low latency, automated trading strategies. Some HFT strategies may be specifically employed to profit from spreads by buying low and selling high at fast speed. Other HFT strategies aim only to consume order book liquidity or ‘front-run’ large directional orders (Arnoldi, 2016). Therefore, the distinction between legitimate and illegitimate traders remains a concern for the trading community.

1.2.3 Market integrity

The rapidly increasing presence of HFT also raises questions about market integrity. O’Hara (2015) asks, for example, whether it is fair for securities exchanges to sell trading data to HFT participants ahead of it becoming fully accessible to all other traders and by the public. HFT is also presenting new regulatory challenges because of its potential to provide fertile ground for market manipulation. Because of the speed of transactions made possible by HFT, and because of the ability provided by HFT to execute almost instantaneously complex algorithms in response to changed market conditions, opportunities are created for traders using HFT to seek to mislead the market by artificially, and unlawfully, raising or lowering asset prices. Regulatory controls have certainly become more rigorous in this regard. However, HFT strategies are also becoming increasingly technologically sophisticated (Arnoldi, 2016; Goldstein, Kumar & Graves, 2014; Sun, Kruse & Yu, 2014).

Further, HFT strategies, whether legitimate or not, are difficult to detect by market regulators because of the speed with which orders may be generated and withdrawn without the need for any human intervention (Angel & McCabe, 2013; Arnoldi, 2016; Brogaard, Hendershott & Riordan, 2014). Illegitimate HFT strategies are designed to generate profits by sending misleading signals about the true value of an asset, thereby inducing uninformed traders and less sophisticated algorithmic systems to make irrational investment decisions. As Liu, Lai, Yen and Zhu (2015) have argued, it is in this way that HFT strategies, which are manipulative in their intent, may jeopardise the confidence of other traders, increase the cost of capital, deter order flow, and lead ultimately to informationally inefficient stock prices.

The argument is made by Kawakatsu and Morey (1999) that financial markets must remain liberalised, in the sense of there being minimal government involvement or regulatory control. The problem of relying on regulatory controls is that the controls are typically implemented *ex-post facto*. The authors also observe that it takes time to develop a sufficient understanding of the impact of new technological developments and to design and implement laws and regulations which can offset any associated adverse impacts on market efficiency and integrity. Of relevance to this issue are the earlier findings of Fischel and Ross (1991) in that government interference in a financial market may directly undermine market participant freedom, as well as the extent of willingness to encourage innovation. Since the publication of these studies, however, technological advances have enabled HFT to occur at speeds that are becoming increasingly difficult to detect by market regulators. Whether these changed conditions should result in a reconsideration of the desirability of having no government intervention and regulatory controls remains a question for further consideration.

1.3 Research Question and Themes

The present investigation addresses a specific gap in the existing literature on market quality. The gap, which was identified initially by Putniņš (2012), concerns the potentially negative impact of the layering manipulation strategy on the efficiency and integrity of securities markets. As Bhattacharya and Daouk (2002) observe, however, empirical research in this area has been difficult to initiate, not only because of the confidential nature of market trading activities but also because of market traders' sensitivities, especially given the possibility that research findings might well reveal illegal trading behaviour.

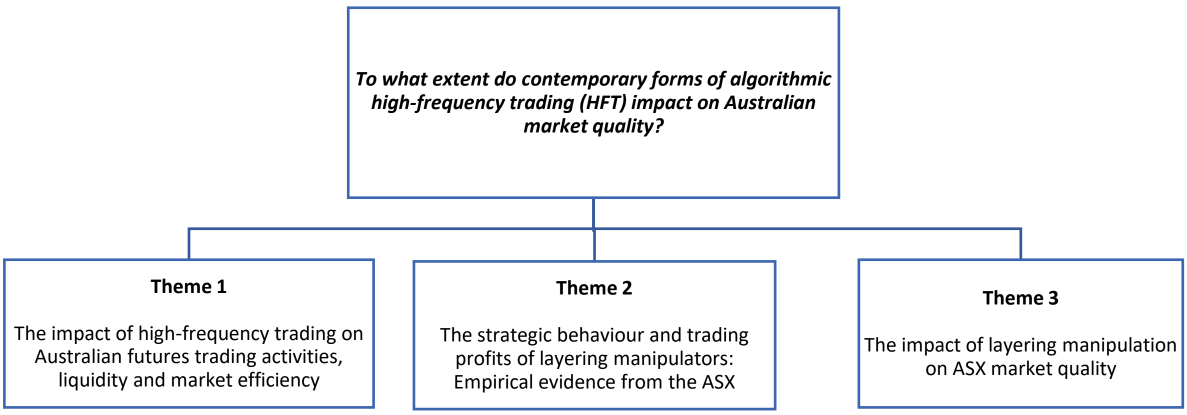
An opportunity arose in 2015 for the researcher to obtain access to a rich data set reporting trading patterns and behaviour on the Australian Securities Exchange (ASX), including its subsidiary, the Sydney Futures Exchange (SFE). This opportunity presented a unique and invaluable opening for examining the relationship between HFT and the efficiency and integrity of the Australian securities market. The research question identified was:

To what extent do contemporary forms of algorithmic high-frequency trading (HFT) impact on Australian market quality?

This question was considered to be important because, as stated earlier in this chapter, investor confidence in securities markets depends on there being a well-founded belief that markets will be both fair and efficient. This belief has, however, been challenged by the frequent recurrence of fraudulent market manipulation made possible by HFT. An additional reason for considering the extent of contemporary forms of algorithmic HFT and its impact upon Australian market quality was that there appeared not to have been any previous empirical investigations conducted on the layering manipulation strategy. An earlier investigation of spoofing, conducted on the Korea Exchange (KRX) by Lee, Eom and Park (2013), provided valuable insights about how to proceed with an investigation of layering in an Australian context. However, Lee, Eom and Park's (2013) model was limited in terms of its value because HFT has become more sophisticated technologically since their data collection in 2002. In addition, their investigation focused on spoofing, rather than the more elusive market manipulation strategy of layering. Additionally, it did so over a relatively short period of time.

When considering empirical research questions for the purposes of addressing the overarching research question, three key market microstructure themes appeared to be most relevant. These themes, and their relationship to the research question, are illustrated graphically in Figure 1.2. Relevant literature, propositions and hypotheses, data and methods and the results of the analyses related to the three themes are reported in Chapters 3, 4 and 5, respectively.

Figure 1.2: Research question and related themes



Source: Developed for this research

The first of the three themes concerns the impact of HFT on Australian futures market trading activities, liquidity and efficiency. A guiding research proposition, therefore, is:

> P_1: The co-location of HFT facilities influences the trading activities, liquidity and efficiency of the Australian futures market.

This proposition requires an analysis of: the effects of co-location facilities on futures market liquidity; the speed at which the futures market adjusts to scheduled macroeconomic announcements; and the determination of volatility persistence for each major announcement type. An empirical investigation of these matters was expected to provide insights into the reaction of financial prices to new information, principally in the form of scheduled macroeconomic announcements, and of the efficiency with which this information is impounded.[7] The present research is informed by data concerning the four most liquid futures contracts: 90-day bank accepted bills, 3-year Treasury bonds, 10-year Treasury bonds, and the SPI200 index.

The second theme involves the market manipulation strategy known as layering. A guiding research proposition in relation to the trading strategies used in layering, therefore, is:

> P_2: Layering manipulation within the ASX achieves a comparative trading advantage and is profitable.

This proposition was investigated by drawing upon a unique data set derived from NASDAQ SMARTS,[8] which included de-identified broker account IDs to examine the detailed trading activities of entities operating on the ASX order book from 1 June to 30 September 2015.[9] In addition to trade and quote data, the data set also contained all order messages from brokers (at the account ID level) subscribing to SMARTS sell-side trade surveillance during the selected period.

The third theme concerns the public aspect of layering. A guiding research proposition, therefore, is:

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[7] In an efficient market, prices should adjust to public macroeconomic announcements quickly enough to avoid unnecessary arbitrage windows. The speed of price adjustment is an important indicator of market efficiency.
[8] More information about NASDAQ SMARTS can be found at: http://business.nasdaq.com/market-tech/market-participants/SMARTS-trade-surveillance-sell-side.
[9] Only four months of broker order messages at the account ID level and ASX order book data over the specified period are available.

P_3: Layering decreases the speed of market adjustment and overall market quality within the ASX.

This proposition was also able to be addressed by drawing upon the same data derived from SMARTS. While the data examined in the second research theme concerns specifically individuals engaged in layering behaviour, the data examined in the third research theme are aggregated at the market level.

1.4 Rationale for the Research Themes

The first research theme is important to explore for both conceptual and practical reasons. As noted earlier, the universal applicability of Fama's hypothesis regarding market efficiency has become less certain in circumstances where HFT may be independently impacting on trading activity, liquidity and market efficiency in the context of a futures market. The first theme seeks to address this matter, as well as the increasing level of concern expressed in the literature about the potentially adverse impact of HFT on market efficiency. Various scholars, including Brogaard, Hendershott and Riordan (2014), Hendershott and Moulton (2011), and Martinez and Rosu (2013), have expressed caution about the implications of HFT on market efficiency. Martinez and Rosu (2013) argue, for example, that because algorithms tend to consume market makers' quotes, HFT has the capacity to destabilise or disrupt market operations by increasing volatility while simultaneously reducing market liquidity. Brogaard, Hendershott and Riordan (2014) and Hendershott and Moulton (2011) also claim that a large order submitted by means of HFT tends to have a higher permanent price impact, which can potentially lead to high adverse selection costs. These authors provide evidence that Fama's EMH might be compromised in an era of HFT.

However, the negative assertion of HFT by these scholars is challenged by other empirical studies, including those by Brogaard, Hendershott and Riordan (2014), Frino, Mollica and Webb (2014), and Hendershott, Jones and Menkveld (2011). Hendershott, Jones and Menkveld (2011), for example, demonstrate that an increase in HFT activity improves the market by encouraging price discovery, and consequently, reduces adverse selection costs, quoted spreads and effective spreads. In this vein, Brogaard, Hendershott and Riordan (2014) further document that the contribution of HFT to price discovery is greater than the contribution made by any of the alternatives. Frino, Mollica and Webb (2014) provide further evidence regarding the positive impact of HFT on market liquidity. The main argument put forward by these authors in support of HFT was that technology helps to improve market liquidity, price discovery and market efficiency. Nevertheless, Hoffmann (2014) argues that an increase in trading volumes as a result of rising HFT activity is a positive signal to the market, but only on face value, and only in efficient markets with a capacity to absorb information quickly.

Taking into account these views, the first theme, which concerns the impact of HFT on Australian futures market efficiency, aims to build on the existing literature by examining the impact of HFT on market liquidity, and by addressing the dynamics of market adjustment in the Australian futures market. The first theme will provide direct evidence regarding the applicability of Fama's EMH in the context of an increasing reliance on HFT. Market efficiency will be shown to be preserved, or increased, if the investigation finds that there is a positive correlation between an increase in the incidence of HFT activity and an improvement in market liquidity. In other words, HFT will have played an integral role in reducing relative spreads following the introduction of co-located HFT facilities. Market efficiency will also be shown to have been preserved, or increased, if the market is found to be capable of responding more rapidly to major scheduled announcements which are likely to affect market prices. The application of a half-life volatility model, capable of estimating the impact of major scheduled announcements, should provide market regulators with a better understanding of the efficiency status, particularly in the semi-strong form sense, of Australian financial markets. It should also provide practitioners with a deeper understanding of the market adjustment process, thereby enabling them to create more effective models for asset pricing, trading strategies and execution optimisation, all of which have a direct impact on investment and the wider economy.

The second research theme, which involves the layering manipulation strategy, is important because it directly addresses the universal applicability of Fama's EMH in the presence of illegitimate HFT layering manipulators. Fama's principal argument was that the market is capable of functioning efficiently regardless of investors' trading behaviour, because equilibrium prices are not impacted by the irrational actions of individuals. In other words, no individual can outperform the market, because financial markets can rely on the fact that any arbitrage opportunities will attract competition, thereby quickly correcting any mispricing. Fischel and Ross (1991) were convinced that market manipulation activities tend to be self-deterring, given that the probability of success in generating profits, specifically from trade-based manipulation, is low.

The problem of distinguishing between legitimate and fraudulent traders is also addressed by the second research theme. Fischel and Ross (1991) point out that, from a regulatory perspective, there exists a challenge in distinguishing between legitimate traders and those traders seeking to manipulate the market. Aggarwal and Wu (2006) and Allen and Gorton (1992) explain that manipulators are capable of disguising themselves as informed traders, thereby taking advantage of investors who actively seek out information about the intrinsic value of securities. Nevertheless, there have been several studies (see, for example, Aggarwal & Wu, 2006; Comerton-Forde & Putniņš, 2011; Gerace, Chew, Whittaker & Mazzola, 2014; Kong & Wang, 2014; Lee, Eom & Park, 2013) providing evidence regarding the plausibility of generating profits via trade-based manipulation. These studies fundamentally challenge the applicability of Fama's EMH. However, these authors' findings are questionable on the basis that their data samples were limited to only successfully prosecuted cases. In other words, such studies, with the exception of Lee, Eom and Park (2013), might be subject to data sample selection bias, which is an issue of non-random sample detection.

The challenge of not having efficient market surveillance, together with the difficulties pertaining to the assembly of a reliable data set, have resulted in a limited number of empirical studies concerning market manipulation. Thus, the second theme aims to address this gap by investigating the strategic behaviour of layering manipulators and their profitability in the context of the ASX. Further, the second theme addresses the extent to which market fairness, which is similar to the notion of market integrity, ought to be considered as an additional set of conditions applying to market efficiency. The second research theme requires the development of a detailed specification for detecting layering behaviour, in accordance with Australian regulatory guidelines and the rules governing trading conduct.[10] A layering alert algorithm would enable market regulators not only to identify suspicious trading behaviour, but also to determine the exact start and finish times of such layering activities. It would also capture the typical characteristics of layering, such as order submission techniques and strategy durations, and help establish the profitability of the strategy.

The third research theme concerns the public aspect of layering and aims to explore the need to develop regulatory controls and government policy to protect market integrity. Several authors (see, Aggarwal & Wu, 2006; Allen, Litov & Mei, 2006; Comerton-Forde & Putniņš,

[10] See https://asic.gov.au/regulatory-resources/markets/markets-disciplinary-panel/mdp-outcomes-register-2014-present/. Conduct that is subject to infringement notices may not be manipulative in nature, but present risks to undermine the integrity of the market. Compliance with the infringement notice is not an admission of guilt.

2011) demonstrate that market manipulation, regardless of its form or strategies, impacts on market quality, especially in terms of spreads, volatility and market depth. In particular, Aggarwal and Wu (2006) demonstrated that market manipulation harms the efficiency of the market from the perspective of price transparency. In a study relating to another manipulation technique known as 'cornering', Allen, Litov and Mei (2006) found that such market manipulation leads to increased market volatility. Comerton-Forde and Putniņš (2011) also found that closing price manipulation reduces market liquidity and increases transaction costs. A question arising, therefore, concerns the point at which the effects of market manipulation are such that regulatory intervention becomes necessary.

Allen and Gale (1992) categorise market manipulation into three forms, these being trade-based, information-based or action-based manipulation. Among these, trade-based manipulation is regarded as the most challenging to detect, given its complex mechanism, equipped with powerful technological advancement. One of the most controversial trade-based market manipulation strategies is spoofing, as shown by Gerace, Chew, Whittaker and Mazzola (2014) and Kong and Wang (2014). While these authors have documented the detrimental effects of spoofing on the market, they also provide some contradictory evidence worthy of consideration. Gerace, Chew, Whittaker and Mazzola (2014) show that bid-ask spreads increase during spoofing manipulation and remain wide afterwards, while Kong and Wang (2014) document the opposite. Nevertheless, in terms of benchmark selection, these authors did not possess robust benchmarks because their evidence relies on aggregated daily measures over multiple trading days. Their benchmarks are questionable because, if the manipulative conduct is only short-lived, how is it possible that its impact can last for more than a trading day, especially in the context of a HFT environment? Therefore, the third theme of the present investigation involves the examination of an intraday benchmark in order to comprehensively understand the effects of layering on market quality.

The empirical evidence derived from the analysis relating to the third theme is expected to reinforce market participants' understanding of layering manipulation behaviour in the context of sophisticated electronic trading and complex global market structures. From a market regulator's perspective, the present investigation may be seen to provide additional guidelines for establishing the illegitimate intentions of layering manipulators. This investigation is also expected to assist regulators in designing appropriate technology surveillance tools to detect and attempt to prevent identified manipulative schemes from harming the efficiency and integrity of financial markets. The findings are expected to offer policymakers and market regulators an improved definition of what constitutes layering behaviour, and ultimately a stronger basis for establishing effective policies and regulations to combat market manipulation such as layering. With so much at stake, especially with over $2 trillion invested in Australia's superannuation industry alone (Heng, Niblock & Harrison, 2015), this research will ultimately help improve market integrity and, therefore, market quality. Any failure on the part of market regulators and policy makers to grasp the complexities associated with fraudulent HFT practices, and to respond with relevant surveillance technologies, will clearly have long-term ramifications for Australian investment markets, as well as for the economy. The implications for other national investment markets also endorse the importance of this study.

1.5 Organisation of the Thesis

This thesis is presented over six chapters. Chapter 1 introduces the proposed research. Chapter 2 presents a review of the literature, focusing principally on market manipulation strategies (e.g., spoofing and layering) and relevant market quality empirical studies. The chapter also provides a platform for the development of propositions and testable hypotheses concerning market efficiency and market integrity. Chapter 3 addresses the impact of co-location facilities and the capacity of the Australian futures market to absorb information into prices. Specifically, the chapter explores the notion of market efficiency, the practice of co-locating HFT facilities and the capability of the Australian futures market to absorb major scheduled announcements into financial prices. Chapters 4 and 5 are concerned with the existence of market manipulation in the Australian market, and hence seek to address the notion of market integrity. These chapters present an empirical examination of the competitive advantages and levels of profitability generated by layering strategies, as well as the impact of layering practices on Australian equity market quality. Chapter 6 concludes the thesis by providing an overview of the key findings and a discussion of the conceptual and practical significance of the investigation. Limitations of the study are acknowledged and potential future lines of enquiry are canvassed.

Chapter Two

LITERATURE REVIEW

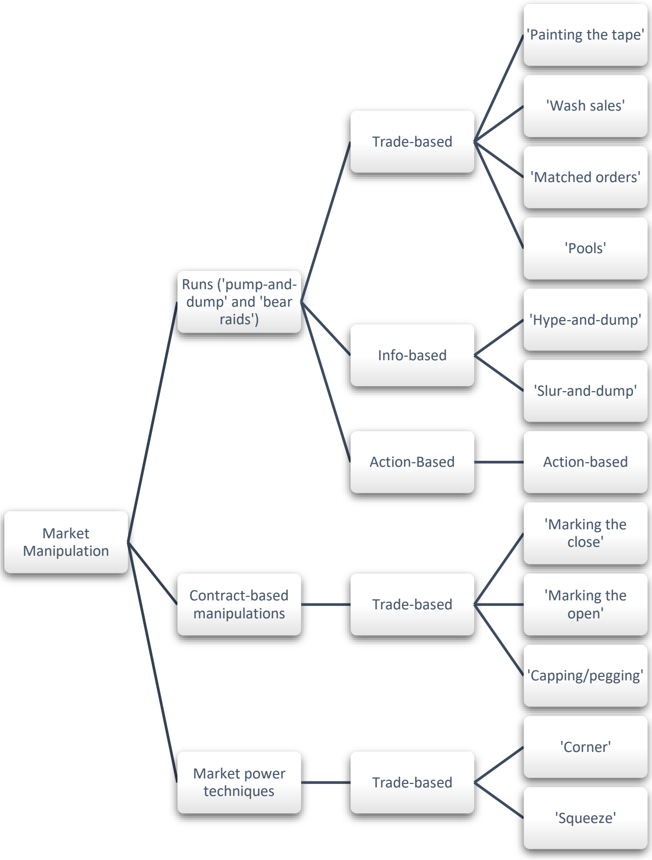
2.1 Introduction

This chapter, which is presented in the form of a literature review, is concerned with documenting various market manipulation strategies and techniques, with particular attention provided to layering and spoofing. The chapter establishes the need for empirical research into both the capacity of the Australian market to absorb information into prices and the existence of market manipulation in the Australian market. The chapter is organised as follows: Section 2.2 begins with a review of the main contemporary market manipulation strategies and techniques. Section 2.3 reports relevant empirical research concerning price reactions to public information and securities market manipulation. Section 2.4 provides concluding remarks and the platform required for the development of propositions and testable hypotheses concerning market efficiency and market integrity, as documented in Chapter 3 (*Theme 1*), Chapter 4 (*Theme 2*) and Chapter 5 (*Theme 3*).

2.2 Market Manipulation Strategies

Market manipulation is complex, sophisticated and exists in many forms. Putniņš (2012) achieved a better understanding than was previously available of the different forms of manipulation by developing a taxonomy of market manipulation techniques, which were then clustered into three strategies, these being ‘runs’, ‘contract-based manipulations’ and ‘market power techniques’ (see Figure 2.1). In accordance with the work of Allen and Gale (1992), market manipulation techniques were also categorised as ‘trade-based’, ‘information-based’ or ‘action-based’.

Figure 2.1: Taxonomy of market manipulation strategies and techniques



Source: Putniņš (2012, p. 30)

A 'runs' strategy refers to a situation where manipulators take a long or short position in a security with a view to misleading other participants. They do so by creating liquidity with a view to inflating or deflating prices to their advantage, according to Putniņš (2012). Manipulators then lock in profits by reversing their positions to trade at the artificial prices created. Two classic examples of this manipulation strategy are known as 'pump-and-dump' and 'bear raids' strategies. A 'pump-and-dump' strategy involves artificially increasing the price of a security, then short selling it when the price has risen beyond a certain target level. A 'bear raids' strategy involves the use of short-selling tactics, such as 'trash and cash',[11] intended to influence other market participants to sell through the dissemination of misleading or negative information about the security. The manipulators then cover or close their positions at a lower price to realise profits. Thinly traded securities are most vulnerable to these

[11] Trash and cash is specifically mentioned in Chapter 2, Section 2.3, Paragraph 9 (d) in the ESMA market abuse regulation (The European Securities and Markets Authority, 2015).

strategies, due perhaps to a lack of information and high price pressure effects, as has been argued by Fischel and Ross (1991).

Putniņš (2012) characterised the 'runs' strategy as being typically long-term in implementation and executed through the use of techniques such as 'painting the tape', 'wash sales', 'matched orders', 'pools', 'hype and dump', and 'slur and dump'. Some of these techniques are briefly explained in this chapter. 'Painting the tape', or as it is more commonly known, 'ramping' is a trade-based technique and often results in unusual intraday price movements. After causing a short-term imbalance between the supply and demand for a security, the ramping manipulator then reverses the direction of the trading activities to profit from the price movements generated. Bernhardt and Davies (2005) explained how fund managers have considerable incentives to implement this technique as a method of manipulating securities within their portfolios, particularly towards the end of evaluation periods. Such activity infers that it is advantageous for fund managers to minimise investment distortions and price impacts at the beginning of evaluation periods, with a view to luring other investors into securities held within their portfolios. Aitken, Harris and Ji (2014) have shown how ramping can be successfully implemented in two stages: 'marking the close' and 'reversing at the start of the next trading day'.

Another technique is that of 'wash sales', which refers to an arrangement of either purchases or sales of a financial instrument without beneficial interest or market risk. This act of concealing or colluding usually involves an individual or a group of individuals exchanging transactions concerning a financial instrument between themselves, without any change in price. If one entity keeps using the same account to place a buy order against a sell order for the same beneficial owner, it is referred to as 'wash trade'.[12] Another term for this practice commonly used by market regulators is 'concealing ownership'.[13]

In Figure 2.1, a second strategy identified by Putniņš (2012) is described as 'contract-based manipulations'. Market manipulators adopting this strategy typically gather profits from derivative contracts, which are external to the manipulated markets. A classic example of the use of this strategy occurs where a manipulator takes a position in the derivatives market while

[12] Wash sales and trades are specifically described in Chapter 2, Section 2.3, Paragraph 8 (a) in the ESMA market abuse regulation (The European Securities and Markets Authority, 2015).
[13] Concealing ownership is specifically described in Chapter 2, Section 2.3, Paragraph 8 (d) in the ESMA market abuse regulation (The European Securities and Markets Authority, 2015).

simultaneously inflating or deflating prices in the spot market.[14] In contrast to the 'runs' strategy, the 'contract-based manipulations' strategy does not require the manipulator to strategically misguide other market participants in order to trade at artificial prices. Therefore, contract-based manipulation tends to be more mechanical in terms of its design.

Putniņš (2012) characterised the 'contract-based manipulations' strategy as being executed through the use of techniques such as 'marking the close', 'marking the open', and 'capping/begging'. The technique of 'marking the close',[15] for example, also known as 'trading at the end of the day', refers to the deliberate buying or selling of a particular security at the end of a trading session, with the ultimate objective of increasing, decreasing or maintaining the closing price to the advantage of the manipulators. Manipulating the closing price and/or opening price imposes a tremendous cost on the market, given the common practice of valuing the market situation of an instrument on that day, and even more so because it is the basis for assigning a fair price for the following day's opening price. It is important to note that if the price of a security changes dramatically during the following day (due to the manipulator's liquidation), the possibility of manipulation becomes more likely. The rewards for undertaking such manipulation include being able to achieve higher short-term cash flow, boosting credibility in order to demonstrate outstanding asset management, and ultimately, obtaining lucrative management compensation.

The 'market power techniques' strategy referred to by Putniņš (2012) (see Figure 2.1) involves market manipulators having a considerable level of influence over the supply and demand of the order book (Allen & Gale, 1992). Common techniques for implementing this strategy are known as 'cornering' and 'squeezing'.[16] Cornering the market refers to a typical manipulation technique employed to abuse market power (or market position) by creating a dominant position from which to control either the supply or the demand side of both the derivative and underlying instruments. Cornering manipulators may then exploit the investors' need to close out their short positions. To successfully execute this technique, cornering manipulators would, for example, acquire a large amount of a commodity (which is the underlying asset in most physical derivative contracts) in order to decrease the supply of the commodity and so shift

[14] Further empirical evidence of contract-based manipulation strategies involving underlying securities and derivative contracts can be found in Jarrow (1992, 1994).
[15] Marking the close is specifically described in Chapter 2, Section 2.3, Paragraph 10 (d) and Paragraph 12 (a) in the ESMA market abuse regulation (The European Securities and Markets Authority, 2015).
[16] Cornering or squeezing are terms used in the market abuse regulation. Further details can be found in Chapter 2, Section 2.3, Paragraph 8 (d) (The European Securities and Markets Authority, 2015).

market price equilibrium. This action would then lead to strong price pressure being placed on the demand side. While there is nothing illegal in having significant market power, a manipulator's intention and approach to using their market power may constitute a contribution to the determination of market manipulation.

'Squeezing the market' refers to scenarios whereby manipulators continue to accumulate large positions. As Pirrong (1995) has explained, manipulators can profit handsomely from the increasing marginal cost of delivery with their very considerable market positions on derivatives markets, as well as from the surge of buying activity that causes a temporary increase in the underlying security price, because other short position holders are forced to close their positions at inflated underlying prices. It is not uncommon for a squeezing technique to be applied in conjunction with a cornering technique, as Allen, Litov and Mei (2006), Jarrow (1992, 1994), and Pirrong (1995) have shown.

There are many other market manipulation strategies, including 'front-running', 'pinging', 'phishing', 'quote stuffing', 'layering' and 'spoofing', that are not referred to in Figure 2.1. 'Front-running' refers to a manipulative strategy in which the sequence of a proprietary account executes orders on a security for their own profit (as principal) before buying or selling on to its agency accounts. This strategy can dramatically impact price drift and impact on the market, resulting in high execution costs for large orders, especially on the buy side, as has been demonstrated by Angel and McCabe (2013), Arnuk and Saluzzi (2009), Jarrow (1994), Sun, Kruse and Yu (2014), and Tong (2015).

HFT activities have also given rise in certain circumstances to sophisticated manipulation tactics. Kratz and Schöneborn (2014) observe that some investors, particularly institutional investors, have turned to dark platforms[17] with the objective of achieving optimal liquidation and execution costs. However, such trading activities might not be entirely protected when traded upon these platforms. For instance, 'pinging'[18] occurs when manipulators enter multiple small orders as a way of unearthing large hidden orders, with the aim of targeting particularly those resting in dark trading venues and undisplayed order types at exchanges, as Goldstein, Kumar and Graves (2014) have identified. These misleading orders are usually in the form of

[17] A dark pool is defined as an automated trading venue without pre-trade transparency, enabling investors to trade anonymously and often at mid-quote pricing independent of order-size (He & Lepone, 2014).
[18] Pinging and phishing techniques are described in Chapter 2, Section 2.3, Paragraph 6(c) and 6(d), respectively, in the market abuse regulation (The European Securities and Markets Authority, 2015).

‘fill or kill’ order types. If unsuccessful, these misleading orders are deleted immediately before they are executed.

A particular strategy for stifling market liquidity is known as ‘phishing’, which is similar to ‘pinging’, but the main difference is that it is not necessarily used to target dark trading platforms. Though phishing shares some of the characteristics of pinging,[19] the key difference is that, according to The European Securities and Markets Authority (2015), phishing manipulators typically enter a series of orders to trade, not only to examine the market, but also to uncover any hidden orders before sending a large order, which effectively takes advantage of the special knowledge obtained. After realising a large order from an institutional investor, an illegal HFT algorithm is, therefore, able to take advantage of the large stop-loss order by submitting a small bid order at the best ask price, followed by a large bid order, at or above the best bid price. The result of this activity then places pressure on the stop-loss order to become a market order, which leads to the sell-off of any remaining volume at a relatively unfavourable price.

Yet another, well-recognised HFT manipulation tactic concerns ‘quote stuffing’, or ‘flickering quotes’.[20] Quote stuffing involves the practice of entering a large number of orders to buy or sell, but with no intention to trade. Therefore, these misleading orders are typically cancelled or amended almost immediately, since their main purpose is to create uncertainty and confusion among other market participants. This practice slows their trading process and/or camouflages the manipulator’s strategy, as Egginton, Van Ness and Van Ness (2016) have explained. They also reported that this technique is able to be implemented not only by HFTs but also by smart order routers and other algorithmic traders.

Finally, there is the market manipulation strategy of ‘layering’, which is often also referred to as ‘spoofing’. Layering and spoofing are regarded by NASDAQ (2018) as sophisticated, technologically-driven and highly contentious market manipulation strategies. The two strategies are often confused because both strategies involve entering multiple orders into the order book, with the intention of impacting upon price signals of supply and demand in the market, thereby illegally influencing other competitors’ understanding of market trends, and in turn, their buying or selling actions.

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[19] Pinging and phishing techniques are described in Chapter 2, Section 2.3, Paragraph 6(c) and 6(d), respectively, in the market abuse regulation (The European Securities and Markets Authority, 2015).

[20] Quote stuffing is described in Section 2.3, Paragraph 9(e) in the market abuse regulation (The European Securities and Markets Authority, 2015).

As reported in Chapter 1, layering and spoofing have much in common, which is not surprising in light of the emergence of layering as a more recent and sophisticated form of spoofing. NASDAQ (2018) explains that spoofing may be achieved by placing an excessively high proportion of orders that are entered, deleted and/or amended in the order book at the end of the trading day. By contrast, layering involves intentionally placing orders at 'multiple price steps' into the book in order to deceive the market and influence prices in the manipulator's favour. According to Aitken, Cumming and Zhan (2015), Arnoldi (2016), and Cumming, Johan and Li (2011), the distinctive characteristics of layering strategies are that: first, the order volume must be sufficiently large enough to have the potential to send a misleading signal to the market; and second, the order must be withdrawn shortly after it has been placed. Once the market price has moved in the direction intended by the layering manipulator, a real order follows, which takes advantage of the more favourable price. Also, the difference between layering and spoofing has not always been acknowledged by legal experts. In the case of *SEC vs Biremis* (2012), the judge referred to manipulative trading strategies as layering, spoofing or gaming.[21] A similar use of these terms is evident in a seminar series paper by Justice Black in Australia (Black, 2014).

2.3 Empirical Research

2.3.1 Price reaction to public information

The review provided here presents the context for the research reported in Chapter 3, which concerns how quickly information is impounded into market prices on the Sydney Futures Exchange (SFE) from 2010 to 2017. As such, it addresses previous research relating to issues of market adjustment speed. There is evidence that financial asset prices respond differently to scheduled announcements based on the conditions of the economy and markets (Andersen, Bollerslev, Diebold & Vega, 2003). The intertemporal capital asset pricing model developed by Merton (1973) suggests that predicting time variation in future investment opportunities should be included in asset pricing models. For instance, macroeconomic variables such as gross domestic product (GDP), consumption growth, employment rates and interest rates should be regarded as important candidates for building multi-factor asset pricing models.

[21] In the case of *SEC vs Biremis* (2012, p. 3), layering is described as "when a trader creates a false appearance of market activity by entering multiple non-bona fide orders on one side of the market, at generally increasing (or decreasing) prices, in order to move that stock's price in a direction where the trader intends to induce others to buy (or sell) at a price altered by the non-bona fide orders."

Within an efficient market, prices should adjust to public macroeconomic announcements quickly enough to avoid unnecessary arbitrage windows. The speed of price adjustment is an important indicator of market efficiency. There has been a substantial number of studies (Andersen & Bollerslev, 1998; Andersen, Bollerslev, Diebold & Vega, 2003; Bomfim, 2003; Ederington & Lee, 1993), from both the disciplinary fields of finance and economics, which have shown the effects of news on asset prices. Nevertheless, there has been limited attention given to the actual impact of monetary policy news on market volatility. This situation applies especially in the context of the Australian futures markets.

Market efficiency theory suggests that if a market is efficient, new information is quickly reflected in financial prices, and so macroeconomic announcements should have no long-lasting effects on financial prices. Ederington and Lee (1993, 1995), Frino and Hill (2001), and Kim and Sheen (2001) nonetheless support at least a semi-strong form level of efficiency within the markets they investigated. Ederington and Lee (1993) utilised advanced frequency data which monitored the movement of volatility around the release of 19 macro announcements on interest rate and foreign exchange markets. They found that volatility tends to be abnormally high for fifteen minutes after announcements, but then rapidly declines, though it may remain slightly elevated for several hours (Ederington & Lee, 1993). Their bid-ask spread results implied that the lack of trading activity prior to an announcement release may have been caused by market makers tending to protect themselves from informed traders. Building on their initial work, Ederington and Lee (1995) then examined the market reaction at 10 second intervals for twelve minutes after market announcements. They found that there was significant statistical evidence to suggest that markets in the United States (US) tended to overreact to news within the first 40 seconds, but then the market corrected itself within three minutes.

Volatility following macroeconomic announcements and periodic volatility patterns are important to market efficiency, as has been argued by Ederington and Lee (1993, 1995). Examples of periodic decomposition have been provided by Andersen and Bollerslev (1998) and Fleming and Remolona (1997). Fleming and Remolona (1997) examined the intraday Treasury cash market securities in the market in the US, identifying eight significant announcements for price volatility and eleven for trading volume. They observed that trades of the largest 25 price shocks and 25 greatest trading surges were associated with just-released macroeconomic announcements. Andersen and Bollerslev (1998) studied the characteristics of volatility in the Deutschmark (DM)-USD foreign exchange market, using an annual sample of five-minute returns from 1992 to 1993. Within the realised volatility framework with volatility computed as the sum of high-frequency absolute returns, their empirical analysis identified the sensitivity of short-term and long-term volatility in USD/DM and USD/yen FOREX quotes, which could meaningfully point to the driving forces behind the adjustment process. Nevertheless, Andersen and Bollerslev (1998) affirmed the importance of Ederington and Lee's (1993, 1995) study. Their findings indicated the significant positive effect of US announcements on volatility movement. However, Andersen and Bollerslev (1998) argued that seasonal factors, such as the opening of local markets, lunch breaks and some specific days of the weeks, namely Thursday and Friday, may also contribute to an increase in volatility in the US market for societal reasons. Andersen and Bollerslev's (1998) findings were also consistent with those of Harvey and Huang (1991), who hypothesised that high volatility occurs in the opening hours of Thursday and Friday, due to the release of US macroeconomic news. In this vein, Goodhart and O'Hara (1997) stressed that a comprehensive explanation of volatility behaviour could only be achieved if the striking empirical regularities in return volatility were detectable, not only over regular trading versus non-trading periods, but also within the trading day, trading week and over holiday periods.

Frino and Hill (2001) replicated Ederington and Lee's (1993, 1995) framework to examine SPI200 futures contracts in the Australian futures market between 1995 and 1997. They found that major macroeconomic announcements were impounded into prices quickly, specifically within 240 seconds after the announcement. Their findings contrast with those of Tan (1992), who reported that the Australian futures market did not respond to news announcements due to the fact that information should already be impounded in futures prices based on Fama's EMH. Furthermore, Smales (2013) studied the impact of macroeconomic announcements on Australia's interest rate futures, specifically 30-day interbank futures, 90-day bank bill futures, 3-year government bonds and 10-year government bonds, from 2004 to 2010. Like Frino and Hill (2001), Smales (2013) focused on scheduled announcements at 11:30 am only, using the argument that most major macroeconomic announcements are released at 11:30 am. His empirical analysis examined eight announcement types (i.e., building approvals, Consumer Price Index (CPI), employment rate, Gross Domestic Product (GDP), private capital expenditure, producer price index, retail sales, and wage cost index). Smales (2013) concluded that the interest rate market in Australia tended to digest information quickly, that is, within a matter of 30 seconds, although price volatility tended to be heightened for up to 50 seconds after the release of major announcements. These studies pointed to the importance of a market's capacity to digest and adjust to new information. However, none of the above mentioned studies examined the speed of adjustment for individual major announcements.

2.3.2 Securities market manipulation

The review now turns to providing the context for the research reported in Chapters 4 and 5, which concerns how layering manipulation impacts upon market quality, drawing upon data collected from the ASX full order book for the four-month period commencing 1 June 2015. The review particularly addresses how different market manipulation strategies may have a negative overall impact on market quality. The fundamental question confronting researchers and market regulators regarding prospective manipulation behaviour is: how is it possible to differentiate between the intentions of manipulators as distinct from the intentions of skilful and well-informed traders? Despite the existence of numerous theoretical models pertaining to market manipulation (see, for example, models developed by Aggarwal & Wu, 2006; Allen & Gorton, 1992; Allen, Litov & Mei, 2006; Comerton-Forde & Putniņš, 2011; Lee, Eom & Park, 2013; Pirrong, 1995), there are few studies that have provided empirical evidence and real-case visualisations of abnormal/illegal market trading behaviour.

Key literature on the paradigm of price-setting (see, for example, De Long, Shleifer, Summers & Waldmann, 1990; Stein, 1987) studying the impact of speculators on financial prices has established avenues for enquiry that are concerned with the connection between market manipulation and volatility. Hart and Kreps (1986) hypothesised that speculation can destabilise prices and lead to an increase in volatility, in that uninformed traders cannot distinguish between rational speculators and informed traders with private information. Similarly, Allen and Gorton (1992) employed the framework developed by Glosten and Milgrom (1985)[22] to better understand how manipulators mimic informed traders' behaviour. Allen and Gorton (1992) stated that trade-based manipulation was possible when there is uncertainty about whether purchasers of shares possess asymmetric information about the prospects of a firm's intrinsic value, or whether they simply attempt to manipulate such security prices.

[22] Glosten and Milgrom (1985) and Kyle (1985) assert that financial markets consist of informed traders, liquidity takers (or noise traders) and competitive market makers.

The potential ramifications of manipulation on financial markets is the subject of considerable controversy, as discussed by Fischel and Ross (1991). The question concerns whether introducing more regulatory rules in order to combat market manipulators might be the right approach. For example, a simple signalling technique might constitute a manipulator repeatedly buying stocks, with the aim of impacting the supply/demand of the order book before selling orders to realise profits from inflated prices. Allen and Gorton (1992) concluded that difficulties in identifying the intention of liquidity traders arise from the possibility of manipulation due to the asymmetry of price elasticities. Aggarwal and Wu's (2006) study further developed the above-mentioned models by demonstrating how a pooling equilibrium, in which information seekers cannot differentiate between a manipulator and an informed trader, can possibly occur. They argued that trade-based manipulation can be successful, even among momentum traders. Therefore, information asymmetry is of critical importance to the success of any such manipulation strategies.

Not withstanding the preceding evidence, Fischel and Ross (1991) argued, however, that it was not plausible to achieve profits from market manipulation in an informationally efficient market. In contrast, Jarrow (1992), who built on Hart's (1977) study, investigated a deterministic economy with a time homogenous price process and was able to demonstrate that manipulation strategies can work in dynamically unstable markets, and further, in certain cases, in stable economies. Notably, Jarrow (1992) argued that it is possible for large traders to disrupt the momentum of securities prices and execute transactions to their advantage; and that it is possible for this outcome to occur without large traders taking a degree of risk. One of the underlying assumptions of Jarrow's (1992) model is that, although large traders may not possess privileged information, they continue to have the capacity to abuse their market power (e.g., by using market cornering strategies) to create misleading signals. As a consequence, other traders tend to react to artificial price changes, which in turn are driven by manipulative strategies, in the belief that those increases or decreases in prices might have a permanent impact on future liquidity trading. In this vein, Comerton-Forde and Putniņš (2011) studied the effects of closing price manipulation in an experimental market using prosecuted manipulation cases. Their findings suggest that manipulators have a significantly detrimental effect on price accuracy, and thus, reduce market liquidity. Therefore, market manipulation appears to pose negative ramifications for market efficiency.

Chakraborty and Yilmaz (2004, 2008) explored another form of market abuse, concerning when informed traders profit from long-lived private information. Their findings suggest that such strategies may result in short-term losses for manipulators, which may have been acceptable to them at the time because of an anticipation of long-term profits. However, such artificial noise, once created, would enable them to retain an informational advantage for an extended period of time, and then, financially benefit from this long-lived information. These findings are in line with Kyle's (1985, p. 1323) earlier observation that manipulators benefit "by first destabilizing prices with unprofitable trades made at the n^{th} auction, then recouping the losses and much more with profitable trades at future auctions."

A further manipulation strategy to be considered is known as 'spoofing'. Lee, Eom and Park (2013) examined microstructure-based spoofing strategies implemented by entities trading on the Korea Exchange (KRX). They defined spoofing as:

> [a] bid/ask with a size at least twice the previous day's average order size and with an order price at least six (6) ticks away from the market price, followed by an order on the opposite side of the market, and subsequently followed by the withdrawal of the first order. (Lee, Eom & Park, 2013, p. 232)

Using a data set of individual accounts from the KRX, they examined how, over a two and half month period during 2002, certain traders floated orders that were significantly above or below the best market price, for the sole purpose of shifting the best market price in a direction that was favourable to them. Notably, the KRX did not have an order disclosure rule during the period in question, which meant that prices were not displayed at the time of collection. In these circumstances, it was possible for layering manipulators to float orders on the KRX that were significantly lower, or higher, than the best bid/ask (or touch) that could still move the market, as the proximity of the orders was unknown to other market participants. However, once the KRX introduced an order disclosure rule, the practice became less common, as reported by Lee, Eom and Park (2013).

With regard to the effects of manipulation on market quality status, Aitken, Harris and Ji (2014) built on market efficiency theory to argue that an efficient market cannot effectively be an aggregator of equilibrium price information in the presence of asymmetric information generated by such manipulative behaviour. They emphasised that such schemes would disrupt natural volatility, and consequently, discourage other participants, such as quasi-market makers, who were content to earn spread in mean-reverting price sequences, from contributing to market liquidity. Foucault's (1999) argument supports this view by developing a theoretical game model of price formation and order placement decisions[23] in a dynamic limit-order market. Foucault (1999) claimed that when volatility increases, market participants tend to be more cautious and less aggressive by leaning towards limit orders, in order to avoid pick-off risk. Such a tendency implies that limit-order submitters prefer higher compensation in a more volatile market. This, in turn, results in a larger spread and higher transaction costs, which ultimately jeopardises the efficiency of a market's operation.

2.4 Concluding Remarks

This chapter has reviewed a body of literature pertaining to the impact of trading behaviour and market manipulation on market quality, addressing also the significant role of efficient markets in providing a protected and fair trading environment. Key contemporary market manipulation strategies and techniques were also identified. A brief review of the empirical literature on price reaction to public information and securities market manipulation over the last three decades was also provided. It is evident that there remains a considerable amount to be understood about the impact of HFT and market manipulation practices (e.g., layering) on market quality, especially given the increasing sophistication of algorithms currently being utilised by HFTs. For instance, the negative impact of layering strategies on the efficiency and integrity of financial markets is widely recognised, yet there have been relatively few empirical investigations concerning the practice. Lee, Eom and Park (2013) have conducted one of the few empirical investigations available concerning the impact of spoofing manipulation on financial prices, but their algorithm was intended to take advantage of technology and regulations specific to the market and time of their investigation. Notably, their focus was on spoofing, rather than layering, which is a closely-related manipulation practice that is more recent in terms of its development. It is clear from the review conducted that there is a pressing need to empirically examine the impact of HFT and layering manipulation strategies on market quality in an Australian context.

[23] Foucault (1999) asserted that order placement consists of two order components, namely: (1) market orders; and (2) limit orders. Market orders refer to aggressive orders, which are executed against the prevailing best bid or ask prices. The placement of market orders represents the demand for liquidity. Limit orders, on the other hand, refers to ask orders that are placed with preferable prices waiting for future execution with market orders.

Chapter Three

THE IMPACT OF HIGH-FREQUENCY TRADING ON AUSTRALIAN FUTURES TRADING ACTIVITIES, LIQUIDITY AND MARKET EFFICIENCY

3.1 Introduction

Hoffmann (2014) explains that, in the pursuit of profits, high-frequency traders (HFTs) employ sophisticated technology and resources in order to execute trading strategies, such as submitting a vast amount of order messages at extremely small time intervals. These traders now invest heavily in the human (e.g., information technology/computer science experts and mathematicians) and physical (e.g., co-location, servers, data feeds, etc.) capital considered necessary to achieve a competitive advantage over their peers. HFTs may yield additional revenue from their activities, but the overall impact of these developments in terms of increased market efficiency remains inconclusive (see, for example, Frino, Mollica & Webb, 2014; Hendershott, Jones & Menkveld, 2011; Riordan & Storkenmaier, 2012). O'Hara (2015) has also asked if it is fair for exchanges to sell traders' information to others before it becomes fully accessible to the public, and whether, for the sake of market fairness, exchanges should make co-location services freely accessible to all traders. These are important questions, but first there is a need to better understand the extent to which, at least in the context of the Australian futures market, HFT impacts on trading activities, liquidity and market efficiency.

The first research theme addresses the issue of whether scheduled macroeconomic announcements are being impounded more efficiently into financial prices in the Australian futures market, in which HFT has an important presence. Three aspects of informational efficiency are addressed, namely: trading activities and market liquidity; speed of market adjustment to scheduled major announcements; and the determination of volatility persistence for each major announcement type. The chapter is organised as follows: Section 3.2 presents the propositions derived from the relevant literature. Section 3.3 reports the data and setting for the empirical investigation. Section 3.4 highlights the empirical findings. Section 3.5 discusses the implications of the findings and concludes.

3.2 Propositions

Empirical evidence supporting the notion that the technological revolution in trading (with HFT facilities now being co-located in securities exchanges) has impacted positively on market liquidity, informational efficiency and market volatility, remains equivocal (Hendershott, Jones & Menkveld, 2011). HFT facilities enable trading entities with access to them to obtain and make use of market information much more quickly than is possible by any other means. The effects of this enhancement of informational efficiency require further investigation. Martinez and Rosu (2013) have argued that HFT activities may disrupt or destabilise market operations by increasing volatility while simultaneously reducing liquidity, as HFT algorithms tend to consume market makers' quotes. Cartea and Penalva (2012) have suggested that the ability of traders using HFT facilities to react faster to changing market conditions enables them to profit at the expense of other traders. Faster reaction speeds have the potential to result in an increase in trading volume and volatility, but this increase may also diminish the welfare of liquidity traders. Brogaard, Hendershott and Riordan (2014) and Hendershott and Moulton (2011) claim that a large order submitted by means of HFT tends to have a higher permanent price impact, which can potentially lead to high adverse selection costs. A further negative effect of HFT is referred to by McInish and Upson (2012), who study the impact of the Flicker Quote Exception Rule – a rule that enables intermarket 'trade through' to occur if new prices are displayed in less than one second. This rule also implies that HFTs are able to profit by picking off orders from their slower, less sophisticated counterparts, due to their trading speed advantages and better knowledge of the markets in the sub-second environment at prices inferior to the best bid and offer.

However, empirical studies have also pointed to the positive impact of HFT on market liquidity. These studies include Brogaard, Hendershott and Riordan (2014), Frino, Mollica and Webb (2014), Hendershott, Jones and Menkveld (2011), and Riordan and Storkenmaier (2012). For instance, using futures contracts, Frino, Mollica and Webb (2014) found that the introduction of co-location facilities on the Australian Securities Exchange decreased bid–ask spreads, increased market depth and enhanced liquidity. HFT has also been found to contribute to price discovery, according to Biais, Foucault and Moinas (2015), who showed that the rapidity of order placements due to HFT encourages increased trading activities, and therefore provides mutual gains from transactions. The rapidity of order placements, however, also comes at a price in the form of an increase in adverse selection costs, especially for less sophisticated market participants. In this vein, Hendershott, Jones and Menkveld (2011) examined the impact of the upgrade to the automation of quote dissemination on the New York Stock Exchange in 2003. They used the volume of message traffic, normalised by the number of trades, as a measure of combined agency and algorithmic trading activities. The authors found that an increase in HFT activities improved the market by encouraging price discovery, and consequently, reduced adverse selection costs, quote spreads and effective spreads.

Brogaard, Hendershott and Riordan (2014) also identified a contribution made by HFT to price discovery. Their findings suggested that there is no direct evidence to indicate that HFT jeopardises price-setting mechanisms. Indeed, these authors claimed that there was evidence to suggest that HFT placed marketable orders to trade in a direction which helped minimise transitory pricing errors, both on average days and during periods of financial turmoil, such as, for example, during the Global Financial Crisis in 2008-09. Brogaard, Hendershott and Riordan (2014) noted that this positive input is often overlooked, because most studies have tended to place emphasis on the withdrawal of non-major HFT suppliers' orders from the book, rather than HFTs' involvement in maintaining price stability during periods of financial distress.

In a study of the reduction in latency in Deutsche Boerse trading systems in 2007, Riordan and Storkenmaier (2012) reached a similar conclusion to that of Hendershott, Jones and Menkveld (2011). They found that a technological upgrade of the system improved market liquidity. This upgrade, resulting from the reduction in latency, was associated with an improvement in effective spread (declining from 7.72 basis points to 7.04 basis points), an increase in realised spread (0.97 basis points to 4.45 basis points), and importantly, a reduction in adverse selection costs. However, their findings cannot be regarded as conclusive because their research was mainly applied to securities with low-to-medium market capitalisation. In addition, Ye, Yao and Gai (2013) examined a reduction in trading latency from the microsecond to the nanosecond level and found that there was no effect on the effective spread.

Therefore, the literature pertaining to the speed of market transactions made possible by continuing technological improvements reveals mixed evidence regarding the impact of HFT on market liquidity and efficiency. Against this background, and building on the research conducted by Frino, Mollica and Webb (2014), an examination of the impact of HFT on the trading activities and market liquidity of the Australian futures market is proposed. The sub-proposition is:

$P_{1.1}$: The co-location of HFT facilities influences the trading activities and liquidity of the Australian futures market.

The above sub-proposition focusses on the co-location impacts of HFT on trading activities and liquidity. In addition, it is imperative to examine if the Australian futures market can function efficiently in the presence of rapidly increasing HFT trading activities. Even if the impact of co-location facilities is found to have contributed positively to overall market liquidity, its benefits must be distributed equally to all market participants, not just fast HFT traders. Hence, a further consideration of this present investigation is the speed of market adjustment in incorporating scheduled macroeconomic announcements into financial prices. Hoffmann (2014) argued that an increase in trading volumes as a result of HFT activities is a positive signal to the market, but only on face value. Such a positive signal results because only certain cohorts of traders are likely to benefit from co-location facilities. These cohorts usually have the capacity to adapt to the speed increases generated by evolving technology, and in turn, to improve their trading profits at the expense of slower, less sophisticated traders. The main argument put forward by HFT supporters is that technology helps to improve market liquidity, price discovery and market efficiency. However, Hoffmann (2014) showed that only efficient markets with the capacity to absorb information efficiently can fully appreciate the positive contributions of HFT. Fama (1970, 1991, 1998) also argued that an efficient market should be able to absorb public and private information into financial prices. Therefore, the the sub-proposition is:

$P_{1.2}$: The Australian futures market is semi-strong efficient as prices react quickly to major announcements.

3.3 Institutional Setting, Data and Methods

3.3.1 Institutional setting

The setting for the present investigation is the Sydney Futures Exchange (SFE), which is the largest exchange in the Asia-Pacific region, as measured by market capitalisation (Frino, Peng He & Lepone, 2014). The four most liquid futures contracts[24] (90-day bank accepted bills (90-day bills), 3-year Treasury bonds (3-year bonds), 10-year Treasury bonds (10-year bonds) and

[24] Detailed specifications of the four futures contracts employed in the present investigation can be found in Appendix A.1. Only the most heavily traded/liquid futures contracts, as determined by daily trading volumes, were chosen.

share price index 200 (SPI200)) were utilised. Introduced in 1979 and representing the first interest rate contract to be listed outside the United States (US), 90-day bills are the Australian benchmark for short-term interest rates. In the case of the SPI200 index, 3-year bonds and 10-year bonds, the analysis is confined to the nearest-to-expiry contract, while 90-day bills are confined to the second nearest-to-expiry contract date. Daily trading sessions commence from 8:28 am to 4:30 pm (AEST) [25] for 90-day bill contracts. The trading times for 3-year and 10-year bonds are from 8:30 am to 4:30 pm (AEST) and 5:10 pm to 7:00 am (AEST). Trading times for the SPI200 index are from 9:50 am to 4:30 pm (AEST) and 5:10 pm to 7:00 am (AEST).

3.3.2 Data

Intraday transactions and quote data in the present investigation were obtained from the Thomson Reuters Tick History (TRTH) database, which is maintained and provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA). The sample periods under consideration are between 20 February 2011 and 20 February 2013 (co-location of HFT facilities on trading activities and liquidity) and between 1 January 2010 and 30 June 2017 (market adjustment speed to majorscheduled announcements and efficiency). The sample chosen for this investigation is restricted to contracts with the nearest expiration date. Macroeconomic and cash rate announcement information, together with the relevant details of market expectation, were collected from Bloomberg. Given that most of Australia’s scheduled macroeconomic announcements are released at 11:30 am (AEST), the determined announcement samples are restricted to news occurring at this time.

For the cash rate, the determined announcement sample is restricted to news occurring at 2:30 pm (AEST). This cash rate announcement is usually omitted from empirical investigations in Australia, mainly due to its afternoon release schedule and also to facilitate full attention provided to 11:30 am news announcements, as identified by Frino and Hill (2001). However, Gasbarro and Monroe (2004) demonstrate that the monetary policy actions of central banks have a substantial impact on how market participants correctly value financial securities and manage their portfolios. Hence, the present investigation examines the cash rate announcement separately. Building on previous literature (see, for example, Ederington & Lee, 1993; Frino & Hill, 2001), this investigation considers trade price volatility (TPV) and midpoint price

[25] AEST refers to Australian Eastern Standard Time.

volatility (MPV) at the 5-second interval aligned with event announcement times (11:30 am and 2:30 pm [AEST]) for major announcement days, as well as non-major announcement days. Volatility measures are programmed and generated via market quality technology, with the support of the Capital Market CRC's (CMCRC's) Market Quality Dashboard team.[26] [27]

3.3.3 Methods

3.3.3.1 Co-location of HFT facilities on trading activities and liquidity

As Madhavan (2000) explains, market microstructure studies place strong emphasis on spreads as proxies for measuring liquidity. More specifically, quoted spreads (both absolute value and percentage) and relative spreads are employed as proxy variables for measuring transaction costs. Quoted spreads, also known as bid-ask spreads, for each contract are the difference between the best bid and the best ask (Harris, 2003). The bid-ask spread (absolute value) is estimated as follows:

$$\text{Bid-Ask Spread (Absolute Value)} = \text{Best Ask} - \text{Best Bid} \tag{3.1}$$

where the best ask is the lowest price that a seller is willing to sell. The best bid is the highest price that a buyer is willing to pay.

Quoted liquidity is examined using time-weighted quoted spreads and depth. The time-weight in this regard demonstrates the availability of liquidity throughout the day and is commonly used to capture the degree of market efficiency. Therefore, for each trading day and contract, the mid-point spread is also considered, which standardises the dollar tick spread by the quoted mid-point (Brock & Kleidon, 1992). The bid-ask spread (percentage) is determined as follows:

$$\text{Bid Ask Spread (Percentage)} = \frac{\text{Best Ask} - \text{Best Bid}}{\text{Time Weighted Midpoint}} \tag{3.2}$$

where time-weighted midpoint for each contract is measured by the time-weighted average of midpoint price between the opening and closing times for each contract.

[26] The CMCRC is one of the world's largest market data research centres, particularly in the market microstructure space. More details can be found at https://www.cmcrc.com/ and https://mqdashboard.com/.
[27] All market quality metrics employed in Chapter Three were developed by the author using Uptick programming. All results for Chapter Three were generated via the Amazon Web Service workflow funded by the MQD team.

A further measure of the bid-ask spread is relative spread, which is based on each contract's minimum tick movement. The minimum ticks for the SPI200 (1 tick), 90-day bills (0.01%) and 10-year bonds (0.005%) do not change during the investigated period. However, given ASX regulatory requirements, 3-year bonds generally have a 0.01% minimum tick, with the exception of contracts that are between the 8th day of the expiry month and expiry date, when its minimum tick reduces to 0.005%. The relative spread for each contract is estimated as an average of all tick spreads during the trading day:

$$\text{Relative Spread} = \frac{\text{Best Ask} - \text{Best Bid}}{\text{Minimum Tick Size}} \tag{3.3}$$

Drawing upon Hendershott, Jones and Menkveld's (2011) notion of stability, the present investigation employs algorithmic trade, order-to-trade ratio and electronic message traffic[28] as proxies for algorithmic trading behaviour. Algorithmic trade represents the daily number of electronic message traffic that has been standardised by trading volume. Its association with the quantity of investigated contracts enables the study to observe any changes in HFT order behaviour, specifically submission, amendment, trade and cancellations of limit orders. Hendershott, Jones and Menkveld (2011) assert that using algorithmic trade as an HFT proxy enables an understanding of algorithmic liquidity supply. The formula can be derived as the negative of trading volume for each investigated future contract I on day T derived by the aggregate number of messages submitted by HFT over that trading day:

$$\text{Algorithmic Trade}_{IT} = \frac{-\,\text{Volume}_{\text{IT}}/100}{\text{Message Traffic}_{IT}} \tag{3.4}$$

The message traffic at the aggregated level is derived as follows:

$$\text{Message Traffic} \;=\; \text{The Number of Quotes} \tag{3.5}$$

Order to trade ratio measures the quoting intensity of HFT order submission behaviour. The higher number of order to trade ratio may be indicative of an increase in HFT activities. It highlights how frequent HFT submit, amend or delete their limit order relative to their actual transactions.

$$\text{Order to Trade Ratio} = \frac{\text{Messsage Traffic}_{IT}}{\text{Total Transactions}_{IT}} \tag{3.6}$$

[28] Message traffic consists of electronic order submissions, amendments, cancellations and trade reports.

Consistent with Aspris, Foley, Harris and O'Neill's (2015) notion of resilience, the measure for high-low volatility is calculated by dividing each contract's high-low price range with the time-weight mid-quote. The formula is established as:

$$\text{High\_Low\_Volatility}_{IT} = \frac{\text{High Price} - \text{Low Price}}{\text{Time Weighted Midpoint}} \tag{3.7}$$

To assess impact, a standard event study approach is employed. The following regression specification is used to examine the impact of co-location of technology on market quality:

$$\mathrm{Y_{it}} = \propto_{\mathrm{i}} + \beta_1 \mathrm{Colo_{it}} + \beta_2 \text{Open Interest}_{\mathrm{it}} + \beta_3 \mathrm{Volatility_{it}} + \varepsilon_{\mathrm{it}}\,, \tag{3.8}$$

where Y_{it} is the market quality measure for the relevant contract *i* on day *t* and proxies include relative spread, bid-ask spread (absolute value and percentage), order to trade ratio, message traffic and algorithmic trade. *Colo* is a dummy variable taking a value of 0 prior to the introduction of co-location facilities (e.g., 20 February 2012) and a value of 1 after the introduction of co-location facilities. *Control* is a set of control variables, namely open interest and high-low volatility. These two control variables are chosen as key determinants of market liquidity. The theory supporting these two variables are well established in previous literature such as Cummings and Frino (2011), Ragunathan and Peker (1997) and Wang, Yau and Baptise (1997). Volatility measures the degree of uncertainty in the market and the higher the risk, the higher the compensation sought by liquidity providers. The number of outstanding contracts in the futures markets is commonly referred to as open interest. This control variable can be used to capture the intensity of trading activity, as demonstrated by Wang, Yau and Baptise (1997). These authors assert that the changes in the open interest have an impact on the expected physical position of hedgers. High open interest indicates an increase in future transactions; thus, having a positive relationship with trading volume. Given the implementation of co-location facilities coincides with the introduction of a cost recovery charge (CRC) by the Australian Securities and Investments Commission (ASIC), the investigation also controls for CRC effects. The CRC[29] was introduced on the 1st of January 2012 as a means of charging market participants a message traffic and trading fee to recover market supervision fees. The CRC was only intended for the equities market, and therefore, may indirectly have an impact on the SPI futures contracts. This is because SPI 200 is the main index representation for the

[29] More information about the cost recovery charge can be found here: https://www.asx.com.au/documents/public-consultations/ASX_submission_options_for_amending_ASIC_cost_recovery_arrangements.pdf

underlying equities market. Having taken the CRC effects into consideration, the investigation estimates the regression model for SPI 200 with an additional control for CRC. The CRC dummy variable is set to 0 prior to the 1st January 2012 and set to 1 following the introduction.

3.3.3.2 Market adjustment speed and efficiency

Consistent with Ederington and Lee's (1993, 1995) study, the impact of major scheduled announcements on the SPI200 and three interest rate futures contracts, based on market reaction (as captured by midpoint price value (MPV) and trade price value (TPV)), are examined. Intraday volatility is measured as the standard deviation at 5-second intervals throughout the investigation period. The respective formulas are defined as follows:

$$\mathrm{MPV} = \mathrm{ST.DEV}\ (\text{Quote Midpoint Price}) \tag{3.9}$$

$$\mathrm{TPV} = \mathrm{ST.DEV}(\text{Trade Price}) \tag{3.10}$$

MPV is chosen as an alternative measure to TPV for two reasons. First, it minimises the effects of bid-ask bounce induced volatility, as suggested by Frino and Hill (2001). Second, Cummings and Frino (2011) explained that midpoint price helps to avoid issues related to infrequent trading. Therefore, MPV is employed in this study as a dependent variable to determine major announcements based on statistical evidence of its impact on market volatility.[30] A linear regression model using heteroscedasticity-consistent standard errors is used to determine such major announcements, which is consistent with Long and Ervin's (2000) study. The dependent variables are $\mathrm{MPV}_{(0,\,30)}$ in the first 30 second period (*j*) following announcements (*t*). Dummy variables D_{kt} are defined as 1 on major announcement days and 0 on non-major announcement days. In particular, the present investigation focuses on the volatility at the 5-second interval so there are 6 observations per announcement (30/5). The regression in equation 3.11 (below) used to analyse the data does not rely on just one 30-second MPV estimate, rather 30-second MPV calculated every announcement day over the timeframe from 1 January 2010 to 30 June 2017. It should be noted that there are 1332 announcements released during the investigated period. The six observations are then multiplied by the number of announcements.

The following regression is estimated over 3,478 trading days:

[30] Alternative measures of volatility are the variance of trade prices (Ederington & Lee, 1993), the variance of returns based on the midpoint price of the last quote in interval t (Frino & Hill, 2001), and the standard deviation of returns based on the midpoint of the bid-ask quote (Smales, 2013).

$$\mathrm{MPV_{jt}} = a_{0j} + \sum_{k=1}^{K} a_{kj} D_{kt} + e_{jt}$$

(3.11)

The coefficient a_{kj} is positive and significant if announcement type *k* has a significant impact on volatility. However, a negative value, or an approximate zero value of the coefficient, implies that an announcement has little or no impact on volatility. Ederington and Lee (1993) note that $(\pi/2)^{0.5}$ a_{0j} provides an estimate of volatility in interval *J* on non-major announcement days. An estimate of volatility in interval *J* on days when *k* is announced can be provided by 1.2533 ($a_{0j} + a_{kj}$).

The price adjustment process in the present investigation captures the duration of full adjustment speed and half-life adjustment speed based on MPV and TPV. Unlike previous studies (see, for example, Ederington & Lee, 1995; Frino & Hill, 2001; Smales, 2013), in which 12-minute intervals were adopted (that is, two minutes prior to scheduled announcements and 10 minutes after scheduled announcements), the present investigation employs one-tail t-tests to discover the breakpoint at which information in each futures contract becomes fully impounded into prices. The one-tail t-test is the preferred statistical test compared to the 2-tail tet because the present investigation concerns the possibility of the relationship between major announcements and non-major announcements in one direction. Specifically, the t-tests examine whether there is a significant difference between the estimated mean value of the major announcement days and the non-major announcement days, based on rolling means across each 5-second interval. The full adjustment time represents the first-time interval where there is no significant statistical difference between the announcement and benchmark periods. The half-life adjustment speed is also captured. The half-life volatility metric estimates the duration of a shock where the volatility moves back to halfway from its peak towards the unconditional mean following announcement days. The unconditional mean refers to the benchmark derived by volatility (MPV or TPV) calculated on non-major announcement days.

Consistent with Ederington and Lee’s (1995) study, the magnitude of price adjustment patterns in each interval is estimated by obtaining an average adjustment return (AAR). The AAR measure captures the adjustment from the old price to the approximate new equilibrium price. The adjusted return (AR) for each interval is defined as:

$$\mathrm{AR_t} = \mathrm{R_t} \times \mathrm{D_t}, \tag{3.12}$$

where five-second intervals are employed, R_t represents returns calculated using the quote midpoint price and D_t = +1, -1 or 0 if the (0, 30) return is positive, negative, or zero, respectively. The quote midpoint price returns over the first 30 seconds after the announcements signal whether the news is good/positive or bad/negative. If there is no information leakage on announcement days, the AAR_t is expected to be zero (even during the adjustment period) and the AAR_t should also be zero at the completion of this price adjustment. The AARs are also summed to form a cumulative average adjusted return (CAR).

Volatility persistence is well-regarded as a measure of how macroeconomic announcements influence financial prices at the daily level in the international macroeconomic literature (see, for example, Chortareas & Kapetanios, 2012; Jones, Lamont & Lumsdaine, 1998; McMillan & Ruiz, 2009; Reyes, 2001). Inspired by Jones, Lamont and Lumsdaine (1998), who examine the reaction of daily Treasury bond prices to the announcement of US macroeconomic news, the present investigation investigates the speed of adjustment of each futures contract to major Australian macroeconomic and cash rate announcements using high-frequency data. The half-life of the shocks is estimated by applying MPV and TPV with one autoregressive component and other lagged differences. Half-life is defined as a time period that a volatility series requires normally to halve its distance from the mean. For instance, the deviation of the logarithm of volatility at the 5-second interval y_t is constant following an autoregressive process of order one. Therefore, y_t enables the relationship between major announcements and volatility to be captured. The half-life model is described as follows:

$$(\mathrm{y_t} - \mathrm{y_{t-1}}) = \beta_\mathrm{t} + \beta_\mathrm{t}(\mathrm{y_{t-1}}) + \epsilon_\mathrm{t}, \tag{3.13}$$

where β_t captures the speed of mean-reversion. ϵ_t is white noise. Half life can be estimated according to the estimated speed of mean-reversion β_t. The formula is defined as follows:

$$\mathrm{t}^{1/2} = \frac{\log(0.5)}{\log(\hat{\beta})}, \tag{3.14}$$

where $\hat{\beta}$ denotes the estimate of β_t.

3.4 Empirical Results and Discussion:

3.4.1 Impact of co-location of HFT facilities on futures market trading activities and liquidity

Table 3.1 provides the results of regression analyses of the impact of co-location technology on HFT activities in the Australian futures market.[31]

Table 3.1: Impact of co-location of HFT facilities on trading activities[32]

Variable	SPI200		90-day bills		10-Year bonds		3-Year bonds	
Message Traffic	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Intercept	(-5,832.26)	(-0.19)	3,252.32	3.29 ***	(-33,470.00)	(-4.44) ***	5,603.28	3.28 ***
Colocation	(-66,380.00)	(-4.55) ***	6,396.19	17.59 ***	23,300.00	18.12 ***	16,330.00	23.53 ***
CRC	36,460.00	2.75 ***						
Open Interest	0.39	2.68 ***	(-0.00)	(-0.30)	0.15	7.33 ***	(-0.00)	(-0.08)
Intraday Volatility	11,780,000	20.06 ***	3,779,000	9.36 ***	11,030,000	6.89 ***	7,852,000	13 ***
Adjusted R2	***0.57***		***0.48***		***0.49***		***0.63***	
Order to Trade Ratio	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Intercept	10.27	6.51 ***	10.96	13.85 ***	9.47	10.13 ***	6.93	12.47 ***
Colocation	(-3.25)	(-3.45) ***	4.05	14.63 ***	0.09	0.54	2.41	11.91 ***
CRC	4.46	4.74 ***						
Open Interest	0.00	0.18	(-0.00)	(-4.08) ***	0.00	0.16	(-0.00)	(-4.16) ***
Intraday Volatility	273.53	4.97 ***	(-402.18)	(-3.29) ***	(-449.98)	(-2.30) **	95.90	1.04
Adjusted R2	***0.16***		***0.43***		***0.004***		***0.44***	
Algorithmic Trade	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Intercept	(-0.00)	(-12.50) ***	(-0.04)	(-6.66) ***	(-0.01)	(-6.28) ***	(-0.06)	(-7.58) ***
Colocation	(-0.00)	(-3.82) ***	0.02	13.40 ***	0.00	13.19 ***	0.03	13.88 ***
CRC	0.00	7.33 ***						
Open Interest	0.00	0.02	(-0.00)	(-2.38) **	(-0.00)	(-2.29) **	(-0.00)	(-3.93) ***
Intraday Volatility	0.03	5.25 ***	4.55	3.21 ***	1.05	3.43 ***	10.61	5.70 ***
Adjusted R2	***0.16***		***0.31***		***0.25***		***0.42***	

Note: This table reports regression analyses of the impact of co-location technology on HFT activities in the Australian futures market. A dummy variable is used to set co-location to 0 prior to 20 February 2012 and 1 after 20 February 2012. Control variables are open interest and intraday volatility or high-low time-weighted midpoint price volatility. A dummy variable titled 'CRC' is also employed to control for the introduction of cost recovery charge imposed by ASIC on 1st January 2012. The CRC is set 0 prior to the cost recovery charge and 1 after following the introduction.

***, ** and * indicates statistical significance at the 1%, 5% and 10% levels, respectively.

The regression results for the four contracts are mostly significant, implying that HFT activities seem to have increased after the co-location technology was introduced. Specifically, with the exception of the SPI200, the regression analysis shows that message traffic is positive and significant at the 1% level for 90-day bills, 3-year bonds and 10-year bonds. The results of the order-to-trade ratio[33] also indicate that there are more order submissions; however, only 90-

[31] The regression results inclusive of trading volume are reported in Appendix A.3.2.
[32] The regression results inclusive of trading volume are reported in Appendix A.3.3.
[33] The virtualisation of this market design change for all four contracts is provided in Appendix A.2.

day bills and 3-year bonds are positive and significant at the 1% level. The results of algorithmic trade suggest that there is an increase in HFT activities, which is consistent with Frino, Mollica and Webb (2014). The findings suggest that the purpose of promoting HFT activities has been achieved in the context of a 12-month window pre/post the introduction of co-location technology on 20 February 2012. While Frino, Mollica and Webb (2014) indicate mixed evidence in terms of the order to trade ratio and HFT proxies developed by Hendershott, Jones and Menkveld (2011), the results of the present analysis suggest that there is a clear increase in the order to trade ratio for the 90-day bills and 10-year bonds. Using the examination of the co-location variables results as a reference point, Table 3.2 shows whether an increase in HFT activities led to an improvement in market liquidity. The findings confirm an improvement in liquidity. In particular, the co-location variables for all spread proxies are negative and significant. However, while the effective spread suggests that there is a decrease in the cost of trading in the investigated contracts (with the exception of 10-year bonds), the co-location coefficient is significant only in the case of the 90-day bill contract. The results of the adjusted R^2 are not high for this spread measure, especially for government bonds, where both products only generate an adjusted R^2 of just under 3%, whereas the SPI200 and 90-day bills have an adjusted R^2 of 10% and 13%, respectively. In particular, the reduction in an effective spread for 90-day bills can be associated with the considerable increase in its quote messages and, especially, order to trade ratio in the aftermath of the introduction of co-location, as shown in Table 3.1.[34] Furthermore, the reduction in examined bid-ask spreads across all four contracts indicates that there is more available liquidity in the market. Riordan and Storkenmaier (2012) explain that the decrease in quoted and effective spread arises from the decline in adverse selection costs. This is because the increased number of HFT activities reduce the competition for liquidity provision. This phenomenon is in line with Hendershott, Jones and Menkveld (2011). However, overall, it would appear that the co-location of HFT facilities reduces the examined spreads across the four contracts, thus reinforcing its positive contribution to the liquidity of the Australian futures market.

[34] It should be noted that the effective spread for 90-day bills is observed to decrease by 0.0003 or 0.3 basis points post co-location with a statistical significance at 1%. This phenomenon could be associated with an increase in the number of transactions and the reduction in trade size together with the overall improvement in bid-ask spreads. More information regarding the summary statistics of market activity measures pre and post the introduction of co-location can be found in Appendix A.3.1.

Table 3.2: Impact of co-location of HFT facilities on market liquidity[35]

Variable	SPI200		90-day bills		10-Year bonds		3-Year bonds	
Bid-ask spread (tick)	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Intercept	1.22520	13.84200 ***	0.00980	17.87800 ***	0.00580	25.53800 ***	0.01010	96.04100 ***
Colocation	(-0.15300)	(-5.90800) ***	(-0.00030)	(-2.75400) ***	(-0.00040)	(-10.56700) ***	(-0.00020)	(-7.22000) ***
Open Interest	0.0000009	2.02200 **	0.00000	1.24000	(-0.00000)	(-1.97300) **	0.00000	0.20500
Intraday Volatility	12.69550	8.17000 ***	1.25160	6.32700 ***	0.30050	5.51100 ***	0.23540	9.67300 ***
Adjusted R2	***37.70%***		***28.70%***		***25.20%***		***27.90%***	
Bid-ask spread (percentage)	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Intercept	0.02830	11.82200 ***	0.01040	18.19000 ***	0.00610	25.91200 ***	0.01050	100.80300 ***
Colocation	(-0.00210)	(-2.98500) ***	(-0.00050)	(-4.23500) ***	(-0.00050)	(-12.97200) ***	(-0.00040)	(-12.63700) ***
Open Interest	0.00000	0.22300	0.00000	1.15800	(-0.00000)	(-1.92300) *	0.00000	0.99300
Intraday Volatility	0.45430	10.28200 ***	1.28640	6.31600 ***	0.28990	5.12900 ***	0.19770	7.98300 ***
Adjusted R2	***42.30%***		***29.90%***		***30.60%***		***40.90%***	
Relative Spreads	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Intercept	1.22520	13.84200 ***	98.26340	17.87800 ***	115.51110	25.53800 ***	101.09160	96.04100 ***
Colocation	(-0.15300)	(-5.90800) ***	(-3.02370)	(-2.75400) ***	(-8.07570)	(-10.56700) ***	(-2.26520)	(-7.22000) ***
Open Interest	0.00000	2.02200 **	0.00003	1.24000	(-0.00002)	(-1.97300) **	0.00000	0.20500
Intraday Volatility	12.69550	8.17000 ***	12,520.00000	6.32700 ***	6,009.04890	5.51100 ***	2,354.13890	9.67300 ***
Adjusted R2	***37.70%***		***28.70%***		***25.20%***		***27.90%***	
Effective Spread	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
Intercept	(-0.00002)	(-0.22700)	0.00010	40.79400 ***	0.00005	3.54300 ***	0.00010	17.24000 ***
Colocation	(-0.00001)	(-0.27300)	(-0.00000)	(-4.78200) ***	0.00000	0.18400	(-0.00000)	(-0.79800)
Open Interest	0.00000	2.16500 **	(-0.00000)	(-0.16100)	0.00000	0.04000	0.00000	1.06800
Intraday Volatility	0.01150	3.88000 ***	0.00380	2.27600 **	0.01790	3.22200 ***	0.00440	1.84200 *
Adjusted R2	***10.40%***		***12.60%***		***2.90%***		***2.60%***	

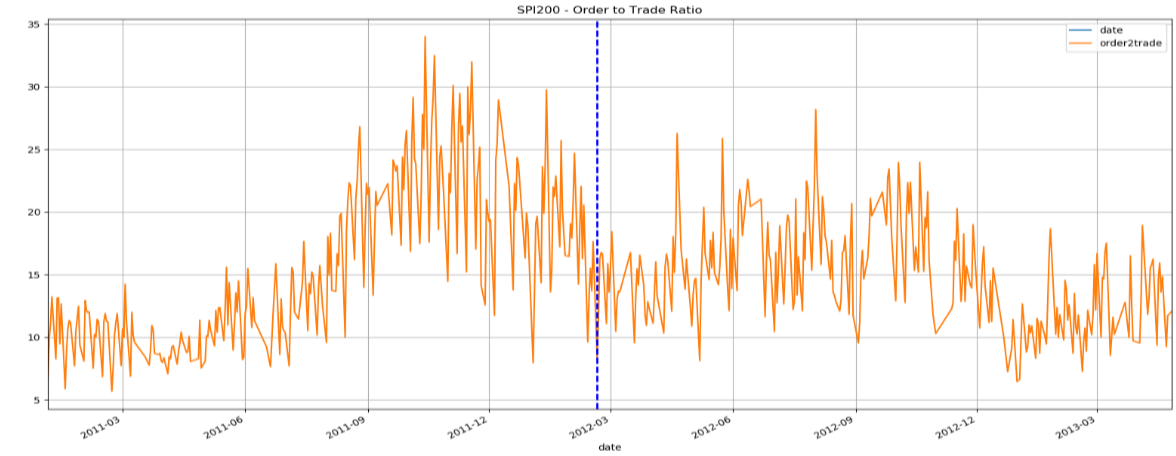
Note: This table reports the impact of co-location technology on Australian futures market liquidity. Changes in quoted spread (absolute value and percentage), relative spread (constrained at minimum tick) and volume-weighted effective spread are also presented. A dummy variable is used to set co-location to 0 prior to 20 February 2012 and 1 after 20 February 2012. Control variables are open interest and intraday volatility or high-low time-weighted midpoint price volatility. ***, ** and * indicates statistical significance at the 1%, 5% and 10% levels, respectively.

The above analyses show that while there is an increase in market liquidity, there is a decrease in quote messages of the SPI200. According to Frino, Mollica and Webb (2014), this phenomenon can be explained by the introduction of the ASX equities market message traffic charge in January 2012, as shown by the structural break in Figures 3.1 and 3.2.[36] Regardless of this finding, the liquidity of the SPI200 is found to increase notably after the co-location technology is introduced, which could be explained by increased HFT message traffic. Figure 3.1 indicates the order to trade ratio for the SPI200 contract 12 months pre/post the introduction of the co-location technology. The y-axis indicates the order to trade ratio, while the x-axis represents trading days. The structural break in January 2012 was likely caused by the introduction of the equities market traffic message charge, which had direct implications for HFT firms with arbitrage activities in equities and futures markets. Figure 3.2 indicates the absolute relative spread for the SPI200 contract 12 months pre/post the introduction of the co-location technology. The y-axis represents the absolute relative spread, while the x-axis

[35] The regression results inclusive of trading volume is reported in Appendix A.3.3.
[36] The virtualisation for each futures contract can be found in Appendix A.2.

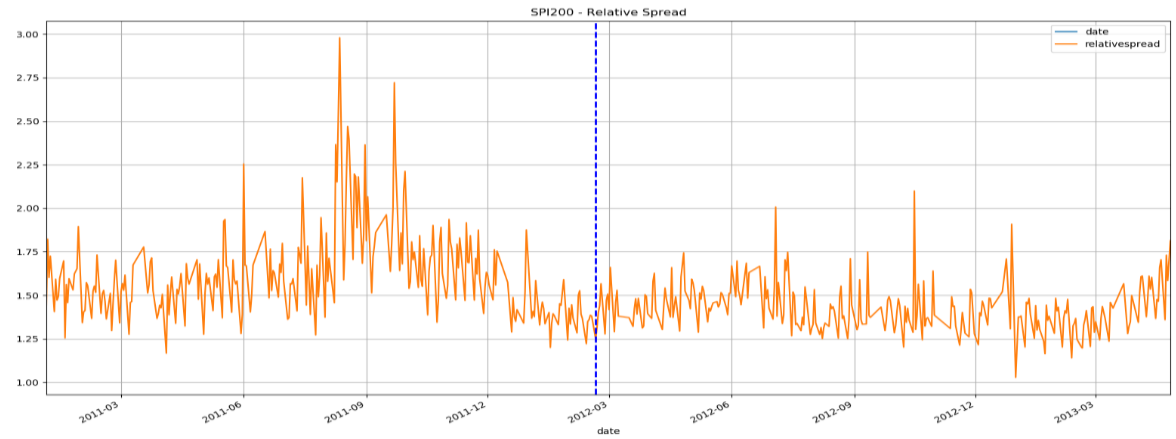
indicates trading days. It is clear that there was a sharp decrease in the spread after 20 February 2012, implying higher liquidity in the aftermath of the upgrade.[37]

Figure 3.1: Order to trade ratio of SPI200 pre/post co-location



Source: Developed for this research

Figure 3.2: Absolute relative spread of SPI200 pre/post co-location



Source: Developed for this research

From the above discussion, it can be asserted that the increase of HFT activities due to co-location facilities/technology seems to have positively impacted the Australian futures market,

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[37] As observed in Figure 3.1, the market participants' reaction to the announcement of the cost recovery charge may influence the empirical results of this investigation. In order to ensure the robustness of the empirical findings, the present investigation also generates the empirical evidence regarding the impact of co-location of HFT facilities on trading activities without the month of November and December in year 2011. It is observed that the findings remain robust even after controlling for the impacted months. The details can be found in Appendix A.3.4.

contributing to the increased liquidity of all four contracts under investigation. It is also important to establish whether the Australian futures market has the capacity to absorb information efficiently and effectively so that the likelihood of arbitrage trading opportunities can be kept to a minimum. Therefore, the remainder of this chapter addresses how to identify major announcements, placing particular emphasis on how quickly major announcements become impounded into financial prices by examining the adjustment speed of the Australian futures market. However, the next section (Section 3.4.2) is a pre-requisite for the investigation of market adjustment speed, as it provides empirical evidence to support the selection criteria of major macroeconomic news announcements, which will be employed in analysing the impact of HFT activities on the speed of market adjustment in the remainder of the chapter.

3.4.2 Identification of major scheduled announcements

Table 3.3 demonstrates the impact of major macroeconomic announcements on volatility across the four futures contracts. The common macroeconomic announcements across all four contracts are building approvals, consumer price index, gross domestic product, home loans, investment lending, NAB business confidence, producer price index, retail sales and the unemployment rate. Unlike Smales (2013), who identified that interest rate contracts share the same reaction to macroeconomic announcements, the present investigation suggests that 10-year bonds seem to react more to some announcements compared to other interest rate contracts (e.g., 90-day bills and 3-year bonds). This finding signals a need to explore each contract according to specific major macroeconomic announcements.

In the case of the SPI200, most major macroeconomic announcements, except announcements regarding private capital expenditure and the private credit sector, seem to have a substantial impact on MPV, which contradicts the findings of Frino and Hill (2001). This difference may be attributable to the announcement sample size and timeframe (2 August 1995 to 21 August 1997) employed by the authors at that time. Moreover, most of their investigated announcements were found to be statistically insignificant, as some announcement types only had six or fewer data points in the sample. The findings of the present investigation suggest that the SPI200 is sensitive to macroeconomic announcements. As the SPI200 is widely used as a derivative benchmark for hedging the Australian equity market, this makes the SPI200 an ideal candidate to examine the efficiency status of the Australian futures market.

Table 3.3: The impact of major macroeconomic announcements on volatility at 11:30 am

Dependent Variable: MPV	**SPI200**		**90-day bills**		**10-year bonds**		**3-year bonds**		**Other**	
	Coefficient	***t-statistics***	***Coefficient***	***t-statistics***	***Coefficient***	***t-statistics***	***Coefficient***	***t-statistics***	**Sample**	**Frequency**
Intercept	19.6	13.739 ***	0.01	1.68 *	0.01	1.43	0.01	1.39		
ANZ job advertisements	39	3.422 ***	(-0.02)	(-0.42)	(-0.02)	(-0.69)	(-0.03)	(-0.55)	90	Monthly
Building approvals	248.7	15.86 ***	0.6	8.04 ***	0.7	12.11 ***	0.9	10.02 ***	89	Monthly
Company operating profit	44.1	4.158 ***	0.02	0.56	0.1	2.99 ***	0.1	2.22 **	30	Quarterly
Construction work done	153	8.106 ***	0.09	1.49	0.2	3.49 ***	0.2	2.32 **	30	Quarterly
Consumer price index	380.4	15.315 ***	4.2	9.94 ***	3	16.74 ***	5.9	14.67 ***	30	Quarterly
Current account balance	104.9	4.7 ***	0.3	2.44 **	0.3	2.93 ***	0.2	1.1	29	Quarterly
Dwelling starts	66.5	2.712 ***	0.01	0.23	0.08	1.35	0.2	2.47 **	11	Quarterly
Export price index	126.1	6.763 ***	(-0.05)	(-1.28)	0.1	2.82 ***	0.2	2.54 **	30	Quarterly
Gross domestic product	176.2	5.257 ***	0.6	4.77 ***	0.7	5.08 ***	1	4.82 ***	30	Quarterly
Home loans	29.7	6.875 ***	0.06	3.4 ***	0.08	5.68 ***	0.08	4.15 ***	90	Monthly
House price index	53.9	3.251 ***	0.02	0.4	0.2	2.99 ***	0.1	1.61	34	Quarterly
Inventories SA	44.1	4.158 ***	0.02	0.56	0.1	2.99 ***	0.1	2.22 **	30	Quarterly
Investment lending	29.7	6.875 ***	0.06	3.4 ***	0.08	5.68 ***	0.08	4.15 ***	90	Monthly
Job vacancies	114.2	6.785 ***	(-0.00)	(-0.07)	(-0.00)	(-0.09)	0.06	0.94	30	Quarterly
NAB business confidence	34.4	4.608 ***	0.09	2.68 ***	0.1	5.54 ***	0.2	4 ***	90	Monthly
New motor vehicle sales	133.2	12.195 ***	(-0.02)	(-0.53)	0.06	2.04 **	0.1	2.06 **	89	Monthly
Private capital expenditure	4	0.364	0.2	2.23 **	0.1	2.22 **	0.2	2.04 **	30	Quarterly
Private sector credit	-11.4	(-1.5780)	(-0.03)	(-0.73)	0.02	0.77	0.01	0.25	90	Monthly
Producer price index	85.7	5.447 ***	0.5	4.38 ***	0.4	4.94 ***	1.1	6.62 ***	30	Quarterly
Retail sales	107.7	7.253 ***	0.5	7.05 ***	0.6	10.3 ***	1	9.97 ***	90	Monthly
Trade balance	76.5	6.182 ***	0	0.07	0.2	4.07 ***	(-0.03)	(-0.41)	90	Monthly
Unemployment rate	513.5	27.826 ***	3.3	17.58 ***	2.5	25.39 ***	4.7	24.8 ***	90	Monthly
Wage price index	97.3	5.668 ***	0.1	1.86 *	0.2	3.7 ***	0.3	3.11 ***	30	Quarterly
Adjusted R2	***35.50%***		***32.70%***		***44.70%***		***45.60%***			

Note: This table demonstrates the impact of major macroeconomic announcements on volatility across the four futures contracts. The dependent variable is MPV in the first 30-second interval following the respective macroeconomic announcement over the timeframe investigated (e.g., 1 January 2010 to 30 June 2017). A significant level of 0.005 is employed to identify major announcements. The reported coefficients are 1,000 times actual coefficients. ***, ** and * denotes statistical significance at the 0.5%, 5% and 10% level, respectively.

The cash rate (unreported in Table 3.3) is chosen as an additional announcement because of its significance to the Reserve Bank of Australia's (RBA's) monetary policy settings. For instance, Smales (2012) demonstrates that the RBA employs the cash rate as a primary instrument to maintain balance in the official money market at a set rate. In the present investigation, a particular focus is placed on the cash rate for two reasons: first, unlike the US and European markets, the cash rate announcement is independent of liquidity factors in Australia; and second, the outcomes of the RBA's policy decisions are understood to be binary. The results imply that all participants will become aware of the cash rate decision simultaneously at the scheduled announcement time (2:30 pm). Given the importance of the RBA cash rate announcement to Australian financial markets, a comprehensive review of the associated market adjustment speed across the four contracts was warranted. Hence, empirical results for the remainder of the chapter are presented in two parts: the first part is titled 'Macroeconomic announcements' and refers to all major macroeconomic announcements that are released at 11:30 am; and the second part is titled 'Cash rate announcement', which refers only to the release of the RBA's daily cash rate decision at 2:30 pm.

3.4.3 Market adjustment speed

The speed at which macroeconomic announcements become impounded into the prices of the four futures contracts is addressed in this subsection. MPV and TPV are employed to capture the market reaction speed to the macroeconomic and cash rate announcements, as specified above. Both volatility measures should increase when the information first arrives, and then return to normal once the information is acknowledged and impounded into financial prices. Table 3.4 shows one-tail t-test results in an attempt to determine the completion of information adjustment into the financial prices of the four contracts. The TPV findings suggest that the market requires only 1 minute and 45 seconds for the SPI200, 3 minutes 10 seconds for 10-year bonds, 8 minutes and 15 seconds for 3-year bonds, and 14 minutes and 30 seconds for 90-day bills, for information conveyed in the macroeconomic announcements to become fully impounded. However, the results based on MPV suggest that the market requires more time to digest information, as it takes longer for the market to agree on what is the best price after major macroeconomic announcements. For example, the MPV results indicate that the SPI200 requires approximately 32 minutes 35 seconds for information to become impounded. Completed adjustment times for 90-day bills, 10-year bonds and 3-year bonds are somewhat less, being 20 minutes 50 seconds, 15 minutes 40 seconds and 10 minutes 30 seconds, respectively.[38]

Table 3.4: Volatility persistence on major macroeconomic announcement days at 11:30 am

Panel A: Midpoint Volatility (MPV)	**SPI200**	**90-day bills**	**10-year bonds**	**3-year bonds**
t_statistic	1.9218	1.8255	1.7528	1.8035
p_value	0.0274	0.0342	0.04	0.0359
Benchmark	134.0176	0.1197	0.1332	0.1168
Announcement days	116.5192	0.0387	0.0875	0.051
Adjustment Time (24-hour clock)	***12:02:35***	***11:50:50***	***11:45:40***	***11:40:30***
Half-life benchmark	203.9245	0.4565	0.3782	0.6056
Peak volatility on announcement days	270.4971	1.5387	0.9097	2.0079
Half-life adjustment time(24-hour clock)	***11:30:20***	***11:30:20***	***11:30:25***	***11:30:20***
Panel B: Trade Price Volatility (TPV)				
t_statistic	2.385	1.7893	2.2983	2.1236
p_value	0.0086	0.0392	0.011	0.0174
Benchmark	143.7658	0.3415	0.273	0.3932
Announcement days	112.1909	0	0.1431	0.1203
Adjustment Time (24-hour clock)	***11:31:45***	***11:44:30***	***11:33:10***	***11:38:15***
Half-life benchmark	205.9266	0.686	0.7614	1.0678
Peak volatility on announcement days	293.5326	1.9091	1.3721	2.6705
Half-life adjustment time (24-hour clock)	***11:30:15***	***11:30:10***	***11:30:10***	***11:30:15***

Note: Panels A and B report estimates of market adjustment speed in response to major macroeconomic announcements for each contract based on MPV and TPV, respectively. MPV and TPV values are reported 1,000 times the actual value. Benchmark refers to the unconditional means of non-major announcement days. Announcement days refers to a particular interval where financial prices become completely impounded. Half-life benchmark refers to the benchmark where volatility value decays half-way from its peak volatility. Peak volatility refers to the value when the volatility spike reaches its maximum on announcement days.

In relation to the half-life market adjustment speed, both MPV and TPV commend the efficiency of the Australian futures market, highlighting that it takes only a matter of just a few seconds for the market to halve its unconventional benchmark after reaching peak volatility. For instance, Panel A shows that MPV decays half-way 20 seconds after major announcements

[38] As a robustness check, an exchange-traded fund (ETF), known as STW, was chosen as a proxy for the Australian equity market. ETFs are commonly used to track underlying equity benchmarks or fund indices, especially at the intraday level (Gallagher & Segara, 2005). Scheduled macroeconomic announcements are found to have minimal impact on the Australian equity market; therefore, there is a lack of trading activities around announcement days. As expected, investors would prefer to trade the SPI200 as a means of hedging and rebalancing their portfolios. Empirical results for STW are reported in Appendix A.5.

(with the exception of 10-year bonds, which require an additional 5 seconds). Panel B demonstrates that the market is even more efficient when it is observed through the lens of TPV. In particular, TPV comes back to half after its peak within 15 seconds for SPI200 and 3-year bonds, and only 10 seconds for the 90-day bills and 10-year bonds.

It can be observed that the peak volatility values of both MPV and TPV on major announcements across the four futures contracts are substantial relative to their half-life benchmarks. As shown in Table 3.4, for instance, in the case of 90-day bills, 3-year bonds and 10-year bonds, their volatility values increase more than threefold on major announcement days compared to non-major announcement days. The SPI200 is also responsive to major announcements but not as much compared to its peers, only increasing by approximately 33%[39] on average compared to non-major announcement days. The above half-life adjustment time findings suggest that the Australian futures market is efficient, particularly given that information is being impounded into financial prices in less than 25 seconds in terms of MPV, and 15 seconds in terms of TPV, across the interest rate contracts and SPI200.[40]

The empirical results of the analysis reported in Table 3.4 suggest that Australian futures market efficiency has improved significantly since the time of the studies undertaken by Frino and Hill (2001) and Smales (2013), who reported that the SPI200 and interest rate futures contracts rapidly adjusted to major announcements within 30 seconds. In terms of full adjustment speed, the Australian futures market also seems to have improved, as the SPI200 is found to return to normal after 1 minute and 45 seconds, which is considerably faster than the full adjustment speed of four minutes reported by Frino and Hill (2001). Although Frino and Hill (2001) employed non-major parametric, Brown-Forsythe modified Levene F-tests to capture the full adjustment speed of the SPI200 using MPV, they did not specify when MPV returns to normal.

The findings of the present investigation contribute to the literature by showing that the SPI200 takes more than 30 minutes to become fully adjusted to major macroeconomic announcements. This is longer compared to TPV. However, both volatility metrics focus on different features of the market adjustment speed. TPV captures market participants' response to major announcements through actual transactions, whereas MVP captures market responses by

[39] MPV of the SPI200 increases from 203.92 on non-major announcement days to 270.49 on announcement days, whereas TPV increases from 205.93 on non-major announcement days to 293.53 on announcement days.
[40] Virtualisation of the market adjustment speed for the four futures contracts can be found in Appendices A.2 and A.4.

through quotations placed into the order book. It is logical for the TPV to get corrected faster, as some investors may be impatient if not overestimate the precision of their private information, as demonstrated by Benos (1998). Therefore, market participants tend to agree on an actual trading price more efficiently compared to the reference price or the midpoint price. However, the midpoint price is significantly influenced by the way more informed traders like market makers agree on the equilibrium value of the contracts. The longer adjustment for MPV implies that the market requires more time to establish a new best price, as market participants (e.g., business/investment analysts) need to comprehend such announcements and form decisions based upon what they understand to be the likely impacts. Further, Ederington and Lee (1993) explained that even in an efficient market, volatility may remain high for some time, as the market takes time to absorb such information; however, it is unlikely that trading profits can be achieved if volatility is caused by independent information within the market.

Table 3.5 illustrates the empirical results of market adjustment speed to cash rate announcements. It can be observed that the cash rate announcement seems to have a greater impact in short maturity futures, explicitly ranked in order from 90-day bills, 3-year bonds, 10-year bonds and the SPI200. The difference between MPV at its peak and the benchmark is documented in Panel A. In particular, it shows that MPV increases significantly for 90-day bills, rising about 2,624% (from 0.021 to 0.57). For the remaining contracts, there is an increase of 682% (from 0.0795 to 0.622) for 3-year bonds, 155% (from 0.1328 to 0.3381) for 10-year bonds and 35% (from 140.09 to 189.32) for the SPI200. Despite the significant differences reported, the four contracts are found to adjust to information conveyed in the cash rate announcement relatively efficiently.

Table 3.5 also indicates that the 90-day bill is the quickest to respond compared to its counterparts, requiring only 11 minutes to reach its completion stage based on MPV. It is followed by 3-year bonds, 10-year bonds and the SPI200, taking 18 minutes 30 seconds, 23 minutes 50 seconds, and 38 minutes, respectively, before establishing best prices. A similar observation is noted for the results based on TPV, with the market reaching a resolution to information uncertainty relatively quickly. The present investigation documents the full adjustment time to be 8 minutes and 20 seconds for 90-day bills, 10 minutes and 45 seconds for 3-year bonds, 6 minutes 50 seconds for 10-year bonds, and 9 minutes and 55 seconds for the SPI200. In terms of half-life adjustment times, Panels A and B indicate that the SPI200 is the quickest contract among its peers to respond, taking only 10 seconds to decay to half-life after peak volatility. The half-life speed for 90-day bills decreases from 15 seconds to 10 seconds, while the 3-year bond's half-life adjustment remains unchanged. Lastly, Panels A and B show that 10-year bonds take approximately 15 seconds and 20 seconds to return to half-life, respectively.

Table 3.5: Volatility persistence on cash rate announcement days at 2:30 pm

Panel A: Midpoint Volatility	**SPI200**	**90-day bills**	**10-year bonds**	**3-year bonds**
t_statistic	2.0228	2.1535	2.1999	1.9634
p_value	0.0216	0.0159	0.0140	0.0250
Benchmark	103.3066	0.1146	0.1159	0.1667
Announcement days	86.2437	0.0263	0.0616	0.0667
Adjustment Time (24-hour clock)	***15:08:00***	***14:41:00***	***14:53:50***	***14:48:30***
Half-life benchmark	140.0954	0.0210	0.1328	0.0795
Peak volatility on announcement days	189.3290	0.5721	0.3381	0.6220
Half-life adjustment time (24-hour clock)	***14:30:10***	***14:30:15***	***14:30:15***	***14:30:15***
Panel B: Trade Price Volatility				
t_statistic	1.7268	1.8217	1.6703	2.2675
p_value	0.0423	0.0367	0.0479	0.0122
Benchmark	90.7533	0.4746	0.2333	0.5842
Announcement days	69.1997	0.0000	0.1177	0.174
Adjustment Time (24-hour clock)	***14:39:55***	***14:38:20***	***14:36:50***	***14:40:45***
Half-life benchmark	141.2370	0.1071	0.2728	0.3323
Peak volatility on announcement days	224.4693	1.6879	0.6797	1.7140
Half-life adjustment time (24-hour clock)	***14:30:10***	***14:30:10***	***14:30:20***	***14:30:15***

Note: Panels A and B report estimates of market adjustment speed in response to the cash rate announcement for each contract based on MPV and TPV, respectively. MPV and TPV values are reported 1,000 times the actual value. Benchmark refers to the unconditional means of non-major announcement days. Announcement days refers to a particular interval where financial prices become completely impounded. Half-life benchmark refers to the benchmark where volatility value decays half-way from its peak volatility. Peak volatility refers to the value when the volatility spike reaches its maximum on announcement days.

3.4.4 Price adjustment patterns

Table 3.6 reports the speed of the midpoint price adjustment after major macroeconomic announcement days. The magnitude of price adjustment in each 5-second interval is estimated by calculating the AAR based on the midpoint price. The AARs and CARs are obtained for announcement days. The results show that there are positive and significant t-stats at the 0.1% level across all four futures contracts, particularly within 30 seconds after the announcements.

Table 3.6: Average adjusted return based on midpoint price on major macroeconomic announcement days at 11:30 am

5-second Return Interval	SPI200			90-day bills			10-year bonds			3-year bonds		
	AAR	t-stat	CAR	AAR	t-stat	CAR	AAR	t-stat	CAR	AAR	t-stat	CAR
(0, 5)	6.77	7.27 ***	6.77	1.96	2.73 **	1.96	0.60	3.24 ***	0.60	0.82	2.85 **	0.82
(5, 10)	6.55	7.11 ***	13.32	2.02	3.09 **	3.98	0.61	3.37 ***	1.20	0.89	3.24 ***	1.71
(10, 15)	6.70	7.19 ***	20.01	1.94	3.20 ***	5.92	0.62	3.37 ***	1.82	0.80	3.08 **	2.50
(15, 20)	6.72	7.12 ***	26.74	1.81	3.09 **	7.74	0.59	3.24 ***	2.41	0.88	3.24 ***	3.38
(20, 25)	6.74	7.12 ***	33.48	2.03	3.32 ***	9.77	0.68	3.64 ***	3.09	0.89	3.24 ***	4.27
(25, 30)	6.73	7.33 ***	40.21	1.81	3.42 ***	11.58	0.61	3.50 ***	3.70	0.79	3.24 ***	5.06
(30, 35)	1.17	1.53	41.38	0.62	1.46	12.20	0.00	0.01	3.71	(-0.04)	(-0.25)	5.02
(35, 40)	1.31	2.12 *	42.69	(-0.09)	(-0.32)	12.11	0.08	0.39	3.78	0.00	0.01	5.02
(40, 45)	0.51	0.92	43.20	(-0.10)	(-0.39)	12.01	(-0.11)	(-0.90)	3.67	0.20	1.67 *	5.22
(45, 50)	(-0.39)	(-0.70)	42.81	(-0.19)	(-0.64)	11.82	0.00	0.00	3.67	0.12	1.34	5.34
(50, 55)	0.35	0.57	43.15	0.39	1.07	12.21	0.11	0.68	3.78	(-0.00)	(-0.01)	5.34
(55, 60)	(-0.01)	(-0.02)	43.14	(-0.31)	(-1.15)	11.90	0.23	1.50	4.01	0.21	1.67 *	5.55
(60, 65)	(-0.47)	(-0.75)	42.67	(-0.10)	(-0.33)	11.80	0.08	0.44	4.09	(-0.17)	(-1.63)	5.38
(65, 70)	0.16	0.27	42.83	0.00	0.00	11.80	(-0.08)	(-0.57)	4.01	0.17	1.26	5.56
(70, 75)	0.49	0.94	43.31	0.21	1.00	12.01	(-0.16)	(-1.41)	3.85	0.26	1.74 *	5.82
(75, 80)	1.54	2.48 **	44.85	0.20	0.72	12.21	0.08	0.71	3.93	(-0.33)	(-2.01)	5.49
(80, 85)	(-0.03)	(-0.05)	44.82	0.52	2.25 *	12.74	0.20	1.00	4.13	(-0.04)	(-0.46)	5.44
(85, 90)	0.56	1.05	45.39	0.11	0.59	12.85	0.08	0.81	4.21	0.04	0.45	5.49
(90, 95)	0.21	0.37	45.60	0.42	2.01 *	13.27	0.00	0.02	4.22	(-0.00)	(-0.00)	5.49
(95, 100)	1.38	2.17 *	46.98	0.22	1.42 3.00	13.50	(-0.08)	(-1.00)	4.13	0.32	1.95 *	5.81
(100, 105)	(-0.66)	(-1.19)	46.31	(-0.23)	(-1.42)	13.27	(-0.00)	(-0.01)	4.13	0.14	1.34	5.95
(105, 110)	0.30	0.62	46.62	0.22	1.42	13.49	0.00	0.01	4.13	(-0.19)	(-1.08)	5.76
(110, 115)	0.35	0.76	46.97	0.35	1.74 *	13.84	(-0.21)	(-1.52)	3.92	0.19	1.27	5.95
(115, 120)	0.35	0.74	47.33	(-0.12)	(-0.45)	13.73	(-0.04)	(-0.34)	3.87	(-0.05)	(-1.00)	5.91
(120, 125)	(-1.02)	(-2.09)	46.30	0.11	1.00	13.84	(-0.17)	(-1.42)	3.71	0.19	1.42	6.09

Note: *, ** and *** denotes 5%, 1% and 0.1%, respectively. The results of AAR and CAR are reported at 1,000,000 times their actual value.

Table 3.7: Average adjusted return based on midpoint price on cash rate announcement days at 2:30 pm

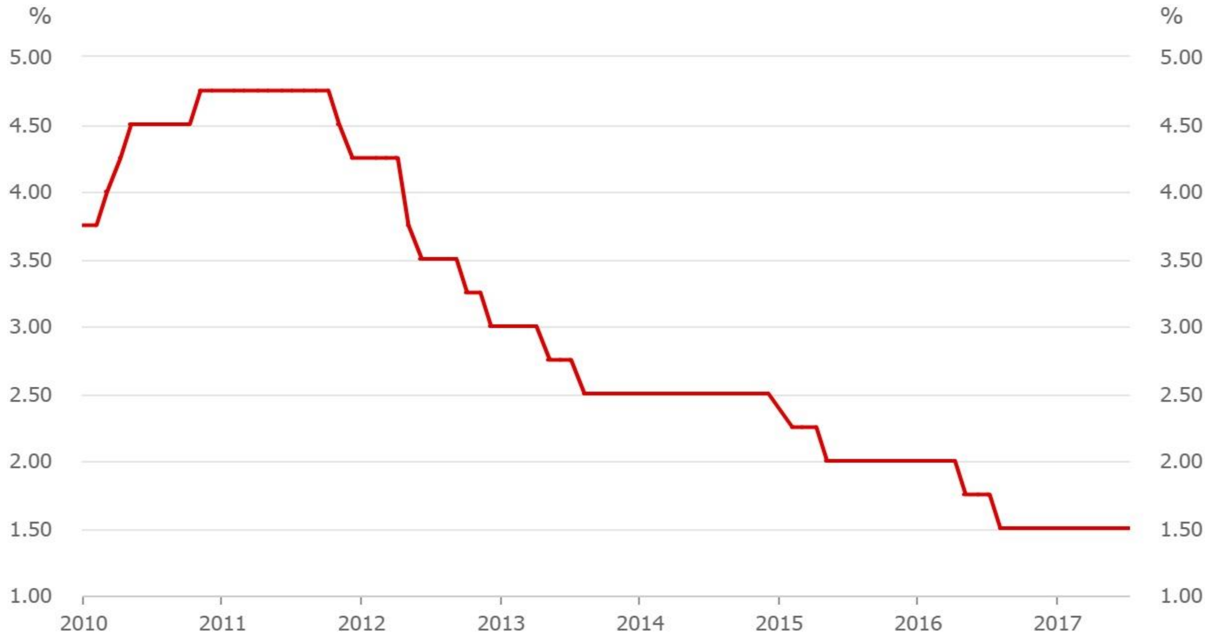
5-second Return Interval	SPI200			90-day bills			10-year bonds			3-year bonds		
	AAR	t-stat	CAR	AAR	t-stat	CAR	AAR	t-stat	CAR	AAR	t-stat	CAR
(0, 5)	(-0.01)	(-0.00)	(-0.01)	2.66	0.77	2.66	1.24	1.14	1.24	2.35	1.77 *	2.35
(5, 10)	1.33	0.55	1.32	2.27	0.77	4.93	1.28	1.15	2.53	2.07	1.77 *	4.42
(10, 15)	1.33	0.55	2.66	4.72	1.77 *	9.64	1.97	1.94 *	4.5	2.66	2.05 *	7.08
(15, 20)	(-0.01)	(-0.00)	2.65	2.30	0.77	11.94	1.13	1.14	5.63	2.84	2.06 *	9.92
(20, 25)	(-0.01)	(-0.00)	2.64	2.14	0.77	14.09	1.13	1.14	6.76	2.70	2.05 *	12.62
(25, 30)	(-0.01)	(-0.00)	2.63	2.72	1.00	16.81	1.43	1.43	8.19	2.63	2.05 *	15.25
(30, 35)	7.1	1.97 *	9.73	(-2.23)	(-0.84)	14.57	(-1.80)	(-1.71)	6.39	(-1.99)	(-1.36)	13.25
(35, 40)	0.00	n/a	9.73	1.41	0.50	15.98	0.36	1.01	6.75	0.67	1.01	13.93
(40, 45)	(-2.50)	(-0.92)	7.23	(-2.88)	(-1.66)	13.10	0.73	1.43	7.48	(-0.00)	(-0.00)	13.92
(45, 50)	4.65	1.39	11.87	(-0.00)	(-0.00)	13.09	(-2.33)	(-1.77)	5.15	0.00	0.00	13.92
(50, 55)	0.02	0.01	11.89	(-2.89)	(-1.67)	10.21	(-1.50)	(-0.95)	3.66	0.68	1.01	14.61
(55, 60)	(-1.26)	(-0.53)	10.64	(-0.73)	(-1.01)	9.48	0.75	1.01	4.41	(-0.02)	(-0.02)	14.59
(60, 65)	(-0.26)	(-0.13)	10.38	(-0.03)	(-0.01)	9.45	0.00	n/a	4.41	(-1.35)	(-1.43)	13.24
(65, 70)	(-0.26)	(-0.13)	10.11	(-3.68)	(-1.70)	5.77	(-0.39)	(-0.60)	4.02	0.00	n/a	13.24
(70, 75)	1.57	0.62	11.68	0.00	0.00	5.77	(-0.00)	(-0.00)	4.02	0.00	n/a	13.24
(75, 80)	1.46	1.01	13.14	0.75	0.45	6.52	0.39	1.01	4.41	(-0.70)	(-1.01)	12.54
(80, 85)	(-0.03)	(-0.01)	13.11	3.78	1.94 *	10.30	0.41	0.61	4.82	0.68	1.01	13.22
(85, 90)	1.42	1.01	14.54	(-2.30)	(-1.35)	8.00	(-0.37)	(-1.01)	4.45	0.00	n/a	13.22
(90, 95)	1.30	1.01	15.83	(-0.02)	(-0.01)	7.98	(-1.89)	(-1.16)	2.56	0.00	n/a	13.22
(95, 100)	3.50	1.11	19.33	(-0.73)	(-1.01)	7.25	1.16	1.36	3.72	0.00	n/a	13.22
(100, 105)	2.78	1.43	22.12	2.35	1.77 *	9.60	0.41	1.01	4.14	0.00	n/a	13.22
(105, 110)	(-1.39)	(-1.01)	20.72	(-0.73)	(-1.01)	8.87	0.82	1.44	4.96	1.46	1.43	14.68
(110, 115)	3.08	1.06	23.8	(-0.82)	(-1.01)	8.05	(-0.79)	(-1.44)	4.17	0.00	n/a	14.68
(115, 120)	1.42	1.01	25.22	(-0.72)	(-0.59)	7.32	0.38	1.01	4.55	0.00	n/a	14.68
(120, 125)	(-0.15)	(-0.07)	25.07	(-0.75)	(-0.59)	6.57	0.39	0.58	4.94	0.00	n/a	14.68

Note: *, ** and *** denotes 5%, 1% and 0.1%, respectively. The results of AAR and CAR are reported at 1,000,000 times their actual value.

The (30, 35) AAR interval is small and statistically insignificant, implying the adjustment is completed within 30 seconds. These results are similar to those reported by Ederington and Lee (1995), Frino and Hill (2001), and Smales (2013), who found that the completion of price adjustment was less than 40 seconds. It should also be noted that these results are similar to the findings reported in the previous sub-section, which asserted that the adjustment process occurs within approximately 20 seconds or less; however, volatility may last longer based on MPV. While the AARs provide insight into the trajectory of the midpoint price movement, MPV represents market agreement on the best price. Hence, it would be difficult to generate abnormal profits after 30 seconds of announcement releases in the Australian futures market, as most traders require time to gradually work through the order book before they are able to fully comprehend the full implications of such news and agree on a new equilibrium price. However, it is possible that sophisticated market participants, assisted by high-speed computing technology, could potentially generate excess returns within 30 seconds of the announcement release. For instance, HFT can rapidly automate trading decisions to capture the implications of such information before prices become fully adjusted (i.e., fishing for market signals).

In the case of the cash rate announcement, the market seems to absorb information efficiently (see Table 3.7). In particular, AARs are found to be small and significant at the 5% level within the first 30 seconds for 3-year bonds, 15 seconds for 90-day bills and 10-year bonds following cash rate announcements. No significant evidence is found for the SPI200. Again, this is consistent with the MPV finding, which indicates that the impact of cash rate announcements on the SPI200 is less profound compared to interest rate contracts. These findings show that the Australian futures market impounds information from the cash rate decision announcement quickly and efficiently. This efficiency could be due to the RBA's ability to communicate effectively and transparently. A further reason could be that market participants find RBA cash rate announcements relatively easy to comprehend, particularly given that the cash rate has remained fairly stable since 2014 (see Figure 3.3).

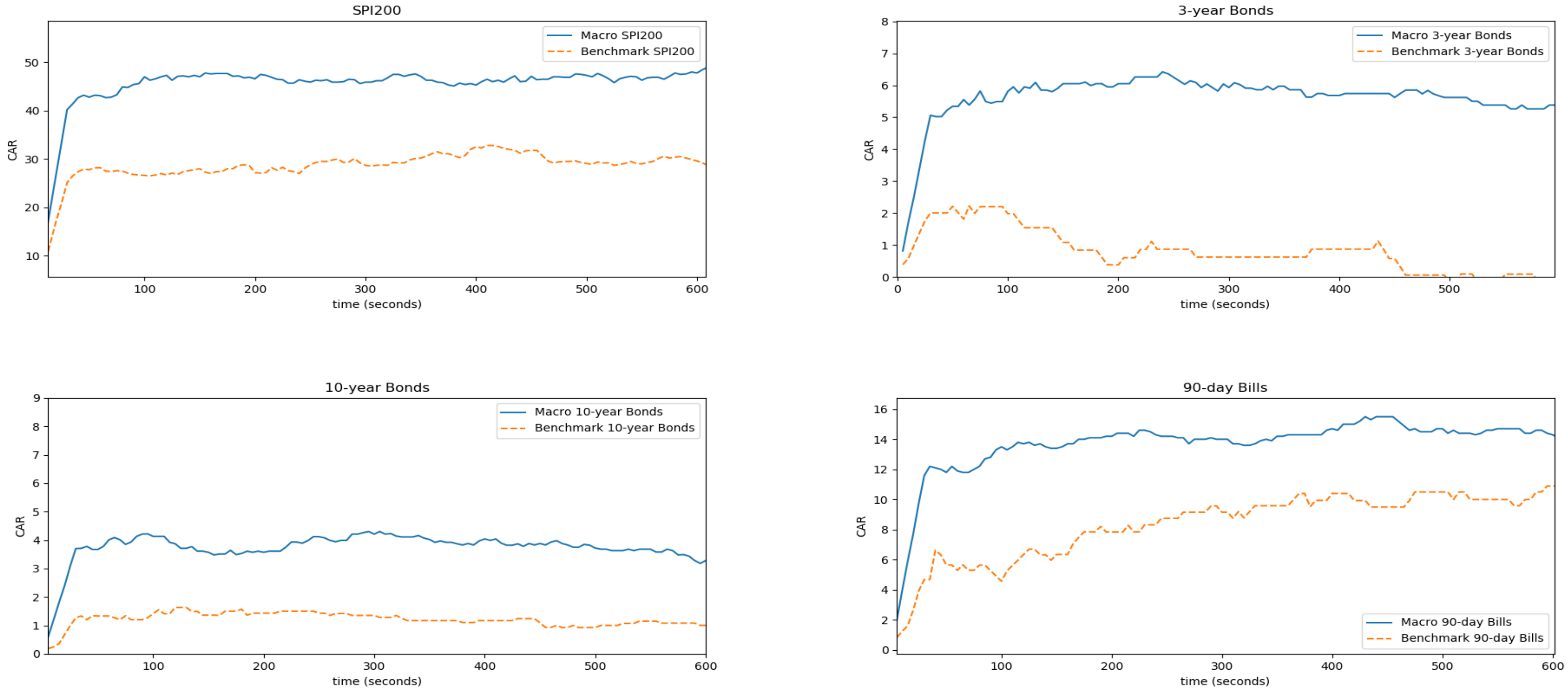
Figure 3.3: Australian cash rate from 1 October 2010 to 30 June 2017



Source: RBA (2017)

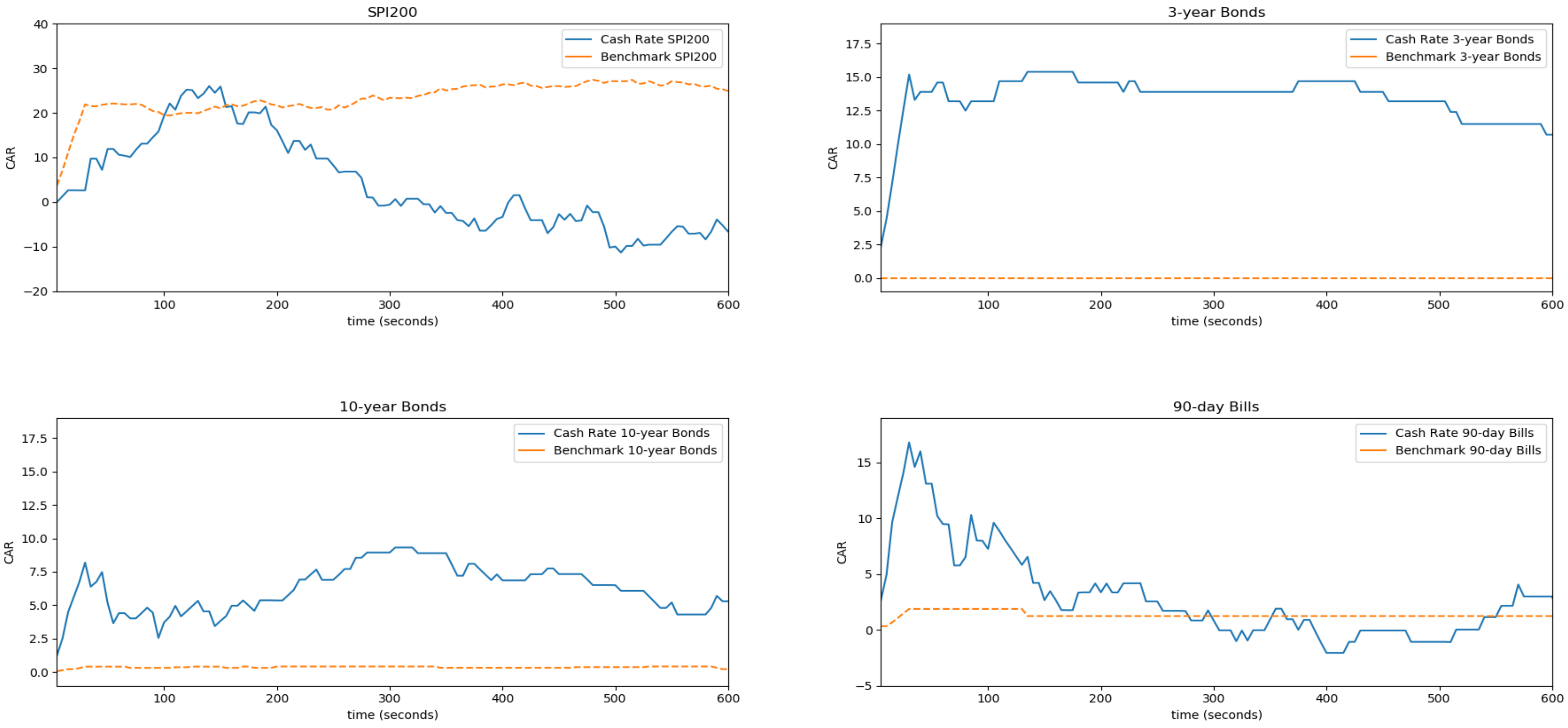
Figures 3.4 and 3.5 also show the midpoint price movement of the four futures contracts after major macroeconomic and cash rate announcements, respectively. As expected, most major market reactions occur mostly within the first 30 seconds for major macroeconomic announcements at 11:30 am. In the case of the SPI200, the release of scheduled macroeconomic announcements is observed to have an impact, whereas there is no evidence of significant returns during cash rate announcements. In the case of the interest rate contracts, AARs seem to be the highest for 90-day bills, followed by 3-year bonds and 10-year bonds. Up to this point, the present investigation has mainly been concerned with aggregated results based on all major announcements within the data set period. However, it is now of interest to examine how the market reacts to each major announcement, and further, to be able to capture the half-life decay of MPV and TPV.

Figure 3.4: Cumulative average adjusted return based on midpoint price on major macroeconomic announcement and non-announcement days at 11:30 am



Note: The solid line represents major macroeconomic announcement days. The dashed line represents major macroeconomic non-announcement days. Reported CARs are actual returns times 1,000,000. *Source*: Developed for this research

Figure 3.5: Cumulative average adjusted return based on midpoint price on cash rate announcement and non-announcement days at 2:30 pm



Note: The solid line represents cash rate announcement days. The dashed line represents cash rate non-announcement days. Reported CARs are actual returns times 1,000,000. *Source:* Developed for this research

3.4.5 Speed of volatility adjustment for each major announcement

This sub-section shows the half-life decay of shocks to volatility for each major announcement. All 5-second intervals of MPV and TPV are included in the half-life model (as per Equation 3.13) in an attempt to estimate the intercept for each major announcement. The intercept value for each announcement represents the half-life of the mean-reverting series, or in other words, the duration of the volatility shock to decay up to half-way towards adjusting to its normal condition. The intercept value is then multiplied by 5 seconds in order to obtain a meaningful figure that can help explain how long it takes an individual announcement to decay half-way from its full adjustment. The significance of such major announcements are able to be observed, based on the length of the speed of the half-life volatility adjustment.

Table 3.8 categorises the announcement type based on the half-life speed of adjustment ranking (from highest to lowest) according to MPV. The results suggest that the unemployment rate is the most important of the scheduled announcements, requiring a half-life adjustment duration of 13.84 seconds for the SPI200, 15.44 seconds for 90-day bills, 17.10 seconds for 10-year bonds and 15.96 seconds for 3-year bonds. This implies that unemployment rate announcements are important to the Australian futures market, particularly with regard to government bonds. Other announcements which are of high importance include the consumer price index, retail sales, cash rate, building approvals and gross domestic product. It should be noted also that the cash rate announcement is more significant to interest rate products, as it takes longer to decay: 10.38 seconds for 90-day bills; 12.01 seconds for 10-year bonds; and 11.48 seconds for 3-year bonds. In contrast, the SPI200 only takes 7.69 seconds to decay in response to the cash rate announcement.

Table 3.8: Half-life decay of shocks to MPV for each major announcement

Persistence of Volatility for Each Major Macroeconomic Announcement "Midpoint Price Volatility"											
SPI200	**Constant**	**Duration of the mean reversion (in seconds)**	**90-day bank bills**	**Constant**	**Duration of the mean reversion (in seconds)**	**10-year bonds**	**Constant**	**Duration of the mean reversion (in seconds)**	**3-year bonds**	**Constant**	**Duration of the mean reversion (in seconds)**
Unemployment rate	2.77	13.84	Unemployment rate	3.09	15.44	Unemployment rate	3.42	17.10	Unemployment rate	3.19	15.96
Consumer price index	1.89	9.44	Cash Rate	2.08	10.38	Cash Rate	2.40	12.01	Cash Rate	2.30	11.48
Retail sales	1.55	7.76	Building approvals	1.61	8.03	Building approvals	2.01	10.06	Consumer price index	2.15	10.75
Cash Rate	1.54	7.69	Retail sales	1.48	7.38	Retail sales	2.00	10.02	Retail sales	1.71	8.56
Building approvals	1.49	7.43	Building approvals	1.26	6.29	Consumer price index	1.93	9.66	Building approvals	1.56	7.81
Gross domestic product	1.19	5.94	NAB business confidence	0.94	4.70	Trade balance	1.40	7.00	Gross domestic product	1.07	5.37
Trade balance	1.16	5.81	Gross domestic product	0.90	4.50	Gross domestic product	1.21	6.07	Producer price index	1.02	5.09
New motor vehicle sales	1.06	5.31	Producer price index	0.80	4.01	Current account balance	1.19	5.94	NAB business confidence	0.94	4.71
Company operating profit	1.02	5.10	Home loans	0.80	3.99	NAB business confidence	1.08	5.38	Wage price index	0.79	3.94
Inventories SA	1.02	5.10	Investment lending	0.80	3.99	Home loans	1.00	5.02	Home loans	0.75	3.77
Current account balance	0.96	4.81				Investment lending	1.00	5.02	Investment lending	0.75	3.77
Export price index	0.92	4.60				Company operating profit	0.98	4.88			
Home loans	0.92	4.59				Inventories SA	0.98	4.88			
Investment lending	0.92	4.59				Producer price index	0.97	4.87			
NAB business confidence	0.91	4.53				Construction work done	0.89	4.44			
Producer price index	0.89	4.46				Export price index	0.84	4.20			
House price index	0.88	4.40				House price index	0.84	4.18			
Construction work done	0.88	4.40				Wage price index	0.82	4.09			
Wage price index	0.87	4.37									

Note: This table provides results of the half-life of volatility shocks for each major announcement across all four futures contracts. The degree of the shock is derived from the half-life duration (which is half the value of the estimated constant of MPV, as described in Equation 3.14). The duration of the mean revision is then obtained by multiplying the constants by 5 seconds in order to obtain meaningful interpretation of the half-life day of shocks to MPV for each major announcement.

Table 3.9: Half-life decay of shocks to TPV for each major announcement

Persistence of Volatility for Each Major Macroeconomic Announcement "Trade Price Volatility"											
SPI200	**Constant**	**Duration of the mean reversion (in seconds)**	**90-day bank bills**	**Constant**	**Duration of the mean reversion (in seconds)**	**10-year bonds**	**Constant**	**Duration of the mean reversion (in seconds)**	**3-year bonds**	**Constant**	**Duration of the mean reversion (in seconds)**
Unemployment rate	1.82	9.12	Cash Rate	1.09	5.44	Unemployment rate	1.63	8.15	Unemployment rate	1.63	8.15
Consumer price index	1.12	5.60	Consumer price index	1.00	5.02	Cash Rate	1.29	6.46	Cash Rate	1.34	6.72
Retail sales	1.08	5.38	Unemployment rate	0.83	4.13	Consumer price index	1.09	5.45	Consumer price index	1.12	5.58
Building approvals	1.07	5.35	Building approvals	0.73	3.64	Retail sales	0.83	4.15	Gross domestic product	0.89	4.46
Cash Rate	1.07	5.33	Gross domestic product	0.73	3.64	Building approvals	0.82	4.12	Building approvals	0.79	3.93
Gross domestic product	0.90	4.48	Retail sales	0.70	3.48	Gross domestic product	0.80	4.00	NAB business confidence	0.76	3.82
Trade balance	0.83	4.16	Producer price index	0.69	3.47	Company operating profit	0.77	3.87	Retail sales	0.75	3.75
New motor vehicle sales	0.83	4.15	Home loans	0.69	3.45	Inventories SA	0.77	3.87	Producer price index	0.72	3.58
Company operating profit	0.83	4.13	Investment lending	0.69	3.45	Trade balance	0.76	3.81	Home loans	0.70	3.49
Inventories SA	0.83	4.13	NAB business confidence	0.68	3.38	NAB business confidence	0.75	3.77	Investment lending	0.70	3.49
Construction work done	0.82	4.12				Export price index	0.73	3.65	Wage price index	0.66	3.32
Home loans	0.82	4.11				Wage price index	0.72	3.59			
Investment lending	0.82	4.11				Construction work done	0.70	3.48			
Current account balance	0.80	4.01				Current account balance	0.69	3.45			
House price index	0.79	3.94				Producer price index	0.69	3.43			
Producer price index	0.76	3.80				Home loans	0.67	3.35			
Wage price index	0.76	3.80				Investment lending	0.67	3.35			
NAB business confidence	0.74	3.69				House price index	0.66	3.31			
Export price index	0.74	3.68									

Note: This table provides results of the half-life of volatility shocks for each major announcement across all four futures contracts. The degree of the shock is derived from the half-life duration (which is half the value of the estimated constant of TPV, as described in Equation 3.14). The duration of the mean revision is then obtained by multiplying the constants by 5 seconds in order to obtain meaningful interpretation of the half-life day of shocks to TPV for each major announcement.

The results presented in Table 3.9 further illustrate the importance of major announcements and their impact on the Australian futures market. This is because half-life volatility, based on TPV, consistently identifies the same major announcements shown in Table 3.8. Notably, the shock of MPV lasts longer than TPV due to disagreement in terms of the supply and demand equilibrium. Also, volatility may remain high for several minutes after major announcements because of a gradual adjustment of prices to new equilibrium levels, as market participants attempt to comprehend the new information. However, the significant part of the adjustment occurs within approximately 20 seconds or less for most investigated contracts, according to TPV and MPV. This 20-second or less adjustment period may present arbitrage opportunities for HFTs that possess the speed advantages to be able to exploit initial price reactions to such announcements.

3.5 Concluding Remarks

This chapter has empirically established the market efficiency status of the Australian futures market by examining three aspects, namely: trading activities and market liquidity; speed of market adjustment to scheduled major announcements; and the determination of volatility persistence for each major announcement type. Co-location facilities were found to have increased HFT activities, indicating a positive relationship between HFT activities and market liquidity. Consistent with Frino, Mollica and Webb (2014), the findings of this study indicate a strong improvement in terms of market liquidity for the contracts investigated. In addition, this investigation also yielded a reduction in effective spread, particularly for 90-day bills. The analyses reported reinforces the prevailing evidence found in the literature by supporting an overall improvement in HFT activities and liquidity associated with the introduction of co-location facilities. Therefore, $P_{1.1}$ is supported.

The Australian futures market also demonstrated a capacity to absorb information from major scheduled macroeconomic announcements efficiently across the four futures contracts investigated. The volatility persistence findings, particularly the half-life volatility measure, suggest that a majority of price adjustments in the Australian futures market occurs almost immediately following major announcements. For example, using MPV, the four futures contracts were found to incorporate information into their prices within less than 20 seconds following major macroeconomic announcements, and less than 15 seconds in the case of cash rate announcements. Further, volatility remained higher compared to non-announcement days, which could be explained by market participants requiring time to fully appreciate the implications of the new information. Nevertheless, these later price adjustments were independent of the initial price change, so it would be difficult to pursue arbitrage trading opportunities after the first 30 seconds following the release of major macroeconomic announcements. This finding implies that no abnormal trading profits can be achieved if the volatility encountered is caused by independent information. Therefore, $P_{1.2}$ is not rejected.

Overall, the findings demonstrate the rapid market adjustment speed of Australian futures products to major scheduled announcements. Not only does the investigation determine volatility persistence for each major announcement, based on their half-life adjustment speed, but also it provides insight into the semi-strong form status of the Australian futures market. By understanding how prices react to each major announcement, market regulators and policy makers are able to improve their communication methods with market participants. From a general practitioners' perspective, having a precise measure of volatility persistence for each major announcement would optimise their trading execution, asset allocation and risk management, as well as their strategic and financial decision making. From the perspective of HFTs, the half-life model would be a significant financial tool with which to observe market signals and enhance their automated trading strategies.

Chapter 4. Embargo - Commercial in Confidence.

Chapter 5. Embargo - Commercial in Confidence.

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Appendices

Appendix A

Appendix A.1: Futures contract specifications

Note: Futures contract specifications below are obtained from ASX (2016, 2018).

Contract name	**90-day bank accepted bill futures**
Commodity Code	IR
Thomson Reuters	IR/YYM
Contract unit	AUD 1,000,000.00 face value 90-day bank accepted bills of exchange or EBAs
Trading months	March (H) / June (M)/ September (U) / December (Z) up to twenty quarter months or five years ahead.
Tick size	Prices are quoted in yield per cent per annum in multiples of 0.01 per cent. For quotation purposes the yield is deducted from an index of 100. The minimum fluctuation of 0.01 per cent equals approximately $24 per contract, varying with the level of interest rates.
Contract Expiry	12:00 pm on the business day immediately prior to settlement day. The Expiry Settlement Price is determined at 10:00 am on the final trading day.
Settlement Method	One bank accepted bill or EBA or bank negotiable certificate of deposit or ECD issued by an Approved Bank, of face value AUD1,000,000 maturing 85 – 95 days from settlement day and classified as "early" month paper. "Early" month paper matures on business days between the 1st and the 15th of the month.
Last day of trading	The second Friday of the delivery month

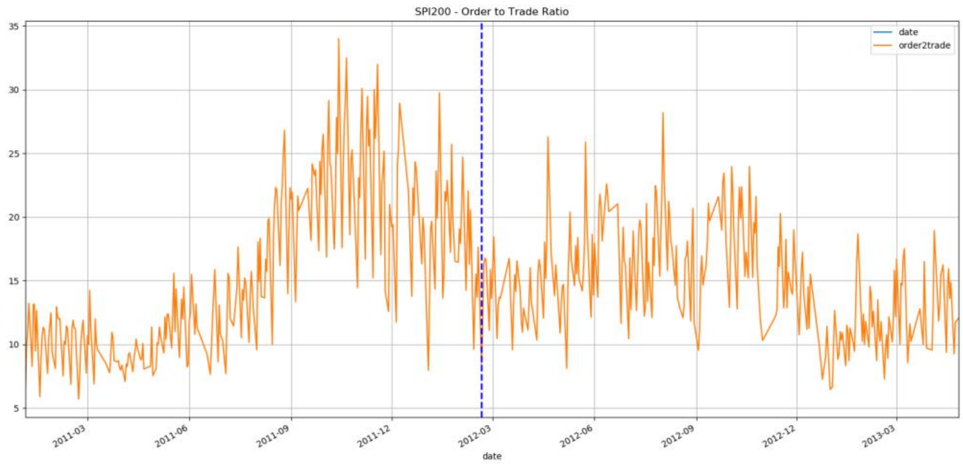
Contract name	**3-year Treasury Bond Futures**
Commodity Code	YT
Thomson Reuters	YT/YTC
Contract unit	AUD 100,000.00; a coupon rate of 6% per annum and term of maturity of three years
Trading months	March (H) / June (M)/ September (U) / December (Z) up to two quarter months ahead
Tick size	Prices are quoted in yield per cent per annum in multiples of 0.005 per cent during the period 5:10 pm on the 8th of the expiry month, or next business day if the 8th is not a business day, to 4:30 pm on the day of the expiry. At all other times the minimum price increment will be 0.01 per cent. For quotation purposes the yield is deducted from an index of 100. The minimum fluctuation of 0.01 per cent equals approximately $30 per contract, varying with the level of interest rates.
Contract Expiry	The fifteenth day of the contract month (or the next succeeding business day where the fifteenth day is not a business day). Trading ceases at 12:00 pm.
Settlement Method	The arithmetic mean, taken at 9:45 am, 10:30 am and 11:15 am on the last day of trading by 8 dealers, randomly selected for each time, at which they would buy and sell a series of bonds previously declared by ASX 24 for that contract month, excluding the two highest and two lowest buying quotations and the two highest and two lowest selling quotations for each bond. All bought and sold contracts in existence as at the close of trading in the contract month shall be settled by the Clearing House at the cash settlement price.
Trading hours	5:10 pm to 7:00 am and 8:30 am to 4:30 pm (for period from second Sunday in March to first Sunday in November) 5:10 pm to 7:30 am and 8:30 am to 4:30 pm (for period from first Sunday in November to second Sunday in March)
Last day of trading	The second Friday of the delivery month
Settlement days	The business day following the last permitted day of trading.

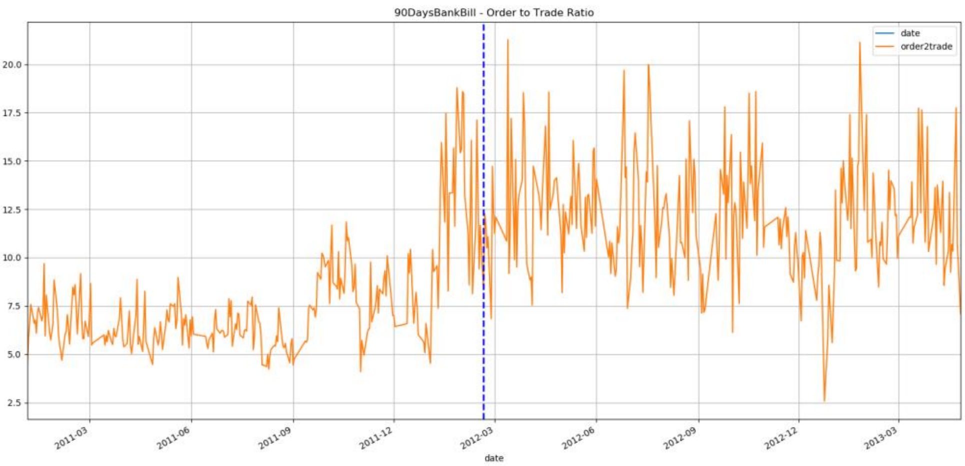
Contract name	**10-year Treasury Bond Futures**
Commodity Code	XT/YYM
Thomson Reuters	YTT
Contract unit	AUD 100,000.00; a coupon rate of 6% per annum and term of maturity of ten years
Trading months	March (H) / June (M)/ September (U) / December (Z) up to two quarter months ahead
Tick size	Prices are quoted in yield per cent per annum in multiples of 0.005 per cent. For quotation purposes the yield is deducted from an index of 100. The minimum fluctuation of 0.005 per cent equals approximately $45 per contract, varying with the level of interest rates.
Contract Expiry	The fifteenth day of the contract month (or the next succeeding business day where the fifteenth day is not a business day). Trading ceases at 12:00 pm.
Settlement Method	The arithmetic mean, taken at 9:45 am, 10:30 am and 11:15 am on the last day of trading by 8 dealers, randomly selected for each time, at which they would buy and sell a series of bonds previously declared by ASX 24 for that contract month, excluding the two highest and two lowest buying quotations and the two highest and two lowest selling quotations for each bond. All bought and sold contracts in existence as at the close of trading in the contract month shall be settled by the Clearing House at the cash settlement price.
Trading hours	5:12 pm to 7:00 am and 8:32 am to 4:30 pm (for period from second Sunday in March to first Sunday in November) 5:12 pm to 7:30 am and 8:32 am to 4:30 pm (for period from first Sunday in November to second Sunday in March)
Last day of trading	The second Friday of the delivery month
Settlement days	The business day following the last permitted day of trading.

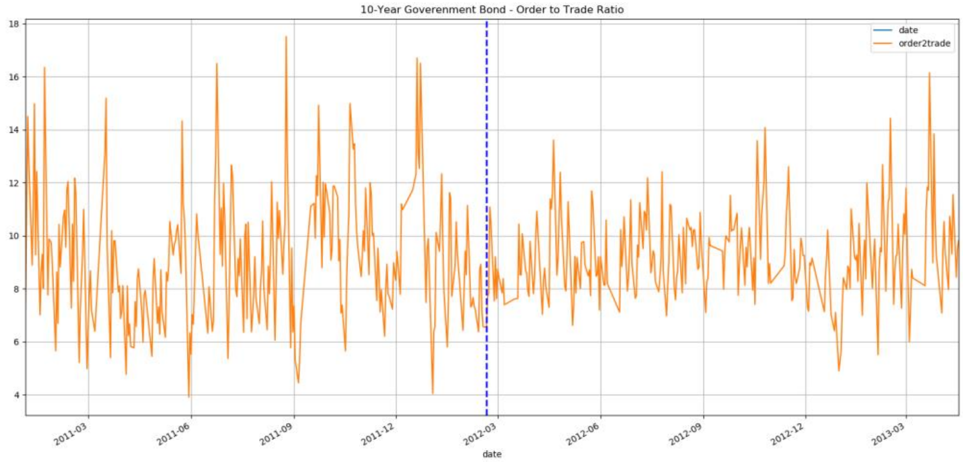
Contract name	**ASX SPI200 Index Futures**
Commodity Code	XT/YYM
Thomson Reuters	YAP
Contract unit	Valued at AUD 25 per index point (e.g., $150,000 at 6,000 index points).
Trading months	March (H) / June (M)/ September (U) / December (Z) up to six quarter months ahead
Tick size	Prices are quoted in yield per cent per annum in multiples of 0.005 per cent. For quotation purposes the yield is deducted from an index of 100. The minimum fluctuation of 0.005 per cent equal approximately $45 per contract, varying with the level of interest rates.
Contract Expiry	The fifteenth day of the contract month (or the next succeeding business day where the fifteenth day is not a business day). Trading ceases at 12:00 pm.
Settlement Method	The Special Opening Quotation of the underlying S&P/ASX 2002 Index on the Last Trading Day. The Special Opening Quotation is calculated using the first traded price of each component stock in the S&P/ASX 2002 Index on the Last Trading Day, irrespective of when those stocks first trade in the ASX trading day. This means that the first traded price of each component stock may occur at any time between ASX market open and ASX market close (including the Closing Single Price Auction) on the Last Trading Day. Should any component stock not have been traded by ASX market close on the Last Trading Day, the last traded price of that stock will be used to calculate the Special Opening Quotation.
Trading hours	5:10 pm – 7:00 am and 9:50 am – 4:30 pm (For period from second Sunday in March to first Sunday in November) 5:10 pm – 8:00 am and 9:50 am – 4:30 pm (For period from first Sunday in November to second Sunday in March)
Last trading days	All trading in expiring contracts ceases at 12:00 pm on the third Thursday of the settlement month. Non-expiring contracts will continue to trade as per the stated trading hours.
Settlement days	The first business day after expiry, ASX Clear (Futures) publishes the final settlement price of the contract. On the second business day after expiry, ASX Clear (Futures) settles cash flows as a result of the settlement price.

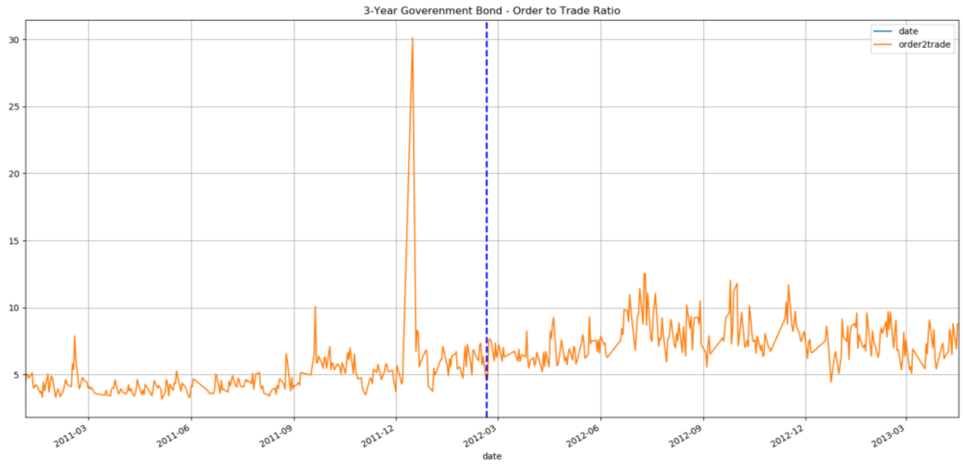
Appendix A.2: Virtualisation of the effects of co-location of HFT facilities on Australian futures contracts

Order to trade ratio: 12 months before and after the introduction of co-location for the SPI200, 90-day bills, 10-year bonds and 3-year bonds

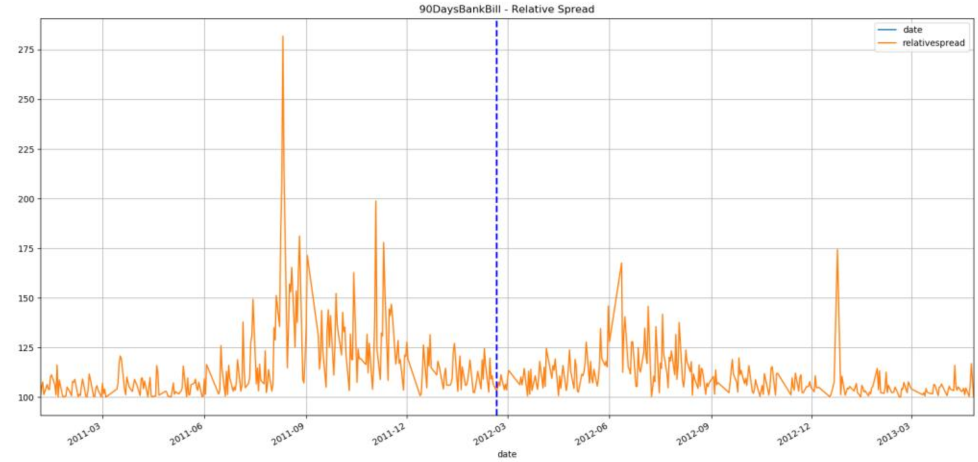


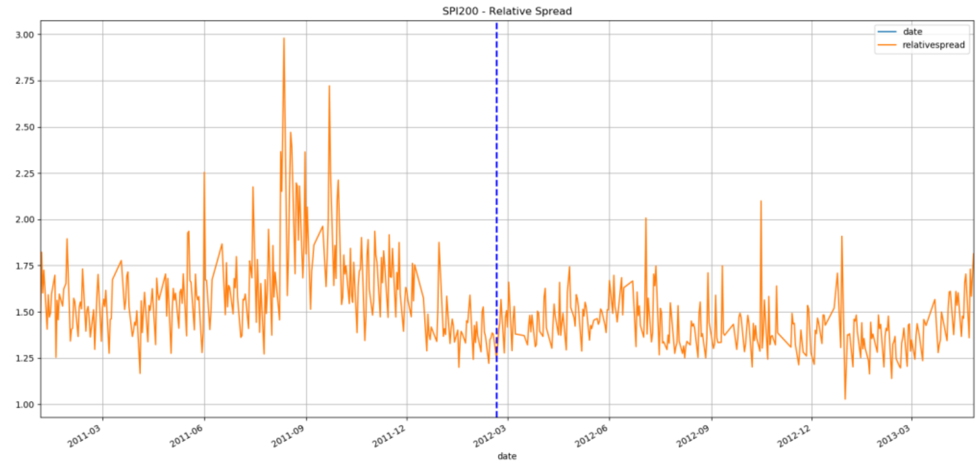


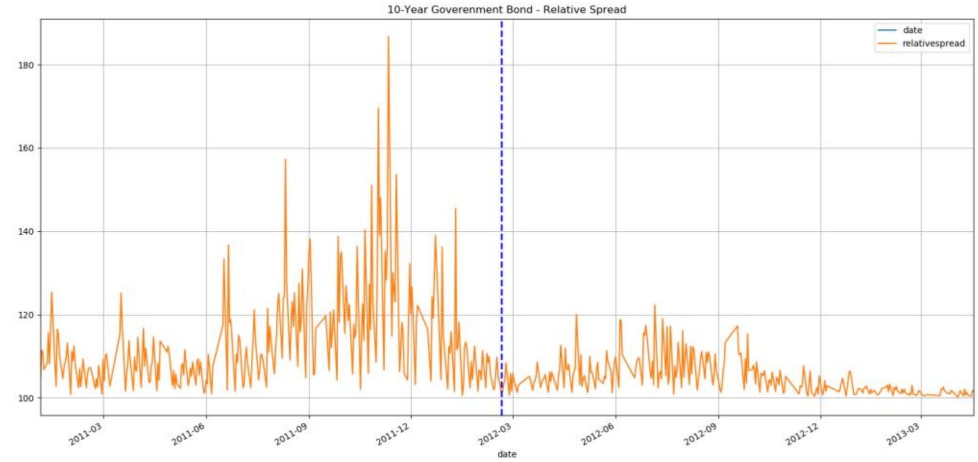

10-Year Goverenment Bond - Order to Trade Ratio
date
order2trade
2011-03
2011-06
2011-09
2011-12
2012-03
2012-06
2012-09
2012-12
2013-03
date

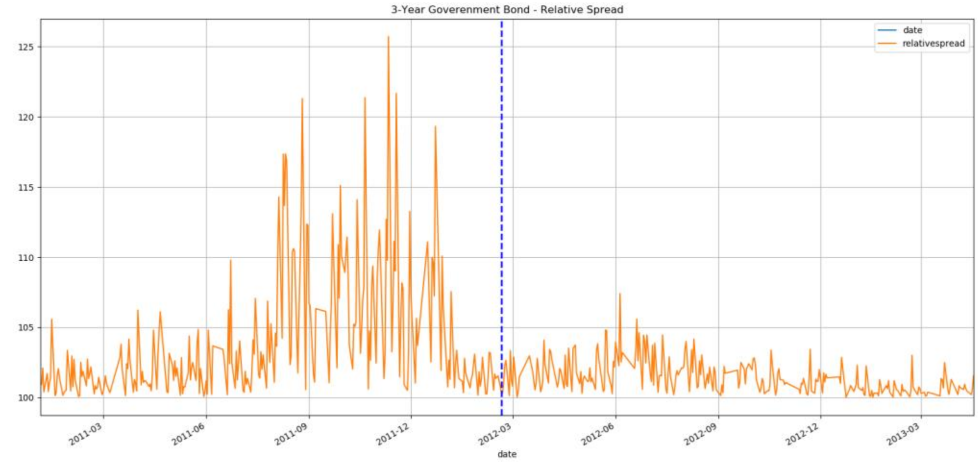

3-Year Goverenment Bond - Order to Trade Ratio
date
order2trade
2011-03
2011-06
2011-09
2011-12
2012-03
2012-06
2012-09
2012-12
2013-03
date

Relative Spread: 12 months before and after the introduction of co-location for the SPI200, 90-day bills, 3-year bonds and 10-year bonds

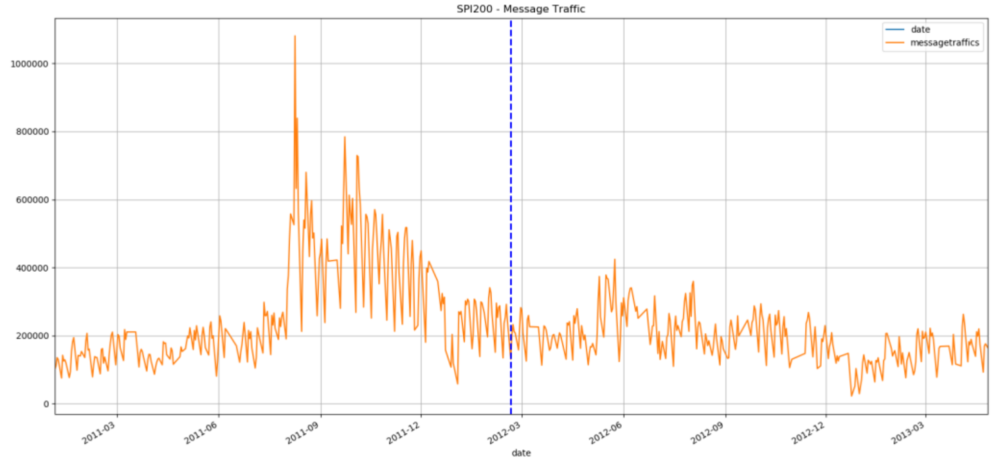


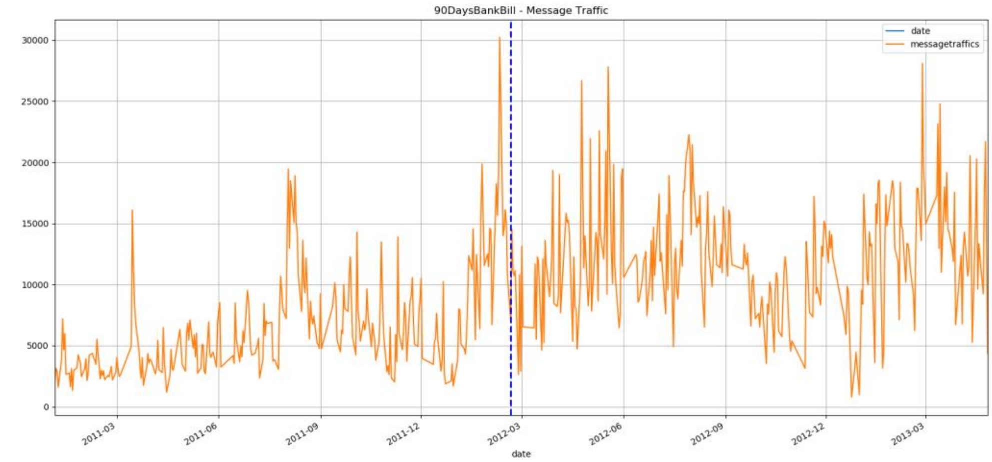


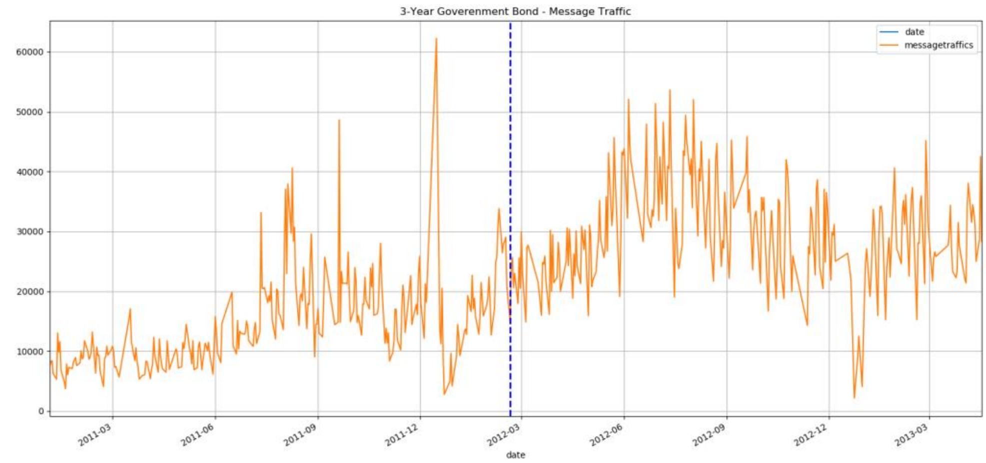

10-Year Goverenment Bond - Relative Spread
date
relativespread
180
160
140
120
100
2011-03
2011-06
2011-09
2011-12
2012-03
2012-06
2012-09
2012-12
2013-03
date


3-Year Goverenment Bond - Relative Spread
date
relativespread
125
120
115
110
105
100
2011-03
2011-06
2011-09
2011-12
2012-03
2012-06
2012-09
2012-12
2013-03
date

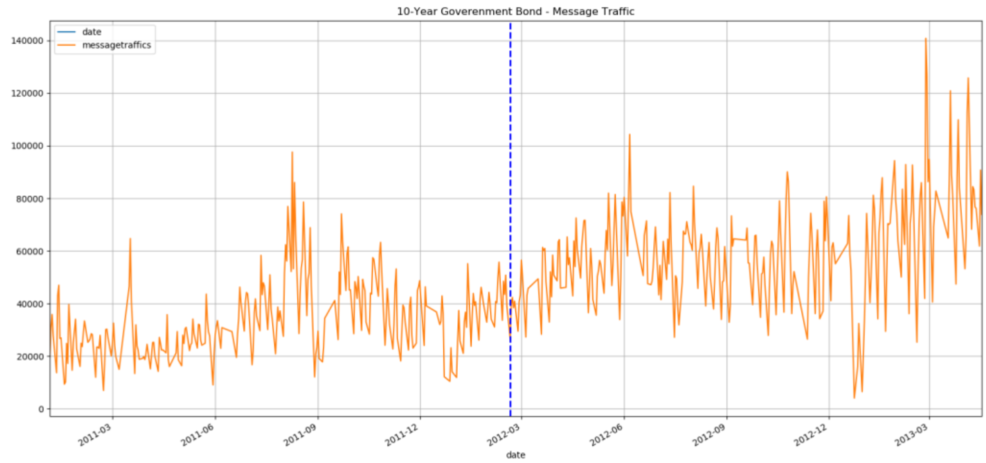
Traffic Message: 12 months before and after the introduction of co-location for the SPI200, 90-day bills, 10-year bonds and 3-year bonds





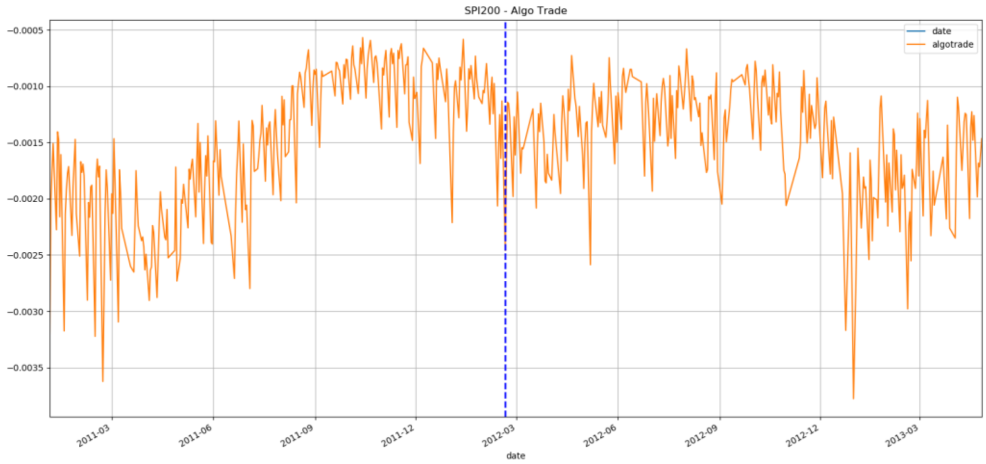


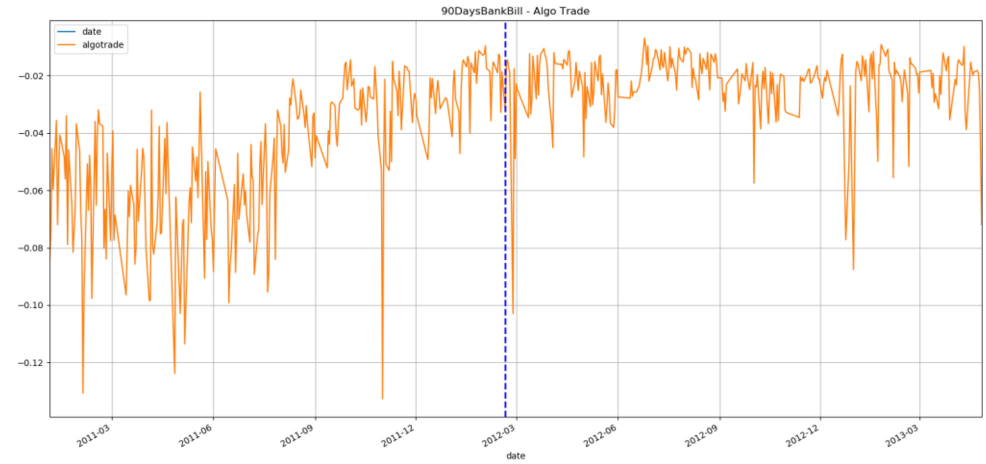
3-Year Goverenment Bond - Message Traffic
date
messagetraffics
60000
50000
40000
30000
20000
10000
0
2011-03
2011-06
2011-09
2011-12
2012-03
2012-06
2012-09
2012-12
2013-03
date

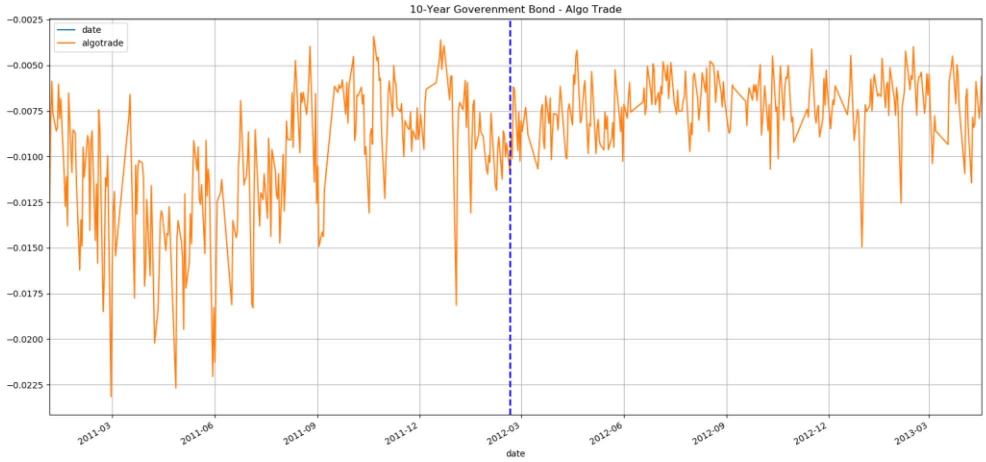


10-Year Goverenment Bond - Message Traffic
date
messagetraffics
140000
120000
100000
80000
60000
40000
20000
0
2011-03
2011-06
2011-09
2011-12
2012-03
2012-06
2012-09
2012-12
2013-03
date

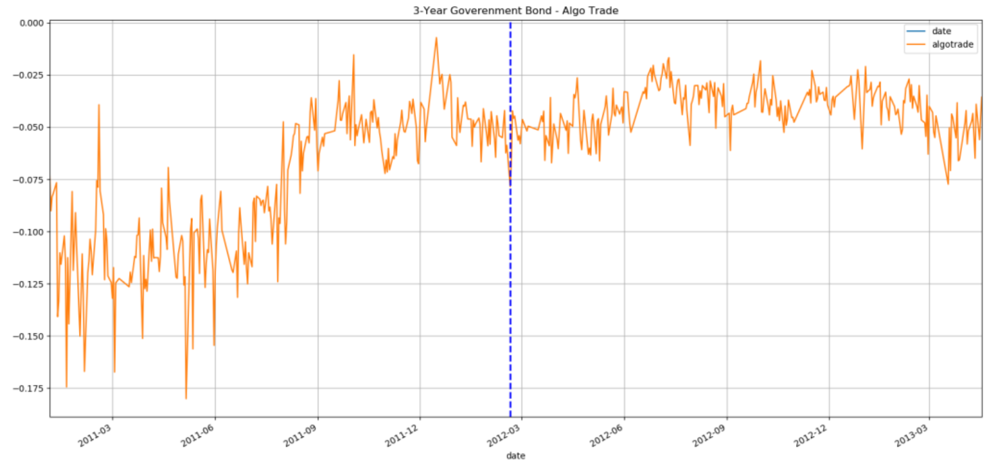
Algorithm Trade: 12 months before and after the introduction of co-location for the SPI200, 90-day bills, 10-year bonds and 3-year bonds







10-Year Goverenment Bond - Algo Trade
date
algotrade
−0.0025
−0.0050
−0.0075
−0.0100
−0.0125
−0.0150
−0.0175
−0.0200
−0.0225
2011-03
2011-06
2011-09
2011-12
2012-03
2012-06
2012-09
2012-12
2013-03
date



3-Year Goverenment Bond - Algo Trade
date
algotrade
0.000
−0.025
−0.050
−0.075
−0.100
−0.125
−0.150
−0.175
2011-03
2011-06
2011-09
2011-12
2012-03
2012-06
2012-09
2012-12
2013-03
date

Appendix A.3.1: Market activity measures pre and post the introduction of co-location facilities

	Message Traffic	Order to Trade Ratio	Algorithmic Trade	Bid-Ask Spread (Tick)	Bid-Ask Spread (%)	Effective Spread	Quote Count (per second)	Trade Count (per second)	Trade Count	Trade Size	Volume	Open Interest	Volatility
SPI200													
pre	279,368.28	15.72	(-0.002)	1.6169	0.0366	1.7401	1.4143	0.28	17,285.49	8,919.71	34,685.76	202,558.13	0.017
post	195,630.50	14.93	(-0.001)	1.4285	0.0321	1.6468	1.2615	0.21	13,053.02	8,928.82	26,042.06	243,124.52	0.012
Difference	(-83,737.78)	(-0.79)	0.000	(-0.1884)	(-0.0045)	(-0.0933)	(-0.1528)	(-0.07)	(-4,232.47)	9.11	(-8,643.69)	40,566.39	(-0.006)
t-statistic	(-7.68)	(-1.76)	1.306	(-10.3809)	(-8.8232)	(-0.8179)	(-2.8894)	(-5.48)	(-10.31)	0.13	(-9.91)	16.27	(-8.475)
	***	*		***	***		***	***	***		***	***	***
90-day bills													
pre	6,605.38	7.57	(-0.047)	0.0117	0.0122	0.0103	0.0717	0.01	910.54	3,017.07	26,670.91	215,690.24	0.001
post	12,206.25	12.10	(-0.022)	0.0110	0.0114	0.0101	0.1329	0.02	1,043.69	2,430.59	24,351.47	185,256.57	0.001
Difference	5,600.87	4.54	0.025	(-0.0007)	(-0.0009)	(-0.0003)	0.0611	0.00	133.15	(-586.49)	(-2,319.44)	(-30,433.66)	(-0.000)
t-statistic	14.15	18.50	14.636	(-4.6831)	(-5.7463)	(-3.4373)	13.1532	2.32	2.76	(-6.60)	(-1.84)	(-10.14)	(-4.044)
	***	***	***	***	***	***	***	**	***	***	*	***	***
10-Year bonds													
pre	34,298.10	9.13	(-0.010)	0.0057	0.0060	0.0070	0.2055	0.06	3,824.51	838.65	32,756.62	380,653.86	0.001
post	59,952.73	9.26	(-0.007)	0.0052	0.0054	0.0071	0.3849	0.09	6,478.02	623.80	41,923.78	400,595.81	0.001
Difference	25,654.64	0.13	0.003	(-0.0004)	(-0.0005)	0.0001	0.1794	0.03	2,653.52	(-214.85)	9,167.16	19,941.95	(-0.000)
	17.12	0.69	12.455	(-11.0016)	(-13.3140)	0.2471	20.3873	13.40	17.82	(-16.20)	8.14	5.92	(-1.399)
	***		***	***	***		***	***	***	***	***	***	
3-Year bonds													
pre	14,834.49	4.86	(-0.080)	0.0104	0.0109	0.0107	0.1405	0.05	3,109.55	3,401.33	106,598.51	579,321.32	0.001
post	30,068.79	7.63	(-0.041)	0.0101	0.0104	0.0106	0.2474	0.06	4,008.40	2,926.39	121,809.24	479,273.46	0.001
Difference	15,234.30	2.77	0.039	(-0.0003)	(-0.0004)	(-0.0001)	0.1069	0.01	898.85	(-474.94)	15,210.73	(-100,047.86)	(-0.000)
	21.32	18.54	17.375	(-8.9750)	(-15.2998)	(-0.8317)	13.6960	5.58	7.47	(-6.96)	3.66	(-9.45)	(-2.800)
	***	***	***	***	***		***	***	***	***	***	***	***

This table reports the summary statistics of market activities pre and post co-location facilities on the ASX. ***, ** and * indicates statistical significance at the 1%, 5% and 10% levels, respectively.

Appendix A.3.2: Impact of co-location of HFT facilities on trading activities (inclusive of daily trading volume as robustness test)

Variable	SPI200			90-day bills			10-Year bonds			3-Year bonds		
Message Traffic	coef	t-stat		coef	t-stat		coef	t-stat		coef	t-stat	
Intercept	(-54,900.00)	(-1.71)	*	3,234.74	3.26	***	(-12,080.00)	(-1.85)	*	5,404.87	3.39	***
Colocation	(-59,030.00)	(-4.43)	***	6,158.65	17.39	***	17,620.00	15.69	***	14,120.00	20.30	***
CRC	51,210.00	3.85	***									
Volume	3.86	5.64	***	0.10	5.53	***	0.83	12.72	***	0.07	8.70	***
Open Interest	0.25	2.00	**	(-0.01)	(-1.72)	*	0.04	2.00	**	(-0.01)	(-2.83)	***
Intraday Volatility	8,390,000.00	11.33	***	2,695,000.00	6.72	***	5,201,000.00	3.45	***	5,524,000.00	10.46	***
Adjusted R2	**0.614**			**0.526**			**0.679**			**0.692**		
Order to Trade Ratio	coef	t-stat		coef	t-stat		coef	t-stat		coef	t-stat	
Intercept	12.430	8.046	***	10.972	14.200	***	8.912	9.282	***	6.963	12.934	***
Colocation	(-3.574)	(-3.849)	***	4.184	15.547	***	0.243	1.324		2.749	14.954	***
CRC	3.813	4.146	***									
Volume	(-0.000)	(-5.001)	***	(-0.000)	(-6.236)	***	(-0.000)	(-2.509)	**	(-0.000)	(-5.991)	***
Open Interest	0.000	1.166		(-0.000)	(-3.003)	***	0.000	1.220		(-0.000)	(-3.362)	***
Intraday Volatility	422.867	10.852	***	201.800	1.235		(-299.505)	(-1.415)		456.085	3.999	***
Adjusted R2	**0.210**			**0.458**			**0.015**			**0.472**		
Algorithmic Trade	coef	t-stat		coef	t-stat		coef	t-stat		coef	t-stat	
Intercept	(-0.0019)	(-11.4460)	***	(-0.0380)	(-8.2090)	***	(-0.0106)	(-8.5900)	***	(-0.0591)	(-10.7150)	***
Colocation	(-0.0003)	(-4.2170)	***	0.0265	16.8760	***	0.0039	14.5640	***	0.0455	18.3390	***
CRC	0.0005	6.6900	***									
Volume	(-0.0000)	(-4.3720)	***	(-0.0000)	(-12.0720)	***	(-0.0000)	(-5.5920)	***	(-0.0000)	(-11.9030)	***
Open Interest	0.0000	0.8620		0.0000	0.1820		0.0000	0.8000		(-0.0000)	(-1.8520)	*
Intraday Volatility	0.0414	10.4020	***	14.7511	9.3390	***	1.5928	4.8700	***	21.8432	12.6010	***
Adjusted R2	**0.1990**			**0.5210**			**0.3180**			**0.5850**		

Appendix A.3.3: Impact of co-location of HFT facilities on market liquidity (inclusive of daily trading volume as robustness test)

Variable	SPI200			90-day bills			10-Year bonds			3-Year bonds		
Bid-ask spread (tick)	coef	t-stat		coef	t-stat		coef	t-stat		coef	t-stat	
Intercept	1.1986	12.8310	***	0.0098	19.5540	***	0.0057	25.1220	***	0.0101	103.5110	***
Colocation	(-0.1403)	(-5.5470)	***	(-0.0002)	(-1.8110)	*	(-0.0004)	(-10.7660)	***	(-0.0002)	(-5.6900)	***
Volume	0.0000	1.5280		(-0.0000)	(-6.8220)	***	(-0.0000)	(-1.9550)	*	(-0.0000)	(-5.6380)	***
Open Interest	0.0000	1.8520	*	0.0000	2.4780	**	(-0.0000)	(-1.1370)		0.0000	1.4950	
Intraday Volatility	10.5728	5.1020	***	1.7482	8.2380	***	0.3214	5.5450	***	0.3040	10.7300	***
Adjusted R2	**0.3810**			**0.3780**			**0.2550**		***	**0.3280**		
Bid-ask spread (percentage)	coef	t-stat		coef	t-stat		coef	t-stat		coef	t-stat	
Intercept	0.0279	10.9330	***	0.0104	19.8260	***	0.0060	25.4260	***	0.0105	106.2570	***
Colocation	(-0.0019)	(-2.7320)	***	(-0.0004)	(-3.3420)	***	(-0.0005)	(-13.4160)	***	(-0.0003)	(-11.8170)	***
Volume	0.0000	1.0660		(-0.0000)	(-6.6530)	***	(-0.0000)	(-1.7710)	*	(-0.0000)	(-4.6790)	***
Open Interest	0.0000	0.0610		0.0000	2.3580	**	(-0.0000)	(-1.1580)		0.0000	1.9950	**
Intraday Volatility	0.4152	7.7030	***	1.7883	8.1420	***	0.3093	5.1380	***	0.2543	9.0170	***
Adjusted R2	**0.4250**			**0.3840**			**0.3080**			**0.4370**		
Relative Spreads	coef	t-stat		coef	t-stat		coef	t-stat		coef	t-stat	
Intercept	1.1986	12.8310	***	98.3411	19.5540	***	113.9372	25.1220	***	101.1493	103.5110	***
Colocation	(-0.1403)	(-5.5470)	***	(-1.9362)	(-1.8110)	*	(-7.6660)	(-10.7660)	***	(-1.6138)	(-5.6900)	***
Volume	0.0000	1.5280		(-0.0004)	(-6.8220)	***	(-0.0001)	(-1.9550)	*	(-0.0000)	(-5.6380)	***
Open Interest	0.0000	1.8520	*	0.0001	2.4780	**	(-0.0000)	(-1.1370)		0.0000	1.4950	
Intraday Volatility	10.5728	5.1020	***	17,480.0000	8.2380	***	6,427.3777	5.5450	***	3,040.3800	10.7300	***
Adjusted R2	**0.3810**			**0.3780**			**0.2550**			**0.3280**		
Effective Spread	coef	t-stat		coef	t-stat		coef	t-stat		coef	t-stat	
Intercept	(-0.3928)	(-0.8900)		0.0100	41.2350	***	0.0055	3.9040	***	0.0097	17.3180	***
Colocation	0.0044	0.0280		(-0.0001)	(-2.1370)	**	0.0001	0.2060		0.0001	0.5980	
Volume	0.0000	2.7490	***	(-0.0000)	(-2.3080)	**	0.0000	1.1010		(-0.0000)	(-1.2840)	
Open Interest	0.0000	2.2240	**	0.0000	0.7650		(-0.0000)	(-0.4770)		0.0000	1.2220	
Intraday Volatility	17.8148	1.2600		0.5109	2.5760		1.6385	3.0220		0.5782	2.3040	
Adjusted R2	**0.09**			**0.1270**			**0.0300**			**0.0260**		

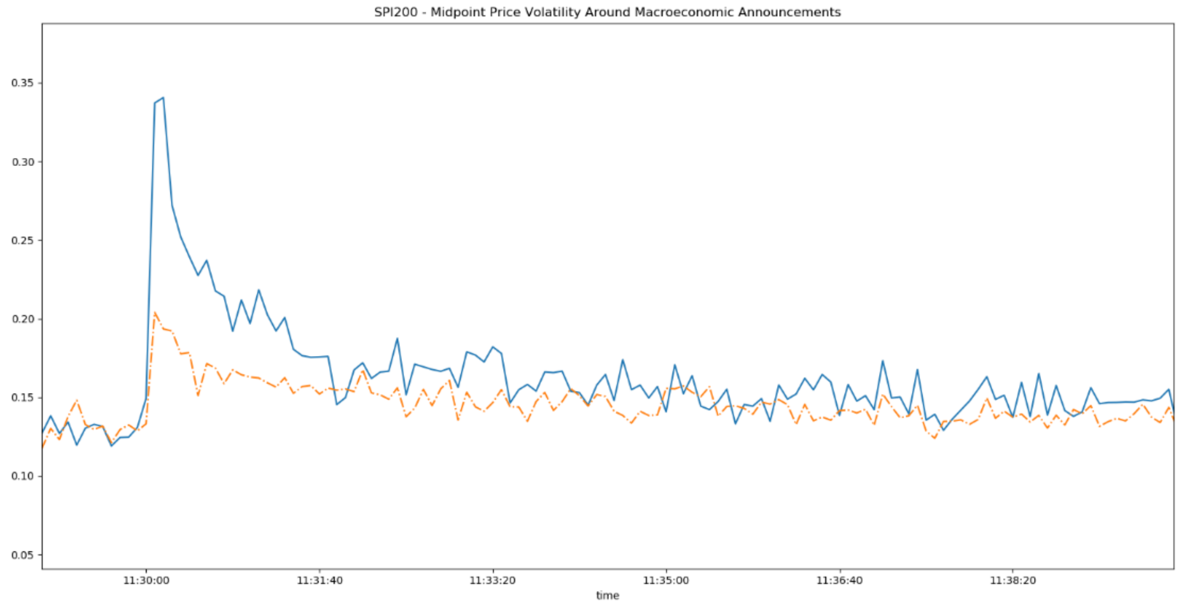
Appendix A.3.4: Impact of co-location of HFT facilities on trading activities (exclusive of November and December 2011)

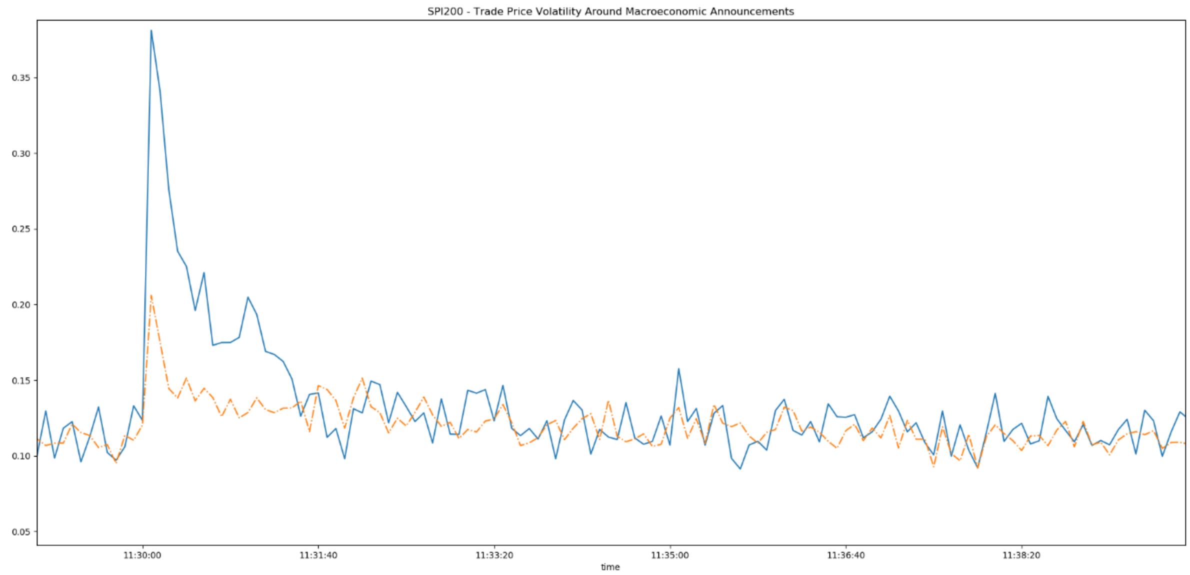
Variable	**SPI200**			**Variable**	**SPI200 (With Volume)**		
Message Traffic	coef	t-stat		*Message Traffic*	coef	t-stat	
Intercept	(-7,876.85)	(-0.26)		Intercept	(-69,000.00)	(-2.08)	**
colocation	(-63,930.00)	(-4.35)	***	colocation	(-56,420.00)	(-4.25)	***
CRC	45,340.00	3.41	***	CRC	67,060.00	4.97	***
Open Interest	0.35	2.32	**	Volume	4.38	5.96	***
Intraday Volatility	11,890,000.00	19.85	***	Open Interest	0.20	1.61	
				Intraday Volatility	7,895,000.00	9.69	***
Adjusted R2	**0.58**			**Adjusted R2**	**0.63**		
Order to Trade Ratio	coef	t-stat		*Order to Trade Ratio*	coef	t-stat	
Intercept	9.51	6.50	***	Intercept	11.11	7.14	***
colocation	(-3.17)	(-3.39)	***	colocation	(-3.37)	(-3.64)	***
CRC	5.62	6.12	***	CRC	5.05	5.54	***
Open Interest	(-0.00)	(-0.08)		Volume	(-0.00)	(-3.25)	***
intraday_volatility	265.92	5.03	***	Open Interest	0.00	0.56	
				intraday_volatility	370.60	9.24	***
Adjusted R2	**0.20**			**Adjusted R2**	**0.22**		
Algorithmic Trade	coef	t-stat		*Algorithmic Trade*	coef	t-stat	
Intercept	(-0.00)	(-13.31)	***	Intercept	(-0.00)	(-11.70)	***
colocation	(-0.00)	(-3.71)	***	colocation	(-0.00)	(-3.97)	***
CRC	0.00	8.77	***	CRC	0.00	7.99	***
Open Interest	(-0.00)	(-0.20)		Volume	(-0.00)	(-2.72)	***
Intraday Volatility	0.03	5.30	***	Open Interest	0.00	0.32	
				Intraday Volatility	0.04	8.73	***
Adjusted R2	**0.204**			**Adjusted R2**	0.219		

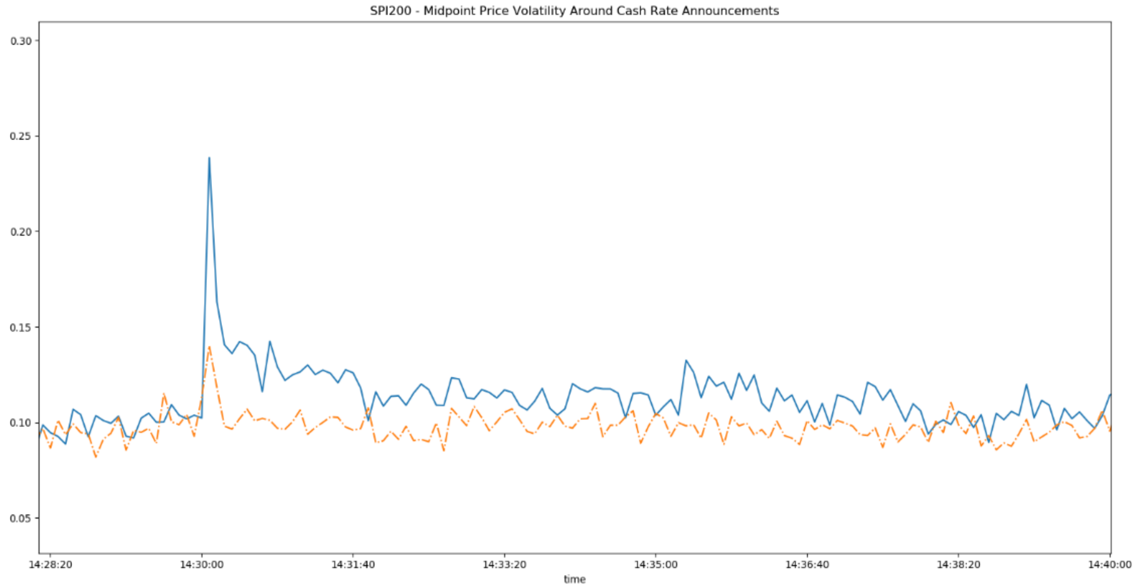
Note: This table reports robustness results of the impact of co-location technology on HFT activities in the Australian futures market, specifically for SPI200 contracts. A dummy variable is used to set co-location to 0 prior to 20 February 2012 and 1 after 20 February 2012. Control variables are open interest and intraday volatility or high-low time-weighted midpoint price volatility. A dummy variable titled 'CRC' is also employed to control for the introduction of cost recovery charge imposed by ASIC on 1st January 2012. The CRC is set 0 prior to the cost recovery charge and 1 after following the introduction. As market participants' reaction to the announcement of the cost recovery charge may influence the empirical results of this investigation, the investigation removes the month of November and December in year 2011 from the sample for robustness purposes.

***, ** and * indicates statistical significance at the 1%, 5% and 10% levels, respectively.

Appendix A.4: Virtualisation of market adjustment speed of Australian futures contracts following major scheduled macroeconomic announcements






SPI200 - Midpoint Price Volatility Around Cash Rate Announcements
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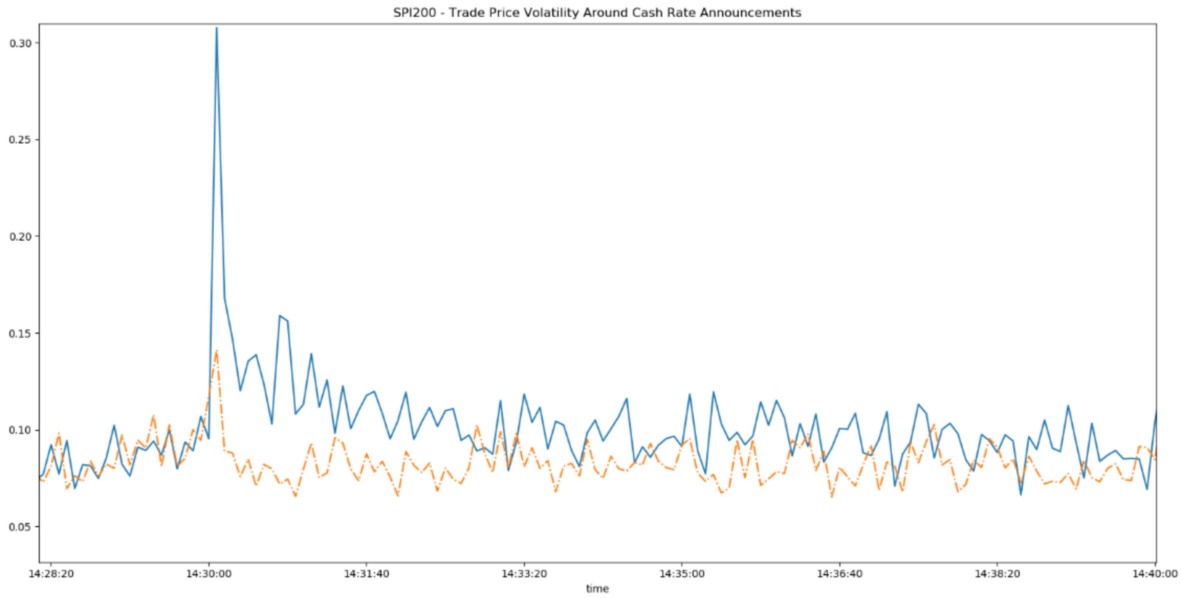
14:40:00
time


SPI200 - Trade Price Volatility Around Cash Rate Announcements
0.30
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0.15
0.10
0.05
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14:33:20
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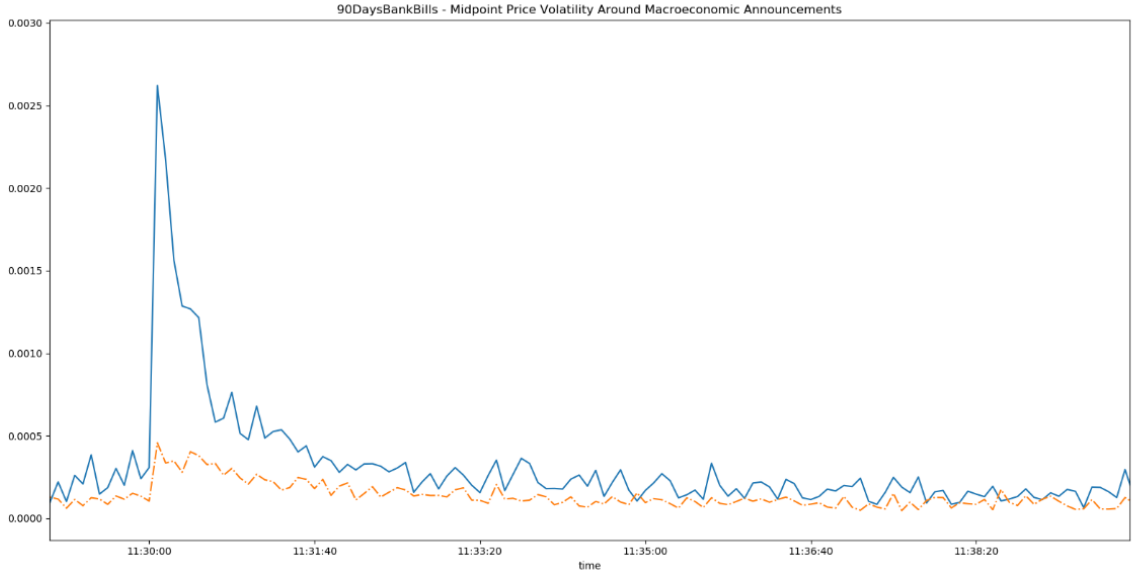
14:36:40
14:38:20
14:40:00
time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0.0020
0.0015
0.0010
0.0005
0.0000
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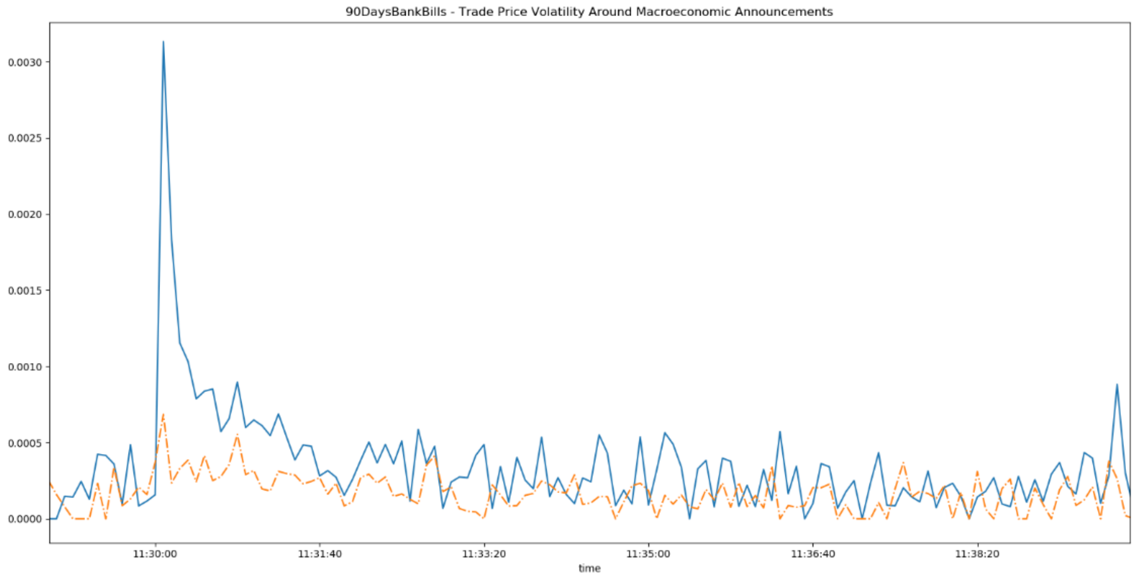
11:33:20
11:35:00
11:36:40
11:38:20
time


90DaysBankBills - Trade Price Volatility Around Macroeconomic Announcements
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0.0025
0.0020
0.0015
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0.0000
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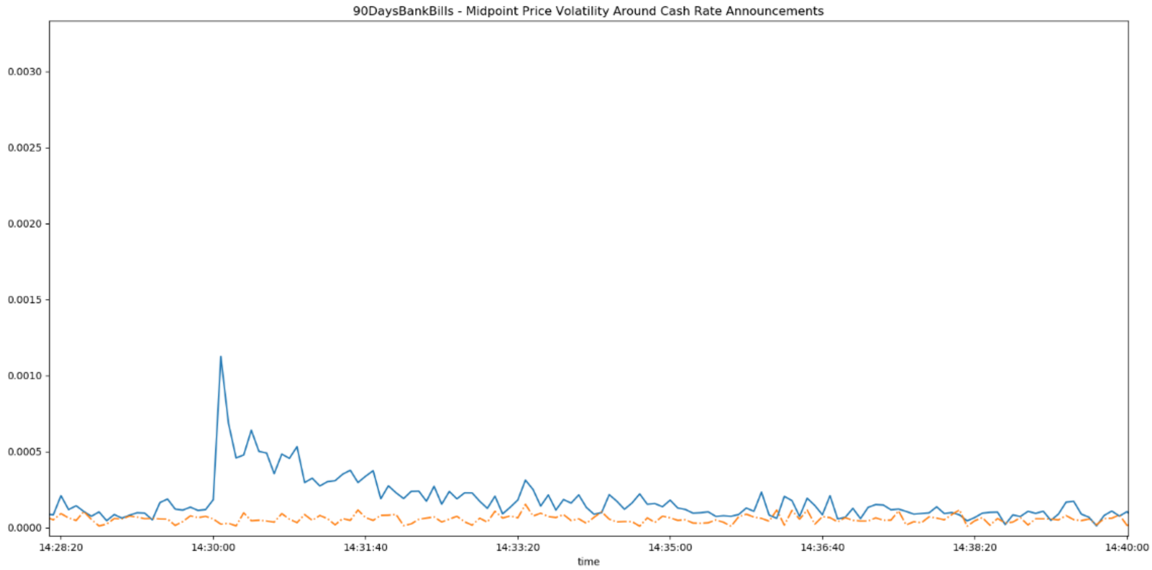
11:31:40
11:33:20
11:35:00
11:36:40
11:38:20
time



90DaysBankBills - Midpoint Price Volatility Around Cash Rate Announcements
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0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
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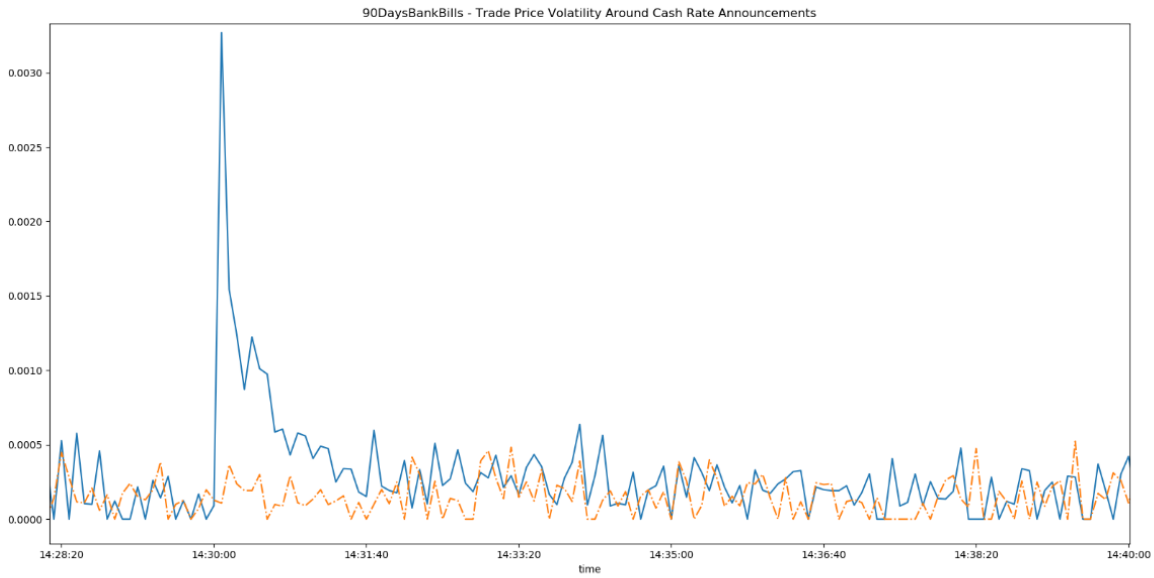
14:31:40
14:33:20
14:35:00
14:36:40
14:38:20
14:40:00
time



90DaysBankBills - Trade Price Volatility Around Cash Rate Announcements
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0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
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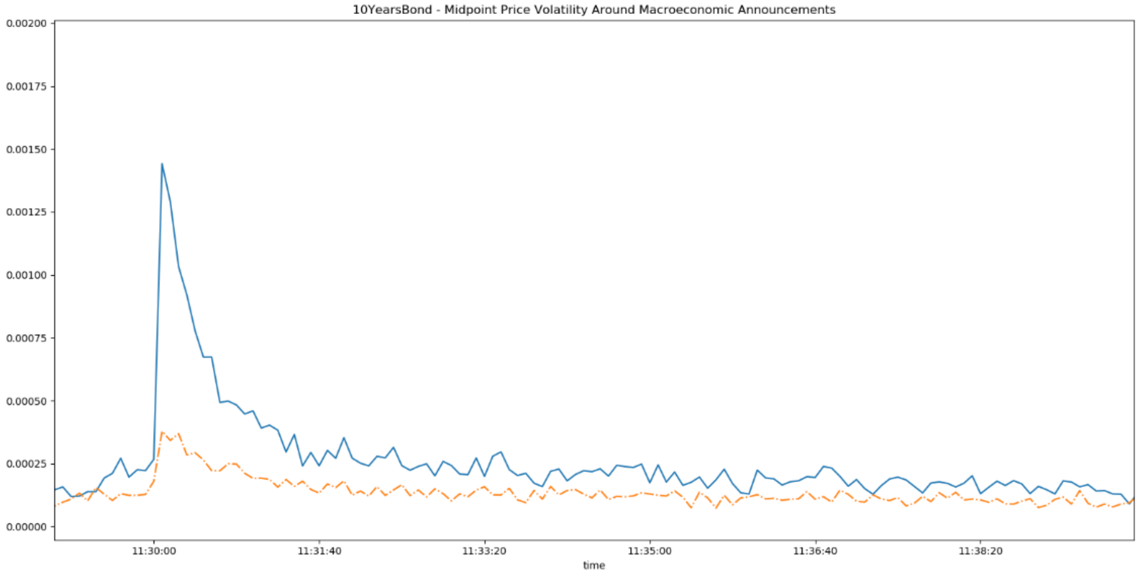
14:30:00
14:31:40
14:33:20
14:35:00
14:36:40
14:38:20
14:40:00
time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0.00150
0.00125
0.00100
0.00075
0.00050
0.00025
0.00000
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11:31:40
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11:35:00
11:36:40
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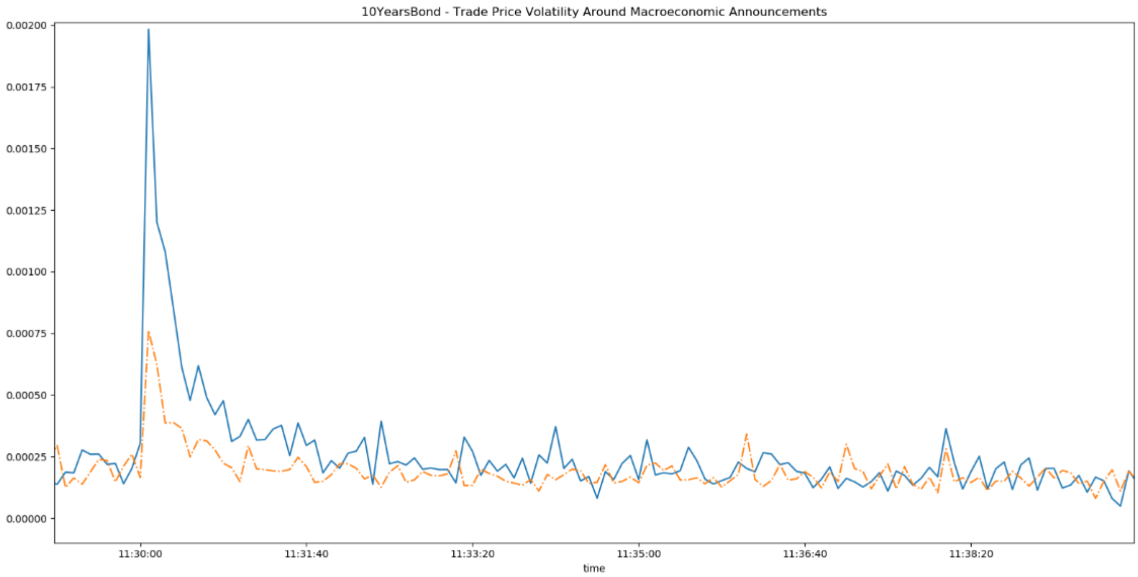
time


10YearsBond - Trade Price Volatility Around Macroeconomic Announcements
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0.00175
0.00150
0.00125
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0.00075
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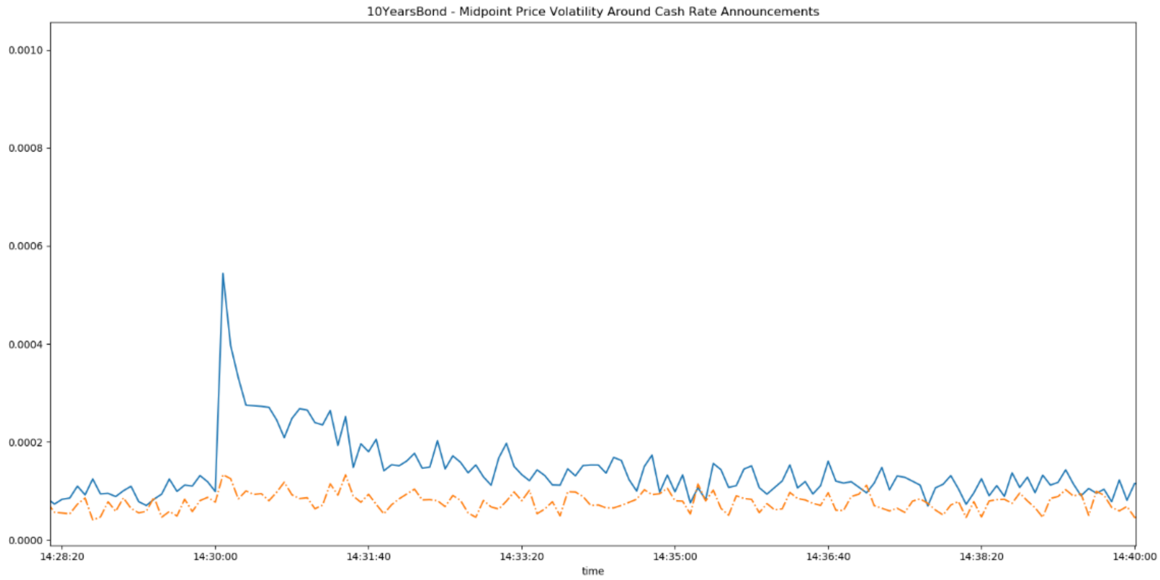
10YearsBond - Midpoint Price Volatility Around Cash Rate Announcements
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0.0000
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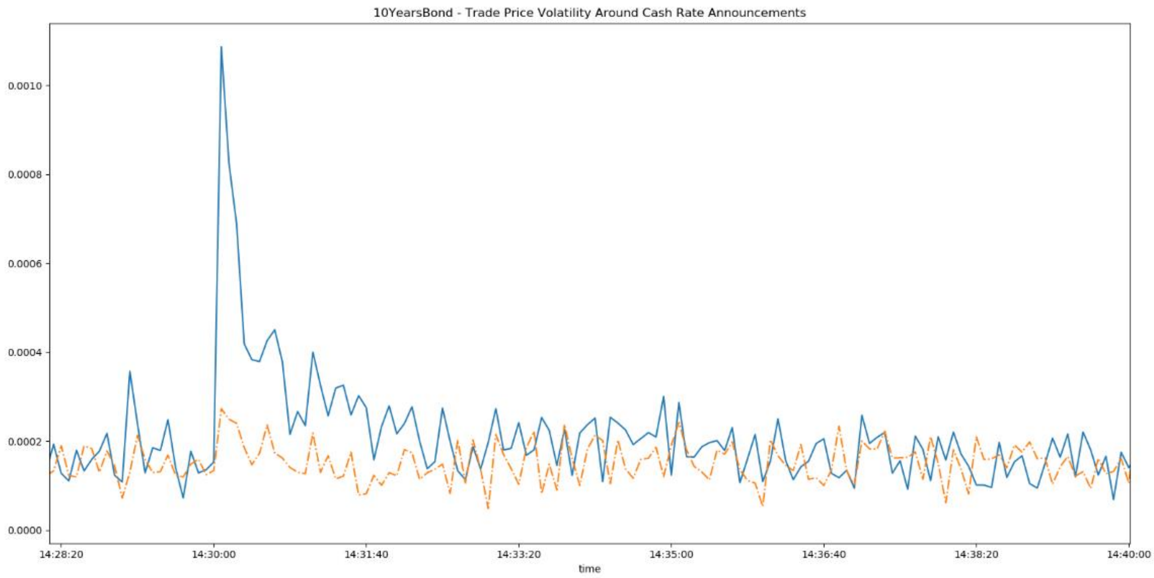
14:40:00
time


10YearsBond - Trade Price Volatility Around Cash Rate Announcements
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0.0008
0.0006
0.0004
0.0002
0.0000
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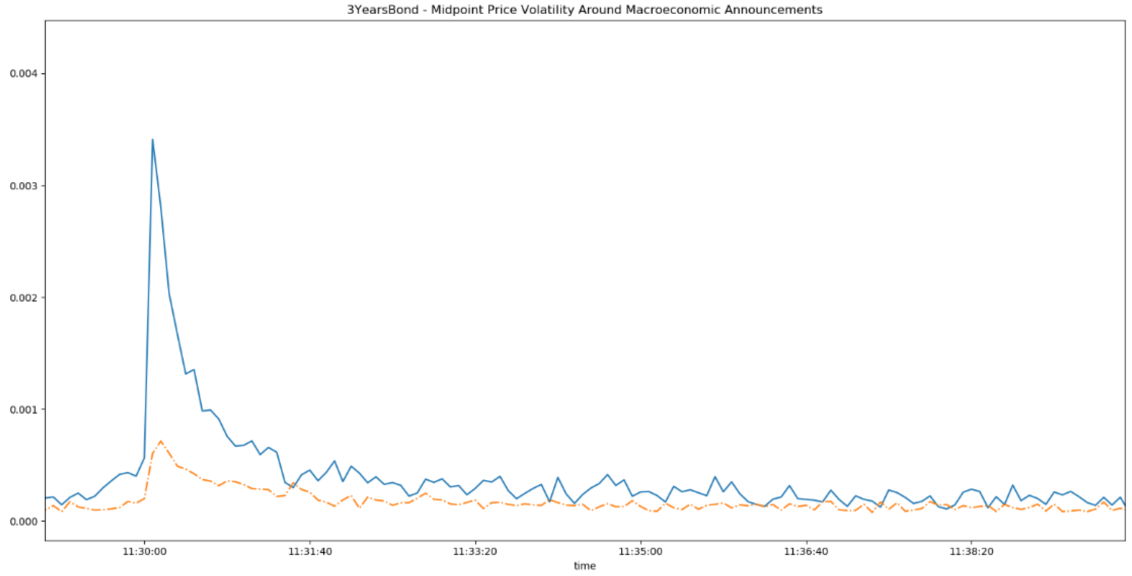
14:40:00
time


3YearsBond - Midpoint Price Volatility Around Macroeconomic Announcements
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0.003
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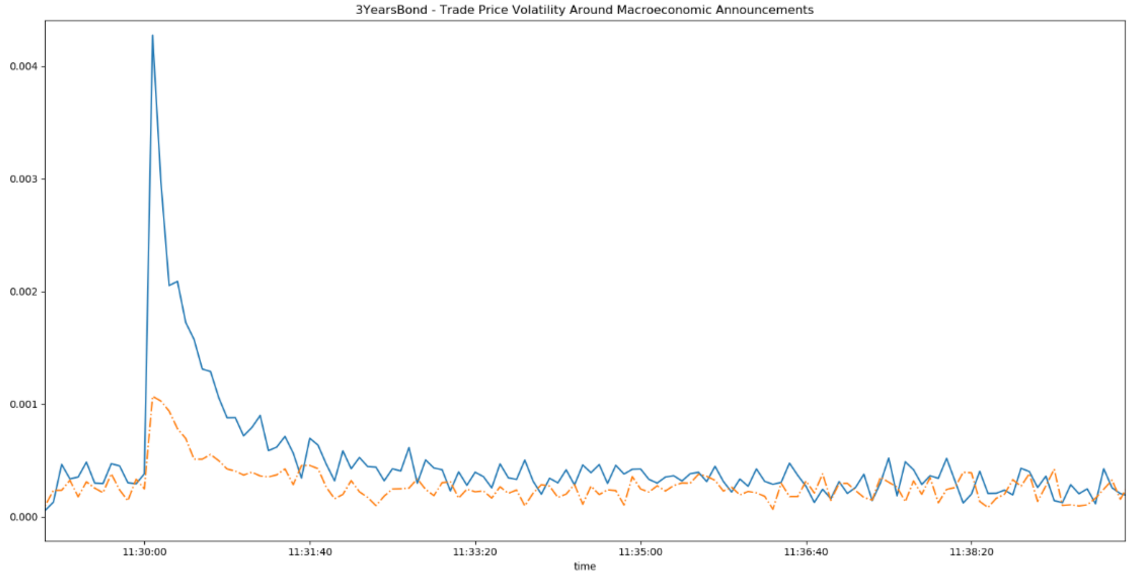
time


3YearsBond - Trade Price Volatility Around Macroeconomic Announcements
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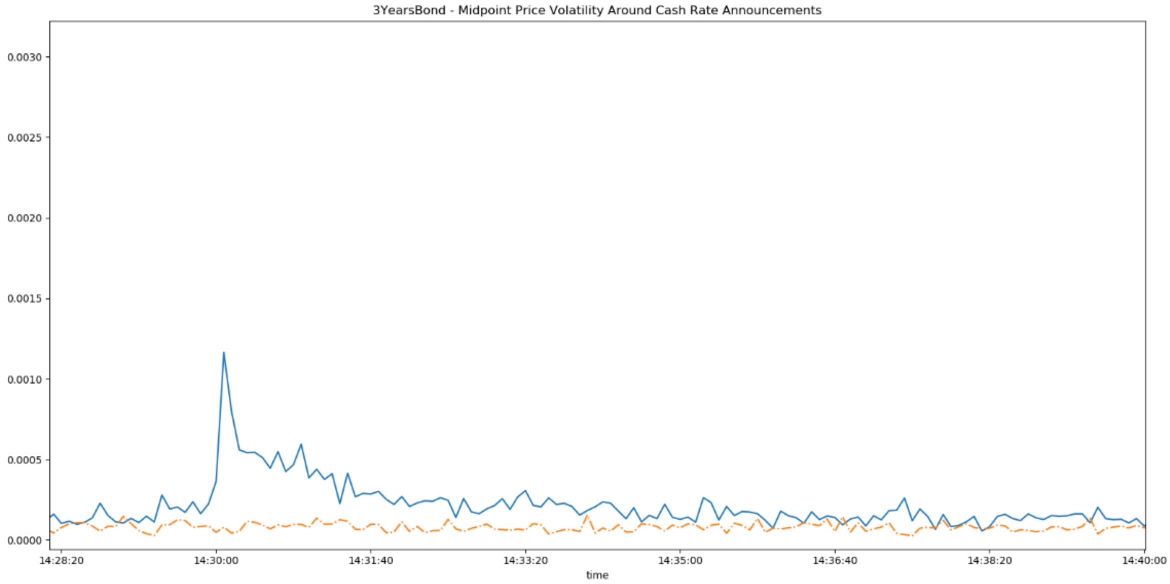
3YearsBond - Midpoint Price Volatility Around Cash Rate Announcements
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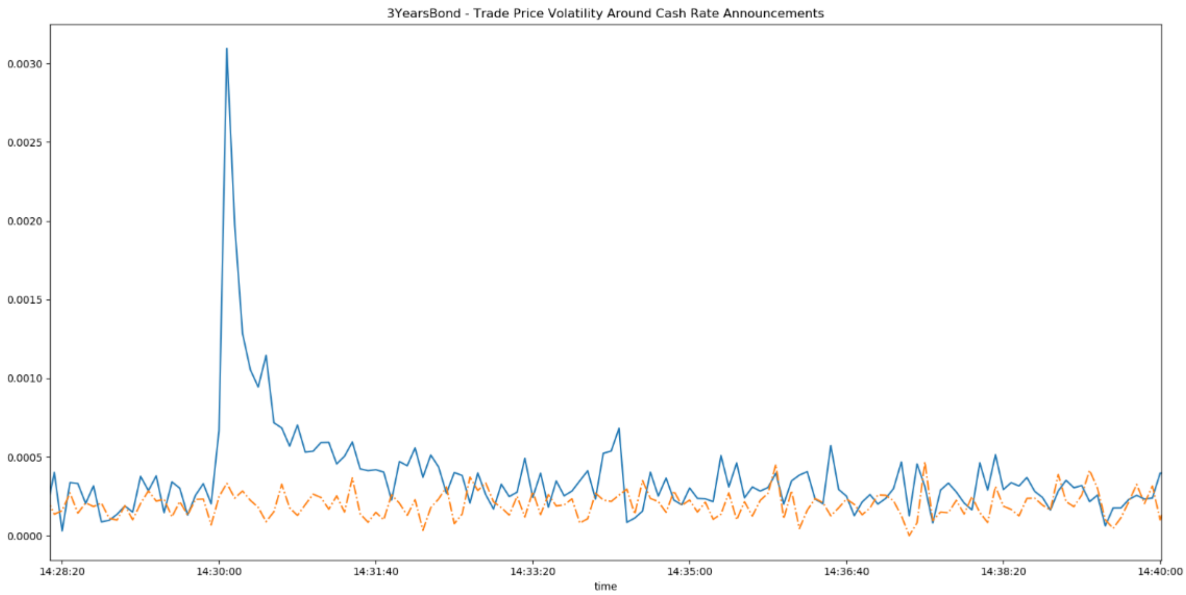
time


3YearsBond - Trade Price Volatility Around Cash Rate Announcements
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14:35:00
14:36:40
14:38:20
14:40:00
time

Appendix A.5: Volatility persistence on macroeconomic and cash rate announcements for STW

Volatility Persistence on Macroeconomic Announcement Days					
Panel A: Midpoint Volatility	SPI200	90-day bank bill	10-year bond	3-year bond	STW
t_statistic	1.9218	1.8255	1.7528	1.8035	2.2260
p_value	0.0274	0.0342	0.0400	0.0359	0.0131
Benchmark	134.0176	0.1197	0.1332	0.1168	0.0014
Announcement days	116.5192	0.0387	0.0875	0.0510	0
Adjustment Time	0.5018	0.4936	0.4900	0.4865	0.4802
Half-life benchmark	203.9245	0.4565	0.3782	0.6056	0.0017
Peak volatility on Announcement days	270.4971	1.5387	0.9097	2.0079	0.0096
Half-life adjustment time	0.4794	0.4794	0.4795	0.4794	0.4793
Panel B: Trade Price Volatility					
t_statistic	2.3850	1.7893	2.2983	2.1236	N/A
p_value	0.0086	0.0392	0.0110	0.0174	
Benchmark	143.7658	0.3415	0.2730	0.3932	
Announcement days	112.1909	-	0.1431	0.1203	
Adjustment Time	0.4804	0.4892	0.4814	0.4849	
Half-life benchmark	205.9266	0.6860	0.7614	1.0678	
Peak volatility on Announcement days	293.5326	1.9091	1.3721	2.6705	
Half-life adjustment time	0.4793	0.4793	0.4793	0.4793	

Volatility Persistence on Cash Rate Announcement Days					
Panel A: Midpoint Volatility	SPI200	90-day bank bill	10-year bond	3-year bond	STW
t_statistic	2.0228	2.1535	2.1999	1.9634	1.9306
p_value	0.0216	0.0159	0.0140	0.0250	0.0268
Benchmark	103.3066	0.1146	0.1159	0.1667	0.0002
Announcement days	86.2437	0.0263	0.0616	0.0667	0
Adjustment Time	0.6306	0.6118	0.6207	0.6170	0.6059
Half-life benchmark	140.0954	0.0210	0.1328	0.0795	0.0010
Peak volatility on Announcement days	189.3290	0.5721	0.3381	0.6220	0.0371
Half-life adjustment time	0.6043	0.6043	0.6043	0.6043	0.6043
Panel B: Trade Price Volatility					
t_statistic	1.7268	1.8217	1.6703	2.2675	N/A
p_value	0.0423	0.0367	0.0479	0.0122	
Benchmark	90.7533	0.4746	0.2333	0.5842	
Announcement days	69.1997	-	0.1177	0.1740	
Adjustment Time	0.6111	0.6100	0.6089	0.6116	
Half-life benchmark	141.2370	0.1071	0.2728	0.3323	
Peak volatility on Announcement days	224.4693	1.6879	0.6797	1.7140	
Half-life adjustment time	0.6043	0.6043	0.6044	0.6043	