Exchange Initiatives and Market Efficiency: Evidence from the Australian Securities Exchange

A dissertation submitted for the Degree of Doctor of Philosophy

Jagjeev Dosanjh

Discipline of Finance
University of Technology Sydney

February 2, 2017

Certificate of authorship

I certify that the work in this dissertation has not previously been submitted for a degree and nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the dissertation has been written by me. Any help that I have received in my research work and the preparation of the dissertation itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

Signature of Student

Acknowledgements

First and foremost I give thanks to my supervisor, Professor David Michayluk. His patience and support has been invaluable throughout this journey while his skills and experience have significantly enhanced the quality of this thesis. I would also like to thank Dr Vito Mollica, Professor Talis Putnins and Dr Angelo Aspris for their timely feedback and insightful comments throughout my candidature.

I thank my industry partner, the Financial Markets Research Centre (FMRC) and the Capital Markets Cooperative Research Centre (CMCRC) for their financial assistance, resources and facilities.

I am greatly appreciative of the comments received from presentations at the University of Technology Sydney Business School and the Multinational Finance Society Conference 2014 (Prague). Special thanks goes to University of Technology Sydney Business School for providing a platform to present my research and the financial aid to do so.

I would like to thank my friends and colleagues George Issa, Jimmy Liu, Vinay Patel and Tony Zhang for their encouragement and support.

Finally, sincere thanks goes to my family for their continued love and care.

Abstract

The stated objectives of most market regulators are to ensure the fair and efficient operation of capital markets. In this dissertation, the focus is on the latter regulatory objective. We define market efficiency as minimising transaction costs while maximising price discovery and assess the efficiency effects of 3 Australian Securities Exchange (ASX) market design initiatives.

The first essay examines the effect of the broker anonymity rule on trading patterns. We find that following the introduction of broker anonymity, the price discovery process is inhibited as information asymmetry levels increase. We also determine that the need for stealth trading, identified by Frino et al. (2010 b), is reduced.

The second essay assesses the market efficiency effects of the Equity Research Scheme. Consistent with the prior literature, we find the stocks exhibit greater informational efficiency as a result of the Scheme. In addition to increased price discovery, we find positive liquidity and price reaction effects.

The third essay examines the liquidity and profitability effects of the ETF Marker Making Scheme. Hence, we support the fact that the scheme was effective in decreasing the bid-ask spread and increasing depth for selected stocks. Further analysis shows that market makers are net suppliers of liquidity; however, they are willing to sacrifice liquidity profits to make position-taking gains.

Table of Contents

List of Figures and Tables

Chapter 1: Introduction

An exchange is a marketplace designed for investors to buy and sell financial instruments. The primary market of a stock exchange provides the platform for firms, governments and other associations to raise capital from the investing public. The secondary market allows investors and other market participants to trade these securities via a centralised service. The principal purpose of the secondary market is to ensure non-discriminatory and orderly trading as well as the efficient dissemination of price information. This can be summarised through the specified objectives of most market regulators, which is to ensure the fair and efficient operation of capital markets. In this thesis, we focus upon the latter regulatory objective. We define efficient markets as those which minimize transaction costs while maximizing price discovery.

Globally, the past decade has seen numerous exchange evolvements in the quest for optimal market design. These changes have generally lead to increased competition and are often driven by technological advancements. Exchange markets have moved to more effective structures incrementally through experimentation. This dissertation addresses the market efficiency impact of three Australian Securities Exchange (ASX) market design initiatives: the introduction of broker anonymity, the Equity Research Scheme and the Exchange Traded Fund (ETF) Market Making Scheme.

The ASX was formed in 2006 through a merger between the Australian Stock Exchange and the Sydney Futures Exchange. Until the introduction of Chi-X Australia in 2011, the ASX held a virtual monopoly in Australian equities trading. The Australian Stock Exchange was previously formed in 1987 through the amalgamation of six state-based exchanges. This process facilitated the introduction of the Stock Exchange Automated Trading System (SEATS). SEATS are the most widely used among global exchanges, allowing for a comparison of our results with other markets. Trading hours range between 10am and 4pm and minimum tick sizes are set according to share price. Like most major markets, off-market trading is conducted for crossing and large block trades.

On 28 November 2005, the ASX removed the real-time display of broker identifiers from their trading screen. Previous to this, market participants could observe the brokers behind buy and sell transactions via SEATS. As markets across the globe are moving toward greater anonymity, numerous studies demonstrate that trader anonymity affects the behaviour of market participants. Earlier research finds that transparent markets improve liquidity and decrease transaction costs (e.g. Pagano et al., 1996; Baruch, 2005). More recently, a second school of thought is offered. Foucault et al. (2007) argue that the compulsory disclosure of broker identification can increase bid-ask spreads. Testing their theory on Euronext Paris, Foucault et al. (2007) conclude that broker anonymity leads to improvements in market liquidity as more aggressive orders narrows the bid-ask spread. Extending the analysis of Foucault et al. (2007) to include markets in Paris, Tokyo and Korea, Comerton-Forde et al. (2005) also reach qualitatively consistent conclusions.

Utilising data attained prior to the introduction of anonymity on the ASX, Frino et al. (2010 b) find a larger permanent price-impact with successive uni-directional trades when a single broker initiates these rather than by different brokers, consistent with the hypothesis that broker identity conveys information. The authors state that markets are more likely to be efficient when broker identities are disclosed. Assessing the market quality effects of the removal of broker identifiers on the ASX, Comerton-Forde et al. (2009) document a decline in time-weighted spread and order aggressiveness and an increase in order book depth. They conclude that broker anonymity is beneficial in fragmented markets, particularly for larger stocks.

The introduction of anonymity to the ASX combined with the contrasting evidence on its effects on market efficiency, particularly on the ASX, forms the motivation for Chapter 2. Applying the methodology employed in Frino et al. (2010 b)[1], our findings suggest that market participants no longer attribute greater information content to successive uni-directional trades by a single broker compared to successive uni-directional trades by different brokers following the introduction of anonymity on the ASX. With successive uni-directional trades by a single broker eliciting less of a permanent price impact post-anonymity, the price discovery process is inhibited. This is a striking result as it is in contrast with empirical evidence supporting anonymity due to observed market efficiency benefits. We also find that need for stealth trading in a transparent market, identified by Frino et al. (2010 b), is reduced as there is no difference in the information-content across size categories for buy- and sell-side

[1] The methodology is employed with broker identification information that was not available at the time of the transaction.

transactions. Supplementary to Comerton-Forde et al. (2009), this Chapter contributes to the existing literature by presenting a more complete picture when assessing the market quality impact of broker anonymity on the ASX.

As information asymmetry can act as a barrier to market efficiency, there is an incentive for regulators and exchanges to ensure investors are better-informed. Financial intermediaries such as stock analysts are relied upon to provide the information necessary to make an investment decision. As financial analysts publicise their findings, they lessen the advantage of investors with inside knowledge and improve the informational efficiency of capital markets (Moyer et al., 1989). Doukas et al. (2005) find a reduction in information asymmetry following the release of financial reports. In an attempt to maintain competitiveness and enhance the declining participation in their market, the ASX introduced a twelve-month trial of the Equity Research Scheme in July 2012. Under the stipulations of the scheme, analysts are required to produce financial reports on small and medium-size firms that have either received no coverage or minimal coverage prior to the scheme.[2] On 31 July 2013, the ASX announced a 12-month expansion of ERS. The expansion included increased funding, participating firms and financial analysts.

[2] The ERS stipulates three types of reports, determined by firm size. Firms with a market capitalisation below $50 million are issued a Company Snapshot including only publicly available information. Firms with a market capitalisation between $50 million and $200 million are issued a Retail Research Report. A Retail Research Report may or may not contain a formal recommendation and is a standard retail research report aimed at retail clients. Finally, companies with market capitalisations between $200 million and $1 billion are issued an Institutional Report. Institutional Report are produced to attract institutional investors in the hope to expand the business horizons of these companies. We limit our analysis to firms issued an Institutional Report.

The empirical evidence in support of financial analysts to improve market efficiency combined with the ASX's introduction of the ERS forms the motivation of Chapter 3. The second essay of this dissertation assesses the market efficiency effects of the ERS and finds that the release of the initiation reports is a significant and informative event for market participants. Using the price delay measure developed by Hou et al. (2005), we find that stocks exhibit greater informational efficiency following the introduction of the ERS. This is consistent with Holden et al. (1992) and Foster et al. (1993). The improvement in informational efficiency suggests that the ERS has been successful in improving the lengthier price discovery process that may be expected due to the staggered release of financial reports adopted in Australia. This can result in a more prolonged abnormal return structure which is observed when assessing cumulative abnormal returns over four intervals up to 12 months. Testing this theory, we note that the ERS was responsible for positive abnormal returns following the release of the initiation reports. This is consistent with Womack et al. (1996) and Boni et al. (2006). We also find enhancements in liquidity, namely the time-weighted proportional bid-ask spread, volume and turnover. This is also consistent with Kyle's (1985) model which predicts that market participants become more confident about the 'true' value of the security.

Unlike the majority of the existing literature, Chapter 3 assesses market efficiency effects of exogenously initiated analyst coverage. The findings extend the literature by providing evidence in support for exchange and regulator intervention when the levels of research are low. Through their information-collecting process and engagement with firms, our research shows that security analysts play a role in reducing the information asymmetry inherently established between participants with inside information and those without. As the financial analysts' reports are distributed, more investors are better informed and simultaneously, the advantage that insiders have is significantly reduced. As more investors become informed, asset prices become more informative and efficient. As a result, the job that security analysts do in reducing information asymmetry leads to more efficient prices and greater liquidity.

An efficient market minimises transaction costs. Despite their level of information, the number of market participants actively seeking to buy or sell a security at any particular moment in time can be quite small (Desmetz, 1968; Garbade et al., 1982). The primary role of a market maker is to provide immediacy for other investors by supplying liquidity. On 1 August 2010, The ASX implemented the ETF Market Making scheme. Interested trading participants were given the choice of entering the scheme as either an Advanced Market Maker or a Regular Market Maker[3]. Appendix 1.1 provides the list of relevant ETFs and their assigned market makers. The scheme grouped ETF's into a specific quoting schedules, each with its own spread and quantity requirements. In total, ten quoting schedules were established for equity ETFs. Details about quoting schedules can be found in Appendix 1.2. The scheme states that market makers are required to meet the relevant schedule 80% of the time over a calendar month from 10:15am until commencement of the Pre-CSPA (Closing

[3] Advanced Market Makers are contracted to make markets on a tranche of ETF products whereas Regular Market Makers have the option to pick which products they would like to be appointed to. We have been advised by the ASX to consider all market makers as Advanced Market Makers.

Single Price Auction) Session State (generally 4:00pm) on any trading day. Upon meeting the ETF requirements, the ASX will rebate all trading and clearing fees. A table of historical trading fees applicable to our sample period[4] can be found in Appendix 1.3. Rebated amounts are dependent on the identity of the other side of each trade. Appendix 1.4 provides the schedule of fee rebates.

The extant literature generally supports the involvement of market makers to optimise market efficiency. Support is reasoned due to observed liquidity improvements due to market makers. The third, and final, research chapter provides an event study to examine the market efficiency and market maker profitability effects of the ASX's ETF Market Making scheme. This study is motivated by three factors. Firstly, compared to other, more traditional markets, academic analysis of the Australian ETF industry is limited. This study provides a valuable insight to the efficiency of the ASX's ETF market by analysing both spreads and depth. Secondly, by studying the trades of market makers, we determine whether they are fulfilling their mandated duty of supplying liquidity. Much of the literature finds that market makers use their superior order-flow information to make position-taking gains and this may be in conflict with their obligation to provide liquidity under the scheme. Thirdly, the introduction of the scheme motivates us to study the market efficiency effects and in turn offer empirical evidence that contributes to the debate.

The findings of Chapter 4 highlight improvements in the bid-ask spread and depth across the sample of quoting schedules following the introduction of the scheme.

[4] The selected sample period is 1 August 2009 to 31 July 2011. More detail is provided in Section 4.3.

While market efficiency benefits associated with the introduction of market makers has been well-documented, this essay contributes to the existing literature by providing support for market makers in ETF markets specifically. Using trade data that identifies each market maker, we find that our sample of market makers are net suppliers of liquidity and set the spread to earn profits 83% of the time after the introduction of the scheme. However, when studying the interaction between liquidity and position-taking profitability, we find that market makers make positive position-taking gains 75% of time when liquidity losses are incurred. This finding is consistent with Copeland et al. (1983), who identifies an inverse relationship between a market makers liquidity and position-taking profitability. We also find no significant change in liquidity or position-taking profitability for market makers after the introduction of the scheme, suggesting that the liquidity improvements are not at the expense of other investors.

The rest of the dissertation is organised as follows. Chapter 3 examines the impact of broker anonymity on the ASX. Chapter 4 evaluates the effect of the ERS. Chapter 5 explores the ASX's ETF market making scheme. Chapter 6 provides concluding remarks.

Appendix – Chapter 1

Appendix 1.1

Exchange Traded Funds - Equity						
	Market Maker					
ASX ETF Code	Susquehanna Pacific	Citigroup Global Markets Australia	IMC Pacific	Deutsche Securities Australia	Optiver Australia	UBS Securities Australia
DGA	x					
EEU	x					
ENY	x	x				
FIN	x	x				
FIX	x	x				
IAA	x	x				
IBK	x	x				
IDD	x	x				
IEM	x	x				
IEU	x	x				
IHD	x	x		x	x	x
IHK	x	x				
IJP	x	x				
IJR	x	x				
IKO	x	x				
ILC	x	x		x	x	x
IOO	x	x				
IOZ	x	x		x	x	x
IRU	x	x				
ISG	x	x				
ISO	x	x		x	x	x
ITW	x	x				
IVE	x	x				
IVV	x	x				
IXI	x	x				
IXJ	x	x				
IZZ	x	x				
MAM	x	x				

OZF	x	x		x		
OZR	x	x		x		
POU	x					
QRE	x		x		x	
QFN	x		x		x	
RDV	x			x		
RVL				x		
RSR	x	x				
SFY	x	x		x		
SLF	x	x	x	x		
SSO	x	x		x		
STW						
SYI	x	x		x		
USD	x	x	x		x	
VAP	x	x		x		
VAS	x	x		x		
VEU	x	x		x		
VHY	x	x		x		
VLC	x	x		x		
VSO	x	x		x		
VTS	x	x		x		

Appendix 1.2

Quoting Schedules for Equity ETFs		
Schedule 1		
Bid Price in $AUD for Shares	Maximum Spread	Minimum Quantity
$5<	2c	$50,000 worth of stock
>$5	40 bps of best bid	$50,000 worth of stock
Schedule 2		
Bid Price in $AUD for Shares	Maximum Spread	Minimum Quantity
$5<	3c	$30,000 worth of stock
>$5	60 bps of best bid	$30,000 worth of stock
Schedule 3		
Bid Price in $AUD for Shares	Maximum Spread	Minimum Quantity
$5<	5c	$25,000 worth of stock
>$5	1% of best bid	$25,000 worth of stock
Schedule 4		
Bid Price in $AUD for Shares	Maximum Spread	Minimum Quantity
$5<	7c	$20,000 worth of stock
>$5	1.5% of best bid	$20,000 worth of stock
Schedule 5		
Bid Price in $AUD for Shares	Maximum Spread	Minimum Quantity
$5<	10c	$17,500 worth of stock
>$5	2% of best bid	$17,500 worth of stock
Schedule 6		
Bid Price in $AUD for Shares	Maximum Spread	Minimum Quantity
$5<	12c	$15,000 worth of stock
>$5	2.5% of best bid	$15,000 worth of stock
Schedule 7		
Bid Price in $AUD for Shares	Maximum Spread	Minimum Quantity
$5<	17c	$12,500 worth of stock
>$5	3.5% of best bid	$12,500 worth of stock
Schedule 8		
Bid Price in $AUD for Shares	Maximum Spread	Minimum Quantity
$5<	25c	$10,000 worth of stock
>$5	5% of best bid	$10,000 worth of stock
Schedule 9		
Bid Price in $AUD for Shares	Maximum Spread	Minimum Quantity
$5<	37c	$7,500 worth of stock

>$5	7.5% of best bid	$7,500 worth of stock
Schedule 10		
Bid Price in $AUD for Shares	Maximum Spread	Minimum Quantity
$5<	50c	$5,000 worth of stock
>$5	10% of best bid	$5,000 worth of stock

Appendix 1.3

Trading Fees	
Type of Trade	Trade Fee (bps, paid monthly)
1 July 2010 - 1 July 2011	
ETF Trade	0.15 (capped at $75 per trade, per side)
ETF (auction)	0.28 (capped at $75 per trade, per side)
1 July 2011 - 1 July 2012	
ETF Trade	0.15 (capped at $75 per trade, per side)
ETF (auction)	0.28 (capped at $75 per trade, per side)
1 July 2012 - 1 July 2013	
ETF Trade	0.15 (capped at $75 per trade, per side)
ETF (auction)	0.28 (capped at $75 per trade, per side)

Clearing Fees	
Type of Trade	Trade Fee (bps)
ETF	0.25

Appendix 1.4

Trading and Clearing Fee Rebates			
Rebate Side 1	Side 1	Side 2	Rebate Side 2
50%	Reg MM	Reg MM	50%
50%	Reg MM	Adv MM	100%
zero	Customer	Customer	zero
zero	Customer	Adv MM	200%
zero	Customer	Reg MM	120%
100%	Adv MM	Adv MM	100%

Chapter 2: Broker Anonymity and the Information Content of Trading Patterns

2.1. Introduction

Following the move from screen to floor trading at the ASX in 1987, a feature that remained was the ability of brokers alone to identify the counterparty with every order. In 2003, the ASX released a discussion paper proposing a number of reforms. The most significant – and the most contested – was the proposal to remove the transparency privileged that brokers shared. At the time of release, most of the major exchanges (e.g. London, New York and Tokyo) had moved to completely anonymous trading. In an era of transparency, the rationale for broker anonymity was driven by liquidity and fairness concerns. Transparency can foster distorted pricing, market manipulation and increased volatility and the removal of broker ID's in Tokyo was borne out of concerns about market manipulation. The primary focus of the discussion paper was to ensure that all investors are treated equally. What ensued was a varied response. While the anticipated liquidity enhancements were generally acknowledged, the Chartered Secretaries Australia (CSA)[5], representing the majority of public companies listed on the ASX, expressed their concern that the initiative would prevent listed companies accessing important trading information on their own shares, on a timely basis. It was their view that the ASX should be providing share issuers with greater access to trading information rather than seeking to restrict access.

---

[5] Australia's peak membership body for governance and compliance at the time with over 8,000 members.

On 28 November 2005, the ASX no longer allowed market participants to observe the identity of brokers submitting limit orders as well as the identity of buying and selling brokers involved in transactions. Removing this information meant that individual trades could no longer be linked to individual brokers known to trade with specific clients. Any trading patterns designed to conceal their identity in the past would no longer be necessary in the new environment. The degree of pre and post- trade transparency has been a longstanding topic when assessing the optimal design for financial markets. The notion of anonymity in financial markets relates to the knowledge that market participants have about the identity of investors who submit orders. The provision of broker anonymity can take place pre-trade and or post-trade. As markets across the globe are moving toward greater anonymity, numerous studies demonstrate that trader anonymity affects the behaviour of market participants.

A review of the existing literature provides two contrasting schools of thought. Earlier research concerning pre-trade transparency, of which anonymity can be deemed as a subcategory[6], find or argue that pre-trade transparency enhance liquidity and decrease transaction costs (e.g. Pagano et al., 1996; Baruch, 2005). Forster et al. (1992) present a theoretical model that suggests lower execution costs with greater pre-trade transparency for traders who are able to identify liquidity-motivated orders. They use the term “anonymity” to signify the broader scope of transaction-related information (e.g. the direction and size of the trade) and state that the extent of anonymity offered by a market alters the depth of the market and the dissemination of wealth across

[6] Anonymity refers to the transparency with respect to the identity of the broker.

agents. Specifying the trading mechanism by which the motivations of traders are disclosed through revealing their identity is outside the scope of the study.

More recently, with empirical studies dedicated solely to anonymity, a second school of thought is offered. Foucult et al. (2007) state that in the absence of anonymity, uninformed traders determine the proportion of informed traders in the market prior to submitting orders. When identities are concealed, informed traders bid more aggressively as attempts to manipulate uninformed trader's beliefs are less effective[7]. Testing their theory on Euronext Paris following the removal of pre-trade broker identification, Foucult et al. (2007) conclude that broker anonymity leads to improvements in market liquidity as more aggressive orders narrows the bid-ask spread. Extending the analysis of Foucault et al. (2007) to include markets in Paris, Tokyo and Korea[8], Comerton-Forde et al. (2005) also find that liquidity improves with anonymity. Specific to this chapter, Comerton-Ford et al. (2009) assess the market quality of the ASX following the introduction of anonymity in 2005. They find decreases in spreads and increases in order aggressiveness and market depth for larger, more liquid stocks. As the degree of anonymity increases, order flow becomes less informative; elucidating the documented liquidity improvements in anonymous markets (Linnainmaa et al., 2012).

The market attributes greater information content to larger orders (Chan et al., 1995). Prior literature supports the fact that informed investors tend to split a large order to

[7] Simaan, Weaver and Whicomb (2003) find that dealers quote more aggressively on ECNs than Nasdaq as predicted by the collusion hypothesis (dealers' IDs are displayed on Nasdaq but not in ECNs).
[8] As opposed to remove, broker identification was introduced in Korea.

reduce the exploitation of their information advantage (e.g., Vayanos, 2001; Golec, 2007). In a market where broker identities are not concealed, market participants may be able to identify parcels of a block trade if they are executed by the same broker. Frino et al. (2010 b) test the theory that consecutive, same-direction transactions by the same broker convey disproportionate information to the marketplace prior to the introduction of anonymity on the ASX in 2005. They find that investors split larger orders into parcels to reduce the exploitation of their information advantage. This occurs as market participants attribute greater information to larger orders. Frino et al. (2010 b) also find a larger permanent price-impact with successive uni-directional trades when a single broker initiates these rather than by different brokers, consistent with the hypothesis that broker identity conveys information.

The introduction of anonymity on the ASX provides an excellent natural experiment to investigate broker behaviour. One would expect that following anonymity, the inability to identify brokers would eliminate the extra information content attributed to successive, same-direction trades from the same broker. Following Frino et al. (2010 b), we conduct an event-study centred on the introduction of pre-trade broker anonymity to the ASX on 28 November 2005. This chapter uses the methodology employed in Frino et al. (2010 b) to determine the effect of this rule change. Using information not available to the market at the time of trading about broker identity, we find evidence to support the notion that market participants no longer attribute greater information content to successive uni-directional trades by a single broker compared to successive uni-directional trades by different brokers. With successive uni-directional trades by a single broker eliciting less of a permanent price impact following the introduction of anonymity, the price discovery process is inhibited. Supplementary to Comerton-Forde et al. (2009), a more complete picture is presented when assessing the market quality impact of broker anonymity on the ASX.

This chapter is also associated to the literature on stealth trading. The stealth trading hypothesis predicts that informed traders will concentrate their trades on medium sizes to conceal information. Both Barclay et al. (1993) and Chakravarty (2001) find that medium-sized trades convey more information than large trades. Additionally, Alexander et al. (2007) establish that medium-size rounded[9] transactions are more informative than large trades. As there is a greater probability that consecutive trades from the same broker are stealth trades, Frino et al. (2010 b) demonstrate that medium-sized, successive, same-direction trades from the same broker will move prices more than large trades. Following Frino et al. (2010 b), we find evidence that supports the assertion that medium-sized, same-broker trades are more informative than large trades for buy-side transactions in the period before anonymity. This occurs as market participants believe that the broker is executing pieces of a large order. The same result is not found for sell-side trades. Subsequent to the introduction of broker anonymity, there is no difference in the information-content across size categories for buy- and sell-side transactions. Hence the need for stealth trading is reduced.

The remainder of the chapter is organised as follows. Section 2 provides a review of the literature and sets out the tested hypotheses, while section 3 describes the sample

[9] Multiples of 500, 1000 etc.

and methodology employed. Section 4 presents the results and then finally, Section 5 concludes.

2.2. Literature Review and Hypotheses Development

This section invokes the literature and intuitive considerations associated with transparency and broker anonymity to formulate several hypotheses to be tested.

2.2.1. Financial Markets and Asymmetry Information

Asymmetric information and noise trading[10] are often pointed to as barriers to informational market efficiency. Kyle (1985) and Black (1986) suggest that noise trading is pervasive as it delays the impounding of information in stock prices. Asymmetric information exists when some market participants have more information about a security than others. Intuitively, it is unlikely that investors will possess market-wide private information; therefore, asymmetric information is more prominent in individual stocks (Subrahmanyam, 1991). Investors that can more accurately predict the intrinsic value of a security are considered to be more informed than others. While asymmetric information is a clear barrier to strong-form market efficiency, it is also problematic for the fairness and integrity of capital markets (Eleswarapu et al., 2004).

Numerous studies have investigated the relationship between stock prices and information. The concept of economic equilibrium suggests that prices must convey

[10] Trades made by investors who make decisions without the use of fundamental data.

all publicly available information that is required to make optimal choices. However, given the prominence of asymmetric information, it is unlikely that stock prices reflect the expectations of market participants (Grossman et al., 1980). Grossman et al. (1980) expand on this by stating that there would be no incentive for market participants to pursue and gather information if strong-form efficiency existed. Therefore, collecting information is integral in determining the 'true' value of an asset.

Asset pricing models generally do not consider information asymmetry as they assume homogenous information amongst investors (O'Hara, 2003). Diamond et al. (1991) develop a model that recognises the impact private information can have amongst different classes of investors. They argue that while private information is important, sufficient capital must be invested to impact the price of the security. Large, institutional investors are capable of moving the market if trading on privately disclosed information, however smaller firms are unlikely to have a material effect on prices, even in aggregate.

While it is clear that asymmetric information is a barrier to efficient prices, it can be argued that it is essential for market equilibrium (Grossman et al., 1980). For a transaction to clear there must be parties on both sides – something that would not exist if there were no differences among investor opinions and views (Karpoff, 1986). Grossman et al. (1980) also state that investors who seek new information require higher returns. Investors are incentivised to gather new information as long as the marginal benefit is greater than the marginal cost of doing so (Fama, 1991). Well-functioning capital markets exist with incomplete information; prices will not represent all information in equilibrium (Grossman et al., 1980).

The relationship between information asymmetry and liquidity has been well documented in the extant literature. A security is likely to be more liquid when information asymmetry is low; less-informed investors are less willing to trade if they know there are better-informed investors (Akerlof, 1970; Glosten et al., 1985). This is supported empirically by studies such as Welker (1995) and Bartov et al. (1996) who find a rise in the number of trades and trading volume once information asymmetry is reduced. This can be explained by the reduction in adverse selection costs as investors become better informed (Blume et al., 1994; Kim et al., 1997). Intuitively, investors are more likely to trade when they are well informed.

The overriding theme of the competing evidence is that asymmetric information is detrimental to the functioning of capital markets. There is incentive for regulators and exchanges to make investors better-informed.

2.2.2. Transparency: Theoretical Research

There are many elements to market transparency, with the most important dimension being the transparency of prices pre- and post- transactions. In this thesis, an additional component of transparency is studied: broker identities, both pre- and post-trade.

A review of the theoretical literature leads to inconsistent inferences about the effects of transparency in financial markets. Studies in favour of transparency, such as Admati et al. (1991), Pagano et al. (1996) and Baruch (2005), each conclude that transparency improves liquidity. Admati et al. (1991) show that, at the expense of traders who do not disclose, uninformed liquidity investors can benefit from voluntary transparency. In a transparent market, the advantage held by informed traders is mitigated (Chowdhry et al., 1991; Madhavan, 1995; Bloomfield et al., 1999). This is often presented as an explanation to the finding. Distinguishing between informed and uninformed traders, Pagano et al. (1996) find benefits to uninformed traders with increased transparency. This is consistent with the findings of Forster et al. (1992) who prove that enhanced pre-trade transparency reduces execution costs for investors who can signal liquidity-motivated orders.

Relying on the presence of informed limit order traders, Foucault et al. (2007) argues that the compulsory disclosure of broker identification can increase bid-ask spreads. Foucault et al. (2007) begins by modelling dealers whose "stale" limit orders are "picked off" by speculators when future volatility is high. Under the existence of asymmetric information in a transparent market, uninformed dealers gage information from informed dealers regarding future volatility. Therefore, in anticipation of adverse information events, uninformed dealers price-protect themselves and spreads widen. On the other hand, Foucault et al. (2007) also predict that uninformed investors are more likely to post aggressively and narrow the spread when the chance of informed trading is low as the chances of being "picked-off" are lessened. Therefore, in contrast to the aforementioned theoretical studies, this model forecasts narrower spreads in an anonymous market as the LOB becomes less informative.

To effectively study broker identification transparency, informed trading must be range over two periods to allow for bid-ask spread modifications subsequent to the exposure of trade direction. Under the model presented in Foucault et al. (2007), informed investors are not given the opportunity to trade again to exploit their informational advantage. It is the adverse price adjustment from informed traders that results in improved market quality in transparent environments (Maher et al., 2008).

Modelling informed investors who may favour placing limit orders rather than exclusively relying on market orders, Boulatov et al. (2007) find that transparent markets allow these dealers to better anticipate trades pertaining to information. Therefore they can profit from better price discrimination. The less aggressive quoting behaviour of informed investors consequently results in greater profits for themselves and dealers at the expense of uninformed investors. Hence, in contrast to much of the theoretical literature, Boulatov et al. (2007) show that the exposure of dealer identities makes it beneficial to informed dealers as collusion is enabled.

2.2.3. Transparency: Empirical Research

Due to a lack of data, early empirical research on the effects of market transparency was conducted as experiments. Like the theoretical literature, a review of the empirical research surrounding market transparency produces conflicting results. More recently, especially in research devoted to anonymity, it is argued that more opaque markets lead to improved liquidity and reduce transaction costs.

2.2.3.a. Transparency Market Efficiency

Anonymity can lead to benefits by lessening the market impact of trades and assisting brokers and dealers in best execution responsibilities. Commenting on the post-trade anonymity feature on NASDAQ's SuperMontage, the Securities and Exchange Commission (SEC) states that it allows NASDAQ to offer benefits such as minimizing the price impact of institutional orders (SEC, Release No. 34-38257, 2003). In an anonymous environment, traders can conceal their intentions to avoid parasitic trading or front running (Harris, 1997). Market efficiency effects associated with the price impact of anonymous trades are detailed in a number of empirical studies.

Examining the proportion of a stock's cumulative price change, Barclay et al. (2003) find that price movements are due mainly to informed traders' private information on the NYSE. Heidle et al. (1999) assess the risk of trading with an informed traders across alternate exchange structures. They find that the probability of encountering an informed trader is higher in dealer markets than it is in auction markets. This finding is consistent with greater anonymity in dealer markets. With a related hypothesis, Grammig et al. (2001) empirically examines whether the level of broker anonymity is related to the probability of information-based trading. The study focuses on the German stock market where non-anonymous traditional floor based exchanges co-exist with an anonymous computerized trading system. The authors extend the method proposed by Easley et al. (1996)[11], an approach that estimates the intensity of informed and uninformed order flow and therefore provides a direct assessment of the probability of informed trading. The method is further developed by Grammig et al. (2001) to allow for simultaneous estimation of their parallel markets and allows the authors to determine that the probability of informed trading is significantly lower in the floor based trading system. They conclude that a higher degree of anonymity is associated with a higher probability of informed trading and that anonymity is not well suited for smaller stocks.

Foucault et al. (2007) extend their theoretical rationale and test their proposition by studying the behaviour of bid-ask spreads and depth of CAC-40 and *Contnu* A stocks on Euronext Paris. In April 2001, Euronext Paris removed pre-trade transparency. Prior to this, brokers had full access to the full LOB where they could identify the broker responsible for each order. Foucault et al. (2007) centre their analysis on this change and after controlling for trading activity, price volatility and stock prices, find a decline in quoted and effective spreads and price informativeness following a shift to anonymity.

Extending the analysis of Foucault et al. (2007), Comerton-Forde et al. (2005) examine the removal of broker identifications Euronext Paris and the Tokyo Stock Exchange. To supplement their analysis, they also assess the introduction of broker identification for limit orders on the Korea Stock Exchange. They find that a reduction in transparency results in a decrease in both the relative and effective bid-ask spreads

[11] Easley et al. (2006) find that the probability of informed trading is negatively related to firm size.

in the Tokyo Stock Exchange and Euronext Paris. Consistently, the relative bid-ask spread increases on the Korea Stock Exchange as they move to an even higher level of pre-trade transparency. Due to data limitations, it was not possible for the authors to examine effective spreads for Korean stocks.

Replicating the methodology utilised in Foucault et al. (2007), Majois (2007) shows that the reduction in spreads observed in Paris (Comerton-Forde et al, 2005) simultaneously appear on the NYSE, where there was no policy change. The authors state that interpreting changes in liquidity due to alterations in market design should be interpreted with a lot of care. Rather than attribute the liquidity improvements observed in Paris to the introduction of anonymity, Majois (2007) poses a "global liquidity factor" as the determinant. The global liquidity factor, a central focus of Stahel (2005), assesses commonalities in liquidity in an international framework, using samples from Japan, the UK and the US. As the findings of Comerton-Forde et al. (2005) are determined from anonymity changes at three different time periods, Majois (2007) does not produce enough evidence to refute the conclusions made by Comerton-Forde et al. (2005). Majois (2007) only provides contrasting evidence for one of the three independent liquidity improvements attributed to the introduction of anonymity by Comerton-Forde et al. (2005). Offering a different take, Maher et al. (2008) finds the results of Majois (2007) to be unsurprising as the controls, developed in Foucault et al. (2007), are not exogenous as required, but endogenous.

In a study particularly pertinent to this thesis, Comerton-Forde et al. (2009) examine the effects of the removal of broker identifiers from the LOB of the ASX. Comerton-

Forde et al. (2009) specifically replicate the model presented in Foucault et al. (2007) with the addition of a trend term that captures the move to broker identification anonymity. Like Foucault et al. (2007), they document a fall in the time-weighted spread, noting a greater effect for smaller stocks. In line with the hypothesis that limit order traders are more likely to expose their orders when their identity is hidden, they also find a reduction in order aggressiveness and an increase in order book depth.

Continuing their analysis, Comerton-Forde et al. (2009) assess the impact of anonymity within fragmented markets. Madhavan (1995) states that in fragmented markets, order flow should drift toward the more liquid and efficient market. If traders are capable of managing their order exposure risk when trading anonymously, an anonymous market should attract liquidity from the more transparent market (Grossman, 1992). Comerton-Forde et al. (2009) identify investor preference for anonymous markets for large stocks with anonymous markets drawing order flow from non-anonymous alternate markets. This is an intuitive finding as smaller stocks tend to display higher levels of information asymmetry (Hasbrouck, 1991) and is consistent with Theissen (2002). Bloomfield et al. (2000) also determine most dealers prefer a more transparent market and subsequently attain larger profits than dealers in less opaque markets.

Simaan et al. (2003) assess the quoting behaviour of NASDAQ market makers across different trading platforms and argue that a transparent market environment allows investors to informally collude and quote wider spreads. They demonstrate this by showing wider quotes posted via anonymous Electronic Communication Networks

(ECNs) compared to those posted through NASDAQ's transparent dealer quotation system. Simaan et al. (2003) state that NASDAQ dealers are more inclined to quote aggressively when their identities are not disclosed, leading to greater price competition. Similarly, Boehmer et al. (2005) find a decreased depth and order aggressiveness as investors submit and then cancel orders at a faster rate following an increase in pre-trade transparency. It must be noted that Simaan et al. (2003) compare an anonymous automated structure with a non-anonymous structure where liquidity providers can voluntarily trade upon identifying other participants. Hence it is challenging to draw comparisons between such papers as they do not isolate the impact of anonymity from other structural influences.

Moving from equity markets, Frino et al. (2006) find improvements in quoted depth and trading volume as well as meaningful reductions in quoted spreads in the 90 Day BAB, 3 Year Treasury Bond and 10 Year Treasury Bond Futures following the removal of broker mnemonics on the Sydney Futures Exchange.

Once broker identities are removed, the typical result found is that liquidity is improved[12]. Linnainmaa et al. (2012) offer an alternate interpretation of the result in the event study literature. The authors find that the market uses broker identifications to update prices. They state that the price impact of a trade would decrease following anonymity, implying greater liquidity; however, this is at the expense of informational

[12] E.g. Comerton-Forde et al. (2005), Foucault et al. (2007), Theissen (2007), Aspris et al. (2008), Comerton-Forde et al. (2009) and Friederich et al. (2011).

efficiency. As prices, do not adequately adjust to order flow, informed investors can greater profit from their informational advantage.

In contrast to the empirical studies reviewed, Boehmer et al. (2005) find an increase in market depth and reduced effective spreads following the introduction of NYSE's OpenBook in 2002. This is consistent with Hendershott et al. (2005), who analyst the natural experiment that occurred when the Island electronic communications network (ECN) LOB decreased in transparency for the 3 most active exchange-traded funds. They find increased trading costs in the less transparent trading system as well as a loss of market share for Island.

Prior to the introduction of anonymity on the ASX in 2005, Frino et al. (2010 b) test the theory that consecutive, same-direction transactions by the same broker convey disproportionate information to the marketplace. They find that trader motivation is revealed through the disclosure of their identity. The findings are consistent with Pham (2013) who finds that information is disseminated quicker in the KOSDAQ market once broker identifiers were transparent.

Following the introduction of broker anonymity on the ASX subsequent to Frino et al. (2010 b), we develop the following hypotheses:

H_1: Successive, same-direction trades from the same broker will convey more information than successive, same-direction trades from different brokers in the 18 months prior to the introduction of broker anonymity on the ASX.

H_2: Successive, same-direction trades from the same broker will convey the same information as successive, same-direction trades from different brokers in the 18 months subsequent to the introduction of broker anonymity on the ASX.

2.2.3.b. Transparency and Stealth Trading

In an environment where broker identities are not concealed, investors may concentrate their trades on medium sizes[13] to conceal information. This is known as the stealth trading hypothesis. As market participants become privy to this, they may recognise when a broker is executing pieces of a large order.

Coupled with the market efficiency benefits associated with anonymity, discussed in Section 2.3.3.a, Barclay et al. (1993) also find that medium-sized trades convey more information than large trades on the NYSE. Using audit trail data for a sample of NYSE stocks, Chakravarty (2001) shows that medium-sized trades are associated with disproportionately large cumulative stock price changes relative to their proportion of all trades and volume. Intuitively, they attribute the source of these trades to be those initiated by institutions. Alexander and Peterson (2007) also establish that medium-size rounded transactions are more informative than large trades on the NYSE and Nasdaq.

Using ASX trading data, Chakravarty et al. (2011) test the idea that informed traders disguise their trades. The paper examines trading strategies of informed investors

[13] Multiples of 500, 1000 etc.

relative to the level of liquidity in the market. The authors find that traders with information utilise different trading strategies depending on the level of liquidity in the marketplace. During periods of higher liquidity, when the traders' chance of execution is higher, only medium-sized trades result in disproportionate price impacts. When liquidity is lower, the chance of execution is lower and informed traders appear to split their trades into smaller sized trades. The results imply that informed investors trading strategies is a trade-off between the chance of execution and transaction costs. The results of Chakravarty et al. (2011) differ slightly to those found in the U.S markets where only medium-size trades move the market.

Also studying effects specific to the ASX, Frino et al. (2010 b) demonstrate that medium-sized, successive, same-direction trades from the same broker will move prices more than large trades as there is a greater probability that consecutive trades from the same broker are stealth trades. Each of the aforementioned studies provide evidence that supports the stealth trading hypothesis. Following the introduction of broker anonymity on the ASX subsequent to the findings identified in Frino et al. (2010 b), we develop the following hypotheses:

H_3: Successive, medium-sized, same-direction trades from the same broker will convey more information than successive, large-sized, same-direction trades from different brokers in the 18 months prior to the introduction of broker anonymity on the ASX.

H_4: Successive, medium-sized, same-direction trades from the same broker will convey the same information as successive, large-sized, same-direction trades from different brokers in the 18 months subsequent to the introduction of broker anonymity on the ASX.

2.3. Methodology

2.3.1. Sample and Data Sources

We select an event window of 36 months around the introduction of anonymity to the ASX on November 28 2005. This includes an 18-month pre-event window of 28 June 2004 to 27 November 2005 and an 18-month post-event window of 28 November 2005 to 27 June 2007.

Our sample of stocks are the constituents of the All Ords as of 28 November 2005, for each stock, intraday order and trade data are analysed over the sample period. ASX trade and order book data is sourced from the Securities Industry Research Centre of Asia-Pacific (SIRCA). For each security, we obtain the time, bid-price, bid-size, ask-price, ask-size, record-type, price, volume, buyer-broker-ID and seller-broker-ID. The order book data also contains broker identifications, enabling us identify consecutive trades by the same broker. Finally, market capitalisation data is obtained from DatAnalysis.

2.3.2. Analysis

We are comparing the information content of two consecutive trades in the same direction by the same broker (via a market order) with two consecutive trades in the same direction by different brokers. To do so, we follow the methodology employed by Frino et al. (2010 b).

On-market crossings are shown in our data file when the buying and selling broker identification are the same and are eliminated. A market order can execute against a series of standing limit orders at different levels of the order book. This occurrence appears on our data file as separate transactions. Therefore we aggregate any series of trades with the same broker identification for the trade initiator, date and time stamp. Price and misquotes are volume-weighted in such instances.

Our experimental sample consists of buyer-initiated (seller-initiated) trades which are followed by buyer-initiated (seller-initiated) trades where the buying (selling) broker is the same. The control sample is comprised of buyer-initiated (seller-initiated) trades which are followed by buyer-initiated (seller-initiated) trades where the buying (selling) brokers are different. To ensure that the information content of an experimental pair can be attributed to that specific experimental pair, experimental pairs which contain other experimental pairs within 5 transactions of the experimental and control pairs are removed.

When considering the information content of our trade pairs, it is important that the results are not influenced by other factors. A significant and well-documented factor is the size of the trade (Hasbrouck, 1991; Barclay et al., 1993; Chan et al., 2000). We categorize each trade into small, medium and large categories for each stock. Large trades are the largest 2% of trades, small trades are the smallest 55% of transactions and medium-sized trades are the remaining 43% of trades for the particular stock[14]. To control for the information content of the size of a trade we implement a matching procedure. We match each pair of trades in the experimental sample with a pair of trades in the control sample if the control pairs (first and second trade): (1) are in the same direction and in the same stock, and (2) in the same size category as the experimental trades. In the instance of more than one control trade pair for a particular experimental trade pair, we match further on the average size of the trade pair, date and time. Matching on date and time ensures that we are controlling for the market environment. The matching process is conducted without replacement, and the final matched sample of 52,121 buyer-initiated trades and 52,382 seller-initiated trades, executed by 81 different broker firms for the pre-event period. The final matched sample for the post-event period consists of 97,462 buyer-initiated trade pairs and 97,753 seller-initiated trade pairs, executed by 89 different broker firms.

To test $H_1$and H_2 we estimate and compare the 'permanent' price impact of a given pair of transactions for both the experimental and control samples. Like Frino et al. (2010 b) we implement the method used in the block trade literature (Halthausen et al., 1987; Gemmill, 1996). Our permanent price impact measure is:

[14] The classification scheme reported in this paper results in a similar proportion of small, medium and large-sized trades by Barclay and Warner (1993).

$$P_i = ln\frac{M_{t+5}}{M_{t-6}}\,, \tag{2.1}$$

where M_{t-6} is the corresponding midpoint[15] of the bid-ask quotes of the transaction six trades previous, and M_{t+5} is the corresponding midpoint of the bid-ask quotes of the transaction five trades after, the experimental or control trade *t*. The experimental or control trade *t* is defined as the second trade of the pair.

We are comparing the information effect of our experimental pairs to that of our control pairs. To do this effectively, we must control for any other factors that could have an impact on the permanent price impact of a transaction. As well as size, which we have considered in our matching process, it is well-established that the level of information of a given trade is related to the time between transactions (Easley et al., 1998; Chung et al., 2004; McInish, 2005; Frijns, 2006).

We sort all trade pairs by time interval for each stock and categorise them into a small, medium or large category. A short time interval is an interval that falls in the top 2%, long time intervals are those in the bottom 55%, and medium time intervals are those in the remaining 43%. Like Frino et al. (2010 b), we also account for the identity of the broker[16]. If informed, institutional investors are known to trade through particular brokers, then broker identities may contain information prior to the introduction of anonymity. As broker identities are concealed, we do not expect them to have any effect in the post-event environment. We control for these characteristics in the

[15] The midpoint of the bid-ask quotes is used to avoid noise associated with bid-ask bounce. See Lease et al. (1991) for a discussion of the effects of bid-ask ounce on event-study returns.
[16] Frino et al. (2010 b) use the example of systematically better informed clients trading through particular institutional brokers.

following OLS regression model, estimated for buyer-initiated and seller-initiated trades, pre- and post-anonymity:

$$P_i = \propto \; + \beta_1 D_{Large}^{Size} + \; \beta_2 D_{Medium}^{Size} + \beta_3 D_{Short}^{Time} + \beta_4 D_{Medium}^{Time} + \beta_5 D_{Same_{broker}} + \sum_{i=2}^{n} \gamma_i D_{i,t}^{Broker} + \; \varepsilon_i \,, \tag{2.2}$$

where P_i is our permanent price impact measure defined above. D_{Large}^{Size} and D_{Medium}^{Size} are dummy variables for the trade size categories and identify whether trade *t* is a medium or large-sized trade. D_{Short}^{Time} and D_{Medium}^{Time} are dummy variables for the time interval categories and identify whether the time elapsed between a trade pair is short or medium. $D_{i,t}^{Broker}$ are dummy variables for the broker which take on a value 1 if either the second trade in the current trade pair is initiated by broker i, otherwise zero. $D_{Same_{broker}}$ is a dummy variable which is set to 1 if trade *t* is an experimental trade; otherwise zero.

Consistent with the stealth trading hypothesis, Frino et al. (2010 b) find that trades executed through the same broker in the medium size category conveys more information than large trades. We test for this incremental effect both pre- and post-anonymity. Following the introduction of anonymity, we expect any effect to disappear. As market participants can now trade anonymously, the need for stealth trading is reduced. To test this, we run the following OLS regression model:

$$P_i = \propto \; + \beta_1 D_{Large}^{Size} + \; \beta_2 D_{Medium}^{Size} + \beta_3 D_{Short}^{Time} + \; \beta_4 D_{Medium}^{Time} + \; \beta_5 (D_{Same_{broker}} \times D_{Large}^{Size}) + \beta_6 (D_{Same_{broker}} \times D_{Medium}^{Size}) + \beta_7 (D_{Same_{broker}} \times D_{Small}^{Size}) + \; \sum_{i=2}^{n} \gamma_i D_{i,t}^{Broker} + \; \varepsilon_i \; , \tag{2.3}$$

where $D_{Same_{broker}} \times D_{Large}^{Size}$, $D_{Same_{broker}} \times D_{Medium}^{Size}$ and $D_{Same_{broker}} \times D_{Small}^{Size}$ represent interaction variables between our experimental and control pairs and their size category.

2.4. Results

2.4.1. Descriptive Statistics

Table 2-1 reports the size descriptive statistics for the experimental and control samples in the period prior to the introduction of anonymity. It is clear that the matching process has resulted in a close match in the size of trades between the experimental and control samples. The average size of a buyer-initiated experimental pair (7876) is similar to the average size of a buyer-initiated control pair (7798). The same conclusion can be drawn from seller-initiated pairs with an average size of 6958 and 6821 for the experimental and control pairs respectively. The average size of the first and second trades are also comparable across the experimental and control samples for both buyer-initiated and seller-initiated pairs. Similar to Frino et al. (2010 b), we observe a greater average trade size in the second trade for buyer-initiated trades (in the experimental and control samples) but a lower average trade size in the second trade for seller-initiated trades.

Table 2- 1: Descriptive Statistics- Pre-Anonymity

This table provides descriptive statistics for the experimental and control samples which characterize the average size between trades. Transactions are sampled from the constituents of the All Ords on the ASX as of 28 November 2005, over the period 28 June 2004 to 27 November 2005. The experimental sample contains of consecutive trades initiated by the same broker and in the same direction. The control sample contains consecutive trades initiated by different brokers in the same direction. Trade pairs are ordered from largest to smallest by their average size. The largest 2% are the “large” trades, the smallest 55% are “small” trades and the remaining 43% are “medium” trades. Each pair of trades in the experimental samples is matched with a pair of control trades from the same stock, size category and in the same direction. In the instance of more than one suitable control pair, the pair with the closest average trade size, date and time to the experimental pair is selected. Sampling is conducted without replacement.

	Experimental Trades			Control Trades		
	First Trade	Second Trade	Average	First Trade	Second Trade	Average
Panel A: Consecutive buyer-initiated trades (N = 52,121)						
Mean	5308	10445	7876	5706	9891	7798
Median	1702	4002	3547	1716	3229	3458
Std. Dev.	17829	26700	18279	18204	25144	17319
Panel B: Consecutive seller-initiated trades (N = 52,382)						
Mean	8506	5211	6958	8282	5360	6821
Median	2986	1566	2824	2828	1542	2826
Std. Dev.	27260	15772	17911	22919	21613	17389

Table 2-2 reports size descriptive statistics for the experimental and control samples in the period subsequent to the introduction of anonymity. Again, the matching process has resulted in a close match in the size of trades between the experimental and control samples for both buyer- and seller-initiated trades. The difference in the average size of the first and second trades is also negligible across the experimental and control samples for both buyer-initiated and seller-initiated pairs. Interestingly, the number of trade pairs has almost doubled. This indicates that investors are taking less steps to conceal their information advantage in the new environment.

Table 2- 2: Descriptive Statistics- Post-Anonymity

This table provides descriptive statistics for the experimental and control samples which characterize the average size between trades. Transactions are sampled from the constituents of the All Ords on the ASX as of 28 November 2005, over the period 28 November 2005 to 27 June 2007. The experimental sample contains of consecutive trades initiated by the same broker and in the same direction. The control sample contains consecutive trades initiated by different brokers in the same direction. Trade pairs are ordered from largest to smallest by their average size. The largest 2% are the "large" trades, the smallest 55% are "small" trades and the remaining 43% are "medium" trades. Each pair of trades in the experimental samples is matched with a pair of control trades from the same stock, size category and in the same direction. In the instance of more than one suitable control pair, the pair with the closest average trade size, date and time to the experimental pair is selected. Sampling is conducted without replacement.

	Experimental Trades			Control Trades		
	First Trade	Second Trade	Average	First Trade	Second Trade	Average
Panel A: Consecutive buyer-initiated trades (N = 97,462)						
Mean	4020	7790	5905	4301	7438	5870
Median	1006	2068	2045	1039	2048	2046
Std. Dev.	15274	25343	17285	15505	26017	17401
Panel B: Consecutive seller-initiated trades (N = 97,753)						
Mean	6133	3869	5001	5981	3966	4974
Median	1843	999	1720	1774	945	1721
Std. Dev.	19012	15160	13789	23698	15088	15423

The average permanent price impact of experimental and control trades prior to the introduction of anonymity can be found in Table 2-3. Panel A suggests a greater permanent re-assessment of stock value for buyer-initiated transactions by the same broker. Specifically, consecutive buyer-initiated transactions through the same broker exhibit a permanent price impact of 0.020% compared to 0.008% for consecutive buyer-initiated transactions by the different brokers. The same conclusion can be drawn for seller-initiated trades. Consecutive seller-initiated transactions through the same broker display a permanent price impact of -0.019%, while consecutive seller-initiated transactions by different brokers lead to a permanent price impact -0.012%. The difference in means are significant at the 1% and 5% level for buyer-initiated and seller-initiated trades, respectively.

Table 2- 3: Permanent Price Impact of Trades- Pre-Anonymity

This table provides statistics that characterize the permanent price impact (P_i) of experimental and control trades. Transactions are sampled from the constituents of the All Ords on the ASX as of 28 November 2005, over the period 28 June 2004 to 27 November 2005. The experimental sample contains of consecutive trades initiated by the same broker and in the same direction. The control sample contains consecutive trades initiated by different brokers in the same direction. Trade pairs are ordered from largest to smallest by their average size. The largest 2% are the "large" trades, the smallest 55% are "small" trades and the remaining 43% are "medium" trades. Each pair of trades in the experimental samples is matched with a pair of control trades from the same stock, size category and in the same direction. In the instance of more than one suitable control pair, the pair with the closest average trade size, date and time to the experimental pair is selected. Sampling is conducted without replacement. The permanent price impact of calculated as the natural log of the ratio of the bid-ask midpoint from six trades before to five trades after the second of the two consecutive trades. The *t*-test is based on the hypothesis that the mean difference is not statistically different from zero. ***,** and * represent significant at the 1%, 5% and 10% level respectively. All means and standard deviations are multiplied by 100.

	Mean		T-Test	
	Experimental	Control	Difference	*t*
Panel A: Consecutive buyer-initiated trades (N = 52,121)				
P_i	0.020	0.008	0.012	3.45***
Panel B: Consecutive seller-initiated trades (N = 52,382)				
P_i	-0.019	-0.012	-0.007	-2.06**

Table 2-4 reports the average permanent price impact of experimental and control trades following the introduction of anonymity. Panel A reports that consecutive buyer-initiated trades by the same broker result in a permanent price impact of 0.018% while consecutive buyer-initiated transactions by different brokers have a permanent price impact of 0.023%. The difference in means between the experimental and control samples are not significant at the 0.1 level. Panel B reports a price impact of -0.015% for consecutive seller-initiated trades by the same broker and a price impact of -0.008% for consecutive seller-initiated transactions by different brokers. The difference in means between the experimental and control samples are not significant at the 5% level. Our univariate results indicate that there is no difference in the price impact of two consecutive same side trades through the same broker compared to two consecutive same side transactions through different brokers.

Table 2- 4: Permanent Price Impact of Trades- Post-Anonymity

This table provides statistics that characterize the permanent price impact (P_i) of experimental and control trades. Transactions are sampled from the constituents of the All Ords on the ASX as of 28 November 2005 over the period 28 November 2005 to 27 June 2007. The experimental sample contains of consecutive trades initiated by the same broker and in the same direction. The control sample contains consecutive trades initiated by different brokers in the same direction. Trade pairs are ordered from largest to smallest by their average size. The largest 2% are the "large" trades, the smallest 55% are "small" trades and the remaining 43% are "medium" trades. Each pair of trades in the experimental samples is matched with a pair of control trades from the same stock, size category and in the same direction. In the instance of more than one suitable control pair, the pair with the closest average trade size, date and time to the experimental pair is selected. Sampling is conducted without replacement. The permanent price impact of calculated as the natural log of the ratio of the bid-ask midpoint from six trades before to five trades after the second of the two consecutive trades. The *t*-test is based on the hypothesis that the mean difference is not statistically different from zero. ***,** and * represent significant at the 1%, 5% and 10% level respectively. All means and standard deviations are multiplied by 100.

	Mean		T-Test	
	Experimental	Control	Difference	*t*
Panel A: Consecutive buyer-initiated trades (N = 97,462)				
P_i	0.018	0.023	-0.005	0.57
Panel B: Consecutive seller-initiated trades (N = 97,753)				
P_i	-0.016	-0.008	-0.008	-1.81*

After the introduction of anonymity, we expect the result found in Table 2-3 and Frino et al. (2010 b) to disappear given that there is no longer a recognisable difference between our experimental and control samples to the trader. The results presented in Table 2-4 are consistent with our expectations. Frino et al. (2010 b) note that the time elapsed between trades is shorter for control trades. The greater trade frequency exhibited by control trades may explain the results presented in Table 2-3. As we have also not yet considered the identities of the particular brokers submitting orders, it is premature to conclude that consecutive, same-side transactions by the same broker convey more information than consecutive, same-direction trades via different brokers prior to anonymity (and that the introduction of anonymity removed this effect).

2.4.2. Regression Analysis

To prove that two consecutive trades in the same direction executed by the same broker leads to a larger permanent re-assessment of stock value than two consecutive trades in the same direction executed by different brokers we must control for factors that may influence the information content of a transaction. OLS regression results associated with Equation (2.2) prior to the introduction of anonymity are presented in Table 2-5. The table provides estimates of the effect of consecutive, same-direction trades through the same broker on stock prices after controlling for the size of the trade, the time elapsed between trades and broker identity. *F* statistics of 8.22 and 6.73 suggests that the overall model for buyer- and seller-initiated trades is significant at the 0.01 level, respectively.

For buyer-initiated trade pairs, the coefficient of 0.018 on D_{Short}^{Time} is significant at the 1% level and larger than the coefficient of 0.022 on D_{Medium}^{Time} (significant at only the 10% level). Therefore, market participants use the time between trades as a signal for the presence of informed traders. This is consistent with Chung et al. (2005) and Frino et al. (2010 b). A similar result is initially observed for seller-initiated transactions, however neither of the coefficients are significant at the 5% level. The magnitude of the coefficient on D_{Large}^{Size} is greater than the magnitude of the coefficient on

D_{Medium}^{Size} for both buyer-initiated and seller-initiated trades. Each of the coefficients are significant at the 1% level. These results are consistent with Freon et al. (2010) and the previous literature[17] highlighting that larger sized trades have more of a permanent impact on stock values than smaller trades.

Our primary variable of interest, $D_{Same_{broker}}$, is significant at the 1% level for consecutive buyer-initiated and consecutive seller-initiated transactions. The coefficient is positive for buyer-initiated trade pairs and negative for seller-initiated trade pairs. Therefore, after considering the size of the trade, time between trades and broker identities, the experimental sample still exhibits a larger permanent price impact than the control sample and we fail to reject H_1. Consistent with Frino et al. (2010 b), the identity of the broker can result in a permanent price impact. 30% of brokers initiated buy-side trades are associated with a permanent price impact while 35% of brokers cause a significant, permanent re-assessment of stock values.

Prior to the introduction of anonymity to the ASX, the identity of the broker involved in two consecutive trades conveys information to the market. This is true both in isolation and when considered as a conditional variable when interpreting two same-direction, sequential trades and is consistent with the findings of Frino et al. (2010 b).

[17] E.g. Chan and Lakonishok (1995) and Gemmill (1996)

Table 2- 5: Permanent Price Impact of Trades Controlling for Size and Time between Trades- Pre-Anonymity

This table provides OLS regression results for the following model: $P_i = \propto + \beta_1 D^{Size}_{Large} + \beta_2 D^{Size}_{Medium} + \beta_3 D^{Time}_{Short} + \beta_4 D^{Time}_{Medium} + \beta_5 D_{Same_{broker}} + \sum_{i=2}^{81} \gamma_i D^{Broker}_{i,t} + \varepsilon_i$.

Where P_i is the natural log of the return of the bid-ask midpoint from six trades before to five trades after the second of the two consecutive trades in the same direction, named trade *t*. D^{Size}_{Large} and D^{Size}_{Medium} are transaction size dummy variables which identify whether transaction *t* is a large of medium sized trade. Trade pairs are ordered from largest to smallest by their average size. The largest 2% are the "large" trades, the smallest 55% are "small" trades and the remaining 43% are "medium" trades. D^{Time}_{Short} and D^{Time}_{Medium} are dummy variables stating whether the time preceding trade *t* is short or medium. Short time intervals are the smallest 2% of intervals between trade pairs, for each stock. Long-time intervals are those in the bottom 55% and medium time intervals are the remaining 43%. $D_{Same_{broker}}$ is a dummy variable that equals 1 if the trade pair is an experimental pair, otherwise 0. $D^{Broker}_{i,t}$ is a dummy variable that equals 1 if the trade is initiated by broker *i*, otherwise 0. The model is run for the constituents of the All Ords as of 28 November 2005, for the period 28 June 2004 to 27 November 2005. All *t* statistics are adjusted for autocorrelation and heteroskedasticity using the procedure of Newey and West (1987). All means and standard errors are multiplied by 100.

Variable	Buyer-Initiated	Seller-Initiated
Intercept	-0.079***	0.067***
	(-4.23)	(3.55)
D^{Size}_{Large}	0.081***	-0.080***
	(4.96)	(-9.00)
D^{Size}_{Medium}	0.018***	-0.036***
	(5.21)	(-9.64)
D^{Time}_{Short}	0.048***	-0.004
	(4.01)	(-0.29)
D^{Time}_{Medium}	0.022*	-0.001
	(1.87)	(-0.05)
$D_{Same_{broker}}$	0.012***	-0.010***
	(3.59)	(-2.66)
Statistics of $D^{Broker}_{i,t}$	Mean = 0.060 Median = 0.052 Percentile $90^{th} - 10^{th}$ = 0.160 Significant (1%) = 29.27%	Mean = -0.061 Median = -0.052 Percentile $90^{th} - 10^{th}$ = 0.158 Significant (1%) = 35.37%
F	8.22***	6.73 ***
$Adjusted\ R^2$	0.007	0.005

To conclude that there is no difference in the permanent price impact of consecutive transactions in the same direction by the same broker compared to consecutive transactions in the same direction by different brokers following the introduction of anonymity we control for the size of the trade, the time elapsed between trades and broker identity. Table 2-6 presents the OLS regression results associated with Equation (2.2) subsequent to the introduction of anonymity. For buyer-initiated transactions, the *F* statistic of 1.71 suggests that the overall model is significant at the 5% level. The *F* statistic of 4.65 for seller-initiated transactions suggests that the overall model is significant at the 1% level.

The coefficients for the time variables are all statistically insignificant at the 10% level. This result is in contrast to that found in Table 2-5 prior the introduction of anonymity and is counter intuitive as we would expect the time between trades to be more informative after the introduction of anonymity. This result is also inconsistent with Frino et al. (2010 b) and Chung et al. (2005) who suggest the time between trades signals the presence of an informed trader in the market. The coefficients of the size variables are all significant at the 0.05 level at least. Again, the magnitude of the coefficient on D_{Large}^{Size} is greater than the magnitude of the coefficient on D_{Medium}^{Size} for both buyer-initiated and seller-initiated trades; consistent with the extant literature

The important finding presented in Table 2-6 is that of $D_{Same_{broker}}$, which is not significant at the 5% level for both buyer-initiated and seller-initiated trades. These results support the univariate findings of Table 2-1 that the result found in both Table 2-5 and Frino et al. (2010 b) is no longer present as there is no difference in the price impact between experimental and control trade pairs. Therefore we fail to reject H_2. As expected the identity of a broker no longer has a bearing on the price impact of our buyer-initiated trade pairs. Roughly 7% of brokers for seller-initiated trades are associated with a permanent price impact.

Table 2- 6: Permanent Price Impact of Trades Controlling for Size and Time between Trades- Post-Anonymity

This table provides OLS regression results for the following model: $P_i = \propto + \beta_1 D_{Large}^{Size} + \beta_2 D_{Medium}^{Size} + \beta_3 D_{Short}^{Time} + \beta_4 D_{Medium}^{Time} + \beta_5 D_{Same_{broker}} + \sum_{i=2}^{81} \gamma_i D_{i,t}^{Broker} + \varepsilon_i$.

Where P_i is the natural log of the return of the bid-ask midpoint from six trades before to five trades after the second of the two consecutive trades in the same direction, named trade *t*. D_{Large}^{Size} and D_{Medium}^{Size} are transaction size dummy variables which identify whether transaction *t* is a large of medium sized trade. Trade pairs are ordered from largest to smallest by their average size. The largest 2% are the "large" trades, the smallest 55% are "small" trades and the remaining 43% are "medium" trades. D_{Short}^{Time} and D_{Medium}^{Time} are dummy variables stating whether the time preceding trade *t* is short or medium. Short time intervals are the smallest 2% of intervals between trade pairs, for each stock. Long-time intervals are those in the bottom 55% and medium time intervals are the remaining 43%. $D_{Same_{broker}}$ is a dummy variable that equals 1 if the trade pair is an experimental pair, otherwise 0. $D_{i,t}^{Broker}$ is a dummy variable that equals 1 if the trade is initiated by broker *i*, otherwise 0. The model is run for the constituents of the All Ords as of 28 November 2005, for the period 28 November 2005 to 27 June 2007. All *t* statistics are adjusted for autocorrelation and heteroskedasticity using the procedure of Newey and West (1987). All means and standard errors are multiplied by 100.

Variable	Buyer-Initiated	Seller-Initiated
Intercept	0.025	-0.150***
	(0.30)	(-3.03)
D_{Large}^{Size}	0.188***	-0.080***
	(5.04)	(-7.53)
D_{Medium}^{Size}	0.018**	-0.033***
	(2.25)	(-7.55)
D_{Short}^{Time}	0.027	0.004
	(0.96)	(0.28)
D_{Medium}^{Time}	0.001	-0.004
	(0.05)	(-0.26)
$D_{Same_{broker}}$	-0.005	-0.008*
	(-0.63)	(-1.80)
Statistics of $D_{i,t}^{Broker}$	Mean = 0.0004 Median = 0.018 Percentile $90^{th} - 10^{th}$ = 0.002 Significant (1%) = 0%	Mean = 0.162 Median = 0.161 Percentile $90^{th} - 10^{th}$ = 0.202 Significant (1%) = 6.70%
F	1.71**	4.65***
$Adjusted\ R^2$	0.006	0.006

The stealth trading hypothesis predicts that informed traders will concentrate their trades on medium sizes to conceal information. Like Frino et al. (2010 b), we introduce the interaction variables $D_{Same_{broker}} \times D_{Large}^{Size}$, $D_{Same_{broker}} \times D_{Medium}^{Size}$ and $D_{Same_{broker}} \times D_{Small}^{Size}$ to test the incremental effect of experimental pairs across the three size groups. Frino et al. (2010 b) find that medium-sized, successive, same-direction trades from the same broker will move prices more than large trades. Table 2-7 presents the OLS regression results associated with Equation (2.3) prior to the introduction of anonymity. Consistent with Frino et al. (2010 b), we find a positive and significant coefficient on $D_{Same_{broker}} \times D_{Medium}^{Size}$ for buyer-initiated trade pairs. This suggests that same-broker medium-sized transactions convey incremental information. Therefore, we fail to reject H_3 for buyer-initiated transactions. However, we do not find the same result for seller-initiated transactions. We reject H_3 for seller-initiated transactions and conclude that our results are partly consistent with the stealth trading hypothesis.

Table 2- 7: Additional Analysis of the Permanent Price Impact of Different-Sized Same Broker Trades: Pre-Anonymity

This table provides OLS regression results for the following model: $P_i = \propto + \beta_1 D^{Size}_{Large} + \beta_2 D^{Size}_{Medium} + \beta_3 D^{Time}_{Short} + \beta_4 D^{Time}_{Medium} + \beta_5 (D_{Same_{broker}} \times D^{Size}_{Large}) + \beta_6 (D_{Same_{broker}} \times D^{Size}_{Medium}) + \beta_7 (D_{Same_{broker}} \times D^{Size}_{Small}) + \sum_{i=2}^{81} \gamma_i D^{Broker}_{i,t} + \varepsilon_i$. Where P_i is the natural log of the return of the bid-ask midpoint from six trades before to five trades after the second of the two consecutive trades in the same direction, named trade *t*. D^{Size}_{Large} and D^{Size}_{Medium} are transaction size dummy variables which identify whether transaction *t* is a large of medium sized trade. Trade pairs are ordered from largest to smallest by their average size. The largest 2% are the "large" trades, the smallest 55% are "small" trades and the remaining 43% are "medium" trades. D^{Time}_{Short} and D^{Time}_{Medium} are dummy variables stating whether the time preceding trade *t* is short or medium. Short time intervals are the smallest 2% of intervals between trade pairs, for each stock. Long-time intervals are those in the bottom 55% and medium time intervals are the remaining 43%. $D_{Same_{broker}}$ is a dummy variable that equals 1 if the trade pair is an experimental pair, otherwise 0. $D^{Broker}_{i,t}$ is a dummy variable that equals 1 if the trade is initiated by broker *i*, otherwise 0. The model is run for the constituents of the All Ords as of 28 November 2005, for the period 28 June 2004 to 27 November 2005. All *t* statistics are adjusted for autocorrelation and heteroskedasticity using the procedure of Newey and West (1987). All means and standard errors are multiplied by 100.

Variable	Buyer-Initiated	Seller-Initiated
Intercept	-0.080***	0.067***
	(-4.28)	(3.57)
D^{Size}_{Large}	0.085***	-0.070***
	(3.68)	(-5.59)
D^{Size}_{Medium}	0.020***	-0.038***
	(4.29)	(-7.42)
D^{Time}_{Short}	0.048***	-0.003
	(4.01)	(-0.29)
D^{Time}_{Medium}	0.002*	-0.001
	(1.87)	(-0.04)
$D_{Same_{broker}} \times D^{Size}_{Large}$	0.006	-0.105
	(0.19)	(-0.18)
$D_{Same_{broker}} \times D^{Size}_{Med}$	0.009**	-0.080
	(2.01)	(-0.14)
$D_{Same_{broker}} \times D^{Size}_{Small}$	0.014*	-0.085
	(1.65)	(-0.15)
Statistics of $D^{Broker}_{i,t}$	Mean = 0.060 Median = 0.053 Percentile $90^{th} - 10^{th}$ = 0.160 Significant (1%) = 28.92%	Mean = -0.061 Median = -0.053 Percentile $90^{th} - 10^{th}$ = 0.159 Significant (1%) = 34.15%

F	8.04***	6.53***
$Adjusted\ R^2$	0.007	0.006

The OLS regression results from Equation (2.3) are presented in Table 2-8. The size interaction variables are all statistically insignificant at the 0.05 level at least. Consistent with our expectations, trades in the medium and large size categories no longer convey incremental information and we fail to reject H_4. Therefore, the stealth trading hypothesis, reaffirmed partly in Table 2-7 and by Frino et al. (2010 b), is no longer as relevant. As traders, can now trade anonymously, the need for stealth trading is reduced and this is supported by our results.

Table 2- 8: Additional Analysis of the Permanent Price Impact of Different-Sized Same Broker Trades: Post-Anonymity

This table provides OLS regression results for the following model: $P_i = \propto + \beta_1 D^{Size}_{Large} + \beta_2 D^{Size}_{Medium} + \beta_3 D^{Time}_{Short} + \beta_4 D^{Time}_{Medium} + \beta_5 (D_{Same_{broker}} \times D^{Size}_{Large}) + \beta_6 (D_{Same_{broker}} \times D^{Size}_{Medium}) + \beta_7 (D_{Same_{broker}} \times D^{Size}_{Small}) + \sum_{i=2}^{81} \gamma_i D^{Broker}_{i,t} + \varepsilon_i$. Where P_i is the natural log of the return of the bid-ask midpoint from six trades before to five trades after the second of the two consecutive trades in the same direction, named trade *t*. D^{Size}_{Large} and D^{Size}_{Medium} are transaction size dummy variables which identify whether transaction *t* is a large of medium sized trade. Trade pairs are ordered from largest to smallest by their average size. The largest 2% are the "large" trades, the smallest 55% are "small" trades and the remaining 43% are "medium" trades. D^{Time}_{Short} and D^{Time}_{Medium} are dummy variables stating whether the time preceding trade *t* is short or medium. Short time intervals are the smallest 2% of intervals between trade pairs, for each stock. Long-time intervals are those in the bottom 55% and medium time intervals are the remaining 43%. $D_{Same_{broker}}$ is a dummy variable that equals 1 if the trade pair is an experimental pair, otherwise 0. $D^{Broker}_{i,t}$ is a dummy variable that equals 1 if the trade is initiated by broker *i*, otherwise 0. The model is run for the constituents of the All Ords as of 28 November 2005, for the period 28 November 2005 to 27 June 2007. All *t* statistics are adjusted for autocorrelation and heteroskedasticity using the procedure of Newey and West (1987). All means and standard errors are multiplied by 100.

Variable	Buyer-Initiated	Seller-Initiated
Intercept	0.030	-0.147***
	(0.36)	(-2.98)
D^{Size}_{Large}	0.228***	-0.087***
	(4.32)	(-5.78)
D^{Size}_{Medium}	0.008	-0.036***
	(0.97)	(-5.92)
D^{Time}_{Short}	0.028	0.004
	(0.97)	(0.28)
D^{Time}_{Medium}	0.001	-0.004
	(0.06)	(-0.26)
$D_{Same_{broker}} \times D^{Size}_{Large}$	-0.092	0.000
	(-1.25)	(0.03)
$D_{Same_{broker}} \times D^{Size}_{Med}$	0.008	-0.006
	(0.64)	(-1.03)
$D_{Same_{broker}} \times D^{Size}_{Small}$	-0.013	-0.013*
	(-1.21)	(-1.94)
Statistics of $D^{Broker}_{i,t}$	Mean = -0.0007 Median = -0.017 Percentile $90^{th} - 10^{th}$ = 0.206 Significant (1%) = 0%	Mean = 0.161 Median = 0.160 Percentile $90^{th} - 10^{th}$ = 0.203 Significant (1%) = 5.11%

F	1.70**	4.56***
$Adjusted\ R^2$	0.006	0.005

2.5. Conclusion

This chapter tests whether the conclusions drawn from Frino et al. (2010 b) still hold after the introduction of anonymity by the ASX on 28 November 2005. Frino et al. (2010 b) find that prior to the introduction of broker anonymity, the market attributes greater information content to successive same-direction trades when a single broker initiates these transactions rather than by different brokers. Therefore, broker identities convey information.

The introduction of anonymity on the ASX provides an excellent natural experiment to investigate broker behaviour. Using the constituents of the All Ords as our sample of stocks, the evidence for it clarifies that prior to the introduction of anonymity to the ASX, the identity of the broker involved in two consecutive trades conveys information to the market. This is true both in isolation and when considered as a conditional variable when interpreting two same-direction, sequential trades and is consistent with the findings of Frino et al. (2010 b). Using information not available to the market at the time of trading about broker identity, the assertion can be supported that market participants no longer attribute greater information content to successive uni-directional trades by a single broker compared to successive uni-directional trades by different brokers following the introduction of anonymity. While we infer the information content of the same trading patterns pre- and post-anonymity, this chapter does not address the changes in trading strategies borne out of anonymity.

Consistent with the stealth-trading hypothesis, Frino et al. (2010 b) also find that trades through the same broker convey greater information when they are medium-sized trades compared to trades that are categorised as small or large. Prior to the introduction of anonymity, the evidence supports that medium-sized trades convey more information that large trades for buyer-initiated trades. However, we do not find any difference between medium- and large-sized trades for seller-initiated transactions; indicating that our evidence partly supports the stealth-trading hypothesis. Subsequent to the introduction of anonymity, we find that trades in the medium and large size categories no longer convey incremental information (for buyer- and seller-initiated trades) as the need for stealth trading is reduced.

We have shown that trader motivation is now concealed through anonymity and consecutive transactions by the same broker no longer convey disproportionate information to the marketplace. Frino et al. (2010 b) states trading structures that allow market-order traders to remain anonymous are likely to reduce the speed of adjustment to private information. Hence, transparent trading platforms may be associated with greater informational efficiency on the ASX. However, it can also have argued that anonymous markets lower the likelihood of 'front-running' and 'piggybacking' which in turn reduce the chance of over-extending the price discovery process, an additional advantage to the enhanced liquidity identified in Comerton-Forde et al. (2009). The findings are consistent with Linnainmaa et al. (2012) who suggest greater liquidity occurs at the expense of informational efficiency. As prices, do not adequately adjust to order flow, informed investors can greater profit from their informational advantage. As these profits are attained at the expense of uninformed investors, the question must be asked if liquidity has improved to society at large.

These findings can be interpreted in light of Comerton-Forde et al. (2009). Supplementary to Comerton-Forde et al. (2009), a more complete picture is presented when assessing the market quality impact of broker anonymity on the ASX.

Chapter 3: The Impact of Analyst Coverage on Market Efficiency

3.1. Introduction

In July 2012, the ASX introduced the Equity Research Scheme (ERS). Under the ERS, the ASX funds analyst coverage of stocks that were previously not followed[18]. The ASX coordinates the participating firms with a list of analysts from a panel of licensed analysts in Australia. The objective of the ERS is to increase the level of information and the liquidity of ASX listed stocks. This chapter finds that the release of the initiation reports is a significant and informative event for market participants.

With the level of information for small and medium market-capitalisation companies declining, analysts with limited resources tend to cover large (rather than small) companies, resulting in asymmetric coverage[19]. Reasons for the decline include greater liquidity and fees of larger stocks, market capitalisation restrictions on portfolio holdings, stricter regulation preventing selective disclosure[20] and the increasing market share of low-cost brokers. Rapoze (2011) also notes that investment banks have cut their research teams subsequent to the Global Financial Crisis (GFC). In 2005, Bob Greifeld, CEO of NASDAQ, stated that "… a lack of research coverage impacts company valuation, liquidity, and ultimately the welfare and growth of public

---

[18] Some weakly-followed stocks were also included, typically those covered by small brokerage houses.

[19] In 2005, the CEO of NASDAQ, Rob Greifeld, stated that 35% of all publicly traded US firms had no analyst coverage.

[20] As per the SEC's Fair Disclosure Regulation FD in 2004, all U.S. publicly traded firms were required to disclose material information to all investors.

companies." Asymmetric coverage may also lead to inefficient capital raising in Initial Public Offerings (IPOs), poor quality reports and a lack of investor interest for small firms.

Exchanges and regulators worldwide have attempted to address the decline in research coverage. One approach is an exchange-sponsored research program (Cavinet, 2009). Under such programs, investment firms are required to commence and continue coverage in exchange for a fee. Firms that were not previously covered by analysts are typically selected. This chapter conducts an event study around the introduction of the ERS by the ASX. We assess liquidity components, informational efficiency and cumulative abnormal returns to determine whether exchanges and market regulators should intervene to exogenously increase the levels of research coverage when it is currently low.

The existing literature examines markets where analysts working for brokerage houses may be motivated to construct biased reports (McNichols et al., 1997). Analysts that have a prior relationship with the firm are more inclined to issue more favourable reports than unaffiliated analysts (Dugar et al., 1995). Francis et al. (1993) suggest that analysts attempt to appease firm management as they are a source of analyst information. Under the ERS, analysts are directly compensated for their coverage. The ASX matches firms with analysts, adding a level of independence to coverage initiation. The ERS represents a clean event to examine research coverage.

Our results are generalizable to global financial markets as similar schemes have been introduced in recent years. In 2003, the Singapore Stock Exchange (SGX) implemented the Research Incentive Scheme (RIS). In 2005, Bursa Malaysia launched the Capital Market Development Fund (CMDF) – Bursa Research Scheme, cantered on medium to small capitalised companies. In 2010, NASDAQ-OMX expanded an arrangement with Morningstar to comprehensively prepare analyst research reports on NASDAQ-listed companies. To address concerns of low information for small stocks, NYSE Euronext requires Virtua Research to publicise financial models of under-researched companies.

Prior studies focus on dealership markets where exogenous market makers are compensated for supplying liquidity. The commencement of research coverage has not been studied in a pure order-driven market where public traders supply liquidity without any intervention from market makers. As a result, there is an increased prevalence of information asymmetry in markets with quoted spreads. Using the price delay measure developed by Hou et al. (2005), we find that stocks exhibit greater informational efficiency following the introduction of the ERS. This is consistent with Holden et al. (1992) and Foster et al. (1993). Studying order-driven markets – and by implication the ASX – may lead to alternative findings that have wider implications for understanding the information structure of equity markets.

The institutional structure of the Australian equity market differs to those of the U.S. In the U.S, analyst reports are released to the private clients and the public simultaneously. By contrast, analyst recommendations are not released immediately to the public in Australia. This allows for a cleaner examination of the issue, as the public effect can be disentangled from the private effect. Increased informational efficiency suggests that the ERS has been successful in improving the lengthier price discovery process that may be expected due to the staggered release adopted in Australia. This can result in a more prolonged abnormal return structure which is observed when assessing cumulative abnormal returns over four intervals up to 12 months. We note that the ERS was responsible for positive abnormal returns following the release of the initiation reports.

Analyst coverage attracts significant attention from both investors and firms. Jensen et al. (1976) state that security analysts can reduce the agency costs associated with the principle-agent problem[21]. They also argue that the value of analyst coverage is reflected in the higher capitalized value of the ownership claims to corporations. Merton (1987) and Chang et al. (2006) claim that the market value of a company is positively correlated with the number of analysts following that company. Financial analysts play a key role in mitigating information asymmetry and enhanced corporate governance (Dyck et al., 2010). Karpoff (1986) states that as information homogeneity rises following the initiation of analyst coverage, trading activity will increase. Following the introduction of the ERS by the ASX, we note improvements in liquidity, namely the time-weighted proportional bid-ask spread, volume and turnover. This is also consistent with Kyle's (1985) model which predicts that market participants become more confident about the 'true' value of the security.

[21] Problems associated with the separation of ownership (shareholders) and control (managers).

Section 2 provides a review of the extant literature and details the tested hypotheses. Section 3 provides a detailed description of the methodology employed. Section 4 presents the findings and Section 5 concludes.

3.2. Literature Review and Hypotheses Development

This section invokes the literature and intuitive considerations associated with the introduction of the ERS by the ASX in 2012 to formulate several hypotheses to be tested.

3.2.1. Information Asymmetry

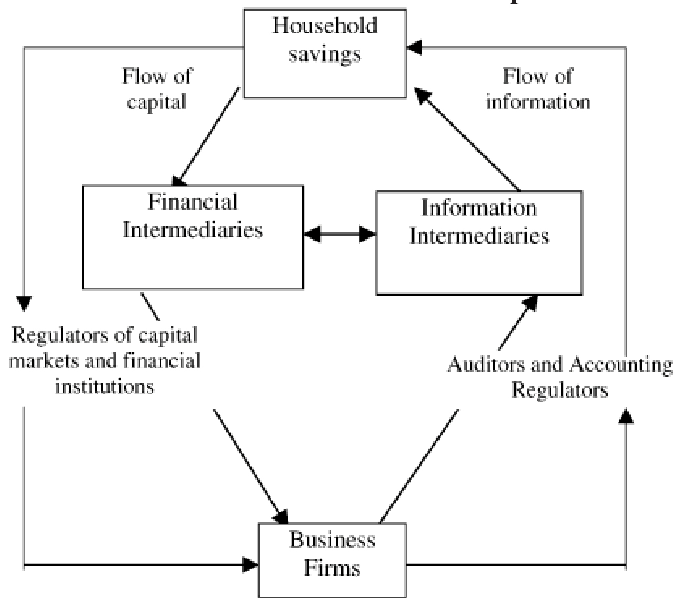
The relationship between information asymmetry and liquidity has been well documented in the extant literature. A security is likely to be more liquid when information asymmetry is low; less-informed investors are less willing to trade if they know there are better-informed investors (Akerlof, 1970; Glosten et al., 1985). This is supported empirically by studies such as Welker (1995) and Bartov et al. (1996) who find an increase in the number of trades and trading volume once information asymmetry is reduced. This can be explained by the reduction in adverse selection costs as investors become better informed (Blume et al., 1994; Kim et al., 1997). Intuitively, investors are more likely to trade when they are well informed.

As reviewed in Section 2.2.1., the overriding theme of the competing evidence is that asymmetric information is detrimental to the functioning of capital markets. There is incentive for regulators and exchanges to make investors better-informed.

3.2.2. The Role of a Financial Analyst

There are various means an investor can use to gather information. Examples include newspapers, investment newsletters, the internet and analyst reports. However, not all investors have the time to collect all of the relevant information, nor do they all possess the financial knowledge to dissect it. As a result, financial intermediaries such as stock analysts are relied upon to provide the information necessary to make an investment decision. In 2001, Healy et al. discuss the role of disclosure, information and financial intermediaries in the working of capital markets. They present a diagram, shown in Figure 3-1, which highlights the role of intermediaries in the flow of capital and information. While individuals can communicate directly with businesses, intermediaries are often used due to their expertise. Financial analysts collect information from all sources, both private and public, to assess firm performance and make predictions about the company's future prospects. Womack (1996) and Boni et al. (2006) suggest that financial analysts do disseminate new and important information after they find positive price changes following the release of analyst reports.

Figure 3- 1: Financial Information Flows in a Capital Market Economy



(sourced from Healey et al., 2001)

Financial analysts collect information from all sources, both private and public, to assess firm performance and make predictions about the company's future prospects. Karpoff (1986) state that analysts' views and outlooks encourage investors to trade on the asset. Womack (1996) and Boni et al. (2006) suggest that financial analysts do disseminate new and important information after they find positive price changes following the release of analyst reports.

In the monitoring of firm performance, financial analysts liaise closely with the company's management. Therefore they are believed to have better access to material information than retail investors. Hong et al. (2000) state that analysts reduce stock misevaluations. The information asymmetry – among investors and between managers and shareholders – is reduced by financial analyst reports (Doukas, et al., 2005). As financial analysts publicise their findings they lessen the advantage of investors with inside knowledge and improve the informational efficiency of capital markets (Chung et al., 1996, Moyer et al., 1989).

The role of financial analysts has also shown to be beneficial to the integrity of financial markets. Due to the close monitoring of firm performance, Dyck et al. (2010) find that analysts can identify earnings management and financial fraud reporting. In 2008, Yu revealed that analyst coverage prompt companies to reduce earnings management. As the efficiency and integrity is improved by financial analysts, investors typically trade on their reports (Mihail et al., 2007). Financial analysts can also be beneficial to firms with a survey from Graham et al. (2005) finding that CEOs believe financial analysts are influential in determining the company's stock price.

Financial analysts are therefore crucial to all market participants: investors, companies and exchanges. Through their information-collecting process and engagement with firms, security analysts play a role in reducing the information asymmetry inherently established between participants with inside information and those without. As the financial analysts' reports are distributed, more investors are better informed and simultaneously, the advantage that insiders have is significantly reduced. As more investors become informed, asset prices become more informative and efficient. As a result, the job that security analysts do in reducing information asymmetry leads to more efficient prices and thereby creates demand for such a role in the capital market.

3.2.3. Analyst Impact on Liquidity, Prices and Information Asymmetry

Financial analysts use their expertise to gather and interpret information. A substantial body of literature suggests that financial analysts do provide valuable information to the market. Ivkovic et al. (2004) attribute this to the ability of security analysts to better identify and interpret material information than the majority of market participants. Boni et al. (2006) contend that analysts have greater stock picking abilities within their given industry. They find a significant price reaction following a recommendation revision in industry. The greater merit and advisory power of analyst recommendations can be attributed to the qualitative component of the report. Aspects of firm operations such as managerial abilities or intangible assets that do not appear in the quantitative signals we examine in analyst findings (Jegadeesh, 2004).

The literature on analyst coverage and stock prices suggest that analysts do have predictive ability, evidenced by the positive price reaction following the release of a report. Analysts' buy (sell) recommendations tend to have a positive (negative) impact on security prices (Stickel, 1995). The degree of the price impact was found to be positively related to the reputation of the analyst, the strength of the recommendation and the marketing ability of the brokerage house. This is supported by Elton et al. (1986) and Womack (1996) who note that firms who receive buy (sell) recommendations tend to earn higher (lower) abnormal returns.

In a global setting, Jegadeesh et al. (2006) explore the importance of analyst recommendations in the Group of Seven (G7) companies' securities in all countries aside from Italy. Stock prices continued to move in line with the recommendation for two to six months. This supports the notion that asset prices adapt accordingly to the release of new information and that financial analysts are integral for efficient pricing in capital markets.

As security analysts release information to the market, investors become more informed and are more likely to trade. Both Chan et al. (1996) and Liu et al. (1990) note the increase in trading activity subsequent to the release of analyst recommendations. Holden and Subrahmanyam (1992) attribute this this to more efficient stock prices while George et al. (1994) believe that the lower cost of adverse selection makes investors more likely to trade.

The relationship between analyst coverage and market liquidity is well-documented in the literature. Considering analysts as informed traders, Brennan et al. (1995) find that the presence of financial analysts decreases the adverse selection component of the bid-ask spread as the competition amongst informed traders is enhanced. Admati et al. (1998) also suggest that an increase in informed traders results in greater liquidity. Chung et al. (1995) highlight the importance of financial analysts and market makers interactively determining the liquidity of an asset. They suggest that market makers note how many financial analysts are following a stock to deduce the adverse selection component of the spread. This stems from the belief that more financial analysts exist for stocks with greater information asymmetry.

As the presence of financial analysts lead to positive price reactions and increased liquidity, it follows that they also improve the efficiency of security prices. As the number of informed investors, including financial analysts, rise, stock prices reflect information more quickly (Holden et al., 1992 and Foster et al., 1993). Chatfield et al. (1989) and Kim et al. (1997) both show that asset prices incorporate new information quicker when they are followed by more analysts while Brennan at al. (1993) and Hong et al. (2000) find empirical evidence showing that firms with lower analyst coverage react slower to new information.

To provide further evidence to show that financial analysts are beneficial to financial markets, recent studies have assessed the impact of terminating analyst coverage. Derrien et al. (2013) provides empirical evidence showing that lowering analysts' coverage results in higher information asymmetry which hence increases the company's cost of capital. Earlier studies such as Stiglitz et al. (1981) and O'Hara (2004) also note the positive relationship between information asymmetry and the cost of capital from a theoretical standpoint. The clear message derived from the literature is that analyst coverage reduces information asymmetry by conveying valuable information, thereby leading to more efficient prices. We therefore develop the following hypotheses:

H_1: Asset prices will be more efficient following the initiation of analyst coverage for the ERS stocks relative to a matched sample of non-ERS stocks that have not received any new recommendations for one year, ceteris paribus.

H_2: There will be greater liquidity for ERS stocks relative to a matched sample of non-ERS stocks that have not received any new recommendations for one year following the initiation of analyst coverage, ceteris paribus.

3.2.4. Initiation of Analyst Coverage

A significant amount of time and resources are expended in producing analyst reports. Types of analyst reports typically include an initiation report or a continuation report. If a firm has not previously received any analyst coverage, its first report is the initiation report. All subsequent reports are continuation reports. Chan et al. (2006) highlight the importance of an initiation report. An initiation report is a concerted effort to persuade investors to trade on a security that has not previously been researched. Continuation reports are more meaningful when there is a change in recommendation. Naturally, the risks associated with producing an initiation report are larger than that of producing a continuation report.

As the first research report issued on a firm, an initiation report represents a noteworthy landmark for the company. Recent studies such Demirogulu et al. (2010)[22] highlight the abnormal return structure following an initiation report. An initiation report brings the security to the public eye and firms can benefit from this publicity. Investors are more likely to trade in covered companies as the awareness and information of the firm increases (Irvine, 2003 and Kim et al., 1997).

[22] Other, previous studies include Branson et al. (1998), Irvine (2003) and Chan et al (2006).

Investors rely on financial analysts to gather information as they do not have the time or expertise to do so themselves. Fundamental to the success of this relationship is objective reporting. Lin et al. (1988) finds that despite having a positive price impact, there is significant evidence of bias in analyst reports. Bias may occur when analysts source information from impartial management (Lim, 2001). Michaely et al. (1999) state that 'buy' recommendations from underwriter analysts are perceived as bias. Investment banking relationships have come under increased scrutiny in recent years with 10 of the largest U.S. brokerage firms ordered to pay a $1.4 billion settlement for the conflict of interest in analyst reports in 2003. Further supporting the existence of bias, Womack (1996) finds that analysts rarely issue negative recommendations.

A number of studies have found significant abnormal returns following the release of initiation reports. Demiroglu et al. (2010) find that positive recommendations lead to higher returns than negative ones. Peterson (1987) identify abnormal returns for firms that had an initiation report published in the investment newsletter 'Value Line Investment Survey'. In 1997, Kim et al., analyse the returns following initiation reports for stocks listed on the NYSE/AMEX and NASDAQ and find abnormal returns of 4% and 7% respectively. Similar findings are also noted in Branson et al. (1998). Irvine (2003) document that the price reaction is greater for initiation reports than it is for continuation reports.

Significant abnormal returns following an initiation report are also identified in the Australian market. Chan et al. (2006) note returns that are significantly different from zero over a 6 month horizon following the release of an analyst report. Unlike many other studies, they do not find a difference between the returns observed following an initiation report and those realised subsequent to a continuation report. The market participants did consider the information revealed in an initiation report to be of greater value than that contained in the corresponding continuing report. In 2011, Comerton-Forde et al., replicate the techniques used in Chan et al. (2006) with a shorter, 10 day, event window. For 'hold' and 'sell' recommendations, the stocks with initiation reports had more negative abnormal returns than those with continuation reports. This is in contrast to Chan et al. (2006)'s findings.

The literature thus far has produced mixed evidence in support for research coverage initiated by exchanges, therefore we develop the following hypothesis:

H_3: ERS stocks will experience a greater price reaction than a matched sample of non-ERS stocks that have not received any new recommendations for one year following the initiation of the ERS, ceteris paribus.

3.3. Methodology

3.3.1. Sample and Data Sources

We select a primary event window of 6 months either side of the initiation report. This includes the 44 firms chosen in the pilot and second stage of the ERS and results in a period of 1 March 2011 to 1 October 2013. To supplement our analysis and confirm the robustness of our results, we extend the sample period to a 12-month event window. Financial analyst firms, report release dates and the stock recommendations for the ERS stocks are sourced directly from the ASX.

We predict that the information efficiency and liquidity and price performance of the ERS stocks will improve following the release of the initiation report. To test this, we construct a matched, control sample from a sample of stocks that have not received any new recommendations or earnings predictions[23] for one year. We begin with all ASX listed firms. Analyst coverage data is sourced from the I/B/E/S database, accessed through Wharton Research Data Services (WRDS). This database is updated monthly with stock recommendation and earnings forecast data. From the I/B/E/S Forecast Details History File and the I/B/E/S Recommendations Detail History File, we determine the stocks had received some new recommendation or earnings forecast in the year preceding 1 March 2011. We remove these firms. To determine the control sample, each ERS firm is matched with a unique firm with the same industry classification and similar market capitalisation. This results in an experimental and control sample consisting of 44 stocks each.

Quote and trade data is sourced Thomson Reuters Tick History (TRTH) database. For each security[24], we obtain the 1 minute intra-day open bid, close bid, open ask and close ask and the end of day high price, low price, volume and turnover. Best level market depth is also sourced from TRTH.

---

[23] Earnings forecasts signify that the stock has received coverage from a financial analyst.
[24] We also attain this data for the ASX All Ordinary Index. This is required for the analysis on Information Efficiency, detailed in Section 3.3.2.

Finally, listing dates, industry classifications and market capitalisation data is attained from DatAnalysis Premium.

3.3.2. Information Efficiency

We predict that security prices of the ERS stocks will be more efficient following the initiation of analyst coverage. The measure we employ to ascertain information efficiency is the stock's short-term return predictability; it's price delay. To calculate the stock's price delay, we adopt the method developed in Hou et al. (2005). We select this approach to simplify the interpretation of our informational efficiency measure. To measure the informational efficiency of a selected stock, we only wish to include to include the response to market return shocks. An alternative approach is the variance ratio provided in Lo et al. (1990). By not selecting this approach we avoid the potential concern of interpreting price delays that would occur when individual stock lags were included. For example, Lo et al. (1990) find positive portfolio return autocorrelation, but negative individual stock return autocorrelation due to cross-correlations among stocks. The approach developed by Hou et al. (2005) determines the stock's short-term return predictability, to the degree that market returns play a role in forecasting the stock's midquote return. If a stock is priced efficiently, it will quickly adjust to market-wide information

For each trading day, the 1-minute midquote stock returns, $r_{i,t,r}$, are determined. We then regress $r_{i,t,r}$ on 1-minute ASX All Ordinaries Index (All Ords) market index returns, $r_{m,t,r}$, and return of ten lags, $\delta_{i,t,k}$, as follows:

$$r_{i,t,r} = a_{i,t} + \beta_{i,t} r_{m,t,r} + \sum_{k=1}^{10} \delta_{i,t,k} r_{m,t,\tau-k} + \varepsilon_{i,t,r}. \tag{3.1}$$

$\beta_{i,t}$ captures the immediate reaction to market-wide information. If $\delta_{i,t,k}$is significantly different from zero, then there is a delay in the price reaction to news. Equation (3.1) determines the delay in price reaction to market-wide information should expected retains be relatively stable. $r_{i,t,r}$ is a low-frequency measure of relative frequency which is appropriate as both Mech (1993) and Swaminathan (2000) state that expected returns are comparatively constant over a short period of time.

Next, we restrict the coefficients on the lagged market return to zero, $\delta_{i,t,k} = 0, \forall k$ and re-estimate the equation. The delay measure is then calculated in the following way:

$$Delay_{i,t} = 100 \left(1 - \frac{R^2_{Constrained,i,t}}{R^2_{Unonstrained,i,t}}\right). \tag{3.2}$$

$Delay_{i,t}$ ranges from 0 to 100 and reveals the discrepancy in a stock's intraday return that is attributed to the lagged market return. The closer $R^2_{Constrained,i,t}$ is to $R^2_{Unonstrained,i,t}$, the less we can attribute the lagged market returns to the stock's return, and the higher the informational efficiency. Hence the higher the value of $Delay_{i,t}$, the lower the informational efficiency.

3.3.3. Liquidity

We predict that there will be greater liquidity for ERS stocks subsequent to the initiation report. Black (1971) contends that liquidity is a complex concept that incorporates tightness, depth, resiliency and immediacy. Consequently, in this chapter we focus on four measures of liquidity: the bid-ask spread, depth, volume and turnover.

The time-weighted proportional bid-ask spread measures the cost of trading. First, the proportional bid-ask spread must be determined using the best bid, best ask and midpoint as follows:

$$PBAS_i = \frac{Ask_i - Bid_i}{(\frac{Ask_i + Bid_i}{2})}. \tag{3.3}$$

Each spread observation i is then adjusted for the proportion of time that the quote is active during the trading day j (τ_i):

$$TWS_i = \frac{PBAS_{i}\tau_i}{\sum_{i=1}^{T}\tau_j}. \tag{3.4}$$

Finally, to compute the daily time-weighted proportional bid-ask spread, all the TWS_i for day t are summed:

$$TWS_{i,t} = \sum_{i=1}^{T} TWS_i . \tag{3.5}$$

As we are studying the events surrounding a structural change[25], we consider the depth component of liquidity. When dealers receive information, they often adjust depth in response (Lee et al., 1983). To measure depth, the quantities at the best bid and ask are summed. Depth is time-weighted using the same technique as above:

$$TWD_i = \frac{D_i \tau_i}{\sum_{i=1}^{T} \tau_j}, \tag{3.6}$$

$$TWD_{i,t} = \sum_{i=1}^{T} TWD_i, \tag{3.7}$$

where D_i is the depth amount, and τ_i again refers to the time that the depth quote was active during the trading day.

The trade –based measures of liquidity selected in this chapter are trading volume and turnover. We select turnover as it is highly correlated with various measures of market depth and bid-ask spreads (Chordia et al., 2000) and thus measure $Turnover_{i,t}$ as the daily dollar value of traded shares. Trading volume is a pertinent determinant of the bid-ask spread (Stoll, 1978) and we measure $Volume_{i,t}$ as the average trading volume for each stock day.

3.3.4. Price Reaction

We predict that ERS stocks will experience a positive price reaction after the initiation of the ERS, compared to our matched sample. This chapter focuses on abnormal

---

[25] Early empirical studies, testing seminal theoretical models, consider only the bid-ask spread components of liquidity.

returns (ARs) at three intervals following the initiation date. Consistent with Comerton Forde et al. (2011), our first interval is selected at two weeks following the initiation report. The final intervals are at 3 and 6. First, we determine the expected return, $R_{m,t}$, of each stock using the Capital Asset Pricing Model (CAPM):

$$R_{m,t} = R_f + \beta_m(R_m - R_f) + \varepsilon_m. \tag{3.8}$$

The AR is then calculated as the difference between the stock's actual return, $R_{i,t}$, and $R_{m,t}$:

$$AR_{i,t} = R_{i,t} - R_{m,t} . \tag{3.9}$$

We determine the mean of the daily ARs by averaging across the sample and compute the cumulative abnormal returns (CARs) by summing the ARs:

$$CAR_{i,t} = \sum_{i=1}^{T} AR_{i,t} . \tag{3.10}$$

The stated objective of the ERS is to increase the trading activity of small stocks. To test this, we estimate cumulative abnormal volume (CAV) around the initiation report. We begin by determining the expected volume, $V_{m,t}$, of each stock using a market model:

$$V_{m,t} = B_0 + \beta_m(V_m) + \varepsilon_m . \tag{3.11}$$

The abnormal volume (AV) is then calculated as the difference between the stock's actual trading volume, $V_{i,t}$, and $V_{m,t}$:

$$AV_{i,t} = V_{i,t} - V_{m,t} \,. \tag{3.12}$$

We determine the mean of the daily AVs by averaging across the sample and compute the cumulative abnormal volumes (CAVs) by summing the AVs:

$$CAV_{i,t} = \sum_{i=1}^{T} AV_{i,t} \,. \tag{3.13}$$

3.3.5. Regression Analysis

We begin preliminary regression analysis by running a standard OLS model. The regression is specified as follows:

$$Ln(y_{i,t}) = \propto + \beta_1 Event_{i,t} + \beta_2 MarketCap_i + \beta_3 Price_{i,t} + \beta_4 Volatility_{i,t} + \varepsilon_{i,t}, \tag{3.14}$$

where $y_{i,t}$ represents our various liquidity metrics as well as $Delay_{i,t}$. We use a logarithmic transformation to minimise the skewness of results; leading to better distributional structure (Benston et al., 1974). Our primary variable of interest, $Event_{i,t}$, takes the value of 1 if day t occurred in the post-event window, and 0 otherwise. We run this model for both the experimental and control sample for the following specifications: size of the firm, share price and price volatility.

When more information is available for a firm, investors are more likely to trade. Aitase (1985) states that company size can be used as a proxy for the amount of information obtainable regarding the firm. Further, as more information is available, the adverse selection component of the bid-ask spread is lowered (Chiang et al., 1998);

suggesting that firm size has a negative relationship with the bid-ask spread. Both Desmetz (1986) and Chae (2005) find that smaller firms have higher levels of information asymmetry than larger firms. Therefore, we consider the size of the firm in our regression analysis. Consistent with Brooks (1994), we use the natural logarithm of the market capitalisation at the beginning of the sample period, $MarketCap_i$ to proxy for firm size.

According to Roulstone (2003), spreads and stock prices are closely related. Low-priced securities generally have higher bid-ask spreads due to the discreetness in their tick-sizes (Jegadeesh et al., 1993 and Walker, 1995). Further, Atigg et al. (2006) find that share prices are negatively related to information asymmetry. As a relationship between stock prices and both liquidity and information efficiency is evident, we include the natural logarithm of the closing daily share price, $Price_{i,t}$, as a control. This is consistent with Roulstone (2003).

Market makers become more uncertain about the cost of holding an asset as volatility increases (Roulstone, 2003). To cover this additional risk, market makers respond by increasing the bid-ask spread. Both Stoll (1978) and Jegadeesh et al. (1993) provide evidence to support the notion that there is a positive relationship stock price variations and market volatility. To the extent that volatility reflects some level of uncertainty about the value of the company, the information asymmetry problem arises. We include volatility as a control in our regression analysis and calculate $Volatility_{i,t}$ as the natural logarithm of the ratio of the day's highest price divided by the lowest price

To ascertain whether the ERS had a positive impact on information efficiency, market liquidity and price reaction, we run the following difference in difference regression model:

$$Ln(y_{i,t}) = \propto + \beta_1 Event_{i,t} + \beta_2 ERS_i + \beta_3 (Event_{i,t} \times ERS_i) + \beta_4 MarketCap_i + \beta_5 Price_{i,t} + \beta_6 Volatility_{i,t} + \varepsilon_{i,t}, \tag{3.15}$$

where ERS_i is a dummy variable that takes the value of 1 if stock i is an ERS stock and 0 if it as a control stock. Difference in difference regression analysis is used when comparing the pre- and post- treatment differences in the outcome of a treatment and a control group. Equation (3.15) calculates the effect of the ERS on $y_{i,t}$ by comparing the average change over time in the for the ERS sample to the average change over time for the control sample. Our primary variable of interest is the interaction variable, $Event_{i,t} \times ERS_{i,t}$.

3.4. Results

3.4.1. Descriptive Statistics

Table 3-1 reports the descriptive statistics on the stock-day information efficiency, liquidity and control metrics for the ERS sample, pre- and post- event date. Panel A, reporting the statistics for our information efficiency metric, $Delay_{i,t}$, shows improvements in both the mean and median following the initiation report. A reduction in the standard deviation also indicates that the information efficiency of ERS stocks is less volatile. Panel B suggests that there are slight liquidity improvements through the time-weighted proportional bid-ask spread and trading volume, however the time-weighted best-depth appears to have decreased.

Table 3- 1: Descriptive Statistics of Liquidity and Efficiency Measures for ERS Stocks

This table provides summary statistics of the information efficiency and liquidity measures during the pre-change and post-change for ERS stocks. $Delay_{i,t}$ measures intraday midquote return predictability using lagged market returns. $TWS_{i,t}$ refers to the natural logarithm of the daily time-weighted proportional spread. $TWD_{i,t}$refers to the natural logarithm of the daily time-weighted depth at the best bid and ask. $Turnover_{i,t}$ refers to the natural logarithm of total daily shares turnover. $Volume_{i,t}$ refers to the natural logarithm of the average daily trading volume. $Price_{i,t}$ refers to the natural logarithm of the daily closing stock price.. $Volatility_{i,t}$ is the natural logarithm of the ratio of the day's highest price divided by the lowest price.

	Mean		Median		Standard Deviation		Skewness	
Panel A: Information Efficiency	Pre	Post	Pre	Post	Pre	Post	Pre	Post
$Delay_{i,t}$	3.44	3.42	4.07	3.42	1.39	1.33	-1.21	-1.09
Panel B: Liquidity								
$TWS_{i,t}$	-4.10	-4.19	-3.94	-4.08	1.03	1.11	-0.09	-0.12
$TWD_{i,t}$	10.11	10.09	10.09	10.06	1.04	1.03	0.10	0.11
$Turnover_{i,t}$	2.43	2.42	2.44	2.43	0.19	0.20	-1.46	-1.28
$Volume_{i,t}$	12.00	12.06	12.33	12.28	2.19	2.12	-0.58	-0.49
Panel C: Explanatory Variables								
$Price_{i,t}$	-0.50	-0.58	-0.34	-0.36	1.62	1.73	-0.37	-0.23
$Volatility_{i,t}$	0.04	0.04	0.03	0.03	0.04	0.03	3.37	2.12

Univariate analysis on the information efficiency and liquidity metrics for the ERS sample is presented in Table 3-2. The mean for the pre- and post- event are provided, supplemented by the difference and the t-statistics computed using the Satterhwaite method[26]. Panel A shows that while $Delay_{i,t}$ appears to have decreased following the ERS, there is no statistical difference in the pre- and post-event periods. Panel B presents the findings for our liquidity metrics. The 4.5% reduction in the spread observed in Table 3-1 is significant at the 1% level, however no differences best depth, turnover and trading volume are noted. Table 3-3 presents the univariate analysis on the information efficiency and liquidity metrics for the control stocks. We observe improvements in trading volume; however, an increase in the time-weighted proportional bid-ask spread and a reduction in the time-weighted best depth indicate deterioration in market liquidity.

[26] The Satterthwaite method assumes difference variances between the pre- and post- periods.

Table 3- 2: Univariate Analysis- ERS Stocks

This table provides univariate analysis for information efficiency and liquidity measures during the pre-change and post-change periods for ERS stocks. $Delay_{i,t}$ measures intraday midquote return predictability using lagged market returns. $TWS_{i,t}$ refers to the natural logarithm of the daily time-weighted proportional spread. $TWD_{i,t}$refers to the natural logarithm of the daily time-weighted depth at the best bid and ask. $Turnover_{i,t}$ refers to the natural logarithm of total daily shares turnover. $Volume_{i,t}$ refers to the natural logarithm of the average daily trading volume. The t-statistics are calculated using the Satterthwaite Method Statistics, assuming different variances between the pre-change and post-change periods. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

	Mean		T-Test	
	Pre	Post	Difference	*t*
Panel A: Information Efficiency				
$Delay_{i,t}$	3.44	3.42	-0.02	-0.39
Panel B: Liquidity				
$TWS_{i,t}$	-4.01	-4.19	-0.10	-4.45***
$TWD_{i,t}$	10.11	10.09	-0.02	-1.90*
$Turnover_{i,t}$	2.43	2.42	-0.01	-1.15
$Volume_{i,t}$	12.00	12.01	0.01	1.08

Table 3- 3: Univariate Analysis- Control Stocks

This table provides univariate analysis for information efficiency and liquidity measures during the pre-change and post-change periods for the control stocks. $Delay_{i,t}$ measures intraday midquote return predictability using lagged market returns. $TWS_{i,t}$ refers to the natural logarithm of the daily time-weighted proportional spread. $TWD_{i,t}$refers to the natural logarithm of the daily time-weighted depth at the best bid and ask. $Turnover_{i,t}$ refers to the natural logarithm of total daily shares turnover. $Volume_{i,t}$ refers to the natural logarithm of the average daily trading volume. The *t*-statistics are calculated using the Satterthwaite Method Statistics, assuming different variances between the pre-change and post-change periods. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

	Mean		T-Test	
	Pre	Post	Difference	*t*
Panel A: Information Efficiency				
$Delay_{i,t}$	3.33	3.39	0.06	1.89*
Panel B: Liquidity				
$TWS_{i,t}$	-3.99	-3.93	0.06	3.02***
$TWD_{i,t}$	10.27	10.20	-0.07	-2.86***
$Turnover_{i,t}$	2.39	2.39	0.00	0.45
$Volume_{i,t}$	12.04	12.14	0.10	2.23**

3.4.2. Information Efficiency

Given the prominence of asymmetric information, it is unlikely that stock prices reflect the expectations of market participants (Grossman et al., 1980). Financial analysts use their expertise to gather and interpret information and thereby attempt to reduce the level of asymmetric information; making asset prices more informationally efficient. Previous studies have documented that price volatility, stock prices and firm size are determinants of information efficiency and liquidity measures (Atkins et al. 1997; Menyah et al., 2000; Brooks et al., 2003). As a result, we control for these factors in our regression analysis.

Ordinary least squares regression results for information efficiency surrounding the introduction of the ERS is presented in Table 3-4. Equation (3.14) is estimated for the experimental sample where $y_{i,t}$ = $Delay_{i,t}$. While the negative sign of coefficient on $Event_{i,t}$ is in line with intuition, it is not statistically significant. Therefore, initial regression analysis suggests that the information efficiency of security prices is unaffected by the ERS. Consistent with Desmetz (1986), the size of a firm is negatively related to its information efficiency. As the size of a firm increases, there is a wider range of asymmetric information; a 1% increase in the market capitalisation of a firm leads to a 0.05% decrease in $Delay_{i,t}$ for ERS stocks. Price volatility is a positive determinant of information efficiency and this is in line with the findings of Jegadeesh et al. (1993). Unlike Jegadeesh et al. (1993), where the stock price was found to have a negative relationship with information efficiency, the coefficient on $Price_{i,t}$ is not statistically meaningful for ERS stocks.

Table 3- 4: Ordinary Least Squares Regression Analysis on Information Efficiency- ERS Stocks

This table provides ordinary least squares regression results for price delay surrounding analyst coverage for the ERS scheme using a 6-month event window. Results are estimated for:

$$Ln(Delay_{i,t}) = \propto + \beta_1 Event_{i,t} + \beta_2 MarketCap_i + \beta_3 Price_{i,t} + \beta_4 Volatility_{i,t} + \varepsilon_{i,t}$$

$Event_{i,t}$ is a dummy variable for all stocks after the initiation of analyst coverage. $MarketCap_i$ is the natural logarithm of the stock's market capitalisation. $Price_{i,t}$ refers to the natural logarithm of the daily closing stock price. $Volatility_{i,t}$ is the natural logarithm of the ratio of the day's highest price divided by the lowest price. Test statistics are reported in brackets under each coefficient. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Variable	$Delay_{i,t}$
$Intercept$	4.417
	(9.47)
$Event_{i,t}$	-0.020
	(-0.70)
$MarketCap_i$	-0.054**
	(-2.19)
$Price_{i,t}$	0.000
	(0.03)
$Volatility_{i,t}$	1.583***
	(3.66)
Observations	10660
Adjusted R^2	0.003
F	7.300***

Ordinary least squares regression results for information efficiency presented in Table 3-5. Equation (3.14) is estimated for the matched sample of control stocks where $y_{i,t}$ = $Delay_{i,t}$. We note a positive and significant coefficient of $Event_{i,t}$. This is unexpected and most likely spurious given that no new recommendations or earnings forecasts were given for these firms in the past 12 months. Similar to the results seen in Table 3-4, the figures for $MarketCap_i$ and $Volatility_{i,t}$ are consistent with the prior literature, however the result for $Price_{i,t}$ is not.

While the findings presented in Table 3-4 and Table 3-5 provide meaningful information regarding our experimental and control samples, no definitive conclusions on the effect of the ERS can be drawn. To determine if the ERS improved the information content of asset prices, we must compare directly to the matched, control sample. We run the difference in difference regression model shown in Equation (3.15) to isolate the contribution of the ERS.

Table 3- 5: Ordinary Least Squares Regression Analysis on Information Efficiency- Control Stocks

This table provides ordinary least squares regression results for price delay surrounding analyst coverage for the control stocks using a 6-month event window. Results are estimated for:

$$Ln(Delay_{i,t}) = \propto + \beta_1 Event_{i,t} + \beta_2 MarketCap_i + \beta_3 Price_{i,t} + \beta_4 Volatility_{i,t} + \varepsilon_{i,t}$$

$Event_{i,t}$ is a dummy variable for all stocks after the initiation of analyst coverage. $MarketCap_i$ is the natural logarithm of the stock's market capitalisation. $Price_{i,t}$ refers to the natural logarithm of the daily closing stock price. $Volatility_{i,t}$ is the natural logarithm of the ratio of the day's highest price divided by the lowest price. Test statistics are reported in brackets under each coefficient. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Variable	$Delay_{i,t}$
$Intercept$	4.348***
	(9.56)
$Event_{i,t}$	0.071**
	(2.23)
$MarketCap_i$	-0.057**
	(-2.36)
$Price_{i,t}$	-0.008
	(-0.59)
$Volatility_{i,t}$	1.825***
	(3.82)
Observations	9183
Adjusted R^2	0.004
F	9.38***

The difference in difference regression results associated with Equation (3.15) are reported in Table 3-6. The coefficient on $Event_{i,t}$ is significant at the 5% level and reveals that firms were 0.07% less informationally efficient following the initiation report. As firms from both the ERS and control sample are included in this model, this finding is not indicative of the scheme itself. We also note that ERS securities are 0.1% less informationally efficient than the matched, control sample. This is significant at the 1% level.

Table 3- 6: Difference in Difference Regression Analysis on Information Efficiency- 6 Months

This table provides ordinary least squares regression results for price delay surrounding analyst coverage for the control stocks using a 6 month event window. Results are estimated for: $Ln(Delay_{i,t}) = \propto + \beta_1 Event_{i,t} + \beta_2 ERS_i + \beta_3 (Event_{i,t} \times ERS_i) + \beta_4 MarketCap_i + \beta_5 Price_{i,t} + \beta_6 Volatility_{i,t} + \varepsilon_{i,t}$. $Event_{i,t}$ is a dummy variable for all stocks after the initiation of analyst coverage. ERS_i is a dummy variable that equals one for experimental stocks and for control stocks. $MarketCap_i$ is the natural logarithm of the stock's market capitalisation. $Price_{i,t}$ refers to the natural logarithm of the daily closing stock price. $Volatility_{i,t}$ is the natural logarithm of the ratio of the day's highest price divided by the lowest price. Test statistics are reported in brackets under each coefficient. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Variable	$Delay_{i,t}$
$Intercept$	6.227***
	(6.56)
$Event_{i,t}$	0.072**
	(2.32)
ERS_i	0.106***
	(3.45)
$Event_{i,t} \times ERS_i$	-0.092**
	(-2.15)
$MarketCap_i$	-1.000***
	(-3.10)
$Price_{i,t}$	-0.004
	(-0.40)
$Volatility_{i,t}$	1.695***
	(5.28)
Observations	19843
Adjusted R^2	0.004
F	12.19***

Our primary variable of interest, $Event_{i,t} \times ERS_{i,}$, measures the price delay of the experimental stocks following the initiation report after considering our control variables. Therefore, this variable captures the effect of the scheme on the information efficiency of the selected stocks. The coefficient on $Event_{i,t} \times ERS_i$ is -0.092 and is significant at the 1% level. The share prices of ERS stocks reflect their 'true' value 0.09% better in the 6 months after the initiation report. Hence, we can attribute this finding to the ERS and fail to reject H_1. This is consistent with the theoretical findings of Suvrahmanyam (1992) and Foster et al. (1993) who predict that stock prices reflect information more quickly as the number of informed investors rise.

The existing literature is littered with empirical studies that produce a qualitatively consistent finding. Moyer et al. (1989) and Kim et al. (1997) show that asset prices incorporate new information quicker when they are followed by more analysts. Assessing the converse situation, Brennan et al. (1993) and Hong et al. (2000) find empirical evidence showing that firms with lower analyst coverage react slower to new information. More recently, Kim et al. (2007) and Derrien et al. (2013) analyse the effect of removing or lowering analyst coverage once it is already there. These studies show that terminating or lowering analyst coverage results in higher information asymmetry which hence increases the company's cost of capital.

The findings for $MarketCap_i$, $Price_{i,t}$ and $Volatility_{i,t}$ are consistent with those seen in Table 3-4 and Table 3-5.

Table 3- 7: Difference in Difference Regression Analysis on Information Efficiency- 6 Months

This table provides ordinary least squares regression results for price delay surrounding analyst coverage for the control stocks using a 6-month event window. Results are estimated for: $Ln(Delay_{i,t}) = \propto\ + \beta_1 Event_{i,t} +\ \beta_2 ERS_{i,t} +\ \beta_3 (Event_{i,t} \times ERS_{i,t}) + \beta_4 MarketCap_{i,t} + \beta_5 Volatility_{i,t} +\ \varepsilon_{i,t}$. $Event_{i,t}$ is a dummy variable for all stocks after the initiation of analyst coverage. $MarketCap_{i,t}$ is the natural logarithm of the stock's market capitalisation. $Volatility_{i,t}$ is the natural logarithm of the ratio of the day's highest price divided by the lowest price. Test statistics are reported in brackets under each coefficient. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Variable	$Delay_{i,t}$
$Intercept$	6.469***
	(8.91)
$Event_{i,t}$	0.071**
	(2.42)
$ERS_{i,t}$	0.104***
	(3.43)
$Event_{i,t} \times ERS_{i,t}$	-0.092**
	(2.15)
$MarketCap_{i,t}$	-1.083***
	(-4.38)
$Volatility_{i,t}$	1.744***
	(5.90)
Observations	19843
Adjusted R^2	0.004
F	14.60***

Table 3- 8: Difference in Difference Regression Analysis on Information Efficiency- 12 Months

This table provides difference in difference regression results for price delay surrounding analyst coverage using a 12-month event window. The model includes observations from both the experimental and matched samples and is stated as: $Ln(Delay_{i,t}) = \propto + \beta_1 Event_{i,t} + \beta_2 ERS_i + \beta_3 (Event_{i,t} \times ERS_i) + \beta_4 MarketCap_i + \beta_5 Price_{i,t} + \beta_6 Volatility_{i,t} + \varepsilon_{i,t}$. $Event_{i,t}$ is a dummy variable for all stocks after the initiation of analyst coverage. ERS_i is a dummy variable that equals one for experimental stocks and for control stocks. $MarketCap_{i,t}$ is the natural logarithm of the stock's market capitalisation. $Price_{i,t}$ refers to the natural logarithm of the daily closing stock price. $Volatility_{i,t}$ is the natural logarithm of the ratio of the day's highest price divided by the lowest price. Test statistics are reported in brackets under each coefficient. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Variable	$Delay_{i,t}$
$Intercept$	5.723***
	(8.09)
$Event_{i,t}$	0.099***
	(4.23)
ERS_i	0.107***
	(4.63)
$Event_{i,t} \times ERS_i$	-0.107***
	(-2.84)
$MarketCap_i$	-0.849***
	(-3.50)
$Price_{i,t}$	-0.003
	(-0.37)
$Volatility_{i,t}$	1.950***
	(7.99)
Observations	36358
Adjusted R^2	0.005
F	23.72***

To avoid any potential bias associated with multicollinearity, we remove $Price_{i,t}$ and re-run Equation (3.15) for robustness. The results are presented in Table 3-7 and are consistent with those reported in Table 3-6. For additional robustness, we re-run Equation (3.15) using a 12-month event window. Table 3-8 presents the findings. The results for all variables are qualitatively consistent with those revealed in Table 3-6. The share prices of ERS stocks reflect their 'true' value 0.11% better in the 12 months after the initiation report. This is only marginally higher than the 0.09% improvement in the first 6 months however is in line with intuition as more potential investors become more informed over time. This may also reflect the increased awareness of the scheme following the implementation of the second phase. We conclude that that the ERS is responsible for more informed security prices, this is both intuitive and consistent with the expectations developed from the prior literature.

3.4.3. Liquidity

The relationship between information asymmetry and liquidity has been well documented in a number of prior studies. A security is likely to be more liquid when information asymmetry is low; less-informed investors are less willing to trade if they know there are better-informed investors (Akerlof, 1970; Glosten et al., 1985). Following Foley et al. (2013), the same control variables used to estimate information efficiency models are applied when estimating our liquidity metrics. The controls include stock price, market capitalisation and volatility.

Ordinary least squares regression results for the liquidity measures surrounding the introduction of the ERS are presented in Table 3-9. Equation (3.14) is estimated for the experimental sample where $y_{i,t} = TWS_{i,t}$, $Turnover_{i,t}$ and $Volume_{i,t}$[27]. We observe

[27] Equation (4.14) was also estimated for the time-weighted depth. The results are not reported for brevity as no meaningful conclusions were drawn.

a 0.12% improvement in $TWS_{i,t}$ and 0.07% improvement in trading volume. These figures are statistically significant at the 1% and 5% levels respectively. Consistent with Chiang et al. (1998), $MarketCap_i$ is a positive determinant of market liquidity. Larger, ERS firms experience greater liquidity across each of the three metrics, all at the 1% significance level. The same qualitative conclusions can be made for a firm's price volatility, consistent with the information asymmetry model developed in Copeland et al. (1983). $Price_{i,t}$ improves both the bid-offer spread and turnover, consistent with Stoll (1978). However, $Price_{i,t}$ is shown to be a negative determinant trading volume. No definitive conclusions are drawn at this stage as we have not considered the matched, control sample.

Table 3- 9: Original Least Squares Regression Analysis on Liquidity- ERS Stocks

This table provides ordinary least squares regression results for price delay surrounding analyst coverage for the ERS scheme using a 6-month event window. Results are estimated for:

$$Ln(y_{i,t}) = \propto + \beta_1 Event_{i,t} + \beta_2 MarketCap_i + \beta_3 Price_{i,t} + \beta_4 Volatility_{i,t} + \varepsilon_{i,t}.$$

$y_{i,t}$ is the dependent variable and refers to either $TWS_{i,t}$, $Turnover_{i,t}$ or $Volume_{i,t}$. $Event_{i,t}$ is a dummy variable for all stocks after the initiation of analyst coverage. $MarketCap_i$ is the natural logarithm of the stock's market capitalisation. $Price_{i,t}$ refers to the natural logarithm of the daily closing stock price. $Volatility_{i,t}$ is the natural logarithm of the ratio of the day's highest price divided by the lowest price. Test statistics are reported in brackets under each coefficient. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Variable	$TWS_{i,t}$	$Turnover_{i,t}$	$Volume_{i,t}$
$Intercept$	2.402***	0.826***	-6.556***
	(10.36)	(15.06)	(-11.71)
$Event_{i,t}$	-0.121***	0.004	0.067**
	(-8.48)	(1.26)	(1.96)
$MarketCap_i$	-0.354***	0.081***	0.915***
	(-18.91)	(27.88)	(30.98)
$Price_{i,t}$	-0.335***	0.024***	-0.711***
	(-53.11)	(15.98)	(-46.80)
$Volatility_{i,t}$	-1.540***	2.261***	24.293***
	(-7.08)	(43.95)	(46.31)
Obvs	10660	10660	10660
Adjusted R^2	0.563	0.32	0.43
F	3025.03***	1114.84***	1773.63***

Ordinary least squares regression results for the liquidity metrics are presented in Table 3-10. Equation (3.14) is estimated for the matched sample of control stocks where $y_{i,t}$ = $TWS_{i,t}$, $Turnover_{i,t}$ and $Volume_{i,t}$. We find a reduction in $Turnover_{i,t}$ following the introduction of the ERS but see no change in the bid-offer spread or trading volume. Again, this is likely to be spurious given that no new recommendations or earnings forecasts were given for these firms in the past 12 months. Consistent with Chiang et al. (1998) and as seen in Table 3-9, $MarketCap_i$ is a positive determinant of the four liquidity measures. Similar to Table 3-9, volatility improves both turnover and volume. Consistent with the ERS sample, $Price_{i,t}$ is a positive determinant of both the bid-offer spread and turnover.

Table 3- 10: Original Least Squares Regression Analysis on Liquidity- Control Stocks

This table provides ordinary least squares regression results for price delay surrounding analyst coverage for the control sample using a 6 month event window. Results are estimated for:

$$Ln(y_{i,t}) = \propto \; + \beta_1 Event_{i,t} + \; \beta_2 MarketCap_i + \; \beta_3 Price_{i,t} + \; \beta_4 Volatility_{i,t} + \; \varepsilon_{i,t}.$$

$y_{i,t}$ is the dependent variable and refers to either $TWS_{i,t}$, $Turnover_{i,t}$ or $Volume_{i,t}$. $Event_{i,t}$ is a dummy variable for all stocks after the initiation of analyst coverage. $MarketCap_i$ is the natural logarithm of the stock's market capitalisation. $Price_{i,t}$ refers to the natural logarithm of the daily closing stock price. $Volatility_{i,t}$ is the natural logarithm of the ratio of the day's highest price divided by the lowest price. Test statistics are reported in brackets under each coefficient. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Variable	$TWS_{i,t}$	$Turnover_{i,t}$	$Volume_{i,t}$
$Intercept$	0.978***	0.411***	-11.729***
	(4.74)	(7.55)	(22.94)
$Event_{i,t}$	0.022	-0.008**	-0.044
	(1.53)	(2.12)	(1.23)
$MarketCap_i$	-0.288***	0.104***	1.204***
	(-26.27)	(36.13)	(44.57)
$Price_{i,t}$	-0.365***	0.035***	-0.630***
	(-59.72)	(21.73)	(-41.80)
$Volatility_{i,t}$	0.117	2.01***	20.283***
	(0.54)	(35.29)	(37.94)
Obvs	9183	9183	9183
Adjusted R^2	0.53	0.356	0.401
F	2400.05***	1174.57***	1423.66***

The difference in difference regression results associated with Equation (3.15) are reported in Table 3-11. Equation (3.15) is estimated for all stocks where $y_{i,t} = TWS_{i,t}$, $Turnover_{i,t}$ and $Volume_{i,t}$[28]. We observe that all stocks experienced a minor reduction in turnover following the introduction of ERS. As firms from both the ERS and control sample are included in this model, this finding is not indicative of the scheme itself. We also note that $TWS_{i,t}$ of ERS securities are 0.1% smaller than the matched, control sample. This is significant at the 1% level.

[28] Equation (4.15) was also estimated for the time-weighted depth. The results are not reported for brevity as no meaningful conclusions were drawn.

Table 3- 11: Difference in Difference Regression Analysis on Liquidity- 6 Months

This table provides difference in difference regression results for price delay surrounding analyst coverage using a 6 month event window. The model includes observations from both the experimental and matched samples and is stated as:
$Ln(y_{i,t}) = \propto + \beta_1 Event_{i,t} + \beta_2 ERS_i + \beta_3 (Event_{i,t} \times ERS_i) + \beta_4 MarketCap_i + \beta_5 Price_{i,t} + \beta_6 Volatility_{i,t} + \varepsilon_{i,t}$. $y_{i,t}$ is the dependent variable and refers to either $TWS_{i,t}$, $Turnover_{i,t}$ or $Volume_{i,t}$. $Event_{i,t}$ is a dummy variable for all stocks after the initiation of analyst coverage. ERS_i is a dummy variable that equals one for experimental stocks and for control stocks. $MarketCap_i$ is the natural logarithm of the stock's market capitalisation. $Price_{i,t}$ refers to the natural logarithm of the daily closing stock price. $Volatility_{i,t}$ is the natural logarithm of the ratio of the day's highest price divided by the lowest price. Test statistics are reported in brackets under each coefficient. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Variable	$TWS_{i,t}$	$Turnover_{i,t}$	$Volume_{i,t}$
$Intercept$	13.059***	-2.691***	-47.178***
	(28.73)	(-23.69)	(-42.32)
$Event_{i,t}$	0.027*	-0.009**	-0.052
	(1.81)	(-2.40)	(-1.45)
ERS_i	-0.105***	-0.004	-0.062*
	(-7.22)	(-1.16)	(-1.74)
$Event_{i,t} \times ERS_i$	-0.147***	0.014***	0.124**
	(-7.25)	(2.68)	(2.49)
$MarketCap_i$	-5.951***	1.720***	19.750***
	(-38.50)	(44.53)	(52.12_
$Price_{i,t}$	-0.351***	0.028***	-0.687***
	(-80.12)	(25.41)	(-64.02)
$Volatility_{i,t}$	-0.752***	2.142***	22.391***
	(-4.89)	(55.69)	(59.35)
Observations	19843	19843	19843
Adjusted R^2	0.549	0.336	0.408
F	3640.26***	1512.25***	2058.87***

Assessing the coefficients on $Event_{i,t} \times ERS_i$, we note consistent liquidity improvements for ERS stocks following the initiation report. Hence we fail to reject H_2. Enhancements in the price-dimension of liquidity can be seen with a 0.15% reduction in the time-weighted proportional bid-ask spread. This is accompanied by increased levels of trading as turnover and volume which grew by 0.01% and 0.12% respectively. These figures are all statistically significant at the 1% level. The evidence suggests that the ERS has been successful in improving the market liquidity of selected stocks, with benefits associated with both the price and size dimensions of liquidity observed.

The improvement in the price-dimension of liquidity – the time-weighted proportional bid-ask spread – is consistent with the adverse-selection theory model developed in Kyle (1985). The release of an initiation report by a financial analyst reduces the level of information asymmetry as some traders become more informed. The model states that, armed with this information, investors are more willing to trade. Empirical studies such as Yohn (1998) and Roulstone (2003) also find evidence of decreasing spreads as the number of analysts rise. Brennan et al. (1995) state that an increase in the number of analysts leads to more competition among informed traders. This is evidenced by the reduction in adverse selection costs as investors become better informed (Blume et al., 1994; Kim et al., 1997). Intuitively, investors are more likely to trade when they are well informed.

The enhancements in the quantity-dimensions of liquidity – turnover and trading volume – are also consistent with a number of past studies. The increase in the information homogeneity between market participants after the initiation of analyst coverage results in increased trading activity (Karpoff, 1986). This is supported empirically by studies such as Welker (1995) and Bartov et al. (1996) who find a rise in the number of trades and trading volume once information asymmetry is reduced. As security analysts release information to the market, investors become more informed and are more likely to trade. Both Chan et al. (1996) and Liu et al. (1990) note the increase in trading activity subsequent to the release of analyst recommendations. Holden et al. (1992) attribute this this to more efficient stock prices while George et al. (1994) believe that the lower cost of adverse selection makes investors more likely to trade. The findings for $MarketCap_i$, $Price_{i,t}$ and $Volatility_{i,t}$ are the same as those seen in Table 3-9.

To avoid any potential bias associated with multicollinearity, we remove $Price_{i,t}$ and re-run Equation (3.15) for robustness. The results are presented in Table 3-12 and are consistent with those reported in Table 3-11. For additional robustness, we re-run Equation (3.15) using a 12-month event window. Table 3-12 presents the findings. The results for each of the liquidity measures are consistent with those revealed in Table 3-11. We conclude that that the ERS is responsible for improvements in market liquidity. Benefits are seen in the bid-offer spread and in actual trading outcomes including turnover and volume. This is both intuitive and consistent with the expectations developed from the prior literature.

Table 3- 12: Difference in Difference Regression Analysis on Liquidity- 6 Months

This table provides difference in difference regression results for price delay surrounding analyst coverage using a 6 month event window. The model includes observations from both the experimental and matched samples and is stated as:
$Ln(y_{i,t}) = \propto + \beta_1 Event_{i,t} + \beta_2 ERS_{i,t} + \beta_3 (Event_{i,t} \times ERS_{i,t}) + \beta_4 MarketCap_{i,t} + \beta_5 Volatility_{i,t} + \varepsilon_{i,t}$. $y_{i,t}$ is the dependent variable and refers to either $TWS_{i,t}$, $Turnover_{i,t}$ or $Volume_{i,t}$. $Event_{i,t}$ is a dummy variable for all stocks after the initiation of analyst coverage. $MarketCap_{i,t}$ is the natural logarithm of the stock's market capitalisation. $Volatility_{i,t}$ is the natural logarithm of the ratio of the day's highest price divided by the lowest price. Test statistics are reported in brackets under each coefficient. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Variable	$TWS_{i,t}$	$Turnover_{i,t}$	$Volume_{i,t}$
$Intercept$	36.548***	-4.552***	-1.143
	(90.28)	(-52.52)	(-1.21)
$Event_{i,t}$	0.049***	-0.011***	-0.010
	(2.83)	(-2.82)	(-0.24)
$ERS_{i,t}$	-0.007	0.005	-0.281***
	(-0.41)	(1.25)	(-7.15)
$Event_{i,t} \times ERS_{i,t}$	-0.152***	0.014***	0.116**
	(-6.40)	(2.69)	(2.10)
$MarketCap_{i,t}$	-13.909***	2.351***	4.163***
	(-90.35)	(78.02)	(12.94)
$Volatility_{i,t}$	-3.932***	1.771***	31.564***
	(23.69)	(48.90)	(81.59)
Observations	19843	19843	19843
Adjusted R^2	0.388	0.312	0.273
F	2270.76***	1627.00***	1343.49***

Table 3- 13: Difference in Difference Regression Analysis on Liquidity- 12 Months

This table provides difference in difference regression results for price delay surrounding analyst coverage using a 12 month event window. The model includes observations from both the experimental and matched samples and is stated as:
$Ln(y_{i,t}) = \propto + \beta_1 Event_{i,t} + \beta_2 ERS_i + \beta_3 (Event_{i,t} \times ERS_i) + \beta_4 MarketCap_i + \beta_5 Price_{i,t} + \beta_6 Volatility_{i,t} + \varepsilon_{i,t}$. $y_{i,t}$ is the dependent variable and refers to either $TWS_{i,t}$, $Turnover_{i,t}$ or $Volume_{i,t}$. $Event_{i,t}$ is a dummy variable for all stocks after the initiation of analyst coverage. ERS_i is a dummy variable that equals one for experimental stocks and for control stocks. $MarketCap_{i,t}$ is the natural logarithm of the stock's market capitalisation. $Price_{i,t}$ refers to the natural logarithm of the daily closing stock price. $Volatility_{i,t}$ is the natural logarithm of the ratio of the day's highest price divided by the lowest price. Test statistics are reported in brackets under each coefficient. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Variable	$TWS_{i,t}$	$Turnover_{i,t}$	$Volume_{i,t}$
$Intercept$	11.898***	-2.273***	-43.036***
	(34.91)	(-27.23)	(-51.83)
$Event_{i,t}$	0.013	-0.010***	-0.085***
	(1.13)	(-3.78)	(-3.12)
ERS_i	0.105***	-0.012***	-0.143***
	(9.55)	(-4.27)	(-5.32)
$Event_{i,t} \times ERS_i$	-0.167***	0.018***	0.192***
	(-10.98)	(4.79)	(5.13)
$MarketCap_i$	-5.547***	1.580***	18.368***
	(-47.85)	(55.64)	(65.03)
$Price_{i,t}$	-0.349***	0.030***	-0.675***
	(-107.09)	(37.13)	(-85.09)
$Volatility_{i,t}$	-0.581***	2.163***	22.686***
	(-4.99)	(75.86)	(35.09)
Observations	36358	36358	36358
Adjusted R^2	0.527	0.322	0.396
F	6070.19***	2588.95***	3576.80***

3.4.4. Price Reaction

Table 3-14 presents the cumulative abnormal returns based on the Capital Asset Pricing Model for ERS stocks around the initiation report[29]. We find a significant and positive CAR of 1.6% two weeks subsequent to the first analyst report. The positive price reaction then dissipates over time with no significant returns realised at subsequent time intervals. An initiation report is a concerted effort to persuade investors to trade on a security that has not previously been researched. The market initially reacts to the published information; however, this effect is lessened over time as; an unsurprising result as these are still smaller, lesser known stocks.

Table 3- 14: Market Model Cumulative Abnormal Returns (CAR) - around Initiation date

This table presents CARs for the ERS sample around the release of an initiation report by an analyst. CAR [t,T] refers to the sum of daily abnormal returns (ARs) between day t and day T surrounding the event. For each CAR [t,T], the average CAR is then measured across recommendations. Robust standard errors are used to compute t-statistics and reported in the parentheses. ***, ** and * represent significance at the 1%, 5% and 10% levels respectively. The hypothesis tested is H_0: CAR [t,T] = 0 versus H_1: CAR [t,T] $\neq$ 0.

Event	ERS Stocks
CAR [0,14]	0.016***
CAR [0,90]	-0.003
CAR [0,180]	-0.016*
N	44

[29] Price reaction analysis was originally split for 'Buy' recommendations. No meaningful conclusions were drawn as the results were qualitatively consistent with the reported analysis, therefore it has not been presented for brevity. 'Buy' recommendations make up 75% of the experimental sample.

Table 3- 15: Market Model Cumulative Abnormal Returns (CAR), Univariate Analysis- All Stocks

This table provides univariate analysis for cumulative abnormal returns following the release of the initiation report for all stocks. CAR [t,T] refers to the sum of daily abnormal returns (ARs) between day t and day T surrounding the event. For each CAR [t,T], the average CAR is then measured across recommendations. The t-statistics is calculated using the Satterthwaite Method Statistics, assuming different variances between the pre-change and post-change periods. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

	Mean		T-Test	
	ERS	Control	Difference	t
Event				
CAR [0,14]	0.016	-0.003	-0.019	-3.65***
CAR [0,90]	-0.003	-0.033	-0.030	-6.54***
CAR [0,180]	-0.016	-0.046	-0.030	-6.85***

Univariate analysis for CARs following the release of the initiation report for all stocks is reported in Table 3-15. ERS stocks experience greater CARs than the matched, control sample at two week, three month and six month intervals. Therefore, we fail to reject H_3. The difference is statistically significant at the 1% level for each of the time intervals. This is consistent with Comerton-Forde at al. (2006) who states that a positive price reaction subsequent to the initiation of analyst coverage is symptomatic of the informational value of financial analysts. Irvine (2003) attributes the positive price reaction to the increased levels of price efficiency and liquidity following the introduction of analyst coverage. The combined effect of reduced spreads and more informative prices leads to an increase in share price and a decrease in the required rate of return demanded by investors (Amihud et al., 1997).

Table 3-16 presents the cumulative abnormal volumes for ERS stocks around the initiation report. We find positive and significant CAV's in the two weeks, three months and six months following the initiation report. Hence trading volume of ERS stocks increases after the release of the report. Univariate analysis for CARs following the release of the initiation report for all stocks is reported in Table 3-17. While the CAV's for ERS stocks appear much larger than the control stocks at each of the three intervals, there is no significant difference between the two samples. In light of the regression results focused on trading volume[30], we conclude that the ERS was effective in boosting the trading activity of the selected stocks.

Table 3- 16: Market Model Cumulative Abnormal Volume (CAV) - around Initiation date

This table presents CAVs for the ERS sample around the release of an initiation report by an analyst. CAV [t,T] refers to the sum of daily abnormal volume (AR) between day t and day T surrounding the event. Robust standard errors are used to compute t-statistics and reported in the parentheses. ***, ** and * represent significance at the 1%, 5% and 10% levels respectively. The hypothesis tested is H_0: CAR [t,T] = 0 versus H_1: CAV [t,T] $\neq$ 0.

Event	ERS Stocks
CAV [0,14]	7,923,046**
CAV [0,90]	57,665,068**
CAV [0,180]	128,340,000**
N	44

[30] Presented in Section 3.3.3.

Table 3- 17: Market Model Cumulative Abnormal Volume (CAV), Univariate Analysis- All Stocks

This table provides univariate analysis for cumulative abnormal volume following the release of the initiation report for all stocks. CAV [*t*,T] refers to the sum of daily abnormal volume (AR) between day *t* and day T surrounding the event. The *t*-statistics is calculated using the Satterthwaite Method Statistics, assuming different variances between the pre-change and post-change periods. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

	Mean		T-Test	
	ERS	Control	Difference	*t*
Event				
CAV [0,14]	7,923,046	3,865,541	4,057,504	0.78
CAV [0,90]	57,665,068	6,150,301	515,514,767	1.71*
CAV [0,180]	128,340,000	42,757,761	85,582,239	1.23

3.5. Conclusion

This chapter examines the impact of the ASX's Equity Research Scheme on market quality. Following the introduction of the ERS, 44 initiation reports have been released. The initiation reports represent the first exogenous assessment of the firm's future prospects, designed to assist in investment decision making. By conducting an event study and comparing the effect on the ERS stocks to a matched, control sample of stocks, our findings supports the notion that the ERS was responsible for market efficiency improvements in price efficiency and liquidity. The reduction in information asymmetry also leads to a positive price reaction in ERS stocks.

Financial analysts use their expertise to gather and interpret information and thereby attempt to reduce the level of asymmetric information. As more information is released to the market, market participants become more confident about the 'true' value of the asset. Consistent with the expectations developed by the existing literature, we find that the ERS is responsible for more informed security prices with ERS stocks 0.11% more informationally efficient in the 6 months following the initiation report.

If information asymmetry is reduced and security prices are more efficient, investors are more likely to trade. We find that the ERS improved both the price and size-dimensions of market liquidity in the selected stocks. A 0.15% reduction in the time-weighted proportional bid-ask spread occurs after the release of the initiation report. Therefore, the price of immediacy decreased. This is accompanied by improved trading outcomes as turnover and volume grew by 0.01% and 0.12% respectively. This suggests that analyst reports do play a role in providing new information to the market and stimulating trading activity. The release of an initiation report by a financial analyst reduces the level of information asymmetry; thereby encouraging trading activity.

The literature on analyst coverage and stock prices suggest that analysts do have predictive ability, evidenced by the positive price reaction following the release of a report. We identify a CAR of 1.6% two weeks subsequent to the first analyst report for ERS stocks. Comparing to the matched, control sample, the ERS stocks experience greater CARs over two week, three month and six month intervals. This highlights the informational value in the ERS first-time analyst coverage reports. Asset prices adapt accordingly to the release of new information and that financial analysts are integral for efficient pricing in capital markets.

At a general level, given the inherent significance of the information structure of financial markets, the findings in this chapter highlight the value of financial analysts in providing reliable and useful information to market participants. Given the downward trend of analyst coverage and the ASX's mandate to ensure a fair and efficient capital market, strategies such as the ERS could go a long way in ensuring that market participants have a more homogenous level of access to information. The ASX should therefore maintain the ERS and possibly look into extending such schemes to other assets, particularly those that are susceptible to high information asymmetry. More broadly, exchanges and market regulators worldwide should consider implementing similar policies, primarily due to the decreasing trend of analyst coverage. Such schemes would not only be beneficial market quality, but they may also encourage increased order flow by international investors that are currently concerned that they are disadvantaged relative to better-informed local investors.

Chapter 4: Market Maker Incentives and Market Efficiency

4.1. Introduction

On 1 August 2010, a market making scheme was introduced in the ASX's Exchange Traded Fund (ETF) market. The scheme provided affirmative market maker obligations and rewarded contracted market makers with rebates for meeting spread and volume requirements. The Australian ETF market is rapidly growing but the size in Australia is tiny compared to the ETF markets in the US and Europe. The scheme may be one method to try to improve trading conditions and encourage growth. This chapter investigates the effect of the scheme by conducting an event study and examining the effect on market efficiency and profitability.

This chapter is motivated by three factors. Firstly, compared to other, more traditional markets, academic analysis of the Australian ETF industry is limited. This study provides a valuable insight to the efficiency of the ASX's ETF market by analysing both spreads and depth. Secondly, by studying the trades of market makers, we determine whether they are fulfilling their mandated duty of supplying liquidity. Much of the literature finds that market makers use their superior order-flow information to make position-taking gains and this may be in conflict with their obligation to provide liquidity under the scheme. Finally, the introduction of the scheme motivates us to study the market efficiency effects and in turn offer empirical evidence that contributes to the debate.

Before determining effects of the scheme, it is important to understand the complex role of market makers. The primary role is to provide immediacy for other investors by supplying liquidity. Market makers are often employed but at any particular moment in time, the number of market participants actively seeking to buy or sell can be quite small (Desmetz, 1968; Garbade et al., 1982). Harris (2003) identifies two types of risk faced by market makers: inventory holding risk[31] and adverse selection risk[32]. Bagehot (1971) states that a profit must be made from liquidity traders to compensate for the losses to informed investors. These gains are achieved by setting a spread (Glosten et al., 1985)[33]. Using trade data that identifies each market maker, we find that our sample of market makers are net suppliers of liquidity and set the spread to earn profits 83% of the time after the introduction of the scheme. However, when studying the interaction between liquidity and position-taking profitability, we find that market makers make positive position-taking gains 75% of time when liquidity losses are incurred. Copeland et al. (1983), who identify an inverse relationship between a market maker's liquidity and position-taking profitability. Therefore, market makers are willing to forego their contractual duties to realise position-taking profits.

The level of skill of market makers is debatable since even though they have access to order flow, their profits may be generated by taking advantage of the bid-ask spread. Market makers may naively be considered to be uninformed traders,

[31] Inventory holding risk arises due to events that cause unpredictable price changes (Harris, 2003). Market makers will then adjust their bid and ask quotes to attract the trades of public investors and therefore balance resulting undesired inventory positions.

[32] Like all traders, market makers lose money when they trade with those who are more informed. The risk of doing so is called adverse selection risk.

[33] Benveniste at al., (1992) and Dunpont (2000), argue that specialists are better able to differentiate between informed and uninformed traders compared to limit order traders, and can adjust the adverse selection component of the spread accordingly.

gaining gross trading profits composed entirely of the spread. However, the theoretical findings of Madhavan et al. (1993) implicitly suggest that market makers are likely to derive positive position-taking profits when they actively build positions. Hasbrouck et al. (1993) apply a mark to market approach of determining total NYSE specialist profitability and they find that the principal source of profits is short horizon information. Therefore, while a majority of net gains arise from capturing the spread, specialists are able to derive position-taking profits through the aid of superior order-flow information[34]. Consistent with the idea that market makers are using order flow information to make position profits, we find that market makers on the ASX achieve position taking gains 60% of the time after the implementation of the scheme. However, position-taking profits accrued after the introduction of the scheme are only two-thirds of the value of liquidity profits.

Our univariate analysis notes improvements in bid-ask spreads, depth and volatility following the implementation of the scheme. However, there are many arguments against the implementation of market maker obligations in the extant literature. High frequency traders act as the most active market makers in financial markets, even though they have no obligation to maintain their market presence. Many empirical papers have studied the growth in algorithmic trading and noted the benefits it has on market quality. These findings can be interpreted as empirical support for a market structure where designated market makers may be unnecessary. Black (1971), Stoll (1998) and Bloomfield et al. (2005) all argue that

[34] These findings are later substantiated by Harris and Panchapagesan (2005), who state that when transacting on the NYSE, intermediaries use information to their advantage. Similarly, Frino et al. (2010 a) attributes position-taking net gains by locals on the Sydney Futures Exchange (SFE) to the ability to analyse conditions on the trading floor.

markets are capable of functioning efficiently without the presence of mandated market makers.

The theoretical literature presents plenty of support for the introduction of market makers. Copeland et al. (1983) note that since limit orders represent a free option to other market participants, traders will be reluctant to use a passive order submission strategy when order flow is strongly unidirectional or adverse selection levels are high. Hence periods of market stress will be incredibly difficult to overcome without an exogenous liquidity source. Additionally, Harris (2003) argues that the increased management and order processing costs resulting from market making obligations are compensated by the advantage derived from receiving the entire order flow.

Our empirical findings are consistent with the literature. We find consistent improvements in both bid-ask spreads and depth after the introduction of the scheme, similar to Frino et al. (2008) who find a reduction in spreads when stocks move from an auction market to a specialist market on the Italian Bourse[35]. We find no significant change in liquidity or position-taking profitability for market makers after the introduction of the scheme, suggesting that the liquidity improvements are not at the expense of other investors. Using US options and futures data respectively, Tse et al. (2004) and Anand et al. (2006) both find empirical evidence that market maker introduction leads to improved liquidity. Christie et al. (1994) and Barclay (1997) both find a reduction in transaction costs when firms relocate from NASDAQ (a dealer market) to a specialist market.

[35] Also, investigating the Italian Bourse and reaffirming the conclusions of Frino et al. (2008), Nimalendran and Petrella (2003) find a decline in bid-ask spreads and a rise in trading volume after the introduction of obligated market making.

Therefore, there is also a lot of empirical support, namely the enhancements in market quality, for the introduction of schemes similar to that of the ASX ETF Market Making Scheme.

Section 2 provides a review of the extant literature and details the tested hypotheses. Section 3 describes the data and explains the methodology employed. Section 4 presents all descriptive statistics, univariate and multivariate results. Finally, Section 5 concludes.

4.2. Literature Review and Hypotheses Development

An ETF is a type of fund that owns underlying assets[36] and splits the ownership of those assets into tradable shares. This section invokes the literature and intuitive considerations associated with the 2010 ASX ETF market making mandate changes to formulate several hypotheses to be tested.

4.2.1. ETF and Net Asset Value (NAV)

Unlike open-ended mutual funds that are always purchased and sold at their net asset value (NAV), ETF shares are traded throughout the day at a price determined by the market. The fundamental purpose of an ETF is to track a specific index or sector. Therefore, through the unique creation and redemption feature[37] and the mechanism of arbitrage, investors may assume that the difference between the price of an ETF and its NAV is paltry (Petajisto, 2011). With minimal transaction

---

[36] Underlying assets include shares of stock, bonds, oil, futures, gold, foreign currency, etc.
[37] The supply of ETF shares are controlled through the creation and redemption process. This process involves authorized participants (APs) that create or redeem units of an ETF.

costs, negligible obstacles to information dissemination and therefore little limits to arbitrage, this assumption may be safe.

Ackert et al. (2008) investigate the pricing of ETFs with respect to their fundamental values. The paper attempts to offer new evidence on the capacity to arbitrage mispricing in ETFs by examining the performance of U.S and country ETFs traded in the United States. The study finds that U.S ETF funds are priced closely to the value of their underlying equities. This is consistent with Ackert et al. (2000) and Elton et al. (2002) who also find that U.S. ETF prices are close to their NAVs; however they stress the importance of the redemption feature. Like Jares et al. (2004) and Engle et al. (2006) tri-model approach, Ackert et al. (2008) find contrasting results across country ETFs. The authors attribute this to momentum, illiquidity and size effects. Due to taxes and obstacles to trade, the creation and redemption process for country funds is more complex than a U.S ETF. The offsetting effect is a reduction in liquidity leading to larger mispricing. Examining the relationship between fund premium (mispricing) and market liquidity leads to inconsistent results with the authors concluding that more active trading leads to lower mispricing but only after a certain level of liquidity is reached.

Advancing from Engle et al. (2006) with an alternate approach, Petajisto (2011) also compares the difference between the ETF price and its NAV. Using a cross-sectional average price for funds that track identical or nearly identical indices, the study controls for the stale pricing in some underlying assets. The paper finds that international equities, international bonds and illiquid U.S. traded securities[38] have the highest premium volatilities. The results are attributed to limits to arbitrage and the riskiness of the overall market environment. Petajisto (2011) also finds that the cross-sectional differences in ETF premiums can be exploited through trading strategies that lead to attractive profits (before transaction costs); representing a large hidden cost for ETF investors.

4.2.2. ETF Inception

With ETFs rapidly rising in popularity it is vital to comprehend the impact they have on various market factors.

As an ETF is designed to track a particular sector or index, it follows that its introduction will have direct impacts on the underlying securities. While the bulk of the ETF literature investigates the impact, ETFs have on various market measures, Bae et al. (2012) explore the after-market effects on the underlying securities. The study shows increases in systematic volatility, short interest, and institutional ownership of their underlying stocks, specifically those of small firms. The paper also finds that ETFs have a negative and significant effect on their underlying stocks firm value, particularly for small firms. Surges in stock liquidity and institutional ownership caused by the introduction of an ETF have a negative valuation effect as they lead to a rise in short-selling activities by investors. This is contrary to general positive impact that a rise in stock liquidity and institutional ownership has on firm value.

[38] Such as municipal bonds and high-yield bonds.

Upon inception, ETF's have been shown to tighten the spot-futures no-arbitrage price relation (Park et al., 1995; Switzer et al., 2000; Kurov et al., 2002). Traditionally, this is explained by Kurov et al. (2002) and Hegde et al. (2004) who both argue that it is the increased arbitrage activity following the introduction of an ETF that results in a tightening of the spot-futures-no-arbitrage price relation. Using the Lyxor CAC 40, Deville et al. (2012) seeks to further elucidate this finding. Similar to the aforementioned literature, a significant decrease in mispricing frequency following the inception of an ETF is found. Deville et al. (2012) fail to attribute the improvement to arbitrage trades or the liquidity enhancements noted in index stocks. Improvements in spot-futures price efficiency may be a result of a change in how index traders allocate amongst index markets, with the ETF market attracting liquidity from hedgers and passive index traders (Deville et al., 2012).

4.2.3. ETF Costs and Volatility

A primary concern for ETF investors is how closely their ETF tracks its required index or sector. However, a survey conducted by Greenwich Associates (2011) also reveal that 61% of institutional funds and 79% of asset managers name liquidity as one of the top ETF selection criteria. Therefore, of pertinent interest to ETF investors are the costs involved with ETF trading.

Borkovec et al. (2012) investigate the liquidity and cost characteristics of ETFs and their underlying securities. Results are obtained from a selected group of ETFs that track popular U.S. equity indices. The paper defines liquidity as "the ability to transact quickly without exerting a material effect on prices". Using the matching technique presented by Huang et al. (1996)[39] to compare the characteristics of ETFs and common stocks, the study finds that ETF liquidity is determined by the liquidity of the underlying securities via the crucial creation/redemption mechanism. Greater liquidity is noted in the ETF market where limit order books are deeper, especially at price levels immediately surrounding the prevailing mid-quote.

The study then simulates optimal, block trade scheduling and finds price impact costs two to five times lower for ETFs when compared to the matched, control sample. The authors argue that the unique arbitrage mechanism does not completely eradicate the gap between secondary market costs and the basket costs for large orders. The higher commissions involved with trading in a basket the non-discretionary accumulation is given as viable explanations.

4.2.4. Market Maker Microstructure Theories

The primary role of a market maker is to provide immediacy for other investors by supplying liquidity. Market makers are often employed but at any particular moment in time, the number of market participants actively seeking to buy or sell can be quite small (Desmetz, 1968; Garbade et al., 1982).

The intricacy of real-world capital markets often leads to stylised assumptions when developing market microstructure models. Market participants are generally considered to be rational, economic agents; they take actions to maximize their own expected utility. To facilitate the analysis of classical market maker theories, a

[39] For each ETF, 5 stocks are selected that come closest to the ETF in terms of median daily dollar volume, price, historical volatility and spread.

simplistic trading mechanism is formed. Market maker behaviour is examined in an environment where they have no information and must maintain two-way quotes. Assuming that the market structure is quote-driven limits the usefulness when applying the models to order-driven and hybrid market structure where traders can submit limit orders. Trade size is also considered to be a constant unit; a significant generalisation as it implies that market maker activity is captured entirely by the revision of bid and ask quotes.

A Walrasian market (or "call market") exists when simultaneous orders are collected and a clearing price is set so that the total demand of the good equals the total supply. Blume et al. (1990) state that Walrasian depiction assumes there will not be any friction in the exchange process. However, the tendency for temporary order-flow imbalances to arise is an inherent component of any continuous auction market. Classical market maker theories explicitly consider the asynchronous nature of order flow in the sense that traders arrive sequentially, leading to a timing problem[40]. Desmetz (1968) states that this time component of trading hinders market makers as they are exposed to risks associated with stochastic order flow. O'Hara (1995) notes two main patterns in the literature: inventory holding and adverse selection, both reflecting a component of market maker risk[41].

Inventory holding risk refers to the price risk faced by market makers when holding a security. Garman (1976) constructs a setting where the only source of uncertainty due to the random influx of buy and sell orders. Market makers are

[40] Engle and Russell (1998) identify the complex issue of arrival times as a point process. This is not typically considered in the market marker literature.
[41] Manaster and Mann (1996) state that models for inventory holding and adverse selection risk consider each risk in isolation rather than determining the combined effect.

assumed to set a bid and ask quote once at $t = 0$ and are shown to fail in the long term if the quotes are set independently of their inventory levels[42]. Hence continuous price consideration is crucial when monitoring inventory levels.

The inventory holding literature consists of studies such as Amihud et al. (1980), Ho et al. (1983) and Biais (1993) that have attempted to solve the pricing problem within different settings. It is generally accepted that market makers with undesired short (long) positions will increase (reduce) their bid and ask quotes, enticing public investors to sell (buy) the security. This suggests that rather than a stochastic process, inventory positions will display strong mean reversion and inventory cycles will tend to be short[43] (Manaster et al., 1996). This quoting behaviour also implies that market maker gross trading profits will be comprised entirely of the bid-ask spread and that position-taking profits will be zero, on average.

Adverse selection risk refers to the risk faced by market makers when dealing with informed investors. Asymmetric information exists when some market participants have more information about an asset than others. Adverse selection models rely on this existence and class market participants into two categories: 1. Informed investors that attempt to predict price movements and 2. Liquidity motivated traders. As market makers are not considered to be informed investors, Bagehot (1971) first postulated that market makers must earn a profit from liquidity traders to offset losses to investors with more information.

[42] This is known as the Gambler's Ruin problem.
[43] As market makers are considered to be informed, target inventory levels will be typically be zero.

This concept has since been modelled by studies such as Copeland et al. (1983), Glosten et al. (1985) and Easley et al. (1987). In contrast with the inventory control literature, a consistent theme among these studies is the prediction that average market maker position-taking profits are negative. Furthermore, in a competitive market maker environment where average gross trading profits are zero, these position-taking losses will be equal to the liquidity earnings attained from the bid-ask spread. Each of these models assumes market maker indifference with regard to inventory levels. Intuitively, as the variability of position-taking profits is dependent on the size of the position held (Easley et al., 1987), market maker position-taking profits are more volatile than implied by the inventory control hypothesis. A deeper review on the literature surrounding market maker profitability is given in Section 4.2.6.

4.2.5. Trading Environment

A review of the extant literature does not provide a complete understanding of the market quality effects of market makers in an order-drive LOB market. Intuitively, if voluntary, exogenous market making was a lucrative activity[44], traders submitting limit orders would naturally assume these responsibilities. This is consistent with Panayides (2007), with market making profits declining when market quality is improved. That is, while market maker restrictions are necessary for market makers to be effective, they are not sufficient. Therefore, it can be argued that to improve market quality, market maker's profits must not increase following market maker mandate changes.

[44] Outside of any monetary inducements provided by the exchange.

The viability of market makers is also dependent on the state of the market. The literature offers contrasting perspectives on the requirement of market makers in periods of market stress. The first perception contends that market participants are incapable of seeing through adverse market conditions without an exogenous liquidity supply. In an environment with large order imbalances and high adverse selection levels, market participants will be disinclined to use a passive quote submission approach as this represents a free option to other traders (Copeland et al., 1983). Consequently, the price discovery process is restricted due to the lack of liquidity, leading to the need of market maker intervention.

Studies such as Black (1971), Stoll (1988) and Bloomfield et al. (2005) offer the converse perspective and maintain that financial markets can operate efficiently without designated market makers. This view largely stems from assessing the hybrid NYSE structure in which a specialist functions and focuses on the adverse consequences of price stabilization regulations. Widening the scope, Glosten (1994) finds that under extreme periods of adverse selection, order-driven LOB markets offer equilibrating levels of liquidity. This leads him to state that the substantial resources used to incentivise exogenous market making are misallocated.

The necessity of market making is also related to the characteristic of the traded asset. Market making is more suitable if the bid-ask spread reflects levels of information asymmetry rather than other components such as inventory costs. To this point, the bid-ask spread for thinly-traded securities would represent higher levels of inventory costs (Desmetz, 1968). Therefore, on the ASX's market, where

ETF's are traded relatively infrequently, it may be socially optimal for the bid-ask spread to be wide. Empirical studies such as Tse et al. (2004), Eldor et al. (2006), Anand et al. (2006) and Venkataraman et al. (2007) are more consistent in their findings, commonly concluding that market makers enhance market quality.

Liquidity providers have a business agreement with Euronext to act as market makers in the ETF market. These liquidity providers are vital in contributing to the liquidity of the ETF market. Similarly, Menkveld et al. (2009) find that contracted designated market makers on Euronext are vital in improving liquidity levels and reducing the liquidity risk of small-cap stocks. Easley et al. (1996) and Gajewski et al. (2007) also find that market makers are capable of attracting the least informed traders and therefore the most profitable order flow of securities traded in hybrid markets.

The contrasting evidence provided brings to question whether market maker mandates have an economic role on the ASX's ETF market. As mentioned in Section 4.2.4, the primary role of a market maker is to provide immediacy for other investors by supplying liquidity. The rebates, as specified in Section 4.1.2, have been carefully designed to incentivise a continued market making presence on the ASX's ETF market. Quoting requirements have been stylised to the characteristics of the corresponding ETFs in a boost to encourage trading activity. Consequently, we develop the following hypotheses:

H_1: Spreads will decrease in the 12 months following the introduction of the ETF market making scheme compared to the 12 months prior to the scheme for ETF's in Quoting Schedule 1.

H_2: Spreads will decrease in the 12 months following the introduction of the ETF market making scheme compared to the 12 months prior to the scheme for ETF's in Quoting Schedule 2.

H_3: Spreads will decrease in the 12 months following the introduction of the ETF market making scheme compared to the 12 months prior to the scheme for ETF's in Quoting Schedule 3.

H_4: Spreads will decrease in the 12 months following the introduction of the ETF market making scheme compared to the 12 months prior to the scheme for ETF's in Quoting Schedule 4.

H_5: Spreads will decrease in the 12 months following the introduction of the ETF market making scheme compared to the 12 months prior to the scheme for ETF's in Quoting Schedule 5.

H_6: Depth will increase in the 12 months following the introduction of the ETF market making scheme compared to the 12 months prior to the scheme for ETF's in Quoting Schedule 1.

H_7: Depth will increase in the 12 months following the introduction of the ETF market making scheme compared to the 12 months prior to the scheme for ETF's in Quoting Schedule 2.

H_8: Depth will increase in the 12 months following the introduction of the ETF market making scheme compared to the 12 months prior to the scheme for ETF's in Quoting Schedule 3.

H_9: Depth will increase in the 12 months following the introduction of the ETF market making scheme compared to the 12 months prior to the scheme for ETF's in Quoting Schedule 4.

H_{10}: Depth will increase in the 12 months following the introduction of the ETF market making scheme compared to the 12 months prior to the scheme for ETF's in Quoting Schedule 5.

4.2.6. Market Makers and Profitability

The empirical literature elicits two approaches when assessing market maker profitability. One method, adopted by Huang et al. (1996b), is to assume the only profits attained by market makers is the realised half-spread when supplying liquidity. This approach is most pertinent to dealer markets where market makers provide liquidity in every trade. Another method is to analyse the elements of gross trader profits to deduce the behaviour and role of market makers.

Hasbrouck et al. (1993) apply a mark to market approach[45] of determining total NYSE profitability in the context of specialists[46]. Deconstructing specialist profitability, they find that the principal source of profits is short horizon information. Studies such as Brock et al. (1992) and McInish et al. (1995) highlight the advantages specialists receive when they hold a near-monopoly on the market. Specifically, McInish et al. (1995) recognise that their control of order flow allows

[45] Hasbrouck and Sofianos (1993) apply spectral analysis. Spectral analysis is analysis in terms of a spectrum of frequencies or related quantities. In this instance, the spectrum is time.
[46] A specialist is a dealer representing a NYSE specialist firm. A specialist is a type of market maker.

specialists to "hide" limit orders[47]. Hasbrouck et al. (1993) conclude that the majority of net gains arise from capturing the spread, however specialists are able to derive position-taking profits through the aid of superior order-flow information[48].

In contrast to the market-making provisions provided by designated market makers or specialists at securities exchanges, market making at exchanges functioning as open-outcry markets is achieved through market participants referred to as locals[49]. Locals compete with one another for order flow through their bid and ask prices. Unlike designated market makers, locals do not have an obligation to trade, however the academic literature recognises that their behaviour mimics market making (Silber, 1984; Kuserk et al., 1993).

Assessing local trading behaviour on the Chicago Mercantile Exchange (CME), Manaster et al. (1992) find that like the NYSE specialist, locals realise profits through favourable price movements. Using the Fishman et al. (1992) methodology to decompose gross profits, they determine that 67% of local income is attained through position-taking gains. Like Hasbrouck et al. (1993), this finding is accredited to the advantages provided to locals when accessing order-flow. Consistent results are also found on the Sydney Futures Exchange (SFE). Interestingly, Frino et al. (2010 a) find that these position-taking gains are associated with lower levels of information; implying that locals are able to assess market movements from the trading floor. As the position-taking gains are also

[47] NYSE specialists were replaced with Designated Market Makers on the NYSE in 2008. Designated Market Makers were given no order-flow information advantages.
[48] These findings are later substantiated by Harris and Panchapagesan (2005), who state that when transacting on the NYSE, intermediaries use information to their advantage.
[49] They are also referred to as scalpers.

associated with greater trade frequency and volatility, the findings of Frino et al. (2010 a) further authenticate the order-flow information theory.

Contrary to classical market maker models, the overriding theme from the empirical evidence suggests that market makers are not passive liquidity providers. This has led to theoretical studies such as Madhavan et al. (1993) and Cao et al. (2006) considering market makers as informed, active traders. In observing this deviation from market maker models, it is important to note that traditional market maker theory is subject to the assumption of a dealer-driven market. The above theoretical studies are centred on order-driven or hybrid trading platforms. Order-driven and hybrid markets differ from dealer-driven markets in that public traders may also supply liquidity, therefore conclusions drawn from market maker models may not be applicable to order-driven markets (Madhavan et al., 1998).

It is also crucial that we consider the market making environment when comprehending market maker behaviour. Intuitively, the nature of the market maker mandate plays an imperative role in any outcomes achieved. Understanding this relationship is challenging as it is tricky to evaluate different market maker responsibilities across exchanges. Panayides (2007) tackle this issue by assessing NYSE specialist profitability in periods where participation is voluntary and compulsory. Specifically, Panayides (2007) study specialist profitability during periods where they are constrained by the obligation to provide liquidity under the Price Continuity rule[50] and in periods where they are not. The importance of the mandate is highlighted when specialists are shown to make net losses in periods

[50] The Price Continuity rule requires specialists to "smooth" trade prices by providing extra liquidity when necessary to keep trade price changes small.

where the Price Continuity rule is enforced but are more than reimbursed when it is not, a result that is consistent with theoretical conclusions presented in Dutta et al. (1997). The results suggest that market making mandates may enhance market quality, but inflict considerable costs on the specialist; an important concern for exchanges to ensure the practicality of market makers.

Given that the market making scheme imposes more stringent liquidity requirements, we anticipate that market maker liquidity profits will increase following the implementation of the scheme. Consequently, we develop the following hypothesis:

H_{11}: Market maker liquidity profits will increase in the 12 months following the introduction of the ETF market making scheme compared to the 12 months prior to the scheme.

Jarnecic et al. (2008) provide evidence that ASX option market makers realise positive position-taking profits. We anticipate that a more continuous market presence will allow market makers to further anticipate permanent price shifts to attain position-taking profits. We therefore develop the following hypothesis:

H_{12}: Market maker position-taking profits will decline in the 12 months following the introduction of the ETF market making scheme compared to the 12 months prior to the scheme.

4.3. Methodology

4.3.1. Sample and Data Sources

The sample period is chosen to be 1 August 2009 to 31 July 2011 (504 trading days) to cover the period around the introduction of the ETF Market Maker Scheme by the ASX. The sample is divided into a pre-scheme period of 1 August 2009 to 31 July 2010 (252 trading days) and a post-scheme period of 1 August 2010 to 31 July 2011 (252 trading days). A minimum requirement of 10 trades per day over the entire sample period resulted in a final sample of 14 equity ETFs[51]. The distribution of the ETFs and their corresponding quoting schedule is reported in Table 4-1.

Table 4- 1: ETF Sample Split by Quoting Schedule

This table presents the 14 sample ETFs and their corresponding Quoting Schedule.

Quoting Schedule 1	Quoting Schedule 2	Quoting Schedule 3	Quoting Schedule 4	Quoting Schedule 5
3 ETFs	3 ETFs	5 ETFs	1 ETF	1 ETF

Quote and trade data is sourced from both the Securities Industry Research Centre of Asia-Pacific and the Thomson Reuters Tick History database. Order book data from SIRCA contains broker identifications, enabling us to track the activities of each market maker. The following fields were obtained from the order book request: instrument, date, time, record type, price, volume, value, trade direction, buyer broker ID and seller broker, bid-price, ask-price, bid-size and ask-size.

[51] The sample was selected from a total of 51 equity ETFs.

Combining the two datasets enables us to match the prevailing best bid and ask with each quote and trade. Rebate payment information is not available; however, the data allows us to determine how often market makers were meeting their quoting requirements therefore the ASX rebate payment can be calculated.

4.3.2. Liquidity

To measure the efficiency of the ETF market, we focus on liquidity. The emphasis on the bid-ask spreads as the primary metric for liquidity and a lack of focus on other dimensions typified many early studies. Pascal et al. (2004) note that this one-dimensional emphasis stemmed from microstructure models that assume trades are of a similar size and therefore do not consider depth. As liquidity incorporates both dimensions of spreads and depth, a change in liquidity cannot be identified by spreads alone (Lee et al., 1993). Harris (2003) identifies immediacy, width, depth and resiliency as four dimensions of liquidity. In this chapter, the primary focus is on width and depth. Width refers to the cost of trading at a given size, measured by the bid-ask spread, while depth refers to the size of a trade that can be arranged at a given cost.

As detailed in Section 4.2, market maker requirements are determined for each quoting schedule. Quoting schedules can be viewed as liquidity categories and as a result, rather than performing statistical tests across all ETFs simultaneously, liquidity analysis is conducted within each of the five quoting schedules. The time-weighted proportional bid-ask spread measures the cost of trading. We use the time-weighted proportional bid-ask spread given in Chapter 3, Section 3.3. To measure depth, we determine the daily time-weighted best depth also shown in Chapter 3, Section 3.3.

Other supplementary metrics, including volume, turnover, spread volatility and price volatility, are measured for each trading day. Volume is the number of shares traded, while turnover is the dollar amount of trading. Spread volatility is the variance of $TWS_{t,q}$. Price volatility is computed by the ratio of the day's highest price divided by the lowest price.

For each of the liquidity measures, the mean, median, standard deviation, skewness and kurtosis are estimated. The non-parametric Wilcoxon rank-sum test is used to compare the two periods. The Wilcoxon rank-sum technique tests for differences in the underlying distribution between the two periods. This non-parametric test has been chosen as it is impossible for any of our liquidity measures to be negative and therefore a normal distribution cannot be assumed as positive skewness is likely to be exhibited. Furthermore, Campbell et al. (1997) state that microstructure data is likely to show strong excess kurtosis due to the regularity of outliers.

Using data for the entire sample period, the following regression models are estimated:

$$Ln\left(TWS_{t,q}\right) = \beta_0 + \beta_1 D_t + \beta_2\, ln\left(Volume_{t,q}\right) + \beta_3\, ln\left(Volatility_{t,q}\right) + \beta_3 Time_t^2 + \varepsilon_t \quad (4.1)$$

$$Ln(TWD_{t,q}) = \beta_0 + \beta_1 D_t + \beta_2 \, ln(Volume_{t,q}) + \beta_3 \, ln(Volatility_{t,q}) + \beta_4 \, ln(TWS_{t,q}) + \beta_4 Time_t^2 + \varepsilon_t \, . \quad (4.2)$$

Log-log regressions are used to obtain residuals that are approximately symmetrically distributed around zero. The regressions are estimated using the Generalized Method of Moments (GMM) technique. To adjust for serial correlation, the Parzen Kernel suggested by Gallant (1987) is used.

The primary variable of interest D_t is a dummy variable that assumes the value of 0 if day t is during the pre-scheme period and 1 for the post-scheme period. $Volume_{t,q}$ refers to the total volume traded on day t in the ETFs grouped in quoting schedule q. This variable has been included due to the empirical findings by Hausman (1978) and others that volume is related to the bid-ask spread. Thus $Volatility_{t,q}$ represents the volatility of the ETFs in quoting schedule q on day t. As the Australian ETF market is a growing market, we include the variable $Time_t^2$ to control for any expected liquidity enhancements over time.

Since both the bid-ask spread and depth are used to measure liquidity, the variables explained in the paragraph above are also used as control variables when examining the depth measure. The variable $TWS_{t,q}$ refers to the time-weighted proportional bid-ask spread for the ETFs in quoting schedule q on day t.

4.3.3. Profitability

Market maker profitability is examined during the rebate period following Frino et al. (2010 a). Market maker profits are split into two components: a static liquidity component and a dynamic position-taking component. For a consistent unit of observation, income is measured and analysed for each trading day.

Market makers earn liquidity profits by setting a spread. Investors often pay a premium for immediacy: the difference between the trade price and the fundamental value of the underlying asset. Although the trade price is observed in our data, a proxy for the fundamental value must be determined. The most consistent approach in the prior literature[52] is to use the midpoint of the prevailing bid-ask spread. This proxy is intuitively appealing[53] and presents an unbiased reflection of trader valuations. Glosten et al. (1985) also present a model where the price that would prevail if all investors had the same information as market makers is straddled within the bid-ask spread. As a result, this chapter adopts the same approach. Following this, when supplying liquidity, the market maker's revenue is determined by the difference between the trade price[54] and the midpoint. Investors therefore cross the bid-ask spread and incur a cost equal to half the bid-ask spread when demanding liquidity. Incorporating the quantity of the underlying asset traded, the daily liquidity profits realised by the market maker *M* in ETF *e* across *N* trades on day *t* is:

$$LP_{M,t,e} = \sum_{i=1}^{N}(Q_i \times D_i \times (X_i - P_i)), \tag{4.3}$$

---

[52] Glosten (1987), Stoll (1989) and Frino et al. (2010 a) are examples of papers that have used the midpoint of the prevailing bid-ask spread as a proxy for the fundamental value of the underlying asset.

[53] Given that the average cost of a round-trip transaction is the bid-ask spread, it follows that the cost of liquidity for any initiated trade is half the spread.

[54] The direction of the difference depends on whether the market maker is making a purchase or sale.

where Q_i represents the number of ETFs bought or sold by M in trade i. D_i equals 1 if M purchased e and – 1 if M sold e. Finally, X_i is the midpoint of the prevailing best bid and ask P_i is the trade price.

Total liquidity profits are:

$$TLP_t = \sum LP_{M,t,e} . \tag{4.4}$$

To make position-taking gains, traders must first be demanders of liquidity. Position-taking profits are earned when there is a change in the fundamental value of the asset. The "true" price of the underlying asset is again proxied by the mid-point of the prevailing bid-ask spread. This approach is consistent with the methodology employed in Hasbrouck et al. (1993) where long (short) inventory positions yield positive position-taking profits whenever the midpoint increases (decreases). Again, in determining position-taking profits, the quantity of the underlying asset traded must be considered. Position-taking profits are determined for each transaction in a round trip as follows:

$$PP_{M,t,e} = \sum_{i=1}^{N} (Q_i \times D_i \times (X_c - P_s)) , \tag{4.5}$$

where X_c is the prevailing mid-point at the end of the inventory cycle while P_s is the prevailing mid-point at the start of the inventory cycle.

Total position-taking profits are:

$$TPP_t = \sum PP_{M,t,e} . \tag{4.6}$$

Position-taking profits can only be realised when inventory positions are closed out. If an inventory cycle is incomplete at the end of a trading day, the remaining open positions are marked to market using the midpoint (X_e) of the bid and ask quotes prevailing at the end of the day. This approach is unlikely to have a major impact on our analysis as Kuserk et al. (1993, 1994) document that both scalpers and day traders are unlikely to hold positions overnight. If positions are held overnight, they are typically small.

We refer to the entire net gains made by market makers as total profit. Total profitability per market maker (TP_M) is therefore a summation of liquidity and position-taking profits:

$$TP_M = LP_{M,t,e} = \sum_{i=1}^{N}(Q_i \times D_i \times (X_i - P_i)) + PP_{M,t,e} = \sum_{i=1}^{N}(Q_i \times D_i \times (X_c - P_s)). \quad (4.7)$$

Total profitability is calculated as:

$$TP = \sum TP_M. \quad (4.8)$$

This expression of total market maker profitability simplifies to the expression derived by Fishman et al. (1992). The measure of total market maker profitability in this study is also consistent with the approach outlined in Hasbrouck et al. (1993).

To measure profitability, both components of profitability and interactions between liquidity and position-taking profits are measured in the pre-scheme and post-scheme periods. The earlier univariate tests used for liquidity are also conducted.

Univariate analysis is carried out for total liquidity and position-taking profits across our sample of ETFs to explicitly capture overall profits.

Multivariate analysis is undertaken for profitability over the entire period. The following regression models are estimated:

$$TLP_t = \beta_0 + \beta_1 D_t + \beta_2 \ln(Volume_{t,q}) + \beta_3 \ln(Volatility_{t,q}) + \beta_4 \ln(TWS_{t,q}) + \beta_5 (TPP_t) + \varepsilon_t \tag{4.9}$$

$$TPP_t = \beta_0 + \beta_1 D_t + \beta_2 \ln(Volume_{t,q}) + \beta_3 \ln(Volatility_{t,q}) + \beta_4 (TLP_t) + \varepsilon_t \ . \tag{4.10}$$

We apply the same GMM methodology used in the liquidity analysis. Again, D_t is our primary variable of interest.

The width of the bid-ask spread is likely to influence the liquidity behaviour of market makers. Therefore, the control variable $TWS_{t,q}$ has been included for liquidity profits and not position-taking profits.

4.4. Results

4.4.1. Liquidity

The liquidity descriptive statistics for pre-scheme and post-scheme periods are reported in Table 4-2. As mentioned in Section 4.3, liquidity results are presented for each quoting schedule subsample. A reduction in $TWS_{t,q}$ occurs for quoting schedules one, two, three and five. By far, the greatest improvement in spreads is the 37% drop in quoting schedule one. Like $TWS_{t,q}$, improvements in $TWD_{t,q}$ are shown in all quoting schedules barring quoting schedule four. A rise of 69% in quoting schedule three presents the greatest improvement in depth. An increase in turnover occurs across all five quoting schedules, however the mean daily volume has decreased for quoting schedule one. Spread volatility is very small for all quoting schedules and changes do not exhibit any clear patterns. Price volatility has decreased for all five quoting schedules. Looking at distributional properties, all sub-samples show positive skewness and are leptokurtic, a typical characteristic of microstructure data (Campbell et al., 1997)

Table 4- 2: Liquidity- Descriptive Statistics

This table provides summary statistics of liquidity measures during the pre-scheme and post-scheme periods for ETFs in each of the quoting schedules. TWS refers to the daily time-weighted proportional spread. TWD refers to the daily time-weighted depth at the best bid and ask. Turnover refers to total daily turnover. Volume refers to the daily total number of ETFs traded. Spread volatility refers to the daily volatility of the bid-ask spread. Price volatility denotes the daily volatility of ETF prices.

	Mean		Median		Standard Deviation		Skewness		Kurtosis	
Quoting Schedule 1	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
$TWS_{t,q}$	0.19%	0.12%	0.18%	0.10%	0.06%	0.08%	1.47	10.77	3.68	144.41
$TWD_{t,q}$	$579,736	$843,507	$595,876	852378	$160,620	$202,822	0.03	0.17	0.01	0.18
$Turnover_{t,q}$	$491,343	$553,237	$269,544	$ 366,995	$599,752	$621,544	2.96	2.01	11.49	4.64
$Volume_{t,q}$	7269	6673	3919	4043	9190	8291	3.07	2.44	12.63	7.30
$Spread\ Volatility_{t,q}$	0.000	0.000	0.000	0.000	0.000	0.000	8.84	11.36	83.40	142.04
$Volatility_{t,q}$	1.011	1.008	1.009	1.007	0.007	0.004	2.19	2.66	7.14	13.08
Quoting Schedule 2										
$TWS_{t,q}$	0.46%	0.39%	0.43%	0.30%	0.16%	0.35%	1.94	4.92	5.08	27.25
$TWD_{t,q}$	$166,070	$246,745	$157,221	$224,894	$45,019	$87,724	0.48	1.10	-0.13	0.46
$Turnover_{t,q}$	$76,988	$140,788	$58,310	$86,623	$69,057	$184,289	1.71	3.78	3.04	17.17
$Volume_{t,q}$	1477	2526	1101	1595	1404	2958	1.92	3.21	3.99	12.76
$Spread\ Volatility_{t,q}$	0.001	0.001	0.000	0.000	0.013	0.004	15.54	8.17	244.49	78.86
$Volatility_{t,q}$	1.010	1.008	1.009	1.007	0.006	0.003	5.13	1.53	49.00	4.27

Quoting Schedule 3

$TWS_{t,q}$	0.64%	0.58%	0.60%	0.53%	0.18%	0.20%	3.27	2.73	21.65	10.29
$TWD_{t,q}$	$180,217	$333,743	$171,671	$327,709	$42,469	$94,614	0.70	0.69	0.34	0.93
$Turnover_{t,q}$	$147,129	$254,393	$129,724	$158,213	$91,273	$282,588	1.53	2.73	3.20	8.23
$Volume_{t,q}$	3546	7082	3018	3949	2505	12147	2.53	7.85	10.69	84.78
$Spread\ Volatility_{t,q}$	0.000	0.001	0.000	0.000	0.001	0.003	3.59	6.61	13.24	51.35
$Volatility_{t,q}$	1.012	1.010	1.010	1.009	0.006	0.005	1.91	2.29	6.53	8.07

Quoting Schedule 4

$TWS_{t,q}$	0.74%	0.81%	0.75%	0.79%	0.23%	0.36%	-0.04	2.74	-0.41	13.53
$TWD_{t,q}$	$202,370	$175,542	$198,488	$177,110	$67,794	$77,741	0.41	1.45	0.05	5.95
$Turnover_{t,q}$	$370,913	$527,959	$145,664	$278,972	$779,012	$729,291	6.48	2.95	53.82	12.50
$Volume_{t,q}$	2959	4209	1158	2243	6206	5765	6.45	2.86	53.15	11.61
$Spread\ Volatility_{t,q}$	0.000	0.000	0.000	0.000	0.000	0.003	8.46	13.63	83.23	198.58
$Volatility_{t,q}$	1.009	1.008	1.007	1.007	0.008	0.007	4.89	2.32	42.67	8.94

Quoting Schedule 5

$TWS_{t,q}$	0.94%	0.74%	0.78%	0.59%	0.63%	0.66%	2.73	5.36	10.08	36.80
$TWD_{t,q}$	$89,917	$217,011	$75,767	$96,755	$57,401	$202,568	2.79	1.08	9.71	-0.09
$Turnover_{t,q}$	$81,843	$101,090	$55,396	$59,110	$92,386	$144,278	3.94	4.03	28.42	23.14

$Volume_{t,q}$	1693	2146	1101	1226	1954	3171	4.13	4.21	30.95	25.04
$Spread\ Volatility_{t,q}$	0.007	0.004	0.001	0.001	0.040	0.015	12.77	8.29	181.92	78.90
$Volatility_{t,q}$	1.014	1.008	1.011	1.006	0.014	0.009	3.05	3.01	13.25	13.30

Table 4-3 presents the Wilcoxon rank-sum test results for our five liquidity subsamples. The most consistent statistical change is the decreased volatility in share price. A reduction in price volatility occurs in all five of the quoting schedules and is consistent with the summary statistics presented in Table 4-2. Other compelling evidence of improvements in liquidity are the reduction in spreads and increased depth, our primary liquidity metrics, in all but one of the quoting schedules. As Table 4-2 shows, improvements in spreads and depth do not occur for the ETFs in quoting schedule four in our post-scheme period. Consistent with Table 4-2, the greatest bid-ask spread and depth improvements occur in quoting schedules one and three respectively. There appears to be no adverse effects for turnover and volume, with improvements occurring in quoting schedules two, three and four.

Table 4- 3: Non-Parametric Univariate Analysis of Liquidity

This table presents the results of the non-parametric univariate analysis of liquidity. Statistics refer to the Z score for the Wilcoxon rank-sum U Statistic testing for different underlying distributions between the pre-scheme and post-scheme periods for the ETFs in each of the five quoting schedules. The ASX divides all ETFs into five quoting schedules determined by their liquidity characteristics. ***, ** and * represent significance at the 1%, 5% and 10% level respectively. $TWS_{t,q}$ refers to the daily time-weighted proportional spread. $TWD_{t,q}$ refers to the daily time-weighted depth at the best bid and ask. $Turnover_{t,q}$ refers to total daily turnover. $Volume_{t,q}$ refers to the daily total number of ETFs traded. $Spread\ Volatility_{t,q}$ refers to the daily volatility of the bid-ask spread. $Volatility_{t,q}$ denotes the daily volatility of ETF prices.

Daily	Quoting Schedule 1	Quoting Schedule 2	Quoting Schedule 3	Quoting Schedule 4	Quoting Schedule 5
	Statistic	Statistic	Statistic	Statistic	Statistic
$TWS_{t,q}$	-14.823***	-11.863***	-5.826***	1.648*	-6.049***
$TWD_{t,q}$	13.422***	11.798***	17.251***	-4.217***	7.067***
$Turnover_{t,q}$	-0.619	5.324***	4.235***	2.272**	0.359
$Volume_{t,q}$	1.335	5.268***	5.094***	2.297**	0.495
$Spread\ Volatility_{t,q}$	-9.283***	2.145**	8.810***	6.758***	-0.57
$Volatility_{t,q}$	-4.898***	-5.669***	-3.231***	-1.878*	-7.850***

These findings demonstrate significant liquidity enhancements in the year subsequent to the introduction of the ETF Market Making Scheme. The liquidity improvements are accompanied by consistent changes in actual trading outcomes, indicating that the scheme has been successful in improving quoting behaviour as well as affecting trading activity.

The GMM regression results associated with Equation (4.1) for each of the five quoting schedules are reported in Table 4-4. The period dummy variable D_t reveals that $TWS_{t,q}$ significantly decreases from the pre-scheme period to the post-scheme period in four of the five quoting schedules at the 1% level. Therefore, we fail to reject H_1, H_2, H_3 and H_4 and reject H_5. The improvement is greatest in quoting schedule four, with a reduction of 32% as a result of the scheme. Time-related spread improvements are noted in quoting schedules one, four and five. $ln(Volume_{t,q})$ is a statistically-significant negative determinant of $TWS_{t,q}$ in quoting schedule one only. $ln(Volatility_{t,q})$ is a positive determinant of $TWS_{t,q}$ across our sample at the 1% significance level. This result is consistent with the information asymmetry models of Copeland et al. (1983) that predict wider spreads for volatility and less frequently traded assets[55] as a result of higher adverse selection risk.

[55] Even with a minimum requirement of 10 trades per day over the entire sample period, many of the ETFs are thinly traded.

Table 4- 4: Regression Analysis for Time-Weighted Proportional Bid-Ask Spread across Quoting Schedules

This table reports GMM regression results for the following model: $Ln(TWS_{t,q}) = \beta_0 + \beta_1 D_t + \beta_2 \ln(Volume_{t,q}) + \beta_3 \ln(Volatility_{t,q}) + \beta_3 Time_t^2 + \varepsilon_t$. The model is run for quoting schedules one, two, three, four and five ETFs for the period 1 August 2009 to 31 July 2011. The ASX divides all ETFs into five quoting schedules determined by their liquidity characteristics. The dependent variable is the time-weighted proportional bid-ask spread, $Ln(TWS_{t,q})$. $D_t$takes on a value of zero for the pre-scheme period and one for the post-scheme period. $Ln(Volume_{t,q})$ is the natural logarithm of daily volume. $Ln(Volatility_{t,q})$ is the natural logarithm of daily price volatility. $Time_t^2$ is a quadratic time variable. Test statistics are reported in brackets under the coefficients for each independent variable. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

	Quoting Schedule				
Variable	One	Two	Three	Four	Five
$Intercept$	-6.181***	-5.543***	-5.129***	-5.154***	-5.138***
	(-75.57)	(-48.26)	(-45.53)	(-37.10)	(-63.86)
D_t	-0.281***	-0.188***	-0.083**	-0.320***	-0.035
	(-5.31)	(-3.11)	(-2.07)	(-3.65)	(-0.50)
$Ln(Volume_{t,q})$	-0.032***	-0.006	-0.016	0.019	-0.006
	(-3.45)	(-0.37)	(-1.14)	(0.97)	(-0.64)
$Ln(Volatility_{t,q})$	11.964***	17.317***	14.682***	11.027***	18.984***
	(4.85)	(4.83)	(7.15)	(5.00)	(6.51)
$Time_t^2$	-0.000***	-0.000	0.000	-0.000**	-0.000***
	(-4.02)	(-0.86)	(0.21)	(-1.95)	(-2.58)
$Adjusted\ R^2$	0.401	0.154	0.121	0.105	0.145

Table 4-5 presents the GMM regression results associated with Equation (4.2) for each of the five quoting schedules. The coefficient on D_t indicates improvements in $TWD_{t,q}$ from the pre-scheme period to the post-scheme period in two of the five quoting schedules at the 1% level. Therefore, we fail to reject H_6 and H_7 and reject H_8, H_9 and H_{10}. The improvement is greatest in quoting schedule one, with an increase of 27% as a result of the scheme. The coefficient for $ln(TWS_{t,q})$ is negative and significant quoting schedules one, three and four. $ln(Volume_{t,q})$ has a positive and significant impact on $TWD_{t,q}$ for quoting schedules two, three and four and 5.

Table 4- 5: Regression Analysis for Time-Weighted Depth across Quoting Schedules

This table reports GMM regression results for the following model: $Ln(TWD_{t,q}) = \beta_0 + \beta_1 D_t + \beta_2 ln(Volume_{t,q}) + \beta_3 ln(Volatility_{t,q}) + \beta_4 ln(TWS_{t,q}) + \beta_5 Time_t^2 + \varepsilon_t$. The model is run for quoting schedules one, two, three, four and five ETFs for the period 1 August 2009 to 31 July 2011. The ASX divide all ETFs into five quoting schedules determined by their liquidity characteristics. The dependent variable is the time-weighted depth, $Ln(TWD_{t,q})$. D_t takes on a value of zero for the pre-scheme period and one for the post-scheme period. $Ln(Volume_{t,q})$ is the natural logarithm of daily volume. $Ln(Volatility_{t,q})$ is the natural logarithm of daily price volatility. $Ln(TWS_{t,q})$ is the natural logarithm of the daily time-weighted bid-ask spread. $Time_t^2$ is a quadratic time variable. Test statistics are reported in brackets under the coefficients for each independent variable. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

	Quoting Schedule				
Variable	One	Two	Three	Four	Five
$Intercept$	12.672***	11.704***	10.852***	9.843***	14.633***
	(46.25)	(0.60)	(45.62)	(31.49)	(45.72)
D_t	0.270***	0.028	0.210***	-0.837***	-0.244***
	(5.38)	(0.60)	(5.61)	(-8.26)	(-3.20)
$Ln(Volume_{t,q})$	0.001	0.044***	0.030**	0.074***	-0.034***
	(0.12)	(3.53)	(2.22)	(3.33)	(-3.12)
$Ln(Volatility_{t,q})$	-4.796**	-1.002	-3.324*	1.080	-3.385
	(-2.06)	(-0.36)	(-1.66)	(0.43)	(-1.01)
$Ln(TWS_{t,q})$	-0.092**	0.013	-0.190***	-0.154***	0.452
	(2.17)	(0.37)	(-4.56)	(-2.92)	(7.55)
$Time_t^2$	0.000	0.000***	0.000***	0.000***	0.000
	(1.52)	(8.35)	(11.47)	(16.10)	(0.54)
$Adjusted\ R^2$	0.330	0.390	0.678	0.454	0.210

The results for quoting schedule four five indicate a decrease in depth due to the market making scheme. This is somewhat surprising result as spread enhancements are observed in quoting schedule 4. The quantity quoting requirements become less stringent in the latter quoting schedules, however the results of Table 4-5 suggest that the depth quoting requirements for quoting schedules 4 and 5 may be too high to for scheme participants to consistently make a market in these ETF's.

Overall, the ETF Market Making Scheme demonstrates an improvement in the efficiency of the ETF market, notably through consistent decreases in spreads and increases in depth for certain ETF's. These changes are one aspect of the market makers' activities on the ASX with the other side being trading for their own accounts that may also have been affected by the scheme. Changes in this area would be observable in profitability calculations.

4.4.2. Profitability

Table 4-6 presents descriptive statistics relating to the profitability of all market makers trading in our sample of ETFs in the year subsequent to the ETF Market Making Scheme. A similar table has been constructed for both the entire period and pre-scheme period can be found in Appendix 4.1. Panel A reports that market makers are often achieving profits, with close to three quarters of trading days resulting in positive total profit.

Table 4- 6: Total Market Maker Profitability: Descriptive Statistics (Post-Scheme)

This table reports descriptive statistics relating to the total profitability of all market makers for our sample of ETFs. They are reported for trading that takes place for the period 1 August 2010 to 30 July 2011. The ratio of positive to negative days in Panel A is computed by dividing the number of days with positive total profits, by the number of days with negative total profits. Total market maker profit in Panel B is attained by summing the total profit derived across all days for the sample period. Panel C outlines the distribution of total market maker profitability each day. Panel C also reports a sign and Wilcoxon rank that examines whether the distribution is centred around zero. The respective *p*-values for these tests are the probabilities of a greater absolute value for the centred statistic. The t-statistics test examines whether the mean is significantly different to zero.

Panel A: Distribution of total market maker profitability across all days	
Days with positive total profit	73.81%
Days with negative total profit	26.19%
Days with zero total profit	0.00%
Ratio: Positive: Negative days	2.818
Panel B: Total market maker profitability across all days (sum of all days)	
Total market maker profit	$547370.18
Panel C: Total market maker profitability per day	
Median	1857.238
Mean	2172.104
25th percentile	-113.543
75th percentile	3565.875
Std Dev.	10401
p-value (sign test)	<0.0001
p-value (sign rank test)	<0.0001
t-stat (mean = 0)	3.315
Number of days	252

There are two measures of liquidity that we examine in this chapter. Table 4-7 reports market maker's liquidity profits in the year subsequent to the scheme. The same table for both the entire period and pre-scheme period can be found in Appendix 4.2. Panel A of Table 4-7(a) reports that market makers are net suppliers of liquidity. Panel B also illustrates that that total liquidity profits are positive for the sample period. Therefore, market makers obtain income from supplying liquidity. Negative liquidity profits occur 17% of the time, indicating that market makers are passive in their trading activity. These findings are similar to Silber (1984) who found that his representative scalper supplied liquidity in 77% of all transactions.

Table 4- 7: (a) Market Maker Liquidity Profits: Descriptive Statistics and (b) Market Maker Position-Taking Profits: Descriptive Statistics (Post-Scheme)

(a) This table reports descriptive statistics for market maker liquidity profits over the period 1 August 2010 to 31 July 2011, for the ETFs in our sample. Panel A outlines the frequency of days with positive and negative liquidity profits, as well as the ratio of profitable to unprofitable liquidity profit days. Panel B computes the total liquidity profitability across all days over the period. It is also expressed as a % of total summed market maker profitability. Panel C outlines the per day ETF liquidity profits for all market maker days. Panel C reports a sign and Wilcoxon sign rank that examines whether the distribution is centred around zero. The respective *p*-values for these tests are the probabilities of a greater absolute value for the centred statistic. The t-statistic test examines whether the mean is significantly different to zero.
(b) This table reports descriptive statistics for market maker position-taking profitability over 1 August 2010 to 31 July 2011. Panel A outlines the frequency of cycles with positive and negative position-taking profitability, as well as the ratio of profitable to unprofitable days. Panel B computes the total position-taking profitability across all days over the period. It is also expressed as a percentage of total summed market maker profitability. Panel C outlines the per day ETF position-taking profits for all days. Panel C reports a sign and Wilcoxon sign rank that examines whether the distribution is centred around zero. The respective *p*-values for these tests are the probabilities of a greater absolute value for the centred statistic. The t-statistic test examines whether the mean is significantly different to zero.

(a)	
Panel A: Distribution of market maker liquidity profits across all days	
Days with positive liquidity profits	82.94%
Days with negative liquidity profits	17.06%
Days with zero liquidity profits	0.00%
Ratio: Positive: Negative days	4.862
Panel B: Total market maker liquidity profitability across all days (sum of all days)	
Total liquidity profit	$331345.31
Percentage of total profit	61%
Panel C: Market maker liquidity profitability per day	
Median	1130.236
Mean	1314.862
25th percentile	459.298
75th percentile	2231.415
Std Dev.	4799
p-value (sign test)	<0.0001
p-value (sign rank test)	<0.0001
t-stat (mean = 0)	4.349
Number of days	252
(b)	
Panel A: Distribution of market maker position-taking profits across all days	
Days with positive position-taking profits	59.92%
Days with negative position-taking profits	40.08%
Days with zero position-taking profits	0.00%

Ratio: Positive: Negative days	1.495
Panel B: Total market maker position-taking profitability across all days (sum of all days)	
Total position-taking profit	$216024.87
Percentage of total profit	39%
Panel C: Market maker position-taking profitability per day	
Median	680.958
Mean	857.2416
25th percentile	-1526.945
75th percentile	2627.783
Std Dev.	10650
p-value (sign test)	0.002
p-value (sign rank test)	0.0164
t-stat (mean = 0)	1.278
Number of days	252

Table 4-7(b) provides descriptive statistics for market maker position-taking profitability across all days in the sample period. Similar to liquidity profits, market makers experience more days with positive position-taking profits than days with negative position-taking profits. Only accounting for 39% of total profitability, position-taking profits are not as large as liquidity profits. Therefore, liquidity profits make up a greater proportion of total profits in the period subsequent to the scheme.

Panel C of Table 4-7(a) and Table 4-7(b) indicate that the mean profit is significantly greater than zero at the 1% level. Similarly, the median profits for each day are significantly greater than zero at the 5% level. These results show that the distribution of daily profits is not significantly different.

The relationship between the market maker's liquidity and position-taking profits is reported in Table 4-8. Similar tables for both the entire period and pre-scheme period can be found in Appendix 4.3. Panel A of Table 4-8 provides an insight into the relative distribution of position-taking profits when market makers realise liquidity losses (relatively active traders). Market makers obtain position-taking profits far more often than losses when they are net demanders of liquidity. Specifically, market makers make position-taking profits 74.42% of the days when they demand liquidity and 59.64% of the time when they supply liquidity. Therefore, consistent with Manaster et al. (1996), market makers are willing to forego their contractual duties to realise position-taking profits when they have information regarding the direction of a price movement. Table 4-8, Panel B, reports that when market makers are net suppliers of liquidity, they are less successful in predicting future price movements.

Table 4- 8: Interaction between Market Maker Liquidity and Position-Taking Profitability (Post-Scheme)

This table partitions market maker daily liquidity profits into two states: negative and positive liquidity profitability. For both of these states of liquidity profits, this table reports descriptive statistics for daily "round-trip" position-taking profitability. This analysis is conducted for all ETFs in our sample from 1 August 2010 to 31 July 2011. Position-taking profits for each day are calculated as the movement in the mid-point of the bid-ask quotes between when an inventory position is opened and closed. Liquidity profits in each inventory cycle are calculated as the difference between the transaction price and the quote midpoints. The ratio of positive to negative days is computed by dividing the number of days with positive position-taking income by the number of days with negative position-taking profitability.

Panel A: Days with negative liquidity profits	
Days with	
Positive position-taking profits	74.42%
Negative position-taking profits	25.58%
Zero position-taking profits	0.00%
Ratio: Positive: Negative days	2.909
Number of days	43
Panel B: Days with positive liquidity profits	
Days with	
Positive position-taking profits	59.64%
Negative position-taking profits	43.06%
Zero position-taking profits	0.00%
Ratio: Positive: Negative days	1.385
Number of days	209

Table 4-9 presents Wilcoxon signed rank-sum tests for both liquidity profits and position-taking profits. The results show that both daily liquidity and position-taking profits do not significantly change after the implementation of the scheme.

Table 4- 9: Non-Parametric Univariate Tests of Market Maker Profits

This table presents the non-parametric univariate tests of market maker profits. Statistic refers to the Z score for the Wilcoxon signed rank-sum *U* Statistic testing for different underlying distributions between the pre-change and post-change periods for total daily profits, daily liquidity profits and daily position-taking profits. The *p*-value is the corresponding two-tail *p*-value for the given Z score. ***, ** and * represent significance at the 1%, 5% and 10% level, respectively.

Total Daily Profits		Daily Liquidity Profits		Daily Position-Taking Profits	
Statistic	p-value	Statistic	p-value	Statistic	p-value
902	0.437	520	0.655	1002	0.388

The GMM regression results associated with Equation (4.9) and Equation (4.10) are reported in Table 4-10. As univariate results in Table 4-8 suggest, the coefficient on D_t indicates there is no change in TLP_t or TPP_t from the pre-scheme period to the post-scheme period. We also find that $ln(Volatility_{t,q})$ has a positive effect on TLP_t at the 10% level. In addition, TPP_t and TLP_t have an inverse relationship, with liquidity profits influencing position-taking profits at a greater magnitude. This result is consistent with the relationship noted by Copeland et al. (1983) and reaffirms the conclusions drawn from the descriptive statistics.

Table 4- 10: Regression Analysis for Liquidity and Position-Taking Profits

This table reports GMM regression (3) and (4) results for the dependent variables TLP_t and TPP_t for the period 1 August 2009 to 31 July 2011. D_t refers takes on a value of zero for the pre-rebate period and one for the post-rebate period. $Ln(Volume_{t,q})$ is the natural logarithm of daily volume. $Ln(Volatility_{t,q})$ is the natural logarithm of daily price volatility. $Ln(TWS_{t,q})$ is the natural logarithm of the mean daily bid-ask spread. Position-Taking Profit and Liquidity Profit are the sum earned daily by the market makers for all ETFs in our sample. Test statistics are reported in brackets under the coefficients for each independent variable. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

	Dependent Variable	
Variable	TLP_t	TPP_t
$Intercept$	-12630.600	-5689.340
	(-1.4)	(-0.66)
D_t	90.986	525.576
	-0.22	-0.53
$Ln(Volume_{t,q})$	-61.552	578.748
	(-0.21)	-0.65
$Ln(Volatility_{t,q})$	142162.300*	250059.700
	-1.89	-1.09
$Ln(TWS_{t,q})$	-2503.26	
	(-1.48)	
TPP_t	-0.108*	
	(-1.76)	
TLP_t		-0.628***
		(-3.37)
$Adjusted\ R^2$	0.0915	0.0714

Our results indicate that market makers are net suppliers of liquidity and are therefore fulfilling their mandated duties. In the year following the scheme, liquidity profits are greater than position-taking profits. However, the position-taking gains made on days where liquidity losses are realised and the significant inverse relationship noted between liquidity and position-taking gains strongly imply that market makers would rather make further gains at the sacrifice of their obligated duties. With no change in profitability after the introduction of the scheme, we fail to reject H_{11} and H_{12} and can also state that the efficiency enhancements found in Section 6.4.1 are not at the expense of other investors. As market maker profits, did not decline, it becomes clear that the scheme is beneficial for market quality (Panayides, 2007).

4.5. Conclusion

This chapter examines the market quality and profitability effects of the introduction of the Market Making Scheme on the ETF market on the ASX. Our study examines how market liquidity and efficiency are affected as well as how market maker profitability is impacted and how the incentives of the scheme are related to the market effects.

Market makers are found to be net suppliers of liquidity however we discover that large position-taking gains are often realised on days with liquidity losses. The inverse relationship between liquidity and position-taking profits consistent with the empirical findings in other markets, such by Copeland et al. (1983) and Mann (1996) who study the US equity market. We report significant improvements in both spreads and depth after the introduction of the scheme that are accompanied by consistent changes in actual trading outcomes. Further multivariate analysis supports that profitability does not change after the introduction after the scheme.

Cekauskas et al. (2012) poses the structure of market makers' agreements and compensation is a determinant of their effects on market quality. They suggest that market makers are more likely to improve the quality of exchange markets when they enter agreements with issuers and firms and not when they are mandated by an exchange. This may be due to stronger liquidity requirements imposed by firms or because companies may only employ market makers when they are likely to increase firm value[56]. Consistent with studies such as Nimalendran et al. (2003), Venkataraman et al. (2007) and Anand et al. (2009), our results show market efficiency enhancements following market making arrangements with the exchange.

Our findings have a number of implications. Market makers are often satisfying their contractual duties by supplying liquidity. However, market makers are willing to use their superior order-flow information to make position-taking gains and this behaviour may be in conflict with their obligation to provide liquidity under the scheme. The aforementioned improvements signify that the rebates have been successful in enhancing the efficiency of the ETF market and that this has not occurred at the expense of other investors as profitability remains unchanged.

[56] This is not necessarily the case when an exchange imposes market making conditions across firms.

Appendix – Chapter 4

Appendix 4.1

Table A4- 1: Total Market Maker Profitability: Descriptive Statistics (Total Period)

This table reports descriptive statistics relating to the total profitability of all market makers for our sample of ETFs. They are reported for trading that takes place for the period 1 August 2009 to 31 July 2011. The ratio of positive to negative days in Panel A is computed by dividing the number of days with positive total profits, by the number of days with negative total profits. Total market maker profit in Panel B is attained by summing the total profit derived across all days for the sample period. Panel C outlines the distribution of total market maker profitability each day. Panel C reports a sign and Wilcoxon rank that examines whether the distribution is centred around zero. The respective *p*-values for these tests are the probabilities of a greater absolute value for the centred statistic. The t-statistics test examines whether the mean is significantly different to zero.

Panel A: Distribution of total market maker profitability across all days	
Days with positive total profit	74%
Days with negative total profit	26%
Days with zero total profit	0%
Ratio: Positive: Negative days	2.818
Panel B: Total market maker profitability across all days (sum of all days)	
Total market maker profit	$1087670.99
Panel C: Total market maker profitability per day	
Median	1922.918
Mean	2158.077
25th percentile	-183.738
75th percentile	4197.108
Std Dev.	9060
p-value (sign test)	<0.0001
p-value (sign rank test)	<0.0001
t-stat (mean = 0)	5.347
Number of days	504

Table A4- 2: Total Market Maker Profitability: Descriptive Statistics (Pre-Period)

This table reports descriptive statistics relating to the total profitability of all market makers for our sample of ETFs. They are reported for trading that takes place for the period 1 August 2009 to 31 July 2010. The ratio of positive to negative days in Panel A is computed by dividing the number of days with positive total profits, by the number of days with negative total profits. Total market maker profit in Panel B is attained by summing the total profit derived across all days for the period. Panel C outlines the distribution of total market maker profitability each day. Panel C reports a sign and Wilcoxon rank that examines whether the distribution is centred around zero. The respective *p*-values for these tests are the probabilities of a greater absolute value for the centred statistic. The t-statistics test examines whether the mean is significantly different to zero.

Panel A: Distribution of total market maker profitability across all days	
Days with positive total profit	73.81%
Days with negative total profit	26.19%
Days with zero total profit	0.00%
Ratio: Positive: Negative days	2.818
Panel B: Total market maker profitability across all days (sum of all days)	
Total market maker profit	$540300.81
Panel C: Total market maker profitability per day	
Median	1987.684
Mean	2144.051
25th percentile	-247.125
75th percentile	5034.590
Std Dev.	7504
p-value (sign test)	<0.0001
p-value (sign rank test)	<0.0001
t-stat (mean = 0)	4.536
Number of days	252

Appendix 4.2

Table A4- 3: (a) Market Maker Liquidity Profits: Descriptive Statistics and (b) Market Maker Position-Taking Profits: Descriptive Statistics (Total Period)

(a) This table reports descriptive statistics for market maker liquidity profits over the period 1 August 2009 to 31 July 2011, for the ETFs in our sample. Panel A outlines the frequency of days with positive and negative liquidity profits, as well as the ratio of profitable to unprofitable liquidity profit days. Panel B computes the total liquidity profitability across all days over the period. It is also expressed as a % of total summed market maker profitability. Panel C outlines the per day ETF liquidity profits for all market maker days. Panel C reports a sign and Wilcoxon sign rank that examines whether the distribution is centred around zero. The respective *p*-values for these tests are the probabilities of a greater absolute value for the centred statistic. The t-statistic test examines whether the mean is significantly different to zero.

(b) This table reports descriptive statistics for market maker position-taking profitability over 1 August 2009 to 31 July 2011. Panel A outlines the frequency of cycles with positive and negative position-taking profitability, as well as the ratio of profitable to unprofitable days. Panel B computes the total position-taking profitability across all days over the period. It is also expressed as a percentage of total summed market maker profitability. Panel C outlines the per day ETF position-taking profits for all days. Panel C reports a sign and Wilcoxon sign rank that examines whether the distribution is centred around zero. The respective *p*-values for these tests are the probabilities of a greater absolute value for the centred statistic. The t-statistic test examines whether the mean is significantly different to zero.

(a)	
Panel A: Distribution of market maker liquidity profits across all days	
Days with positive liquidity profits	82%
Days with negative liquidity profits	18%
Days with zero liquidity profits	0%
Ratio: Positive: Negative days	4.599
Panel B: Total market maker liquidity profitability across all days (sum of all days)	
Total liquidity profit	$652520.78
Percentage of total profit	60%
Panel C: Market maker liquidity profitability per day	
Median	48.035
Mean	88.670
25th percentile	6.930
75th percentile	157.360
Std Dev.	992.568
p-value (sign test)	<0.0001
p-value (sign rank test)	<0.0001
t-stat (mean = 0)	7.663
Number of days	504

(b)

Panel A: Distribution of market maker position-taking profits across all days	
Days with positive position-taking profits	61%
Days with negative position-taking profits	39%
Days with zero position-taking profits	0%
Ratio: Positive: Negative days	1.564
Panel B: Total market maker position-taking profitability across all days (sum of all days)	
Total position-taking profit	$435150.21
Percentage of total profit	40%
Panel C: Market maker position-taking profitability per day	
Median	6.900
Mean	59.130
25th percentile	-52.450
75th percentile	137.226
Std Dev.	2304
p-value (sign test)	<0.0001
p-value (sign rank test)	<0.0001
t-stat (mean = 0)	2.201
Number of days	504

Table A4- 4: (a) Market Maker Liquidity Profits: Descriptive Statistics and (b) Market Maker Position-Taking Profits: Descriptive Statistics (Pre-Period)

(a) This table reports descriptive statistics for market maker liquidity profits over the period 1 August 2009 to 31 July 2010, for the ETFs in our sample. Panel A outlines the frequency of days with positive and negative liquidity profits, as well as the ratio of profitable to unprofitable liquidity profit days. Panel B computes the total liquidity profitability across all days over the period. It is also expressed as a % of total summed market maker profitability. Panel C outlines the per day ETF liquidity profits for all market maker days. Panel C reports a sign and Wilcoxon sign rank that examines whether the distribution is centred around zero. The respective *p*-values for these tests are the probabilities of a greater absolute value for the centred statistic. The t-statistic test examines whether the mean is significantly different to zero.
(b) This table reports descriptive statistics for market maker position-taking profitability over 1 August 2009 to 31 July 2010. Panel A outlines the frequency of cycles with positive and negative position-taking profitability, as well as the ratio of profitable to unprofitable days. Panel B computes the total position-taking profitability across all days over the period. It is also expressed as a percentage of total summed market maker profitability. Panel C outlines the per day ETF position-taking profits for all days. Panel C reports a sign and Wilcoxon sign rank that examines whether the distribution is centred around zero. The respective *p*-values for these tests are the probabilities of a greater absolute value for the centred statistic. The t-statistic test examines whether the mean is significantly different to zero.

(a)	
Panel A: Distribution of market maker liquidity profits across all days	
Days with positive liquidity profits	81.35%
Days with negative liquidity profits	18.65%
Days with zero liquidity profits	0.00%
Ratio: Positive: Negative days	4.362
Panel B: Total market maker liquidity profitability across all days (sum of all days)	
Total liquidity profit	$321175.47
Percentage of total profit	59%
Panel C: Market maker liquidity profitability per day	
Median	1307.467
Mean	1274.506
25th percentile	388.622
75th percentile	2315.562
Std Dev.	2436
p-value (sign test)	<0.0001
p-value (sign rank test)	<0.0001
t-stat (mean = 0)	8.305
Number of days	252
(b)	
Panel A: Distribution of market maker position-taking profits across all days	
Days with positive position-taking profits	61.51%
Days with negative position-taking profits	38.49%
Days with zero position-taking profits	0.00%
Ratio: Positive: Negative days	1.598
Panel B: Total market maker position-taking profitability across all days (sum of all days)	
Total position-taking profit	$219125.34
Percentage of total profit	41%
Panel C: Market maker position-taking profitability per day	1084.459

Median	
Mean	869.545
25th percentile	-1744.720
75th percentile	3899.700
Std Dev.	7574
p-value (sign test)	0.0003
p-value (sign rank test)	0.0011
t-stat (mean = 0)	1.822
Number of days	252

Appendix 4.3

Table A4- 5 Interaction between Market Maker Liquidity and Position-Taking Profitability (Total Period)

This table partitions market maker daily liquidity profits into two states: negative and positive liquidity profitability. For both of these states of liquidity profits, this table reports descriptive statistics for daily "round-trip" position-taking profitability. This analysis is conducted for all ETFs in our sample from 1 August 2009 to 31 July 2011. Position-taking profits for each day are calculated as the movement in the mid-point of the bid-ask quotes between when an inventory position is opened and closed. Liquidity profits in each inventory cycle are calculated as the difference between the transaction price and the quote midpoints. The ratio of positive to negative days is computed by dividing the number of days with positive position-taking income by the number of days with negative position-taking profitability.

Panel A: Days with negative liquidity profits	
Days with	
Positive position-taking profits	73%
Negative position-taking profits	27%
Zero position-taking profits	0%
Ratio: Positive: Negative days	2.750
Number of days	90
Panel B: Days with positive liquidity profits	
Days with	
Positive position-taking profits	59%
Negative position-taking profits	42%
Zero position-taking profits	0
Ratio: Positive: Negative days	1.379
Number of days	414

Table A4- 6: Interaction between Market Maker Liquidity and Position-Taking Profitability (Pre-Period)

This table partitions market maker daily liquidity profits into two states: negative and positive liquidity profitability. For both of these states of liquidity profits, this table reports descriptive statistics for daily "round-trip" position-taking profitability. This analysis is conducted for all ETFs in our sample from 1 August 2009 to 31 July 2010. Position-taking profits for each day are calculated as the movement in the mid-point of the bid-ask quotes between when an inventory position is opened and closed. Liquidity profits in each inventory cycle are calculated as the difference between the transaction price and the quote midpoints. The ratio of positive to negative days is computed by dividing the number of days with positive position-taking income by the number of days with negative position-taking profitability.

Panel A: Days with negative liquidity profits	
Days with	
Positive position-taking profits	72%
Negative position-taking profits	28%
Zero position-taking profits	0%
Ratio: Positive: Negative days	2.615
Number of days	47
Panel B: Days with positive liquidity profits	
Days with	
Positive position-taking profits	59.02
Negative position-taking profits	40.98
Zero position-taking profits	0
Ratio: Positive: Negative days	1.440
Number of days	205

Chapter 5: Conclusions

The stated objectives of most market regulators are to ensure the fair and efficient operation of capital markets. In this dissertation, we focus upon the latter regulatory objective. We define market efficiency as minimising transaction costs while maximising price discovery and assess the efficiency effects of three ASX market design initiatives: broker anonymity, the Equity Research Scheme and the Exchange Traded Fund (ETF) Market Making Scheme

5.1. Summary of Findings

The first essay examines the effect of the broker anonymity rule on trading patterns. Prior to the introduction of broker anonymity, Frino et al. (2010 b) determine that the market attributes greater information to successive same-direction trades when a single broker initiates these trades rather than by different brokers. Therefore, broker identities convey information. Using the constituents of the All Ords, the evidence shows that the identity of the broker involved in two consecutive trades conveys information to the market prior to the introduction of anonymity. This is consistent with Frino et al. (2010 b) and is true both in isolation and when considered as a conditional variable when interpreting two same-direction, sequential trades. Using information not available to the market at the time of trading about broker identity, we find that market participants no longer attribute greater information content to successive uni-directional trades by a single broker compared to successive uni-directional trades by different brokers following the introduction of anonymity. Subsequent to the introduction of anonymity, we also find that trades in the medium and large size categories no longer convey incremental information[57] as the need for stealth trading is reduced.

The second essay assesses the market efficiency effects of the Equity Research Scheme. Financial analysts use their expertise to gather and interpret information and thereby attempt to reduce the level of asymmetric information. As more information is released to the market, market participants become more confident about the 'true' value of the asset. Consistent with the expectations developed by the existing literature, we find that the ERS is responsible for more informed security prices with ERS stocks more informationally efficient in the 6 months following the initiation report. If information asymmetry is reduced and security prices are more efficient, investors are more likely to trade. We also find that the ERS improved both the price and size-dimensions of market liquidity in the selected stocks. Hence, the evidence highlight the importance of the role financial analyst reports do play a role in providing new information to the market and stimulating trading activity.

The literature on analyst coverage and stock prices suggest that analysts do have predictive ability, evidenced by the positive price reaction following the release of a report. In addition to enhanced informational efficiency and liquidity, we document positive CAR's in the two weeks subsequent to the analyst report. Comparing to the matched, control sample, the ERS stocks experience greater CARs over two week, three month and six month intervals. Asset prices adapt accordingly to the release of new information provided by financial analysts,

[57] As found in Frino et al. (2010 a)

highlighting the importance financial analysts for efficient pricing in capital markets.

The third essay examines the liquidity and profitability effects of the ETF Marker Making Scheme. Market makers are found to be net suppliers of liquidity however we discover that large position-taking gains are often realised on days with liquidity losses. The inverse relationship between liquidity and position-taking profits is consistent with the empirical findings in other markets, such by Copeland et al. (1983) and Manaster Mann (1999) who study the US equity market. We report significant improvements in both spreads and depth after the introduction of the scheme that are accompanied by consistent changes in actual trading outcomes. Further analysis shows that profitability does not change after the introduction after the scheme.

5.2. Concluding Remarks

Frino et al. (2010 b) poses trading environments that allow market-order traders to remain anonymous are likely to reduce the speed of adjustment to private information. On the whole, our results support this verdict however our findings also suggest that anonymous markets lower the likelihood of 'front-running' and 'piggybacking' which may in turn reduce the chance of over-extending the price discovery process, an additional advantage to the enhanced liquidity identified by Comerton-Forde et al. (2009).

Following anonymity, stock prices do not adequately adjust to order flow. Therefore, informed investors can greater profit from their informational advantage. As these profits are attained at the expense of uninformed investors, the question must be asked if liquidity has improved to society at large. Supplementary to Comerton-Forde et al. (2009), a more complete picture is presented when assessing the market quality impact of broker anonymity on the ASX.

In view of the inherent importance of the information structure of financial markets, the results of the second essay highlight the value of financial analysts in providing reliable and useful information to market participants. Given the downward trend of analyst coverage and the ASX's mandate to ensure a fair and efficient capital market, strategies such as the ERS could go a long way in ensuring that market participants have a more homogenous level of access to information. The ASX should therefore maintain the ERS and consider extending such schemes to other assets, particularly those that are susceptible to high information asymmetry. More broadly, exchanges and market regulators worldwide should consider implementing similar policies, primarily due to the decreasing trend of analyst coverage. Such schemes would not only be beneficial market quality, but they may also encourage increased order flow by international investors that are currently concerned that they are disadvantaged relative to better-informed local investors.

As shown, reducing the levels of information asymmetry is inherent to the informational efficiency of stock prices. When this adverse selection risk is lowered, investors are more likely to trade; resulting in the documented liquidity improvements in the first two essays. The third essay highlights the value of market makers in incentivizing market participants to trade. As the number of participants actively seeking to buy or sell at any particular moment in time can be quite small (Desmetz, 1968; Garbade et al., 1982), investors – with, or without information – may face a large cost for immediacy. Market makers, when incentivised through outcome-based rebates, often satisfy their contractual duties by supplying liquidity, allowing these participants to trade. This leads to increased trading outcomes, enhancing the efficiency of the ASX's ETF market. The ASX should continue the arrangement and look to apply similar, incentive-based schemes to other markets and products where investor participation is low.

Collectively, market design and incentivizing market participants is crucial to market efficiency and competitiveness.

Chapter 6: References

Acker, D., Stalker, M., Tonks, I., (2002). Daily closing inside spreads and trading volumes around earnings announcements. *Journal of Business Finance and Accounting* 29, 1149-1179.

Ackert, L.F., Tian, Y.S., (2000). Arbitrage and Valuation in the Market for Standard and Poor's Depository Receipts. *Financial Management* 29, 71-88.

Admati, A. R., Pfleiderer, P., (1988). A theory of intraday patterns: Volume and price variability. *Review of Financial Studies* 1, 3-40.

Akerlof, G. A., (1970). The market for" lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84, 488-500.

Aktas, N., de Bodt, E., Van Oppens, H., (2008). Legal insider trading and market efficiency. *The Journal of Banking and Finance* 32, 1379-1392.

Alexander, G.J., Peterson, M.A., (2007). An analysis of trade-size clustering and its relation to stealth trading. *Journal of Financial Economics* 84, 435-471.

Amihud, Y., Mendelson, H., (1980). Dealership Market: Market-Making with Inventory. *Journal of Financial Economics* 8, 31-53.

Anand., A., Weaver, D.G., (2006) The Value of the Specialist: Empirical Evidence from the CBOE. *Journal of Financial Markets* 9, 100-118.

Anand A., Subrahmanyam, A., (2008). Information and the intermediary: Are market intermediaries informed traders in electronic markets? *Journal of Financial and Quantitative Analysis* 43, 1-28.

Anand, Y., Hurvic, C.M., Wang, Y., (2009). Multiple-Predictor Regressions: Hypothesis Testing. *Review of Financial Studies* 22, 413-434.

Atiase, R. K., (1985). Predisclosure information, firm capitalization, and security price behavior around earnings announcements. *Journal of Accounting Research*. 23, 21-36.

Atkins, A. B., Dyl, E. A., (1997). Transactions costs and holding periods for common stocks. *The Journal of Finance* 52, 309-325.

Attig, N., Fong, W. M., Gadhoum, Y., Lang, L. H., (2006). Effects of large shareholding on information asymmetry and stock liquidity. *Journal of Banking and Finance* 30, 2875-2892.

Baily, W., Cai, J., Leung, Y., Wang, F., (2009). Stock returns, order imbalances and commonality: Evidence on individual, institutional, and proprietary investors in China. *Journal of Banking and Finance* 33, 9-19.

Bagehot, W., (1971). The Only Game in Town, *Financial Analysts Journal* 27, 29-32.

Baily, W., Cai, J., Leung, Y., Wang, F., (2009). Stock returns, order imbalances and commonality: Evidence on individual, institutional, and proprietary investors in China. *Journal of Banking and Finance* 33, 9-19.

Baker, H. K., Nofsinger, J. R., Weaver, D. G., (2002). International cross-listing and visibility. *Journal of Financial and Quantitative Analysis* 37, 495-521.

Barclay, M.J., (1997). Bid-ask spreads and the avoidance of odd-eighth quotes on NASDAQ: An examination of exchange listings. *Journal of Financial Economics* 45, 35–60.

Barclay, M. J., Hendershott, T., McCormick, D. T., (2003). Competition among trading venues: Information and trading on electronic communications networks. *The Journal of Finance* 58, 2637-2665.

Barclay, M.J., Warner, J.B., (1993) Stealth trading and volatility. *Journal of Financial Economics* 34, 281-305.

Bartov, E., Bodnar, G. M., (1996). Alternative accounting methods, information asymmetry and liquidity: theory and evidence. *Accounting Review* 71, 397-418.

Bekaert, G., Harvey, C. R., (2003). Emerging markets finance. *Journal of Empirical Finance* 10, 3-55.

Benston, G. J., Hagerman, R. L., (1974). Determinants of bid-asked spreads in the over-the-counter market. *Journal of Financial Economics* 1, 353-364.

Benveniste, L.M., Marcus, A.J., Wilhelm, W.K., (1992) What's special about the specialist? *Journal of Financial Economics* 32, 61–86.

Biais, B., (1993). Price Formation and Equilibrium Liquidity in Fragmented and Centralized Markets. *The Journal of Finance* 48, 157-184.

Black, F., (1986). Noise. *The Journal of Finance* 41, 529-543.

Black, F., (1971). Towards a Fully Automated Exchange. *Financial Analysts Journal* 27, 24-87.

Bloomfield, R., O'Hara, M., Saar, G., (2005). The 'Mark or Take' Decision in an Electronic Market: Evidence on the Evolution of Liquidity. *Journal of Financial Economics* 75, 165-199.

Blume, L., Easley, D., O'Hara, M., (1994). Market statistics and technical analysis: The role of volume. *The Journal of Finance*, 49 153-181.

Boehmer, E., Saar, G., Yu, L., (2005). Lifting the veil: An analysis of Pre-trade transparency at the NYSE. *The Journal of Finance* 60, 783-815.

Boni, L., Womack, K.L., (2006). Analysts, industries, and price momentum. *Journal of Financial and Quantitative Analysis* 41, 85-109.

Borkovec, M., Serbin, V., (2012). Create or Buy: A Comparative Analysis of Liquidity and Transaction Costs for Selected U.S. ETFs. *The Journal of Portfolio Management* 39, 118-131.

Boulatov, A., George, T. J., (2013). Hidden and displayed liquidity in securities markets with informed liquidity providers. *Review of Financial Studies*, hhs123.

Branson, B. C., Guffey, D. M., Pagach, D. P., (1998). Information Conveyed in Announcements of Analyst Coverage. *Contemporary Accounting Research* 15, 119-143.

Brennan, M. J., Hughes, P. J., (1991). Stock prices and the supply of information. *The Journal of Finance* 46, 1665-1691.

Brennan, M. J., Hughes, P. J., (1991). Stock prices and the supply of information, *The Journal of Finance* 46, 1665-1691.

Brennan, M. J., Subrahmanyam, A., (1995). Investment analysis and price formation in securities markets. *Journal of Financial Economics* 38, 361-381.

Brennan, M. J., Tamarowski, C., (2000). Investor relations, liquidity, and stock prices. *Journal of Applied Corporate Finance* 12, 26-37.

Brennan, M. J., Jegadeesh, N., Swaminathan, B., (1993). Investment analysis and the adjustment of stock prices to common information. *Review of Financial Studies* 6, 799-824.

Brock, W.A., Kleidon, A.W., (1992). Periodic market closure and trading volume: A model of intraday bids and asks. *Journal of Economic Dynamics and Control* 16, 451–489.

Brooks, R. M., (1994). Bid-ask spread components around anticipated announcements. *Journal of Financial Research* 17, 375-386.

Brooks, R. M., Patel, A., Su, T., (2003). How the Equity Market Responds to Unanticipated Events. *Journal of Business* 76, 109-133.

Brown, S. J., Warner, J. B., (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics* 14, 3-31.

Chakravarty, S., (2001). Stealth trading: Which traders' trades move stock prices? *Journal of Financial Economics* 61, 289-307.

Campbell, J.Y., Lo, A.W., MacKinlay, A.C., (1997) *The Econometrics of Financial Markets*, Princeton University Press, New Jersey.

Cekauskas, K., Gerasimovs, R., Liatukas, V., Putnins, T.J., (2012). The Effects of Market Makers and Stock Analysts in Emerging Markets. *International Review of Finance* 12, 305-327.

Cerrate, M., Sarantis, N., Saunders, A., (2011). An investigation of customer order flow in the foreign exchange market. *Journal of Banking and Finance* 35, 1892, 1906.

Chakravarty, S., Kalev, P., (2011). The Relative Degree of Trade Fragmentation in an Automated, Transparent Stock Exchange. *Trading* 1, 85-101.

Chae, J., (2005). Trading volume, information asymmetry, and timing information. *The Journal of Finance* 60, 413-442.

Chan, S. Y., Fong, W. M., (1996). Reactions of the Hong Kong Stock market to the publication of second-hand analysts' recommendation information. *Journal of Business Finance and Accounting* 23, 1121-1140.

Chan, K., Fong, W., (2000). Trade size, order imbalance, and the volatility–volume relation. *Journal of Financial Economics* 57, 247-273.

Chan, S., Kim, K., and Rhee, S. "Price limit performance: evidence from transactions data and the limit order book." *Journal of Empirical Finance* 12 (2005), 269-290.

Chan, L.K.C., Lakonishok, J., (1995). The behaviour of stock prices around Institutional Trades. *The Journal of Finance 50*, 1147-1174.

Chandra, R. and Rohrbach, K. 1990, A Methodological Note on Determining a Location Shift in the Distribution of Abnormal Returns: A Non-parametric Approach, *Contemporary Accounting Research*, vol. 7, no. 1, pp. 123-141.

Chang, X., Dasgupta, S. and Hilary, G. 2006, 'Analyst Coverage and Financing Decisions', *The Journal of Finance*, vol. 61, no. 6, pp. 3009-3048.

Chen, J., Hong, H., Stein, J., (2002). Breadth of ownership and stock returns. *Journal of Financial Economics* 66, 171-205.

Chung, K.H., Van Ness, B., Van Ness, R., (2004). Specialists, limit order traders and the components of the bid-ask spread. *The Financial Review* 39, 255-270.

Chung, K.H., Li, M.S., Mcinish, T., (2005). Information-based trading, price impact of trades, and trade autocorrelation. *Journal of Banking and Finance* 29, 1645-1669.

Chiang, R., Venkatesh, P. C., (1988). Insider holdings and perceptions of information asymmetry: A note. *The Journal of Finance* 43, 1041-1048.

Chiarella, C., Iori, G., Perelló, J., (2009). The impact of heterogeneous trading rules on the limit order book and order flows. *Journal of Economic Dynamics and Control* 33, 525-537.

Chordia, T., Roll, R., Subrahmanyam, A., (2005). Evidence on the speed of convergence to market efficiency. *Journal of Financial Economics* 76, 271-292.

Chordia, T., Roll, R., Subrahmanyam, A., (2002). Order imbalance, liquidity and market returns. *Journal of Financial Economics* 65, 111-130.

Chordia, T., Roll, R., Subrahmanyam, A., (2000). Commonality in liquidity. *Journal of Financial Economics* 56, 3-28.

Chordia, T., Roll, R., Subrahmanyam, A., (2001). Market liquidity and trading activity. *The Journal of Finance* 56, 501-530.

Chordia, T., Roll, R., Subrahmanyam, A., (2008). Liquidity and market efficiency. *Journal of Financial Economics* 87, 249-268.

Chordia, T., Swaminathan, B., (2000). Trading volume and cross-autocorrelations in stock returns. *The Journal of Finance* 55, 913-935.

Chowdhry, B., Nanda, V., (1991). Multimarket trading and market liquidit. *Review of Financial Studies* 4, 483-511.

Christie, W.G., Huang R.D., (1994). Market structures and liquidity: A transactions data study of exchange listings. *Journal of Financial Intermediation* 3, 300–326.

Chung, D., Hrazdil, K., (2010a). Liquidity and market efficiency: A large sample study. *Journal of Banking & Finance* 34, 2346-2357.

Chung, K. H., Jo, H., (1996). The impact of security analysts' monitoring and marketing functions on the market value of firms. *Journal of Financial and Quantitative analysis* 31, 493-512.

Chung, K. H., McInish, T. H., Wood, R. A., Wyhowski, D. J., (1995). Production of information, information asymmetry, and the bid-ask spread: Empirical evidence from analysts' forecasts. *Journal of Banking and Finance* 19, 1025-1046.

Chung, K.H., Van Ness, B.F., Van Ness, R.A., (1999). Limit orders and the bid-ask spread. *Journal of Financial Economics* 53, 255–287.

Cliff, M. T., Denis, D. J., (2004). Do initial public offering firms purchase analyst coverage with underpricing? *The Journal of Finance* 29, 2871-2901.

Colliard, J., Foucault, T., (2012). Trading Fees and Efficiency in Limit Order Markets. *Review of Financial Studies* 25, 3389-3421.

Comerton-Forde, C., Frino, A., Mollica, V., (2005). The impact of limit order anonymity: Evidence from Paris, Tokyo and Korea. *Journal of Economics and Business* 57, 528-540.

Comerton-Forde, C., Gallagher, D. R., Lai, J., Walter, T., (2011). Broker recommendations and Australian small-cap equity fund management. *Accounting and Finance* 51, 893-922.

Comerton-Forde, C., Tang, K. M., (2009). Anonymity, liquidity and fragmentation. *Journal of Financial Markets* 12, 337-367.

Copeland, T., Galai, D., (1983). Information Effects and the Bid-Ask Spread. *The Journal of Finance* 38, 1457-1469.

Demiroglu, C., Ryngaert, M., (2010). The first analyst coverage of neglected stocks. *Financial Management* 39, 555-584.

Demsetz, H., (1968). The Cost of Transacting. *Quarterly Journal of Economics* 82, 33-35.

Demsetz, H., (1986). Corporate control, insider trading, and rates of return. *The American Economic Review* 76, 313-316.

Derrien, F., Kecskés, A., (2013). The real effects of financial shocks: Evidence from exogenous changes in analyst coverage. *The Journal of Finance* 68, 1407-1440.

Deville, L., Gresse, C., Sevarac, B., (2012). Direct and Indirect Effects of Index ETFs on Spot-Futures Pricing and Liquidity: Evidence from the CAC 40 Index. *European Financial Management* 20, 352-373.

Diamond, D. W., Verrecchia, R. E., (1991). Disclosure, liquidity, and the cost of capital. *The Journal of Finance* 46, 1325-1359.

Domowitz, I., Hansch, O., Wang, X., (2005). Liquidity commonality and return co-movement. *Journal of Financial Markets* 8, 351-376.

Doukas, J. A., Kim, C. F., Pantzalis, C., (2005). The two faces of analyst coverage. *Financial Management* 34, 99-125.

Dugar, A., Nathan, S., (1995). The Effect of Investment Banking Relationships on Financial Analysts' Earnings Forecasts and Investment Recommendations. *Contemporary Accounting Research* 12, 131-160.

Dumitrescu, A., (2010). The strategic specialist and imperfect competition in a limit order market. *Journal of Banking and Finance* 34, 255-266.

Dupont, D., (2000). Market making, prices, and quantity limits. *Review of Financial Studies* 13, 1129–1151.

Dyck, A., Morse, A., Zingales, L., (2010). Who blows the whistle on corporate fraud? *The Journal of Finance* 65, 2213-2253.

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

Easley, D., O'Hara, M., (1987). Price, Trade Size, and Information in Securities Markets. *Journal of Financial Economics* 19, 69-90.

Easily, D., N. Kiefer and M. O'Hara., (1996). Cream-Skimming or Profit-Sharing? *The Journal of Finance* 51, 811-833.

Easley, D., O'Hara, M., (2004). Information and the cost of capital. *The Journal of Finance* 59, 1553-1583.

Eleswarapu, V. R., Thompson, R., Venkataraman, K., (2004). The impact of Regulation Fair Disclosure: Trading costs and information asymmetry. *Journal of Financial and Quantitative Analysis* 39, 209-225.

Elgers, P. T., Lo, M. H., Pfeiffer Jr, R. J., (2001). Delayed security price adjustments to financial analysts' forecasts of annual earnings. *The Accounting Review* 76, 613-632.

Elton, E. J., Gruber, M. J., Grossman, S., (1986). Discrete expectational data and portfolio performance. *The Journal of Finance* 41, 699-713.

Elton, E.J., Gruber, M.J., Comer, G., Li, K., (2002). Spiders: Where are the Bugs? *Journal of Business* 75, 453-472.

Engle, R., Sarkar, D., (2006). Premiums-Discounts and Exchange Traded Funds. *Journal of Derivatives* 13, 27-45.

Fama, E. F., (1970). Efficient Capital Markets: A Review Of Theory And Empirical Work. *The Journal of Finance* 25, 383-417.

Fama, E. F., (1991). Efficient capital markets: II. *The Journal of Finance* 46, 1575-1617.

Fisher, S., (1994). Asset Trading, Transaction Costs and the Equity Premium. *Journal of Applied Econometrics* 9, 571-594.

Fishman, M.J., Longstaff, F.A., (1992). Dual Trading in Futures Markets. *The Journal of Finance* 47, 643-671.

Foley, S., Putniņš, T. J., (2013). Should we be afraid of the dark? Dark trading and market quality. *Working Paper*, accessed from http://www.cmcrc.com/documents/1375771785should-we-be-afraid-of-the-dark.pdf

Foster, F. D., Viswanathan, S., (1993). The effect of public information and competition on trading volume and price volatility. *Review of Financial Studies* 6, 23-56.

Foster, F. D., Viswanathan, S., (1993). Variation in trading volume, return volatility and trading costs: Evidence on recent price formation models. *The Journal of Finance* 48, 187-212.

Foster, M. M., George, T.J., (1992). Anonymity in securities markets. *Journal of Financial Intermediation* 2, 168-206.

Foucault, T., Kadan, O., Kandel, E., (2005). Limit Order Book as a Market for Liquidity. *Review of Financial Studies* 18, 1171-1217.

Foucault, T., Moinas, S., Theissen, E., (2007). Does anonymity matter in electronic limit order markets? *Review of Financial Studies* 20, 1707-1747.

Francis, J., Philbrick, D., (1993). Analysts' decisions as products of a multi-task environment. *Journal of Accounting Research*. 31, 216-230.

Frijns, B., (2006). Inferring public and private information from trades and quotes. *The Financial Review* 41, 95-117.

Frino, A., Gerace, D., Lepone, A., (2008). Limit order book, anonymity and market liquidity: evidence from the Sydney Futures Exchange. *Accounting and Finance* 48, 561-573.

Frino, A., Gerace, D., Lepone, A., (2008). Liquidity in auction and specialist market structures: evidence from the Italian bourse. *Journal of Banking & Finance* 32, 2581-2588.

Frino, A., Jarnecic, E., Feletto, R., (2010 a). Local Trader Profitability in Futures Markets: Liquidity and Position Taking Profits. *The Journal of Futures Markets* 30, 1-24.

Frino, A., Johnstone, D., Zheng, H., (2010 b). Anonymity, stealth trading and the information content of broker identity. *Financial Review* 5, 501-522.

Frino, A., Jones, S., (2005). The Impact of Mandated Cash Flow Disclosure on Bid-Ask Spreads. *Journal of Business Finance and Accounting* 32, 1373-1396.

Frino, A., Lecce, S., Segara, R., (2011). The impact of trading halts on liquidity and price volatility: Evidence from the Australian Stock Exchange. *Pacific-Basin Finance Journal* 19, 298-307.

Gajewski, J., Gresse, C., (2007). Centralised Order Books Versus Hyrbid Order Books: A Paired Comparison of Trading on NSC (Euronext Paris) and SETS (London Stock Exchange). *Journal of Banking and Finance* 31, 2906-2924.

Garbade, K., Silber, W., (1979). Structural Organization of Secondary Markets: Clearing Frequency, Dealer Activity, and Liquidity Risk. *The Journal of Finance* 34, 577–593.

Garfinkel, J., (2009). Measuring Investors' Opinion Divergence. *Journal of Accounting* Research 47, 1317-1348.

Garman, M.B., (1976). Market Microstructure. *Journal of Financial Economics* 3, 257-275.

Garvey, R., Wu, F., (2011). Information, speed vs. cost trade-offs, and order routing decisions in U.S. equity markets. *Journal of Empirical Finance* 18, 408-422.

Gao, X., Ritter, J. R., Zhu, Z., (2013). Where Have All the IPOs Gone? *Journal of Financial and Quantitative Analysis* 48, 1663-1692.

Garfinkel, J.A., Nimalendran, M., (2003). Market structure and trader anonymity: An analysis of insider trading. *Journal of Financial and Quantitative Analysis* 38, 591.

Gemmill, G., (1996). Transparency and liquidity: A study of block trades on the London Stock Exchange under different publication rules. *The Journal of Finance* 51, 1765-1786.

George, T. J., Kaul, G., Nimalendran, M., (1994). Trading volume and transaction costs in specialist markets. *The Journal of Finance* 49, 1489-1505.

Glosten, L., Harris, L., (1988). Estimating the components of the bid-ask spread. *Journal of Financial Economics* 21, 123-142.

Glosten, L. R., Milgrom, P. R., (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics* 14, 71-100.

Glosten, L. R., (1994). Is the electronic open limit order book inevitable? *The Journal of Finance* 49, 1127-61.

Golec, J., (2007). Are the insider trades of a large institutional investor informed? *The Financial Review* 42, 161-190.

Gomes, A., Gorton, G., Madureira, L., (2007). SEC Regulation Fair Disclosure, information, and the cost of capital. *Journal of Corporate Finance* 13, 300-334.

Graham, J. R., Harvey, C. R., Rajgopal, S., (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics 40*, 3-73.

Grammig, J., Schiereck, D., Theissen, E., (2001). Knowing me, knowing you: Trader anonymity and informed trading in parallel markets. *Journal of Financial Markets* 4, 385-412.

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

Grullon, G., Kanatas, G., Weston, J., (2004). Advertising, Breadth of Ownership, and Liquidity. *Review of Financial Studies* 17, 439-461.

Harris, L., (1990). Liquidity, Trading Rules, and Electronic Trading Systems. *New York University Salomon Center Monograph Series in Finance Monograph* 1990-4.

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

Harris, L. E., Panchapagesan, V., (2005). The information content of the limit order book: Evidence from NYSE specialist trading decisions. *Journal of Financial Markets* 8, 25–67.

Hasbrouck, J., (1991). Measuring the information content of stock trades, *The Journal of Finance* 6, 179-207.

Hasbrouck, J., Sofianos, G., (1993). The Trades of Market Makers: An Analysis of NYSE Specialists. *The Journal of Finance* 48, 1565-1593.

Hausman, J.A., (1978). Specification Tests in Econometrics. *Econometrica* 46, 1251-1271.

Hayes, R. M., (1998). The impact of trading commission incentives on analysts' stock coverage decisions and earnings forecasts. *Journal of Accounting Research* 36, 299-320.

Healy, P. M., Palepu, K. G., (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics* 31, 405-440.

Heidle, H. G., Huang, R. D., (2002). Information-based trading in dealer and auction markets: an analysis of exchange listings. *Journal of Financial and Quantitative Analysis* 37, 391-424.

Hendershott, T., Jones, C. M., (2005). Island goes dark: Transparency, fragmentation, and regulation. *Review of Financial Studies* 18, 743-793.

Hegde, P.H., McDermott, J.B., (2004). The Market Liquidity of DIAMONDS, Q's and their Underlying Stocks. *Journal of Banking and Finance* 28, 1043-67.

Ho, T., Stoll, H. R., (1981). Optimal Dealer Pricing Under Transaction and Return Uncertainty. J*ournal of Financial Economic* 9, 47-73.

Holden, C. W., Subrahmanyam, A., (1992). Long-Lived Private Information and Imperfect Competition. *The Journal of Finance* 47, 247-270.

Holthausen, R.W., Leftwich, R.W., Mayers, D., (1987). The effect of large block transactions on security prices: A cross-sectional analysis. *Journal of Financial Economics* 19, 237-268.

Hong, H., Lim, T., Stein, J. C., (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance* 55, 265-295.

Hopman, C., (2007). Do supply and demand drive stock prices? *Quantitative Finance* 7, 37-53.

Hou, K., Moskowitz, T. J., (2005). Market frictions, price delay, and the cross-section of expected returns. *Review of Financial Studies* 18, 981–1020.

Huang, R. D., Stoll, H. R., (1997). The Components of the Bid-Ask Spread: A General Approach. *Review of Financial Studies* 10, 995-1034.

Huang, R., Stoll, H., (1994). Market Microstructure and Stock Return Predictions. *The Review of Financial Studies* 7, 179-213.

Huang, R., Stoll, H., (1996). Dealer Versus Auction Markets: A Paired Comparison of Execution Costs on NASDAQ and the NYSE. *Journal of Financial Economics* 41, 313-357.

Institutional Reports, Australian Securities Exchange (ASX), Sydney, viewed 22 August 2014, < http://www.asx.com.au/professionals/equity-research-scheme.htm >

Irvine, P. J., (2003). The incremental impact of analyst initiation of coverage. *Journal of Corporate Finance* 9, 431-451.

Irvine, P., Lipson, M., Puckett, A., (2007). Tipping. *Review of Financial Studies* 20, 741-768.

Ivković, Z., Jegadeesh, N., (2004). The timing and value of forecast and recommendation revisions. *Journal of Financial Economics* 73, 433-463.

Jares, T.E., Lavin, A.M., (2004). Japan and Hong Kong Exchange-Traded Funds (ETFs): Discounts, Returns and Trading Strategies. *Journal of Financial Services Research* 25, 57-69.

Jegadeesh, N., Kim, W., (2006). Value of analyst recommendations: International evidence. *Journal of Financial Markets* 9, 274-309.

Jegadeesh, N., Subrahmanyam, A., (1993). Liquidity effects of the introduction of the S&P 500 index futures contract on the underlying stocks. *Journal of Business* 66, 171-187.

Jegadeesh, N., Kim, J., Krische, S. D., Lee, C., (2004). Analyzing the analysts: When do recommendations add value? *The Journal of Finance* 59, 1083-1124.

Jensen, M.C., Meckling, W.H., (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics* 3, 305-360.

Karpoff, J. M., (1986). A theory of trading volume. *The Journal of Finance* 41, 1069-1087.

Kelly, B., Ljungqvist, A., (2012). Testing asymmetric-information asset pricing models. *Review of Financial Studies* 25, 1366-1413.

Kim, O., Verrecchia, R. E., (1997). Pre-announcement and event-period private information. *Journal of Accounting and Economics* 24, 395-419.

Kim, S. T., Lin, J. C., Slovin, M. B., (1997). Market structure, informed trading, and analysts' recommendations. *Journal of Financial and Quantitative Analysis* 32, 507-524.

Kothari, S. P., Li, X., Short, J. E., (2009). The effect of disclosures by management, analysts, and business press on cost of capital, return volatility, and analyst forecasts: a study using content analysis. *The Accounting Review* 84, 1639-1670.

Kothari, S. P., Li, X., Short, J. E., (2009). The effect of disclosures by management, analysts, and business press on cost of capital, return volatility, and analyst forecasts: a study using content analysis. *The Accounting Review* 84, 1639-1670.

Kurov, A.A., Lasser, D.J., (2002). The Effect of the Introduction of Cubes on the Nasday-100 Index Spot-Futures Pricing Relationship. *Journal of Futures Markets* 22, 197-218.

Kuserk, G., Locke, P.R., (1993). Scalper behaviour in futures markets: an empirical analysis. *Journal of Futures Markets* 13, 234–276.

Kuserk, G., Locke, P.R., (1994). Market maker competition on futures exchanges. *Journal of Derivatives* 1, 56–66.

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

Lang, M. H., Lins, K. V., Miller, D. P., (1904). Concentrated control, analyst following, and valuation: Do analysts matter most when investors are protected least? *Journal of Accounting Research* 42, 589-623.

Lee, C. M., Mucklow, B., Ready, M. J., (1993). Spreads, depths, and the impact of earnings information: An intraday analysis. *Review of Financial Studies* 6, 345-374.

Lee, C., Ready, M. J., (1991). Inferring trade direction from intraday data. *The Journal of Finance* 46, 733-746.

Leone, M., (2004). The Drought of Sell-Side Coverage. *CFO Magazin*e, viewed 26 August 2014, < http://ww2.cfo.com/banking-capital-markets/2004/07/the-drought-of-sell-side-coverage/ >

Levesque, T., Libby, T., Mathieu, R., Robb, S., (2010). The Effect of Director Monitoring on Bid and Ask Spreads. *Journal of International Accounting Research* 9, 45-65.

Li, M., McCormick, T., Zhao, X., (2005). Order imbalance and liquidity supply: Evidence from the bubble burst of NASDAQ stocks. *Journal of Empirical Finance* 12, 533-555.

Lim, T., (2001). Rationality and analysts' forecast bias. *The Journal of Finance* 56, 369-385

Lin, H. W., McNichols, M. F., (1998). Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics* 25, 101-127.

Linnainmaa, J. T., Saar, G., (2012). Lack of anonymity and the inference from order flow. Review of Financial Studies 25, 1414-1456.
Lipson, M., Mortal, S., (2007). Liquidity and firm characteristics: Evidence from mergers and acquisitions. *Journal of Financial Markets* 10, 342-361.

Liu, P., Smith, S. D., Syed, A. A., (1990). Stock price reactions to the Wall Street Journal's securities recommendations. *Journal of Financial and Quantitative Analysis* 25, 399-410.

Lo, A.W., MacKinlay., (2015). When are Contrarian Profits Due to Stock Market Overreaction? *Review of Financial Studies* 3(2), 175-205.

Madhavan, A., (1995). Consolidation, fragmentation, and the disclosure of trading information. *Review of Financial Studies* 8, 579-603.

Madhavan, A., Sofianos, G., (1998). An Empirical Analysis of NYSE Specialist Trading. *Journal of Financial Economics* 48, 189-210.

Madhavan, A., Smidt, S., (1993). An Analysis of Changes in Specialist Inventories and Quotations. *The Journal of Finance* 48, 1585-1628.

Madhavan, A., Richardson, M., Roomans, M., (1997). Why do security prices change? A transaction-level analysis of NYSE stocks. *Review of Financial Studies 10,* 1035-1064.

Madura, J., Richie, N.I., (2007). Impact of the QQQ on Liquidity and Risk of the Underlying Stocks. *Quarterly Review of Economics and Finance* 47, 411-21.

Manaster, S., Mann, S., (1996). Life in the Pits: Competitive Market Making and Inventory Control. *Review of Financial Studies* 9, 953-975.

Majois, C., (2007). Natural experiments methodology and global liquidity in financial markets. In *20th Australasian Finance & Banking Conference*.

Marsh, I., Payne, R., (2012). Banning short sales and market quality: The UK's experience. *Journal of Banking and Finance* 36, 1975-1986.

McInish, T. H., Wood, R. A., (1992). An analysis of intraday patterns in bid/ask spreads for NYSE stocks. *The Journal of Finance* 47, 753-764.

McInish, T., Van Ness, B., (2002). An intraday examination of the components of the bid-ask spread, *Financial Review*, 507-524.

McNichols, M., O'Brien, P. C. (1997). Self-selection and analyst coverage. *Journal of Accounting Research* 35, 167-199.

Mech, T. S., (1993). Portfolio return autocorrelation. *Journal of Financial Economics* 34, 307-344.

Menyah, K., Paudyal, K., (2000). The components of bid–ask spreads on the London Stock Exchange. *Journal of Banking & Finance* 24, 1767-1785.

Merton, R.C., (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance* 42, 483-510.

Michaely, R., Womack, K. L., (1999). Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies* 12, 653-686.

Mikhail, M. B., Walther, B. R., Willis, R. H., (2007). When security analysts talk, who listens? *The Accounting Review* 82, 1227-1253.

Moyer, R. C., Chatfield, R. E., Sisneros, P. M., (1989). Security analyst monitoring activity: Agency costs and information demands. *Journal of Financial and Quantitative Analysis* 24, 503-512.

Ng, J., Rusticus, T., Verdi, R., (2008). Implications of Transaction Costs for the Post-Earnings Announcement Drift. *Journal of Accounting Research* 46, 661-696.

Newey, W. K., West, D.W., (1987). A simple, positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55, 703–708.

Nimalendran, M., Petrella, G., (2003). Do 'Thinly-Traded' Stocks Benefit from Specialist Intervention? *Journal of Banking and Finance* 27, 1823–1854.

O'Hara, M., (1995). Market Microstructure Theory. *Blackwell, Cambridge, MA.*

O'Hara, M., (2003). Presidential address: Liquidity and price discovery. *The Journal of Finance* 58, 1335-1354.

O'Hara, M., Ye, M., (2011). Is market fragmentation harming market quality? *Journal of Financial Economics* 100, 459-474.

Pagano, M., Roell, A., (1996). Transparency and liquidity: A comparison of auction and dealer markets with informed trading. *The Journal of Finance* 51, 579–611.

Panayides, M., (2007). Affirmative Obligations and Market Making with Inventor. *Journal of Financial Economics* 86, 513-542.

Park, T.H., Switzer, L.N., (1995). Index Participation Units and the Performance of Index Futures Markets: Evidence from the Toronto 35 Index Participation Units Market. *Journal of Futures Markets* 15, 187-200.

Parkinson, M., (1980). The Extreme Value Method for Estimating the Variance of the Rate of Return. *The Journal of Business* 53, 61-65.

Parlour, C., Seppi, D., (2003). Liquidity-Based Competition for Order Flow. *The Review of Financial Studies* 16, 301-343.

Pasual, R., Veredas, D., (2009). What pieces of limit order book information matter in explaining order choice by patient and impatient traders? *Quantitative Finance* 9, 527-545.

Peterson, D. R., (1987). Security price reactions to initial reviews of common stock by the value line investment survey. *Journal of Financial and Quantitative Analysis* 22, 484-494.

Peterson, M., Sirri, E., (2003). Order Preferencing and Market Quality on U.S. Equity Exchanges. *The Review of Financial Studies* 16, 385-415.

Phillips, B., (2011). Options, short sale constraints and market efficiency: A new perspective. *Journal of Banking and Finance* 35, 430-443.

Rakowski, D., Wang-Beardsley, X., (2008). Decomposing liquidity along the limit order book. *Journal of Banking & Finance* 32, 1687-1698.

Ramnath, S., Rock, S., Shane, P., (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting* 24, 34-75.

Roulstone, D. T., (2003). Analyst following and market liquidity. *Contemporary Accounting Research* 20, 552-578.

Schipper, K., (1991). Analysts' forecasts. *Accounting Horizons* 5, 105-121.

Securities and Exchange Commission (SEC) (2003). Ten of Nation's Top Investment Firms Settle Enforcement Actions Involving Conflicts of Interest Between Research *and Investment Banking*. *Securities and Exchange Commission (SEC), U.S.A*, viewed 22 August 2014, < http://www.sec.gov/news/press/2003-54.htm>

Securities and Exchange Commission (SEC) (2004). Fair Disclosure, Regulation FD. *Securities and Exchange Commission (SEC), U.S.A,* viewed 22 August 2014, < http://www.sec.gov/answers/regfd.htm>

Securities and Exchange Commission (SEC) (2010). Concept Release on Equity Market Structure. *Securities and Exchange Commission (SEC), U.S.A,* viewed 22 August 2014, < http://www.sec.gov/rules/concept/2010/34-61358.pdf>

Silber, W.L., (1984). Market Maker Behaviour in an Auction Market: An Analysis of Scalpers in Futures Markets. *The Journal of Finance* 39, 937-953.

Simaan, Y., Weaver, D. G., Whitcomb, D. K., (2003). Market maker quotation behavior and pretrade transparency. *The Journal of Finance* 58, 1247-1267.

Stickel, S. E., (1995). The anatomy of the performance of buy and sell recommendations. *Financial Analysts Journal* 51, 25-39.

Stiglitz, J. E., Weiss, A., (1981). Credit rationing in markets with imperfect information. *The American Economic Review* 71, 393-410.

Stoll, H.R., (1978). The Supply of Dealer Services in Securities Markets. *The Journal of Finance* 33, 1133-1151

Stoll, H.R., (1998). Reconsidering the Affirmative Obligations of Market Makers. *Financial Analysts Journal* 54, 72-82.

Stoll, H. R., (1978). The pricing of security dealer services: An empirical study of NASDAQ stocks. *The Journal of Finance* 33, 1153-1172.

Stoughton, N. M., Wong, K. P., Zechner, J., (2001). IPOs and Product Quality. *The Journal of Business* 74, 375-408.

Su, Y., Huang, H., Hsu, M., (2010). Convergence to market efficiency of top gainers. *Journal of Banking and Finance* 34, 2230-2237.

Subrahmanyam, A., (1991). A theory of trading in stock index futures. *Review of Financial Studies* 4, 17-51

Switzer, L.N., Varson, P.L., Zghidi, S., (2000). Standard and Poor's Depository Receipts and the Perforamnce of the S&P 500 Index Futures Market. *Journal of Futures markets* 20, 705-16.

The Economist (2007). Research in commotion. *The Economist*, viewed 26 August 2014, < http://www.economist.com/node/9378886>

Tse, Y., Zabotina, T., (2004). Do Designated Market Makers Improve Liquidity in Open-Outcry Futures Markets? *Journal of Futures Markets* 24, 479-502.

Venkataraman, K., Waisburd, A.C., (2007). The Value of the Designated Market Maker. *Journal of Financial and Quantitative Analysis* 42, 735-858.

Venkataraman, K., and Waisburd, A., (2007). The value of designated market makers. J*ournal of Financial and Quantitative Analysis* 42, 735-758.

Vega, C., (2006). Stock price reaction to public and private information. *Journal of Financial Economics* 82, 103-133.

Wang, J., (1993). A model of intertemporal asset prices under asymmetric information. *The Review of Economic Studies* 60, 249-282.

Welker, M., (1995). Disclosure Policy, Information Asymmetry, and Liquidity in Equity Markets. *Contemporary Accounting Research* 11, 801-827.

Womack, K. L., (1996). Do brokerage analysts' recommendations have investment value? *The Journal of Finance* 51, 137-167

Yohn, T. L., (1998). Information asymmetry around earnings announcements. *Review of Quantitative Finance and Accounting* 11, 165-182.

Yu, F., (2008). Analyst coverage and earnings management. *Journal of Financial Economics* 88, 245-271.