Individual investors' behaviours, biases and opportunities: Evidence from Australia

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Statement of Originality

This work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Date: 28 October 2019

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Contents

List of Tables

List of Figures

List of Abbreviations

AD	announcement day
ACT	Australian Capital Territory
ASX	Australian Securities Exchange
AUM	asset under management
BFI	Big Five Inventory
CFP	corporate financial performance
CSP	corporate social performance
DST	daylight-saving time
ED	effective day
ESG	Environmental, social and governance
ETF	exchange-traded funds
E-type	Evening-type
KLD	Kinder Lydenberg Domini
MAR	mean abnormal return
MCAR	mean cumulative abnormal return
M-E	Morningness-eveningness
MEQ	Morningness-eveningness questionnaire
M-type	Morning-type
NSW	New South Wales
OLS	ordinary least squares
S&P	Standard & Poor's
SAM	Sustainable Asset Management
SIRCA	Securities Industry Research Centre of Asia-Pacific
SRI	Socially responsible investing
TRTH	Thomson Reuters Tick History
UK	United Kingdom
US	United States

Preface

This dissertation contains three joint studies, which have been presented at conferences or submitted to refereed journals. Chapters 3–5 constitute one working paper each[1].

Chapter 3

Lepone, G. and Yang, Z. (2019). Do early birds behave differently from night owls in stock markets. Paper presented at the Financial Markets and Corporate Governance Conference, Sydney.

This chapter has also been submitted as a manuscript to *Pacific-Basin Finance Journal.*

Chapter 4

Lepone, G. and Yang, Z (2019). Does it pay to invest responsibly? A study of retail investors' ESG preference.

Chapter 5

Lepone, A., Wong, J., and Yang, Z (2017). Index rebalance effects of S&P/ASX 200. Paper presented at the Asia-Pacific Conference on Economics & Finance, Singapore.

[1] A detailed contribution statement which has been agreed upon by all co-authors of the working papers listed in the Preface is provided in Appendix 1.

Synopsis

This dissertation examines individual investors' behaviours in stock markets and identifies two opportunities of potential profitability for stock market participants. Existing literature has proven that investors suffer from behaviour biases rather than being perfectly rational. In addition, individual investors are more often than not the uninformed party in the stock markets, making them liable to being taken advantage of by the informed party. These behaviour biases and information asymmetry result in individual investors' underperformance compared to the market benchmark or institutional investors at least in the long run. Therefore, it is essential to understand the behaviours of individual investors and identify opportunities of potential profitability in the stock markets for them. The importance of understanding the behaviours of individual investors is also underscored by the high proportion of trades executed by them and the fact that even more individuals are making direct investments in stock markets in recent years. Each essay in this dissertation addresses research questions that are either unexplored or for which there are limited prior research findings, providing insights for investors, academic researchers, financial institutions and regulators to understand investors' behaviours and the potential market opportunities.

The first essay (Chapter 3) introduces morningness–eveningness (M-E; that is, human' diurnal rhythm preference) into the field of behavioural finance. Employing proprietary stock trading data from a leading retail brokerage house in Australia, we are able to distinguish morning-type investors (M-type, or 'early birds') from evening-type investors (E-type or 'night owls') based on their order submission time in stock markets. We examine whether demographic features (i.e., age and gender) contribute to the likelihood of being a particular M-E type, and whether M-E can predict investors' tendency towards market behavioural biases. Our analysis results reveal that older investors are more likely to be M-types and that there is no significant gender difference in being a certain M-E type. Further, we provide robust evidence that M-type investors are distinctively different from E-type investors in their proneness to stock market behavioural biases. M-type investors trade more frequently, are more subjected to home bias and have a stronger preference for stock market speculation.

The second essay (Chapter 4) investigates socially responsible investing (SRI) among retail investors. The linkage between environmental, social and governance (ESG) preference, investors' characteristics and their account performance are examined. In addition, the impact of a company's ESG rating on their stock performance is tested. We find that females, older people and investors with a greater wealth (sophistication) level are more likely to take ESG into consideration in investment, while frequent-trading investors and those who prefer mental shortcuts are less likely to consider ESG attributes. Further, SRI can be a market opportunity for retail investors, as we find that a higher ESG score contributes to a company's improved stock market performance in the subsequent year, and that investors holding portfolios with a greater weight of stocks with higher ESG scores are more likely to outperform other investors.

The third essay (Chapter 5) proceeds from a market microstructure perspective and identifies another opportunity in the market that can bring potential profits to market participants: S&P/ASX 200 index rebalancing events. The price, volume, volatility and liquidity effects of such events for the stocks added to (and deleted from) the S&P/ASX 200 index are investigated. We find that both announcement day (AD) and effective day (ED) effects exist for additions and deletions. The price discovery for additions mainly occurs around AD, while for the deletions, it mainly happens around

ED. The liquidity of additions increases while it deteriorates for the deletions. This paper is pioneering in its finding of a negative (positive) correlation between the cumulative abnormal returns of index additions (deletions) during the AD–ED interval and the length of the interval. Specifically, Standard & Poor's (S&P) usually give a one- or two-week interval between the AD and ED of an addition or deletion; in that case, the added stocks with a one-week interval experience a price increase from AD until the day before ED, while the additions with a two-week interval experience a price increase until the fifth trading day after announcement after which the price starts to drop. For the deletions, those with a one-week interval experience a price drop upon the announcement until the day before ED, while for those with a two-week interval, the price starts to drop from four days before ED until ED. The price changes for the additions (deletions) with a shorter AD–ED interval (one week) are of greater magnitude, which amounts to an opportunity for investors: the expected excess return for buying (selling) the additions (deletions) at the end of AD and selling (buying) on the day before revision is up to 2.67% (4.48%).

Chapter 1: Introduction

The assumption that investors are rational and seek to maximise their investment outcome while minimising risk is among the many notions that contemporary finance research has been built on (Barber & Odean, 2013). However, as the literature has proven, investors are not perfectly rational and their investment behaviours and decisions are not necessarily carried out to maximise investment performance. For example, they may tend to sell the winning stocks in their portfolios while keeping the losing ones, resulting in the 'disposition effect'; they may have greater preference for the stocks of companies that are geographically close to their residence or closely related to their profession, reducing the diversification of their portfolio; and they are more likely to buy attention-grabbing stocks, such as those appearing in the news or with large price moves. Researchers in behavioural finance have thus tried to identify the possible contributors to investors' behavioural biases, such as age, gender, education and emotion.

The Kyle (1985) model indicates that, in financial markets, informed traders would gain profits at the cost of uninformed traders. More often than not, due to the information asymmetry in the stock markets, individual investors are the uninformed trading party. Together with the impact from their behavioural biases, the existing literature shows that the investment returns of individual investors underperform institutional investors or the market benchmark, at least in the long-run (see Barber & Odean, 2000; Barber, Lee, Liu & Odean, 2008), even though their investment over the short-horizon can be profitable, as shown by Kaniel, Saar and Titman (2008) and Kaniel, Liu, Saar and Titman (2012). Therefore, it is important to help identify the investment opportunities of potential profitability for market participants.

Understanding the behaviours of individual investors to investigate the factors contributing to their behavioural biases and identify possible profitable investment opportunities for them in the stock market is crucial for the investors themselves, academic researchers, financial institutions and regulators. This is because retail investors' trading behaviours can impact stock price movement (see Battalio & Mendenhall, 2005; Hu & Wang, 2013), and growing numbers of individuals are making direct investments in recent years. In Australia, for example, the number of young people (18–34 years old) who invest in the stock market nearly doubled between 2012 and 2017 (Australian Securities Exchange [ASX], 2017), while in China, retail investors account for 85% of A-share trading by turnover (Sitto, 2018).

Among the literature on the behaviours of individual investors and the market opportunities for them, there are areas unexplored or with limited prior research findings. This dissertation examines individual investors' behaviours in stock markets and identifies two investment opportunities of potential profitability for market participants. The first essay (Chapter 3) introduces morningness–eveningness (M-E) into the field of behavioural finance, investigating whether investors of certain demographic groups are more likely to be a specific M-E type and whether M-E can predict investors' tendency towards stock market behavioural biases. The second essay (Chapter 4) examines socially responsible investing (SRI) among retail investors; in particular, the linkage between investors' environmental, social and governance (ESG) preference, demographic characteristics and account performance. The influence of companies' ESG ratings on their stock market performance is also tested. The results show that SRI can be an investment opportunity for stock market participants. The third essay (Chapter 5) proceeds from a market micro-structure perspective and systematically examines the index rebalancing effects (price, volume, volatility and liquidity) of the S&P/ASX 200 index. The announcement day (AD) – effective day (ED) interval length is found to play a key role in the price effects of the S&P/ASX 200 index rebalancing event, explaining the inconsistent prior findings of Australian indices. Participating in this event with index additions (deletions) with shorter AD–ED intervals can be another potentially profitable opportunity for market participants.

1.1 Do early birds behave differently from night owls in stock markets

M-E describes human beings' diurnal rhythm preference. According to Adan, Lachica, Caci and Natale (2010), morning-types (M-types) or 'early birds' have an earlier than average bedtime, wakeup time and peak-hour period for physical and mental performance. In comparison, evening-types (E-types) or 'night owls' report later than average corresponding activity hours. The concept of marking these individual differences is also termed 'circadian typology'.

In the past two decades, M-E or circadian typology has been studied extensively in medical and psychological research (e.g., Baehr, Revelle & Eastman, 2000; Horne, Brass & Petitt, 1980; Horne & Östberg, 1976; Kerkhof & Van Dongen, 1996; Mongrain, Paquet & Dumont, 2006; Paine, Gander & Travier, 2006; Roenneberg, Wirz-Justice & Merrow, 2003; Smith et al., 2002; Smith, Reilly & Midkiff, 1989; Wallace, 1993). In the behavioural science field, existing studies examine the relationship between M-E and personality traits (e.g., Antúnez, Navarro & Adan, 2015; Díaz-Morales, 2007; Randler, 2008; Tonetti, Fabbri & Natale, 2009) and document M-E's impact on people's behavioural preferences (e.g., Randler, 2009; Tonetti et al., 2010). However, this concept has not been introduced to the literature of stock market decision-making, or behavioural finance in general.

The first essay, presented as Chapter 3 of this dissertation, applies M-E to the behavioural finance field for the first time. In particular, we examine whether there is a link between M-E diurnal rhythms and three well-documented stock market participant behavioural biases: frequent trading, home bias and speculative trading. Taking advantage of proprietary investor data from a leading retail brokerage house in Australia, we are able to classify retail investors into M-types ('early birds') and E-types ('night owls') based on their order submission patterns. In addition, we develop a methodology of defining different M-E types by reliable actual behaviour, instead of using questionnaire responses. Employing stock market data, we examine whether different demographic features including age and gender contribute to the likelihood of being a particular M-E type. We observe that, consistent with existing M-E studies, older people are more likely to be morning types. There is no significant evidence of M-E difference between genders. Our key finding is that M-E difference predicts proneness to stock market behavioural biases. After controlling for demographic differences and other trading characteristics, we find M-types trade more frequently, are more prone to home bias and have a stronger preference for stock market speculation.

Understanding M-E's impact on stock market behavioural preferences furthers the knowledge of investor biases. There is extensive evidence that behavioural biases result in sub-optimal financial decision-making and harm investment performance. Identifying contributors to behavioural biases will not only help the understanding of them, but more importantly, provide more avenues for overcoming these biases and improve investment outcomes.

1.2 Does it pay to invest responsibly? A study of retail investors' ESG preference

SRI or ESG investment is about taking concerns related to sustainability—that is, ethical, social and environmental criteria—into account in making investment decisions, rather than solely considering the financial factors (Friede, Busch & Bassen, 2015; Foo, 2017). In the past 30 years, the development of SRI globally has been significant. According to Bloomberg Briefs (2017), global SRI reached USD 23 trillion in 2016, taking 25% of professional managed investments. SRI growth in Australia and New Zealand has also been rapid in recent years, with a 247% increase from 2014 to USD 516 billion in 2016.

Researchers have studied SRI extensively over the past 40 years. Existing literature examines the linkage between corporate social performance (CSP) and corporate financial performance (CFP). For example, SRI packaged products, such as funds and indices, have been compared to conventional funds and market benchmarks in terms of returns and riskiness (Bauer, Koedijk & Otten, 2005; Bello, 2005; Humphrey, Warren & Boon, 2016; Mackie, Palit, Veeraraghavan & Watson, 2018; Statman, 2000); using portfolios formed based on ESG ratings, high-ESG portfolios have been compared to low-ESG portfolios in terms of performance (Derwall, Guenster, Bauer & Koedijk, 2005; Eccles, Ioannou & Serafeim, 2014; Kempf & Osthoff, 2007; Lee, Fan & Wong, 2018; Statman & Glushkov, 2009); and the impact of ESG rating on companies' stock market returns have been examined (Galema, Plantinga & Scholtens, 2008; Halbritter & Dorfleitner, 2015; Mănescu, 2011). Regarding investors, the cash flow into and out of the SRI funds has been studied (Bollen, 2007; Das, Ruf, Chatterjee & Sunder, 2018; Nofsinger & Varma, 2014; Renneboog, Ter Horst & Zhang, 2011); the possible factors impacting SRI fund managers' decisions have been examined (Cox, Brammer & Millington, 2004; Hong & Kostovetsky, 2012); and surveys have been conducted to understand the preferences and characteristics of socially responsible retail investors (Beal & Goyen, 1998; Rosen, Sandler & Shani, 1991; Sultana, Zulkifli & Zainal, 2018).

The second essay, as presented in Chapter 4 in this dissertation, extends SRI to the behavioural finance field by investigating the linkage between individual investors' ESG preference, demographic and trading characteristics, and account performance. The impact of companies' ESG scores on their stock performance is also examined. Taking advantage of data from a leading Australian retail brokerage house, we obtain an objective 'Account ESG Score' measurement for each individual investor account, as a proxy for their preference for SRI, and to examine the linkage between the investors' Account ESG Score, demographic characteristics and trading features. We find that older and female investors have a greater preference for stocks with higher ESG ratings, so are the wealthier (or more sophisticated) investors. In contrast, investors who are less risk-averse and prefer mental shortcuts are more likely to hold stocks with lower ESG ratings.

Our key finding is that the investors' Account ESG Score has an impact on their account performance. Employing the Carhart four-factor model, we find a positive correlation between account holders' SRI preference and account performance Regarding the impact of companies' ESG rating on their stock market performance, weak evidence of a positive impact is established, which is consistent with existing studies (e.g., Galema et al., 2008; Halbritter & Dorfleitner, 2015). The evidence suggests SRI can be a beneficial investment opportunity for market participants.

1.3 Index rebalancing effects of S&P/ASX 200

Index rebalancing effects have been studied by researchers since the 1980s. During the index revision event, there is a timing difference between the AD and ED of the addition or deletion of the component stocks. Since index exchange-traded funds (ETFs) are constrained by their mandate to track the performance of the underlying indices closely, this provides a window of opportunity for arbitragers to build a position prior to the compulsory buying (selling) by ETF managers around ED.

The indices domiciled in North America, the European regions and Asia have been studied extensively by researchers; while in comparison, the Australian indices are examined to a much lesser extent and the findings are inconsistent. The liquidity effects of Australian market index rebalancing events are unexplored, and there is only one study focusing on the S&P/ASX 200 index, the index covering 80% of Australian equities market capitalisation (Schmidt, Zhao & Terry, 2012). In that study, Schmidt et al. (2012) employ a matched firm method to investigate the price and volume effects, mainly around AD, for the index revisions during 2000–2009.

In addition, Beneish and Whaley (1996) find a positive correlation between the S&P 500 index additions' cumulative abnormal returns during the AD–ED interval and the interval length, suggesting there are arbitragers participating in the S&P 500 index revision event. Considering that Standard & Poor's (S&P) usually gives two weeks' notice for S&P/ASX 200 index revisions compared to a shorter notice period (up to five days) for S&P 500 index revisions, and that the AD–ED interval for S&P/ASX 200 has changed from two weeks to only one week for the March, June and December quarters since 2016, it is necessary to examine the index rebalancing effects of the S&P/ASX

200 systematically, and to re-analyse the impact of the AD–ED interval length using more recent data.

With this motivation, the third essay, presented as Chapter 5 in this dissertation, first investigates the index revision effects of the S&P/ASX 200 index in terms of price, volume, volatility and liquidity, with a more recent sample period of 2011–2016. We find that the announcement and revision effects exist for both index additions and deletions. The price discovery for additions mainly occurs on AD, while for the deletions, it mainly happens on ED. The S&P/ASX 200 rebalancing event improves the liquidity of the stocks added to the index; while for the deletions, the liquidity deteriorates. The impact of the index funds' growth is also examined but no statistically significant correlation is established.

The key contribution of this study is that we find a negative (positive) correlation between S&P/ASX 200 additions' (deletions') cumulative abnormal returns during the AD–ED interval and the interval length. The correlation is in the opposite direction than that established for the S&P 500 index revisions, and explains the different findings on the ASX/S&P 200 rebalancing effects compared to those for the S&P 500 index. Specifically, the longer AD–ED interval of the S&P/ASX 200 rebalancing event gives potential arbitragers sufficient time to build their position upon announcement and then unwind that position to take profits before ED.

S&P normally give a one- or two-week AD–ED interval for S&P/ASX 200 index rebalancing events. The price changes for the additions (deletions) with a shorter AD–ED interval (one week) are of greater magnitude, which amounts to an opportunity for investors: the expected excess return for buying (selling) the additions (deletions) at the end of AD and selling (buying) on the day before revision is up to 2.67% (4.48%).

1.4 Summary

The three essays presented in this dissertation examine the trading behaviours of investors and the contributors to their behavioural biases, resulting in the identification of two opportunities in the stock market of potential profitability for investors: SRI and the opportunities afforded by S&P/ASX 200 index rebalancing events. Each essay incorporates an unexplored, underdeveloped area or an area without a consensus in the existing literature. The evidence provided in this dissertation not only pioneers new directions in behavioural finance but also presents practical investment opportunities for investors. Given the increasing number of investors making direct investments and their influence on stock market price movement, the findings are meaningful for investors themselves, researchers, financial practitioners and regulators alike.

The remainder of this dissertation is organised as follows. Chapter 2 provides a review of the existing literature related to each of the three essays and presents the arising research questions. Chapters 3–5 present the three research essays discussed in this chapter, with each chapter comprising sections describing the data and sample, methodology, empirical results and conclusions. Finally, Chapter 6 presents the overall conclusions of the dissertation and discusses the potential areas of future research.

Chapter 2: Literature Review and Research Questions

This chapter reviews the existing literature pertinent to each of the three essays included in this dissertation and outlines the research questions developed. The chapter is organised as follows. Section 2.1 reviews the literature related to morningness–eveningness (M-E) and investors' stock market behavioural biases. Section 2.2 summarises the prior studies on environmental, social and governance (ESG) investing; the linkage between corporate social performance (CSP) and corporate financial performance (CFP) in terms of packaged products, constructed portfolios and individual firms; and the characteristics of socially responsible investors. Finally, Section 2.3 presents an overview of the index rebalancing effects regarding price, volume and liquidity. At the end of each section, and based on the literature review, the research questions are developed that inform the three essays presented as Chapters 3–5.

2.1 Do early birds behave differently from night owls in stock markets

2.1.1 M-E

Researchers in medical, psychological and behavioural science rely on morningness–eveningness questionnaires (MEQs) to measure people's circadian typology. The most widely used MEQ is that developed by Horne and Östberg (1976). This questionnaire has 19 questions, which each have four or five options, giving different scores. The final total score is used to separate the participants into five groups: definite morning, moderate morning, neither, moderate evening and definite evening. The MEQ has subsequently been developed with a similar rational into the Composite

Scale of Morningness (Smith et al., 1989), the Preference Scale (Smith et al., 2002) and the Munich Chronotype Questionnaire (Roenneberg et al., 2003).

Using the definitions from MEQs, researchers have found that the alertness levels or best performance hours during the day for morning-types (M-types) and evening-types (E-types) differ. For example, Horne et al. (1980), in an experiment in which 20 participants (10 extreme to moderate M-types and 10 extreme to moderate E-types) aged between 18 and 30 years old conducted a production-line faulty-item inspection task over 15 one-hour sessions, find that the performance of M-types peaks around midday, while E-types peak at 8 pm.

Adan (1991) applies the Horne and Östberg MEQ to 24 participants to investigate the body temperature, visual reaction time and verbal memory time of M-types, E-types and Neither-types at six times during the day: 9 and 11 am, and 1, 4, 6 and 8 pm. The study finds that the M-types perform best in terms of reaction time and memory at 9 am, while E-types perform best at 8 pm. Performance has no significant relationship to participants' body temperature pattern.

Smith et al. (2002) use the Preference Scale and the Composite Scale of Morningness to group over 1,700 participants from six countries into five types: extreme morning, moderate morning, intermediate, moderate evening and extreme evening. They find that under both MEQ classifications, M-type participants report that the peak hour for their alertness is 10 am (peak period 8 am to midday), while E-types report that their alertness peaks at 10 pm (peak period 8 pm to midnight).

The influence of demographic factors, work schedules and photoperiod (day length) at birth on M-E preference has been extensively investigated. The findings are consistent for the influence of age: Morningness Score grows with age for adults (Adan, 1992; Chelminski, Ferraro, Petros & Plaud, 1997; Merikanto et al., 2012; Paine et al., 2006). For gender, the findings differ between studies (Adan & Natale, 2002; Merikanto et al., 2012; Paine et al., 2006). Other factors that may influence M-E include work schedule (Adan, 1992; Paine et al., 2006) and photoperiod at birth (Natale & Di Milia, 2011). The relevant studies are now discussed.

Adan (1992) employs the Horne and Östberg MEQ and a reduced version of it to classify 908 subjects aged 17–50 years as M- or E-types, with work schedules and personality questionnaire answers also recorded. The study finds that age, work schedule and personality are all related to M-E, while gender is not. Specifically, older people and morning workers are more likely to be M-types, and M-types are less extroverted. Chelminski et al. (1997), who also used the Horne and Östberg MEQ with their 1,600 participants aged 18–53, similarly find that older individuals are more likely to be M-types, but so are female participants, suggesting that gender has an effect. The role of gender is affirmed by Adan and Natale (2002) in their study with 2,000 participants aged 18–30 years old, also using the Horne and Östberg MEQ. They find that men tend to be night owls, with the result being robust when analysing the answers for each item in the MEQ (Adan & Natale, 2002).

In Paine et al. (2006), 2,526 New Zealand participants aged 30–49 years answered the Horne and Östberg MEQ, with the results revealing that age and work schedule are the most influential factors on M-E preference. Specifically, morningness increases with age, and night workers tend to be definite E-types. Ethnicity and gender are not found to have a significant influence. In Merikanto et al. (2012), over 6,000 Finnish participants aged 25–74 years were classified according to the Horne and Östberg MEQ, identifying a preference for morningness in males and older people.

Mongrain et al. (2006) investigate the linkage between season at birth and morningness. Surveying 1,591 young adults with the Horne and Östberg MEQ, the study finds that participants born in seasons with a shorter photoperiod (i.e., autumn and winter) are more likely to be M-types, while those born in longer photoperiod seasons (i.e., spring and summer) have the opposite tendency. The study suggests that such association reflects the impact of light intensity during the early development of the circadian system. Moreover, the study confirms that females tend to be M-types, with no gender–season interaction. This finding is supported by Natale and Di Milia (2011), in whose study over 1,700 university students responded to the Composite Scale of Morningness, with the finding that female participants and those born in seasons with shorter photoperiods (autumn and winter) are more likely to be M-types.

In addition to the various possible individual influencing factors, researchers have also examined the relationship between circadian typology and people's cognitive process or behavioural traits. Looking at cognitive process, Fabbri, Antonietti, Giorgetti, Tonetti and Natale (2007) asked 1,254 university students to answer a reduced version of the MEQ as well as the Style of Learning and Thinking questionnaire, and find that M-types tend to follow an analytical reasoning style, while E-types display a more intuitive style. Similar conclusions are reached by Díaz-Morales (2007), whose sample of 360 university students answered the Composite Scale of Morningness and questionnaires for thinking and behaving styles, revealing that M-types are more realistic, thought-guided and conservative, while E-types are more intuition-guided, innovation-seeking and unconventional.

Studies investigating the influence of personality for M- and E-types have mainly used the Big Five Inventory (BFI) of personality (Costa & McCrae, 1992): conscientiousness, extraversion, agreeableness, neuroticism and openness. Here, conscientiousness is related to being self-disciplined, organised and goal-oriented; extraversion refers to self-assertiveness and participation in social activity;

agreeableness is defined as being considerate and helpful for others; neuroticism is the incapability to deal with emotional instability and anxiety; and openness refers to a preference for novelty and a willingness to accept different values (Adan et al., 2012; Tonetti et al., 2009).

In their study of over 600 participants who responded to the Horne and Östberg MEQ and BFI questionnaire, Hogben, Ellis, Archer and von Schantz (2007) find conscientiousness to be most closely correlated with morningness. Similarly, Randler (2008), in his study of around 1,200 participants (mostly preadolescents/adolescents) who answered the Composite Scale of Morningness and BFI questionnaires, finds a strong correlation between conscientiousness and morningness, as well as a correlation between neuroticism and eveningness. This finding is supported by Tonetti et al. (2009), whose study involves 500 participants aged 14–59 years and investigates the linkage between circadian typology and the big five personality dimensions. These authors find that M-types are more conscientious, agreeable and less neurotic than E-types.

Other personality traits and temperaments are also related to circadian typology. Randler (2009) employs the Composite Scale of Morningness questionnaire and eight-item proactivity scale with 367 participants, documenting that M-types are more proactive than E-types. Muro, Gomài-Freixanet and Adan (2009) employ a sample of over 500 participants to investigate the linkage between circadian typology and the alternative five-factor model of personality: neuroticism-anxiety, activity, sociability, impulsivity and aggressiveness. Their key finding is that M-types are more active compared to Neither- and E-types, both in general activity and work activity (i.e., a preference for challenging and hard work, and a high energy level).

Based on over 1,000 participants aged 18–30 years, who answered the reduced MEQ and Sensation Seeking Scale, Tonetti et al. (2010) find that males and E-types are more likely to be sensation-seeking. Adan et al. (2010) investigate the relation between circadian typology and seven dimensions of personality (i.e., harm avoidance, novelty-seeking, reward dependence, persistence, self-directedness, cooperativeness and self-transcendence), with 862 participants aged 18–30 years. The study finds that E-types are more novelty-seeking and lower in harm avoidance, while M-types have a greater tendency towards being achievement-oriented, perseverant and self-regulated. Antúnez et al. (2015), who had 2,000 participants complete the reduced MEQ, Connor-Davidson Resilience Scale and the Life Orientation Test, report that M-types are more resilient and optimistic; that is, they are more capable of adapting positively in the face of adversity and expect good things in life.

To summarise, M-types tend to follow an analytical reasoning style (Fabbri et al., 2007) and are more conscientious (Hogben et al., 2007; Randler, 2008; Tonetti et al., 2009), realistic and thought-guided (Díaz-Morales, 2007), resilient, positive and optimistic (Antúnez et al., 2015), proactive (Randler, 2009) and more active in both work and general activities (Muro et al., 2009) than E-types. Conversely, E-types display a more intuitive style (Fabbri et al., 2007) and are more neurotic (Randler, 2008; Tonetti et al., 2009), sensation-seeking (Tonetti et al., 2010) and novelty-seeking (Adan et al., 2010). E-types also tend to be low in harm avoidance (Adan et al., 2010), resilience and positivity (Antúnez et al., 2015).

2.1.2 Frequent trading

Several empirical publications have investigated the trading frequency of individual investors. Based on the trading records and account holdings of 10,000 investors during 1987–1993, Odean (1999) takes the first step towards showing that retail investors, specifically those trading through discount brokerage accounts, trade excessively. In this study, investors' trading gains are not sufficient to offset trading costs, and their return from trading is reduced even when trading costs are ignored. In their subsequent study, Barber and Odean (2000), employing over 60,000 retail investors' trading records over 1991–1997, find that those investors who trade most underperform the market and the average household, indicating that frequent trading is not beneficial to account performance.

The linkages between trading frequency and overconfidence, risk-tolerance level, self-perceived competence and gender are established in the existing literature. According to the theoretical model developed in Odean (1999), overconfidence contributes to stock market trading volume. Using the survey answers and trading records of more than 1,000 German investors, Dorn and Huberman (2005) document that an investor's risk attitude is the most significant factor for their portfolio turnover. To be specific, more risk-tolerant investors trade more aggressively; that is, trading frequency is positively correlated with risk-seeking level. Graham, Harvey and Huang (2009) argue that trading frequency can be driven by investors' own perceived competence. Their study, which used UBS/Gallup survey answers from around 1,000 investors, finds that investors who believe in their competence (i.e., financial knowledge or skill) trade more, even after controlling for overconfidence (i.e., the investor's perception that their portfolio will beat the market in the next 12 months). Regarding gender, based on the portfolio holding and trading data of over 35,000 households in the United States (US), Barber and Odean (2001) find that men trade 45% more than women, resulting in lower returns. Finally, Grinblatt and Keloharju (2009) investigate the effect of two psychological attributes—sensation seeking and overconfidence—on trading frequency among Finnish investors, with a sample period of 1995–1997. Employing the number of speeding tickets received as a proxy for sensation seeking and a psychological assessment to measure overconfidence, the study finds that overconfident investors and those prone to sensation seeking trade more frequently.

2.1.3 Local bias

Local bias refers to investors' propensity to tilt their portfolios disproportionally towards local stocks (Baltzer, Stolper & Walter, 2015). This bias has been shown to exist in various countries, including the US (Huberman, 2001; Ivkovic & Weisbenner, 2005; Seasholes & Zhu, 2010), Sweden (Bodnaruk, 2009; Massa & Simonov, 2006), Finland (Grinblatt & Keloharju, 2001), Germany (Baltzer et al., 2015) and China (Seasholes, Tai & Yang, 2011).

In their study of more than 70,000 US retail investors' portfolios between 1991 and 1996, Ivkovic and Weisbenner (2005) find that investors invest disproportionally more in the stocks of companies whose headquarters are located within 250 miles of the investor's location, and that these local holdings can bring excess returns—up to 3.2% per year—to the investors' portfolios due to the information advantage. Using the same time period as in Ivkovic and Weisbenner (2005), Seasholes and Zhu (2010) test the holdings of local stocks (defined as within 100 miles, 100 km and state boundaries) by individual investors in the US and find that, while investors did tilt their investment towards local stocks, this preference did not help with portfolio performance.

Several studies have relaxed the geographical definition of 'local' to investigate the propensity to invest in the familiar. Huberman (2001) confirms investors' preference to invest in the familiar by examining household account holdings and the amount of money invested in local Regional Bell Operating Companies in the US in late 1996. This paper also points out that the investors' buy-and-hold portfolios suggests that the phenomenon stems from a preference for pure familiarity rather than information advantage. The preference to invest in the familiar also applies to Finnish investors according to Grinblatt and Keloharju (2001), whose paper investigates Finnish retail investors' portfolio holdings and trading activities during 1994–1997, finding influential factors to include the location, language in which the company communicated with investors, and cultural background of the companies' chief executives. Another paper, by Massa and Simonov (2006), documents that during 1995–2000, Swedish investors are more likely to invest in the stocks of firms from the same industry as the investor's profession or that are locally headquartered. The authors suggest this relates to information-based familiarity and helps investors obtain higher returns. Baltzer et al. (2015), using the aggregate quarterly shareholdings of retail investors in Germany during 2005–2009, find that investors pull money out of unfamiliar (geographically remote) stocks and put it into familiar (geographically close) ones during times of market uncertainty. Based on their findings about the insignificant abnormal returns of investors' local investments, they conclude that this phenomenon indicates investors' ambiguity-aversion rather than their possession of advantageous information. Based on the trading history of over 50,000 Chinese retail investors, Liao, Li, Zhang and Zhu (2012) document the preference for stocks listed on the local stock exchange; this is evidence of non-information-driven familiarity because trading in the local stock exchange does not generate abnormal returns for investors.

In summary, researchers have proposed two major explanations for the phenomenon of local bias. One explanation is that local bias stems from investors' information advantage; that is, they are able to exploit superior information about local companies to outperform in their local stock holdings (Bodnaruk, 2009; Coval & Moskowitz, 2001; Ivkovic & Weisbenner, 2005; Massa & Simonov, 2006). An opposing explanation is that investors prefer local stocks because of pure familiarity;

that is, they are more comfortable investing in companies they know or think they know, and such familiarity is not necessarily information-driven or value-based (Baltzer et al., 2015; Grinblatt & Keloharju, 2001; Huberman, 2001; Seasholes et al., 2011; Seasholes & Zhu, 2010).

Although local bias is a behavioural bias, it does not necessarily result in portfolio underperformance. Seasholes and Zhu (2010), Baltzer et al. (2015), and Liao et al. (2012) find that local bias does not help with investors' portfolio performance, however, studies such as Ivkovic and Weisbenner (2005) and Massa and Simonov (2006) suggest that this behavioural bias can help investors obtain abnormal returns.

2.1.4 Preference for stock market speculation

Several studies have examined stock market speculation activity. Barberis and Huang (2008), based on cumulative prospect theory, conclude that stocks with positive skewness can be overpriced because certain investors prefer lottery-like portfolios (i.e., a low probability of large gains) and are thus willing to take a large position in stocks with high skewness or pay higher prices for them. Similarly, Kumar (2009) identifies gambling behaviour in stock markets, evidenced by investment in stocks with lottery features. In Kumar (2009), lottery stocks are defined as those with simultaneously high idiosyncratic volatility, high idiosyncratic positive skew and low price. Using data on individual investors' portfolio holdings and trade records during 1991–1996 provided by a US brokerage house, Kumar compares the aggregate ownership of lottery stocks by individual investors and institutional investors, concluding that the individual investors had a greater preference for the lottery stocks. In addition, he finds that lottery stocks underperform, and that lottery-preferring investors suffer from inferior returns compared to their peers.

Bali, Cakici and Whitelaw (2011) use a more straightforward method to define lottery-like stocks. They rank stocks by their maximum daily returns during the previous month and classify those ranked in the top decile as lottery stocks. However, despite this definition differing to that used by Kumar (2009), Bali et al. (2011) reach a similar conclusion: that lottery stocks underperformed during 1962–2005 in the US.

Han and Kumar (2013), using US trading data for 1983–2000, define retail investors' trades as small trades (USD 5000 or less). They find that stocks with a higher retail trade proportion (RTP) have the speculative attributes of lottery stocks; that is, higher idiosyncratic volatility and skewness and a lower price. They propose that RTP represents speculation in the stock market, and report that speculation is more prominent among retail investors compared to institutional investors. Further, they argue that high RTP stocks are more likely to generate a negative return in the following month, and are thus overpriced.

2.1.5 Research questions for Chapter 3 (Essay 1)

As seen in Section 2.1, although M-E has been studied extensively in medical, clinical and psychological research, it has not been introduced to the literature on stock market decision-making or behavioural finance in general. The current study is thus the first time M-E has been applied to the behavioural finance field. Using retail investors' order submission data, we can identify people's M-E from an objective data-driven perspective rather than through subjective questionnaires. In addition, we test the findings of the existing literature using questionnaires or experiments on whether certain demographic groups are more likely to be a certain M-E type. Both aspects are unexplored in the existing literature, particularly in Australian finance literature.

Given the documented influence of M-E on individuals' behaviour, we conjecture that M-E affects investors' proneness to commonly observed stock market behavioural biases. As has been reviewed in previous subsections, researchers have related local bias to either an information advantage possessed by local investors or pure familiarity. Either explanation suggests a linkage between M-E and local bias: if investors have an information advantage for local stocks, the more goal-oriented M-type investors (Díaz-Morales, 2007; Hogben et al., 2007; Randler, 2008; Tonetti et al., 2009) can be expected to use the information asymmetry to obtain profits by disproportionally investing in locally headquartered companies. If the local bias is simply because of familiarity, M-type investors would still invest more into local stocks compared to E-type investors, because they are more conscientious and less novelty-seeking (Adan et al., 2010) than the E-types, making them more likely to avoid ambiguity when constructing their portfolios (Baltzer et al., 2015) and less likely to invest outside the familiarity boundary. However, given that M-type investors are more conscientious (Díaz-Morales, 2007; Hogben et al., 2007; Randler, 2008; Tonetti et al., 2009), they may also prefer to diversify their portfolios and examine more parts of the stock market beyond their familiar or local stocks, making them less local-biased, and indicating a possible linkage between M-E and investors' local bias. Moreover, given existing findings that M-types are more positive, optimistic (Antúnez et al., 2015), proactive (Randler, 2009) and more involved in both work and general activities (Muro et al., 2009), it is possible that they may also trade more actively and speculate more in the stock market. For E-type investors, who are more likely to be sensation seeking, the positive correlation between sensation seeking and trading frequency (Grinblatt & Keloharju, 2009) can result in them trading more frequently (Adan et al., 2010; Tonetti et al., 2010).

Therefore, in Chapter 3, we test the following research questions:

Research Question 3.1: Do the demographic characteristics of investors affect their likelihood to be a certain M-E type?

Research Question 3.2: Does M-E affect investors' proneness to commonly observed stock market behavioural biases; that is, trading frequency, local bias and the preference for market speculation?

2.2 Does it pay to invest responsibly? A study of retail investors' ESG preference

Over the past 40 years, the linkage between CSP and CFP has been studied extensively by academic researchers. However, for no aspect of financial performance (e.g., market value; accounting-based performance, including return on asset, return on equity or earnings per share; and stock market returns) are the findings consistent among the existing literature (Orlitzky, Schmidt & Rynes, 2003). Friede et al.'s (2015) recent meta-analysis of over 2,000 studies on the relation between CSP and CFP concludes that over 90% of existing studies find a non-negative impact of CSP on CFP, with a large majority inferring a positive relation. This meta-analysis thus concludes that ESG criteria positively influences firms' long-term financial performance.

2.2.1 CSP–CFP relation for packaged products

Among the many studies, one stream of literature has focussed on investigating the financial performance of packaged socially responsible investing (SRI) products, such as SRI funds and indices. For example, Statman (2000) compares the performance of 31 SRI mutual funds against 62 conventional mutual funds in the US, and the performance of the Domini Social Index of socially responsible stocks against the S&P

500 Index between 1990 and 1998; Bauer et al. (2005) examines 103 SRI funds in Germany, the United Kingdom (UK) and the US over 1990–2001; Bello (2005) compares 42 SRI funds and 84 conventional funds in the US during 1994–2001; Barnett and Salomon (2006) test a panel of 61 SRI funds in the US from 1972 to 2000; and Humphrey et al. (2016) investigate 151 SRI funds against over 3000 conventional funds in the US during 2003–2012. No significant difference in performance between the SRI packaged and conventional products is discovered by these studies.

Renneboog, Ter Horst and Zhang (2008) compare a panel of SRI funds from 17 countries and three regions against the conventional equity funds in those regions over 1993–2001, finding that SRI funds underperformed in the US, UK, and most countries in Europe and the Asia-Pacific. However, no significant performance difference is found between the SRI and conventional funds in Japan, France and Sweden.

Concerns have been raised regarding the method of using packaged products such as funds and indices to examine the linkage between CSP and CSF. One concern is that fund managers' stock-picking skills vary across the funds and can greatly impact the fund returns (Baker, Litov, Wachter & Wurgler, 2010; Kosowski, Timmermann, Wermers & White, 2006). Another concern is that, according to Derwall et al. (2005), the different screening strategies of SRI funds can also influence fund performance. Finally, as has been pointed out by Utz and Wimmer (2014), the SRI funds do not necessarily hold more assets of socially responsible firms, nor can these funds ensure the exclusion of unethical companies. The above issues can be avoided by using ESG ratings to check the CSP–CFP relation at the portfolio and individual company levels, as discussed in the following section.

2.2.2 CSP–CFP relation based on ESG ratings

The advantage of employing ESG rating scores for investigating the relation between CSP and CFP is that the ratings are provided by specialised rating agencies, which evaluate the companies with a set of systematic assessment criteria related to sustainability. Thus, the ESG scores can be taken as a direct measurement of CSP at the company level, and lead to a more comprehensive and straightforward understanding of how sustainability affects a company's stock return or a constructed portfolio's performance (Halbritter & Dorfleitner, 2015). The ESG portfolio method—to form portfolios with high ESG ratings and portfolios with low ESG ratings, and then compare their financial performance—has been used in recent studies discussed in this section.

This method also provides a practical strategy for investors participating in the stock market: to long high-ESG-rated stocks and short low-rated ones. This strategy has been confirmed by the existing literature to generate abnormal returns. Derwall et al. (2005), using the Innovest Strategic Value Advisors' corporate eco-efficiency scores over the period 1995–2003, find a sustainably higher return for high-ESG-ranked portfolios of US stocks compared to low-ranked ones. Using the ESG ratings from Thomson Reuters ASSET4 and Sustainable Asset Management (SAM), together with interviews and personal research, Eccles et al. (2014) identify 90 US companies as having high-sustainability and another 90 US firms as having low-sustainability, and find that the high-sustainability companies outperformed their low-sustainability counterparts both in stock market returns and accounting performance over 1993–2009.

Based on the ESG ratings for US stocks from Kinder Lydenberg Domini (KLD) for the period 1992–2004, Kempf and Osthoff (2007) conclude that buying high-ESG-rated stocks and shorting low-rated ones resulted in an abnormal return of 8.7% per year over this period. Statman and Glushkov (2009) find a similar result with data for 1992–

2007, while Galema et al. (2008) reveal the outperformance of the high-ESG-ranked portfolios for each SRI dimension during 1992–2006.

However, there are also studies that have found the opposite: that high-ESG-ranked portfolios do not generate significant excess returns. Humphrey, Lee and Shen (2012) construct portfolios of UK stocks according to the SAM ESG ratings and find no risk-adjusted return difference between high-ranked ESG portfolios and low-ranked ones during 2002–2010. Lee, Faff and Rekker (2013) compare high-ESG-rated US companies against low-rated ones according to their SAM ESG scores and find no significant difference in the risk-adjusted performance between these two portfolios for 1998–2007. Likewise, Halbritter and Dorfleitner (2015), using three different ESG ratings (ASSET4, Bloomberg and KLD), form high- and low-ESG-rated portfolios for the period 2008–2011 in the US market, with no significant return difference identified between the two groups of portfolios.

Beside the linkage between ESG ratings and the financial performance of constructed portfolios, some studies have specifically examined ESG's impact on individual firm's stock return. Galema et al. (2008) use cross-sectional analysis to reveal a positive correlation between companies' ESG scores and their stock market returns during 1992–2006. Mănescu (2011) also adopts cross-sectional analysis to investigate the effect of seven ESG attributes on US firms' market returns during 1992–2008, finding these effects to vary and inferring that the value-relevant effect may not be reflected efficiently in stock prices. Halbritter and Dorfleitner (2015) test stock returns against ESG scores from three different databases (KLD, Bloomberg and ASSET4) and find that the Bloomberg and Thomson Reuters ASSET4 ESG scores are positively correlated with company stock returns during 2002–2012, while the KLD score has the negative correlation.

2.2.3 SRI studies in Australia

Among the over 2,000 ESG empirical studies identified by Friede et al. (2015), the majority focus on North America and Europe, while far fewer focus on the Asia-Pacific region. As early as 2001, the Australian government passed the *Corporations Act 2001*, with the requirement that the providers of financial products with an investment component disclose 'the extent to which labour standards or environmental, social or ethical considerations are taken into account in investment decision-making' (s 1013D).

In academia, SRI research in Australia has mainly focused on SRI funds. Cummings (2000) studies the performance of seven ethical unit trusts and finds no significant performance difference compared to the market benchmarks since their formation date to the year 1996. Tippet (2001) studies three ethical funds and finds that the funds underperformed the market on average during 1991–1998. Bauer, Otten and Rad (2006) investigate 25 ethical mutual funds against 281 conventional ones and find that the SRI funds underperformed the conventional ones over 1992–1996, but outperformed them during 1996–2003, leading the authors to conclude that there is no significant difference in the risk-adjusted return between the two groups of funds during 1992–2003. Jones, Van der Laan, Frost and Loftus (2008) find that, on average, their sample of 89 ethical funds underperformed the market during 1986–2005. Humphrey and Lee (2011) compare 27 SRI funds and 514 conventional mutual funds and find that there is no difference in performance. Mackie et al. (2018) focus on the riskiness of investing in SRI funds during 1998–2003; with a sample of 26 funds, the study concludes that investing in ethical funds does not bring more risk.

Regarding the method of constructed ESG portfolios, Limkriangkrai, Koh and Durand (2017) employ Regnan's ESG ratings and find that there is no significant difference in the risk-adjusted returns of the high- and low-rated ESG portfolios during 2009–2014. Lee et al. (2018) construct portfolios based on Thomson Reuters ASSET4 ESG ratings and conclude that the high-rated portfolios perform better, with lower overall risk than the low-rated ones over 2006–2016.

2.2.4 Investors of SRI funds

Among the studies on the behaviours of socially responsible investors, several empirical publications have focused on the cash flow of SRI funds. Bollen (2007) examines the cash flows of SRI and conventional funds in the US during 1980–2002 and finds that the cash flow into SRI funds is less volatile, more sensitive to prior positive fund performance and less sensitive to previous negative returns. With these findings, the paper suggests that investors may derive utility from the socially responsible attribute. Similarly, Renneboog et al. (2011), with a sample of 321 SRI mutual funds domiciled in more than 20 countries and regions, document that the money flows of SRI funds are less related to past fund performance compared to the conventional funds during 1992–2003; they further point out that socially responsible investors may give more credence to ethical issues than financial returns.

Nofsinger and Varma (2014) compare SRI mutual funds to conventional ones in the US during 2000–2012 and find that the SRI funds outperformed the conventional ones during the financial crisis. In addition, the assets under management (AUM) for the SRI funds increased by over 13% during the financial crisis, while the conventional funds' AUM remained unchanged. Similarly, Das et al. (2018) examine the performance and fund flows for SRI mutual funds in the US over 2005–2016, suggesting that the high-ESG-rated funds outperformed the low-rated ones, and that the cash flow into these funds increased significantly during the financial crisis. Both studies show that SRI funds can provide protection for risk-averse investors who prefer more stable portfolio performance during market downturns.

Another stream of research has focused on the characteristics of individual socially responsible investors, but the findings have been inconsistent. As Sandberg, Juravle, Hedesström and Hamilton (2009) point out, what investors in SRI funds perceive as socially responsible will differ based on their regional, cultural and ideological backgrounds. Rosen et al. (1991) survey 4,000 investors of two mutual SRI funds in the US and find that younger and more educated investors cared more about the ESG aspects. Using survey answers from 825 Australian shareholders of an ethical company, Earth Sanctuaries Limited, Beal and Goyen (1998) conclude that female, older, more educated investors and those with higher household assets are more likely to take environmental concerns into consideration when investing. In their analysis of interview and questionnaire responses from over 300 individual investors in Bangladesh, Sultana et al. (2018) find that age and education are not significant factors influencing the ESG investment decisions; instead, investors with greater stock market investment amounts tended to prefer ESG attributes.

Hood, Nofsinger and Varma (2014) examine the linkage between individual investors' demographic characteristics and their ownership of 'sin' stocks (e.g., tobacco, alcohol and gambling) and the stocks of companies with social concerns in the US during 1991–1996. The paper documents that investors' age, gender, religious beliefs, and political values are influential factors; for example, younger, female and wealthier investors have a greater preference for ESG attributes.

Ruggie and Middleton (2019), summarising the current state of ESG investing, mention that among millennials, women are more likely to invest in firms that incorporate ESG practices. Moreover, over 70% of high-net-worth investors have reviewed their portfolio investment for ESG impact, which is much greater than the overall average rate of only about 30%.

In terms of professional investors, SRI fund managers, Cox et al. (2004) find that, in the UK, institutional ownership of companies is positively correlated with those companies' social performance during 2001–2002; that is, the performance stability of companies with strong corporate governance is appealing to portfolio managers. Further, Hong and Kostovetsky (2012) document that political values have an impact on mutual fund managers' investment in socially irresponsible firms. To be specific, fund managers who donate to the Democrats are less likely to invest in socially irresponsible companies during 1992–2006. Humphrey et al. (2016) study fund manager characteristics as of 2012 and observe that US SRI fund managers tend to have longer tenure and are more likely to be female.

2.2.5 Research questions for Chapter 4 (Essay 2)

As has been reviewed in Section 2.2, although SRI has been explored extensively in terms of its impact on the financial performance of packaged products, formed portfolios and individual companies, its linkage with the demographic characteristics, trading features and portfolio performance of individual investors trading in stock markets has been far less well studied, especially in Australian finance literature.

Existing literature studying the behaviour of socially responsible investors mainly focuses on the cash flows of SRI funds, concluding that socially responsible investors are more risk-adverse and derive utility from ESG attributes (Bollen, 2007; Das et al., 2018; Nofsinger & Varma, 2014; Renneboog et al., 2011). Survey is the most often-used method to understand socially responsible investors' characteristics and preferences (Beal & Goyen, 1998; Rosen et al., 1991). Very few studies have looked at the linkage between individual investors' demographic statistics and their ESG preference. Hood et al. (2014) go some way to filling the gap by examining the ownership of 'sin' stocks and stocks with social concerns by individual investors in the US during 1991–1996. However, in the present study, using retail investors' portfolio-holding data, we can identify people's preferences for SRI from an objective data-driven perspective rather than using subjective survey answers.

Further, the relation between CSP and CFP has been studied extensively at the level of packaged products and structured portfolios; however, the impact of SRI on individual investors' portfolio performance has not been explored. Meta-analysis studies such as Margolis, Elfenbein and Walsh (2007) and Friede et al. (2015) deem the overall CSP–CFP relation to be positive, but there are still studies finding a negative relation.

Finally, compared to the studies for the North American and European regions, SRI research in Australia is not extensive and has mainly focused on SRI mutual funds (Bauer et al., 2005; Humphrey & Lee, 2011; Jones et al., 2008; Mackie et al., 2018) and constructed portfolios (Lee et al., 2018; Limkriangkrai et al., 2017) rather than at the company level. Therefore, the following three research questions are developed and tested in Chapter 4:

Research Question 4.1: What is the linkage between investors' preference for SRI, their demographic characteristics and their trading features?

Research Question 4.2: Is there any impact of SRI, based on ESG ratings, on individual investors' portfolio performance?

Research Question 4.3: Does a company's ESG rating affect its stock market performance in Australia?

2.3 Index rebalancing effects of S&P/ASX 200

2.3.1 Index rebalancing effect on stock prices and volumes

The effect of index rebalancing events on price and volume has been studied by researchers since the 1980s. In their pioneering study on the S&P 500 index, Harris and Gurel (1986) examine the period 1973–1983; however, because Standard and Poor's (S&P) changed its announcement method from mailing to a notification service in 1976, the two periods of 1973–1977 and 1977–1983 are examined separately. The paper finds that the stocks added to the S&P 500 index experience post-announcement increases in trading volumes (volume ratios equal 1.21 for 1973–1977 and 2.81 for 1978–1983) and stock prices (immediate post-announcement abnormal returns equal 0.21% for 1973–1977 and 3.13% for 1978–1983), with abnormal returns fully reversing within two weeks. In comparison, stocks deleted from the index experienced an increase in trading volume and a statistically significant decrease in price after the announcement. In another pioneering study, Shleifer (1986) examines the additions to the S&P 500 index during 1966–1983 and finds the significant positive abnormal returns only partially reversed after revision. Dhillon and Johnson (1991) report positive price and volume effects for the S&P 500 additions during 1984–1988, finding these effects to be permanent. They also document that the options and bonds for these firms responded positively to the announcements. Wurgler and Zhuravskaya (2002) use an S&P 500 additions sample from 1976–1989, and also find a positive abnormal return following the event.

The above studies focus on the period before 1989, the year in which S&P started to pre-announce S&P 500 index changes, thereby beginning the 'S&P 500 Game' (Beneish & Whaley, 1996). Beneish and Whaley (1996) further study of the S&P 500 index rebalancing effects by comparing the periods before and after the change in the announcement scheme (i.e., 1986–1989 v. 1989–1994). Their study finds that the added stocks experienced abnormal volumes and returns during the index rebalancing event for both periods, and that under the new announcement policy, the added stocks experienced greater volume and price increases, which are only partially reversed.

Lynch and Mendenhall (1997) examine the index rebalancing effects with data during 1990–1995 and find that the added (deleted) stocks experience significantly positive (negative) abnormal returns between announcement day (AD) and effective day (ED). The abnormal returns are partially reversed after ED. The largest trading volumes for both additions and deletions occur on ED. Only deleted stocks experience permanent price effects.

Denis, McConnell, Ovtchinnikov and Yu (2003) study S&P 500 changes from 1987 to 1999 and find the added stocks experienced a significantly positive abnormal return during the announcement period and an insignificant cumulative return during the 30-day period after ED.

Elliott and Warr (2003) compare NYSE- and Nasdaq-listed added stocks to the S&P 500 between 1989 and 2000. They find that both NYSE- and Nasdaq-listed additions experience significantly positive abnormal returns on AD and between AD and ED. On ED, Nasdaq-listed additions obtain a return of 3.41%, while the NYSE-listed additions obtain a return of 0.73%. The abnormal returns are both partly reversed after ED, with the NYSE-listed additions' price reversal being quicker than that of the Nasdaq-listed ones.

Hegde and McDermott (2003) examine the index revision effects by checking the additions to the S&P 500 from 1993 to 1998. They find significantly positive excess returns and higher than normal trading volumes around AD and ED. They also find a partial reversal of the price after ED.

Chen, Noronha and Singal (2004) take a longer sample period, 1962–2000, which in addition to including S&P's 1989 change in pre-announcement approach, also include the year of 1976 in which constituent stock changes began to be announced. Their analysis reveals that added stocks experience significantly positive excess returns on AD (5% for 1989–2000) and between AD and ED (8.9% for 1989–2000), with these price effects being permanent for the sample period after 1976; the trading volumes for added stocks on AD and ED are 27 and 11 times the normal level, respectively; stocks deleted experience a negative return on AD and a further loss between AD and ED, with this price effect almost fully reversed within two months after ED; and the volume effects are similar for both stock deletions and additions. Green and Jame (2011), using an S&P 500 addition sample from 1999–2005, find a price effect of 2.76% between AD and ED.

Since the 2000s, there has been a proliferation of studies examining the index rebalancing effects of a broad range of indices and markets. The indices predominantly domicile in North America, the European region and Asia-Pacific markets. In North America, Masse, Hanrahan, Kushner and Martinello (2000) study the revision event of the Canadian TSE 300 index during 1984–1994 and find that the index inclusions experienced significant price increases while the price drop for deletions is insignificant. Biktimirov, Cowan and Jordan (2004) study the Russel 2000 index rebalancing event during 1991–2000 and find that the added and deleted stocks experienced transitory significant price and volume effects. Gowri Shankar and Miller (2006) examine the additions and deletions of the S&P SmallCap 600 index during 1995–2002 and find similar results to those for the Russell 2000 index rebalancing.

In the European region, the most widely studied index is the FTSE 100 in the UK. Gregoriou and Ioannidis (2006) investigate the FTSE 100 index rebalancing event during 1984–2001 and find that both price and volume increased (decreased) for stocks added to (deleted from) the index. Vespro (2006), looking at the inclusions in and exclusions from the FTSE 100 for 1997–2001, finds similar temporary price and volume effects. Mazouz and Saadouni (2007) examine the period 1984–2003 and find that the price for FTSE 100 index additions (deletions) goes up (down) before the AD, and reverse completely within two weeks after ED. With data from 1992–2005, Mase (2007) also finds transitory price effects for FTSE 100 index inclusions and exclusions, concluding that the price effects are due to buying (selling) pressure related to an increase in trading volume. Biktimirov and Li (2014) investigate the revision of FTSE SmallCap index membership during 1998–2008 and find a permanent price increase for stocks moved from a smaller-cap FTSE index to a larger-cap one; a symmetric price effect is also found for stocks moving in the opposite direction. Other European domiciled indices have been studied by researchers, including the Mib 30 and Midex indices in Italy (Barontini & Rigamonti, 2000), the DAX and MDAX indices in Germany (Deininger, Kaserer & Roos, 2000), the KFX in Denmark (Bechmann, 2004), and the CAC 40 and SBF 120 indices in France (Vespro, 2006).

In Asia, the Nikkei 500 and Nikkei 225 indices, domiciled in Japan, have been widely studied. Liu (2000) investigate the price and volume effects of the Nikkei 500 index rebalancing event during 1991–1999 and finds that the added (deleted) stocks experience significant price increases (decreases), with insignificant reversal after the event. The trading volume for both additions and deletions increases significantly during the event, but reverses after the rebalancing. Hanaeda and Serita (2003) examine the changes in the Nikkei 225 index in Japan in April 2000 and find similar price and volume effects; that is, the additions (deletions) obtain excess positive (negative) returns after the announcement, with significant volume increases. Focusing on the added stocks to the same Nikkei 225 index from 1991 to 2002, Okada, Isagawa and Fujiwara (2006) find that the prices of the additions go up from AD until the day before ED, and then start to drop on and after the index rebalancing date. As for trading volume, this goes up immediately on announcement and peaks on the day before ED, after which it starts to decrease gradually. With the Nikkei 225 rebalancing event between 1970 and 2002, Liu (2006) discovers that the price effects for both additions and deletions are permanent despite the temporary reversal; and that the trading volume is significantly higher during the event, before gradually stabilising after ED. Wang, Murgulov and Haman (2015) focus on the CSI 300 index in China and find that during 2005–2012 the prices increase (decrease) significantly for index inclusions (exclusions), reversing after ED; while trading volume increases significantly for both inclusions and exclusions, with partial reversal after the revision.

Several studies have examined a panel of indices. Chakrabarti, Huang, Jayaraman and Lee (2005), looking at the revisions of MSCI Standard Country indices in 29 countries during 1998–2001, find that the additions (deletions) in developed countries experience greater price increases (decreases) during the event than those in emerging markets. The findings are consistent with those in Hacibedel and van Bommel (2006). Looking at the MSCI Emerging Markets index revisions in 24 countries during 1996–2004, Hacibedel and van Bommel (2006) find that the positive (negative) price effects for the index inclusions and deletions are of a smaller magnitude than for the US indices. S&P examines the index revision price effects for the S&P 500, Nikkei225, S&P/TSX 50 and DAX 30 indices over two periods, 1998–2003 and 2003–2008, concluding that the effects have shrunk over time (S&P Dow Jones Indices, 2008).

The following explanations are provided by the existing literature for their findings. Studies such as Harris and Gurel (1986), Elliott and Warr (2003), Biktimirov et al. (2004), Mase (2007) and Green and Jame (2011) explained their findings through the price pressure hypothesis. Shleifer (1986), Beneish and Whaley (1996) and Liu (2000) point to the downward-sloping demand curve hypothesis. Lynch and Mendenhall (1997) conclude that their findings are evidence of both a downward-sloping demand curve and price pressure, and against semi-strong market efficiency. Dhillon and Johnson (1991) and Denis et al. (2003) conclude that S&P 500 revisions are not information-free, which contradicts the price pressure hypothesis and imperfect-substitute hypothesis.

Harris and Gurel (1986) also point out that the growth of the index fund industry in the US explains the different results for 1973–1977 and 1978–1983. Beneish and Whaley (1996) indicate that in addition to the index fund industry growth, the S&P 500 rebalancing price and volume effects are related to another factor: risk arbitragers' buying pressure. The study finds a positive relation between the AD–ED interval length and the abnormal return for S&P 500 additions, thus concluding that the positive correlation indicates that arbitragers are participating in the index revision event and that their demand pushes up the stock price more than do index funds. Other existing literature, such as Lynch and Mendenhall (1997), Elliott and Warr (2003), Chen et al. (2004) and Green and Jame (2011), also attributed the index effects to arbitragers' trading. As for the different price effects of inclusions and exclusions, Chen et al. (2004) imply this phenomenon can be partially explained by the change in investors' awareness and their consequent trading behaviours.

2.3.2 Index rebalancing effect on liquidity

The liquidity effects of index rebalancing events are documented in several publications. Beneish and Whaley (1996) examine trading size and quoted bid-ask spreads during the event and find that trade size is significantly larger than the pre-event level from AD to ED, with this effect lasting for 10 days after ED; for the additions, the biggest trade size appears on ED, indicating that the index funds wait for ED to build their position; and quoted bid-ask spreads are smaller than pre-event level during the event, but the effect is temporary. Using liquidity indicators—quoted spread, effective spread, quoted depth and trade size—Hegde and McDermott (2003) show that added stocks experience a liquidity increase during and after the index revision.

Other studies investigating the liquidity effect of the index revision event include Biktimirov and Li (2014) and Kamal (2014). Examining trading volume, illiquidity ratio and related spread, Biktimirov and Li (2014) find that stocks moving from a small-cap FTST index to a large-cap one experienced liquidly improvement, while stocks moving in the other direction experienced liquidity deterioration. Kamal (2014) examines the deletions from the S&P 500 index during 1989–2011 and confirms that the relative bid-ask spreads for the sample stocks increased (i.e., liquidity decreases) during the event.

2.3.3 Past literature on Australia

Compared to the indices domiciled in North America, the European regions and Asia, the indices domiciled in Australia have been studied to a much lesser extent and the findings are inconsistent.

One pioneering study is that of Chan and Howard (2002), which focuses on the Australian All Ordinaries share price index, an open-ended index whose regular changes can be predicted. Their analysis of prices and volumes shows that the added (deleted) stocks experience a significantly positive (negative) abnormal return before ED, but the prices reverse partially on ED. Moreover, the trading volumes for both additions and deletions peak on the day prior to ED. These findings are consistent with index funds trying to minimise the tracking error and build their position around ED. Chan and Howard (2002) also find that trading activities start to increase months before the rebalancing day and continue until two months after the revision. The explanation provided by the study is that risk arbitragers are trading the added stocks that can be identified beforehand and then trying to unwind their position for profits after the All Ordinaries index revision.

Qiu and Pinfold (2007) examine the index rebalancing effects of the S&P/ASX 100 and 300 indices. According to their study, the S&P/ASX 100 has a negative price effect for both additions and deletions from AD to ED, while the S&P/ASX 300 only shows an insignificant positive abnormal return for additions and a significantly negative abnormal return for deletions from AD to ED. Additions to both indices and deletions from the S&P/ASX 100 experienced abnormal volumes on AD and ED.

One publication focusing on the S&P/ASX 200 index is Schmidt et al. (2012). Their study uses a control firm method to investigate the S&P/ASX 200 revisions from 2000–2009, and finds that the additions experience an abnormal return between AD and the day before ED. The price effect partially reverses on ED and the day after. The deleted stocks experience symmetric price effects between AD and the day before revision, and the abnormal negative returns partially recover on ED.

2.3.4 Research questions for Chapter 5 (Essay 3)

As reviewed in Section 2.3, the existing literature has extensively explored the index rebalancing events of indices domiciled in North America, the European regions and Asia. In comparison, far fewer papers have focused on Australian market indices and the findings are inconsistent. Moreover, the liquidity effects of Australian market index rebalancing events are yet unexamined. Only one publication, Schmidt et al. (2012), has focused on the S&P/ASX 200 index, which covers 80% of Australian equities market capitalisation. Schmidt et al. (2012) employ the matched firm method to investigate price and volume effects, mainly around AD, for additions and deletions during 2000–2009.

Further, we contend that it is necessary to investigate the index rebalancing effects of the S&P/ASX 200 systematically, and to examine the impact of the AD–ED interval length with more recent data. This is because of three factors. First, Beneish and Whaley (1996) find a positive correlation between the S&P/ASX 200 additions' abnormal returns and the number of days between AD and ED, suggesting that arbitragers' participation in the index revision event amplifies the effects. Second, the AD–ED interval differs between the S&P 500 and S&P/ASX 200 indices, and S&P has changed the AD–ED interval from two weeks to only one week for the March, June and December quarters since 2016. Finally, the impact of AD–ED interval length has never been examined in the existing Australian finance literature. Therefore, **Research Questions 5.1** and **5.2** are developed and tested in Chapter 5.

Research Question 5.1: What effect has index rebalancing had on price, volume, volatility and liquidity for the S&P/ASX 200 index since 2010?

Research Question 5.2: What is the linkage between AD–ED interval length and the abnormal returns of S&P/ASX 200 additions (deletions) during the index rebalancing event, and what are the implications?

Finally, another possible contributing factor to the index rebalancing effect, the growth of index funds, has been mentioned in the literature, but without consensus on whether it has an impact (for studies claiming an impact, see Afego, 2017; Beneish & Whaley, 1996; Wurgler & Zhuravskaya, 2002; for studies claiming no impact, see Edmister, Graham & Pirie, 1996; Elliott & Warr, 2003). Intuitively, if the market capitalisation of index funds tracking S&P/ASX 200 grows over the years, there will be more demand from the index funds during the index revision period, considering their mandate to replicate the index compositions and minimise tracking errors. This, in turn, would result in index rebalancing effects of greater magnitude. **Research Question 5.3** is thus developed and tested in Chapter 5:

Research Question 5.3: Has the growth of index exchange-traded funds (ETFs) contributed to the S&P/ASX 200 index rebalancing effects over the years?

Chapter 3: Do Early Birds Behave Differently from Night Owls in Stock Markets

3.1 Introduction

As discussed in Section 2.1, morningness–eveningness (M-E) or circadian typology has been studied extensively by medical, clinical and psychological researchers; however, it remains an unexplored area for behavioural finance research, particularly in the Australian finance literature. This essay seeks to fill this gap. Employing retail investors' order submission data, provided by a leading Australian brokerage house, we can identify people's M-E from an objective data-driven perspective and examine whether different demographic features including age and gender contribute to the likelihood of being a particular M-E type. We observe that, consistent with existing M-E studies, older people are more likely to be morning-types (M-types), and there is no significant evidence of M-E difference between genders, thus answering Research Question 3.1. In addition, given the documented influence of M-E on individuals' behaviour, we conjecture that M-E affects investors' proneness to commonly observed stock market behavioural biases. With three investor behavioural biases tested (i.e., trading frequency, local bias and preference for market speculation), we find that M-type investors trade more frequently, are more prone to home bias and have a stronger preference for stock market speculation, thus providing insight into Research Question 3.2.

This chapter is organised as follows: Section 3.2 outlines the data used in this study; Section 3.3 presents the methodology; Section 3.4 reports and interprets the findings; Section 3.5 reports the results of the robustness tests; and Section 3.6 concludes the chapter.

3.2 Data

3.2.1 Stock and investor data

We obtained four datasets from a leading Australian retail brokerage house. One dataset contains the trading orders submitted to the trading platform by over 140,000 accounts from August 2003 to August 2011, including the account number, order date and time, order type (buy or sell, market or limit), and name of the stock being traded. The second dataset provides account information, including the account holders' birthdate, salutation (which helps to identify gender) and gender, residential address, account creation date, and whether the holder is the primary account holder. The third set of data contains the transaction records (i.e., the stock identifier, transaction price and volume) for more than 40,000 accounts from October 2010 to August 2012. The fourth dataset contains the daily account-holding portfolio (i.e., the date, stock ticker on the Australian Securities Exchange [ASX], and the number of stocks held in the account) for over 64,000 accounts between February 2010 and February 2013.

For the local bias investigation, information on the location of portfolio-held company headquarters is obtained from the Securities Industry Research Centre of Asia-Pacific (SIRCA), while stock market capitalisation information is extracted from Bloomberg. For the examination of lottery stock speculation activities, the prices (open, high, low and last price) of the stocks held and traded by the accounts are extracted from the Thomson Reuters Tick History (TRTH) database, maintained by SIRCA; while other information needed for the definition of lottery stocks are obtained as follows:

stock market capitalisation and book value per share are from Bloomberg, the risk-free interest rate (here we use the 90-day Bank Accepted Bill rate) is from the Reserve Bank of Australia's (RBA) official website, and the market portfolio proxy (here we use the ASX All Ordinaries Accumulation Index end-of-day price) is from Yahoo Finance.

We use the stock orders data file to define account holders' M-E, and clean the merged data between order data and account information as follows: first, accounts whose residential address is incomplete or outside Australia are excluded; second, only those accounts with a single account owner and no other users are kept; third, the account salutations are used to help define the gender of the account owner, and the accounts with missing values are deleted; finally, the accounts with less than eight orders submitted over the sample period of 2003–2011 are excluded. After cleaning, the data comprises 3,257,730 trading orders from 39,562 accounts between 15 December 2004 and 9 August 2011.

3.2.2 Australian time zones and daylight-savings scheme

The order submission date and time given in the data provided by the brokerage house is in Sydney time, which means that we need to change the time to the account holder's residential local time to investigate order submission local time, and classify the market participants into M-types and evening-types (E-types). This step requires consideration of Australian time zones and the daylight-saving time (DST) scheme followed in Australia. An introduction to these two considerations is presented in this section.

The Australian government provides details about Australian time zones and the daylight-saving scheme on its official website. There are three time zones in Australia: Australia Eastern Standard Time ('AEST', equalling to Coordinated Universal Time plus 10 hours (UTC+10)), Australia Central Standard Time (‘ACST’, equalling to Coordinated Universal Time plus 9.5 hours (UTC+9.5)) and Australia Western Standard Time (‘AWST’, equalling to Coordinated Universal Time plus 8 hours (UTC+8)). Queensland, New South Wales (except the town of Broken Hill), Victoria, Tasmania and the Australian Capital Territory fall into AEST; South Australia, the Northern Territory and Broken Hill in New South Wales follow ACST; and Western Australia is on AWST.

However, for half the year, New South Wales, Victoria, South Australia, Tasmania and the Australian Capital Territory follow DST. On the first Sunday in October, at 2 am, clocks in these states are adjusted forward by one hour (to 3 am); and on the first Sunday in April, at 3 am, the clocks are adjusted back one hour (back to 2 am). The DST periods during the order submission sample period of 2004 to 2011 are listed in Table 3.1.

Table 3.1 The DST periods during the sample period

This table contains the DST periods in Australia during the sample period of August 2003 to August 2011.

DST start-date	DST end-date
2004-10-31	2005-03-27
2005-10-30	2006-04-02
2006-10-29	2007-03-25
2007-10-28	2008-04-06
2008-10-05	2009-04-05
2009-10-04	2010-04-04
2010-10-03	2011-04-03
2011-10-02	2012-04-01

3.2.3 Order submission distribution

With consideration of the DST scheme, the order submission times in the orders file were changed to clients’ residential local time. Figure 3.1 and Table 3.2 illustrate the hour distribution of all the orders submitted by the 39,562 accounts during the sample period. It can be inferred that over 40% of all sample orders were submitted within three hours of market open (10:00 to 13:00): almost 20% of the orders were placed in the period 10:00–11:00, nearly 13% during 11:00–12:00, and more than 10% during 12:00–13:00. The next peak hour for order submission was near market close, with more than 10% of orders placed during the hour of 15:00–16:00. Altogether, 71.42% of all the orders in our sample were placed within the ASX's normal trading hours of 10:00 to 16:00. Orders submitted outside normal trading hours are subject to the service provided by the stockbroker; for example, investors can submit conditional orders that can be active for up to 12 months with certain market conditions defined. Such service is also beneficial for investors who might be working during the ASX trading hours which does not allow them to submit orders.

Figure 3.1 Distribution of orders submitted within the 24-hour cycle

This graph illustrates the percentage distribution of the trade orders submitted within each hour across a day by all the accounts during the sample period.

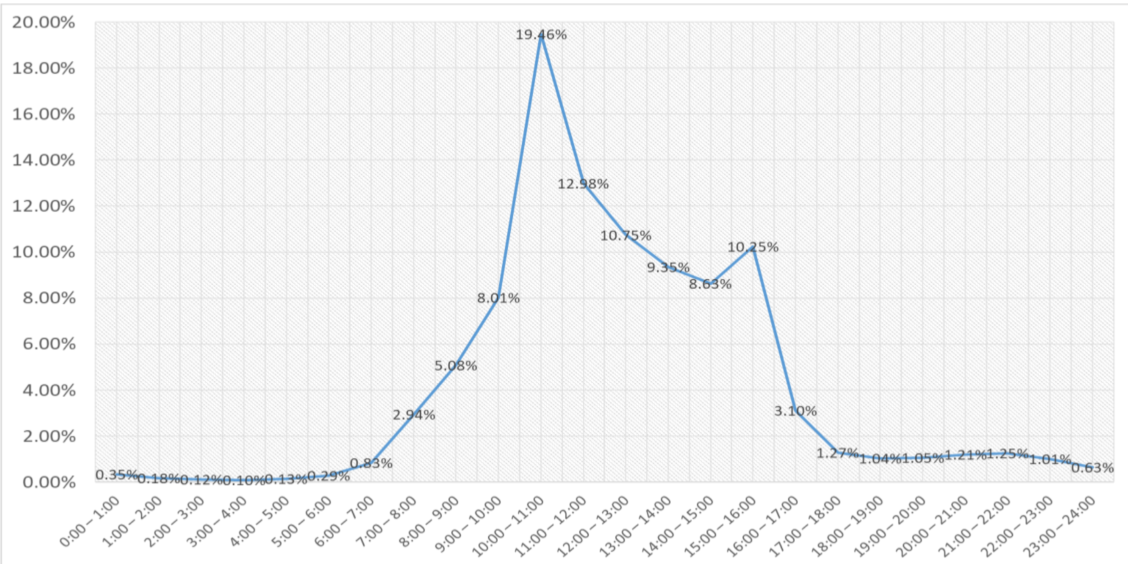


Table 3.2 Distribution of orders submitted within the 24-hour cycle

This table reports the percentage distribution of the trade orders submitted within each hour across a day by all the sample accounts during the sample period.

Time of day	No. of orders submitted	Percentage of all orders (%)
0:00 – 1:00	11,346	0.35
1:00 – 2:00	5,922	0.18
2:00 – 3:00	3,885	0.12
3:00 – 4:00	3,419	0.10
4:00 – 5:00	4,299	0.13
5:00 – 6:00	9,389	0.29
6:00 – 7:00	26,984	0.83
7:00 – 8:00	96,189	2.94
8:00 – 9:00	165,900	5.08
9:00 – 10:00	261,509	8.01
10:00 – 11:00	636,765	19.46
11:00 – 12:00	423,394	12.98
12:00 – 13:00	350,197	10.75
13:00 – 14:00	304,140	9.35
14:00 – 15:00	280,636	8.63
15:00 – 16:00	334,816	10.25
16:00 – 17:00	100,739	3.10
17:00 – 18:00	40,399	1.27
18:00 – 19:00	32,932	1.04
19:00 – 20:00	33,366	1.05
20:00 – 21:00	38,774	1.21
21:00 – 22:00	40,035	1.25
22:00 – 23:00	32,437	1.01
23:00 – 24:00	20,258	0.63

3.3 Methodology

3.3.1 Definition of morning and evening types

We develop a new way to classify investors into M-types and E-types with financial data; an area that has not yet been explored in behavioural finance. Different from the subjective morningness–eveningness questionnaires (MEQs) used in existing studies, in this paper, investors' actual order submission time serves as an objective and reliable representation of investors' M-E in stock markets. The rationale is that, if the order submission times of a certain account are concentrated in the morning, then the account holder is more likely to be an M-type; in comparison, if the orders submitted are more concentrated in the late-afternoon or evening, then the account holder is more likely to be an E-type. The detailed definition is stated in the following sections. To ensure robustness, we use both a continuous Eveningness Score and a categorical M-type and E-type classification to compare the investors' characteristics and behavioural biases.

The traditional MEQs contain several multiple-choice questions, with each response allocated a particular score, to produce a final continuous integer Morningness Score that represents people's diurnal rhythm. Similarly, the first method we use here is to create a continuous 'Eveningness Score' from the accounts' order submission hours. Under this definition, the higher the score is, the later an account's habitual submission time is. That is to say, the E-type is characterised by a high Eveningness Score.

We first delete accounts with orders submitted during 1–5 am, as orders submitted during this period can be either early people who have woken up, or late people who are still awake post-midnight. This choice is supported by Smith et al. (2002), who find that the normal bedtime for E-types is almost 1 am, and the normal wake up time for M-types is 5–6 am. Therefore, we only keep the accounts whose orders are submitted within the normal day–night hours. After this process, 35,203 accounts remained. Scores are then assigned to each hour-period as presented in Table 3.3. The Eveningness Score for each account is then calculated as the average score of all the orders submitted by this account during the sample period. A higher Eveningness Score indicates the account holder's tendency to be an E-type, while a lower Eveningness Score indicates an M-type.

In addition to creating a continuous score, we also undertake a categorical analysis. That is, we classify the account holders into M-type or E-type according to the proportion of orders submitted by them within two periods of the day: one early period and one late period. The two periods were selected using two methods. The first is based on maintaining comparable sample sizes of M-types and E-types using periods before market open and after market close (based on the hour distribution of order submissions presented in Table 3.2). Using this method, we select 5–9 am and 8 pm to midnight as the two periods. The second method uses alertness peak hours, as documented in previous literature; with over 1,700 participants from six countries, Smith et al. (2002) find that M-types' alertness peaks between 8 am and midday, while E-types' alertness peaks during 8 pm to midnight. These time periods are also consistent with Horne et al. (1980) and Adan (1991).

Table 3.3 Scores assigned to each hour during the day for order submission time

This table shows the scores assigned to each hour-period during the day for calculating the accounts' Eveningness Scores.

Time of day	Score assigned
5:00 – 6:00	5
6:00 – 7:00	6
7:00 – 8:00	7
8:00 – 9:00	8
9:00 – 10:00	9
10:00 – 11:00	10
11:00 – 12:00	11
12:00 – 13:00	12
13:00 – 14:00	13
14:00 – 15:00	14
15:00 – 16:00	15
16:00 – 17:00	16
17:00 – 18:00	17
18:00 – 19:00	18
19:00 – 20:00	19
20:00 – 21:00	20
21:00 – 22:00	21
22:00 – 23:00	22
23:00 – 24:00	23
24:00 – 1:00	24

Accordingly, using the first method, we define that if over 50% of orders submitted by an account during the sample period fall within 5–9 am, then the account holder is an M-type; if over 50% of the orders from one account fall between 8 pm and midnight, then the account holder is an E-type. Using the second method, the morning time slot is changed to 8 am to midday and the evening time slot is kept as 8 pm to midnight. Results of the first categorical M-E type definition are presented in detail in Section 3.4. The second categorical M-E definition, used as a robustness test, is presented in Section 3.5. A further two robustness tests are performed using different time periods (5–8 am and 9–midnight, 8–10 am and 8–10 pm).

The categorical definition not only serves as a robustness check, but also helps to address possible questions about the method of defining M-E using the order submission timestamp in the stock market. The first concern can be that market-specific factors, such as trading hours and announcements, can distort the order submission time of investors. In this case, the two time periods to define M-type and E-type investors, 5–9 am and 8 pm to midnight, are outside the ASX's normal trading hours and thus help to eliminate the concern. In addition, in Robustness Test 2 presented in Section 3.5, the narrower timeslots of 5–8 am and 9 pm to midnight are used to ensure that Western Australian M-type investors also have more than 50% of trades submitted before ASX opens. Analysing the stock market and then making trading decisions is an activity that requires mental alertness, and if over 50% of the orders submitted by an investor during 2004–2011 are within the period 5–9 am (or 5–8 am) before market open, it is more likely that the investor is an M-type compared to those submitting orders later in the day.

Another possible concern is that the M-E type derived from the order submission data may not be the real investor type: for example, the investor might be an E-type, but because the person is involved in morning employment, they may submit trading orders in the morning out of convenience. While we do not have the recorded work and life schedules of the investors, this concern is addressed in the literature that investigates M-

E with work schedules. Adan (1991), with a sample of 908 people aged 17–50, finds that morning workers are more likely to be M-types and night workers tend to be E-types; Paine et al. (2006) survey over 2,500 New Zealand adults aged 30–49 and find that night workers are more likely to be definite E-types. Therefore, we see that the 'forced' change of M-E type because of work shifts is unlikely to impact the findings presented in this paper.

3.3.2 M-E against investor characteristics

With the continuous Eveningness Score and categorical M-type and E-type established, we first examine the relationship between investors' M-E and their demographic characteristics; namely, age and gender. For the Eveningness Score, the correlation analysis between the score and the investors' characteristics are examined using the Student's t-test for statistical significance. Further, ordinary linear regression is used to test the Eveningness Score jointly across different possible influencing factors, as follows:

$$Eveningness_i = \alpha_i + \beta_1 * Age_i + \beta_2 * Female_i + \epsilon_{it},$$

$$\text{with } E[\epsilon_{it}] = 0 \text{ and } VAR[\epsilon_i] = \sigma_i^2, \tag{3.1}$$

where $Eveningness_i$ is the average Eveningness Score for account i over the sample period; Age_i is the account holder's age at the last day of the sample period (in years); and $Female_i$ is a dummy variable that equals one if the account holder is female and zero otherwise. Note here that the purpose of Equation 3.1 is to examine the correlation between the investors' M-E and their demographic characterises rather than to establish a model to perfectly predict the Eveningness Score. Following this, a categorical analysis of M-E types is performed, comparing the characteristics of M-type and E-type investors.

3.3.3 Local bias

Local bias is often defined as the difference between the actual weight of local stocks in an account's portfolio and the benchmark portfolio (i.e., the fraction that should have been invested in local stocks if the investor holds a market capitalisation–based portfolio; Baltzer et al., 2015). Specifically, for an account i, the weight of locally headquartered companies in its portfolio on day t is represented by $Local\_Weight_{it}$:

$$Local\_Weight_{it} = \frac{\sum_{s \in Local_t} n_{i,s,t} \, P_{s,t}}{\sum_{s=1}^{N_{it}} n_{i,s,t} \, P_{s,t}}, \tag{3.2}$$

where $Local_t$ are stocks of companies with headquarters located in the same state as the account holder's residential address (based on administrative divisions of states; see Huberman, 2001); N_{it} is the number of stocks held by account i on day t; $n_{i,s,t}$ is the number of shares of stock s held by account i on day t; and $P_{s,t}$ is the close price of stock s on day t.

There are two methods for defining 'local' companies: the first is a distance measurement, where companies within a certain distance of the investor are considered local to that investor; the second uses the administrative divisions of states to determine what is local. Here, we use the administrative divisions of states as the measurement of 'local', as in Huberman (2001). This is because it is not only the headquarter-located region but also the regions of economic interest, such as production sites, that matter to publicly listed firms which are geographically dispersed (Bernile, Delikouras, Korniotis & Kumar, 2019). Huberman (2001) cites different evidence for state-level investment in the familiar phenomenon, such as people's preference for municipal bonds from the state in which they reside. Moreover, retail investors can be swayed in their stock purchasing decisions by the media (Barber & Odean, 2013), such as by local newspaper or broadcast news coverage, which often runs on a state or city basis.

The average holding weight of local stocks in account i across the sample period is then calculated as:

$$Local\_Weight_i = \frac{\sum_{t=1}^{T} Local\_Weight_{i,t}}{\mathrm{T}}, \tag{3.3}$$

where T is the total number of days that account i has portfolio records during the sample period. The local bias measure for account i, $Local\_Bias_i$, is then calculated by subtracting the fraction of locally available market capitalisation of all sample stocks held during the sample period from $Local\_Weight_i$.

3.3.4 Investors' preference for stock market speculation

We use the method in Kumar (2009) to define stocks with lottery-like characteristics (i.e., stocks with negative expected returns and an extremely small probability of a high return). Kumar (2009) considers stock's idiosyncratic volatility, idiosyncratic skewness and price to identify lottery stocks. The idiosyncratic volatility is the residual variance of the fitted model of four factors: excess market return, small market capitalisation minus big; high book-to-market ratio minus low; and a momentum factor. The idiosyncratic skewness is the third moment of the residual of a fitted two-factor model, using the excess market return and its squared value, to the daily stock returns. The lottery stocks for a month are defined as those with above-average idiosyncratic volatility, above-average idiosyncratic skewness and below-average price in the previous six months.

Using the daily holdings of each account from the brokerage dataset, we calculate the lottery stock weight in that account on that day as:

$$Lottery\_Weight_{it} = \frac{\sum_{s \in L_t} n_{i,s,t}\, P_{s,t}}{\sum_{s=1}^{N_{it}} n_{i,s,t}\, P_{s,t}}, \tag{3.4}$$

where $Lottery\_Weight_{it}$ denotes the lottery stock weight of account i on day t; L_t is the lottery stocks identified by Kumar's (2009) method on day t; N_{it} is the number of stocks held by account i on day t; $n_{i,s,t}$ is the number of shares of stock s held by account i on day t; and $P_{s,t}$ is the close price of stock s on day t.

The average lottery stock weight across the sample period of an account is then calculated as:

$$Lottery\_Weight_i = \frac{\sum_{t=1}^{T} Lottery\_Weight_{i,t}}{\mathrm{T}}, \tag{3.5}$$

where T is the total number of days that account i has portfolio records during the sample period.

3.3.5 M-E's impact on investor behaviour

With the continuous Eveningness Score, categorical M-type and E-type, local bias and investors' preference for lottery stocks defined, we proceed to investigate the linkage between M-E and three investor behavioural biases: frequent trading, home bias and stock market speculation. For each of these three behavioural biases, ordinary linear regression analysis is firstly employed to test the joint effect of investors' M-E and characteristics on their trading behaviour, as presented in Equations 3.6, 3.7 and 3.8:

$$Freq_i = \alpha_i + \beta_1 * Eveningness_i + \beta_2 * Age_i + \beta_3 * Female_i + \beta_4 * Order\_V_i + \beta_5 * Price_i + \beta_6 * N_i + \beta_7 * RS_i + \epsilon_{it},$$

$$\text{with } \mathrm{E}[\epsilon_{it}] = 0 \text{ and } \mathrm{VAR}[\epsilon_i] = \sigma_i^2, \tag{3.6}$$

where $Freq_i$ is the total number of trades of account i during the sample period (October 2010 – August 2012); Age_i is the account holder's age on the last day of the sample period (in years); $Female_i$ is a dummy variable that equals one if the account holder is female and zero otherwise; $Order\_V_i$ indicates the average order value by account i; $Price_i$ stands for the average stock price traded by account i; N_i is the daily average number of stocks held by account i, as a proxy for account diversification (Chen, Kim, Nofsinger & Rui, 2007); RS_i is another dummy variable that equals one if the account holder always trades in round volumes (multiples of ten), and zero otherwise; and $Eveningness_i$ is the average Eveningness Score for account i over the period December 2004 – August 2011. Note here that we use data from 2004 to 2011 to define M-E, assuming that M-E is stable over time, and then apply it to the investors' trades data for the period 2010–2012. Merging the two datasets results in a final sample of 14,359 accounts using the continuous Eveningness Score method, and 902 accounts when applying the categorical M-E definition.

$$Local\_Bias_i = \alpha_i + \beta_1 * Eveningness_i + \beta_2 * Age_i + \beta_3 * Female_i + \beta_4 * Freq_i + \beta_5 * Order\_V_i + \beta_6 * Price_i + \beta_7 * N_i + \beta_8 * RS_i + \epsilon_{it},$$

$$\text{with E } [\epsilon_{it}] = 0 \text{ and VAR } [\epsilon_i] = \sigma_i^2, \qquad (3.7)$$

where $Local\_Bias_i$ is the average local bias for account i over the sample period (October 2010 – August 2012); and the other variables are as defined previously. Merging the three datasets results in a final sample of 4,563 accounts for the continuous Eveningness Score method, and 684 accounts for the categorical M-E definition.

$$Lottery\_Weight_i = \alpha_i + \beta_1 * Eveningness_i + \beta_2 * Age_i + \beta_3 * Female_i + \beta_4 * Freq_i + \beta_5 * Order\_V_i + \beta_6 * Price_i + \beta_7 * N_i + \beta_8 * RS_i + \epsilon_{it},$$

$$\text{with E } [\epsilon_{it}] = 0 \text{ and VAR } [\epsilon_i] = \sigma_i^2, \qquad (3.8)$$

where $Lottery\_Weight_i$ is the average lottery stock weight of account i over the sample period (October 2010 – August 2012), and the other variables are as defined previously. Merging the three datasets gives in a final sample of 4,563 accounts for the continuous Eveningness Score method, and 684 accounts for the categorical M-E definition.

Following the multivariate analysis, for each of these three behavioural biases, the pair-wise correlation between the bias and investors' Eveningness Score and characteristics are examined. Finally, the categorical analysis is carried out to compare the presence of each type of investor behavioural bias in M- and E-type investors.

3.4 Results

3.4.1 M-E against investor characteristics

This section presents the results for the linkage between M-E and investors' characteristics. These linkages are shown through the correlation table between Eveningness Score and investors' characteristics, the linear regression analysis results for Equation 3.1, and the categorical analysis for M-type and E-type investors.

Table 3.4 shows the pair-wise correlations between the continuous Eveningness Score and investors' characteristics. It is clear that Eveningness Score is negatively correlated with investor age, and the effect is statistically significant; that is, older investors are more likely to have a lower Eveningness Score and be M-types. The correlation between gender and the Eveningness Score is not statistically significant. The regression results of Equation 3.1, presented in Table 3.5, indicate findings consistent with those in Table 3.4. When considering account holders' age and gender together, both variables are negatively correlated with Eveningness Score, but only age's effect is statistically significant.

Table 3.4 Correlation matrix of investors' Eveningness Score, gender and age

This table reports the correlation matrix of the continuous Eveningness Score and the variables for investors' characteristics. The *Eveningness Score* for each account is calculated as the average score of the order submission hours of an account over the sample period; *Age* is the age of the account owner at the last day of the sample period (9 August 2011); *Gender* is a dummy variable that takes the value of one for female and zero for male. P-values are presented and **(*) indicates statistical significance at the 5% (10%) level.

	Eveningness Score	Age	Gender
Eveningness Score	1		
Age	-0.0144** (0.0070)	1	
Gender	-0.0044 (0.4044)	0.0760** (<0.0001)	1

Table 3.5 Impact of investors' characteristics on Eveningness Score

This table reports the estimates from the linear regression: $Eveningness_i = \alpha_i + \beta_1 Age_i + \beta_2 Female_i + \epsilon_{it}$. The dependent variable $Eveningness_i$ is the Eveningness Score for account i over the sample period; Age_i is the account holder's age at the last day of the sample period (in years); $Female_i$ is a dummy variable that equals one if the account holder is female and zero for male. Student's t-test is performed to test for statistical significance, and p-values are presented; **(*) indicates statistical significance at the 5% (10%) level. N is the number of observations. R^2 is the adjusted R-squared.

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	12.7109	0.0372	341.57	<0.0001**
Age	-0.0021	0.0008	-2.639	0.0083**
Female	-0.0153	0.0242	-0.631	0.5282
N=35203, R^2=0.0002				

The second method to classify investors' M-E is a categorical definition. As stated in Section 3.3, here we report the results of the following categorical M-E type definition in detail: if more than 50% of all the orders submitted by an account during the sample period fall between 5–9 am, then the account holder is an M-type; if over 50% of the account orders fall between 8 pm and midnight, then the account holder is an E-type. By changing the two timeslots and the cut-off percentages, robustness tests are performed, as discussed in Section 3.5.

Table 3.6 summarises the account holders' average age and percentage of females for M-type and E-type investors under the categorical definition. The group difference is tested using the Student's t-test for statistical significance. It shows that M-type investors are older than E-types on average, but the age difference is not statistically significant. The gender effect is also not statistically significant. Overall, the two different measurements of M-E indicate that as people get older, they tend to be M-type investors. This finding is consistent with those in Adan (1992), Chelminski et al. (1997), Paine et al. (2006) and Merikanto et al. (2012).

Table 3.6 Account holders' age and gender under categorical M-E definition

This table presents the comparison between the categorical M-E types. The account holder is an M-type if more than 50% of all the orders submitted by the account during the sample period fall between 5 and 9 am, or an E-type if over 50% of the account orders fall between 8 pm and midnight. *Age* is the account holder's age at the last day of the sample period (in years). Student's t-test is performed to test for the statistical significance of group difference, and p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Total Sample	**Gender (% of females)**	**Age**
Observation	2,276	33.57	44.69
M-types	1,253	32.72	44.85
E-types	1,023	34.60	44.55
M-type and E-type group difference (p-value)		-1.88 (p-value = 0.3450)	0.30 (p-value =0.5750)

3.4.2 M-E's impact on investor behaviour

We first conduct the ordinary linear regressions as presented in Equations 3.6, 3.7 and 3.8 to jointly test the impact of investors' M-E and other characteristics on their trading frequency, local bias and preference for lottery stocks. The results are presented in Table 3.7.

The total number of trades by investors are used here to reflect trading frequency. The regression results of Equation 3.6 indicate that when considering account holders' M-E, age and gender together with their trading features, trading frequency decreases with Eveningness Score. That is, E-type investors tend to submit orders less frequently, or M-type investors are more frequent traders on average, with the effect being statistically significant.

Table 3.7 Impact of eveningness on trading frequency, local bias and preference for lottery stocks

This table reports the estimates from the ordinary linear regression of Equations 3.6, 3.7 and 3.8.
Equation 3.6:
$Freq_i = \alpha_i + \beta_1 * Eveningness_i + \beta_2 * Age_i + \beta_3 * Female_i + \beta_4 * Order\_V_i + \beta_5 * Price_i + \beta_6 * N_i + \beta_7 * RS_i + \epsilon_{it}$. The dependent variable $Freq_i$ is the total number of trades of account i over the sample period (2010–2012); Age_i is the account holder's age at the last day of the sample period (in years); $Female_i$ is a dummy variable that equals one if the account holder is female and zero for male; $Order\_V_i$ indicates the average order value (in thousands of AUD) by account i; $Price_i$ stands for the average stock price traded by account i; N_i is the daily average number of stocks held by account i; RS_i is another dummy variable that equals one if the account holder always trades in round volumes (multiples of ten), and zero otherwise; and $Eveningness_i$ is the average Eveningness Score for account i over the period 2004–2011.
Equation 3.7:
$Local\_Bias_i = \alpha_i + \beta_1 * Eveningness_i + \beta_2 * Age_i + \beta_3 * Female_i + \beta_4 * Freq_i + \beta_5 * Order\_V_i + \beta_6 * Price_i + \beta_7 * N_i + \beta_8 * RS_i + \epsilon_{it}$.
The dependent variable $Local\_Bias_i$ is the average local bias for account i over the sample period (2010–2012), in unit of percentage; $Age_i, Female_i, Freq_i, Order\_V_i, Price_i, N_i$, $Eveningness_i$ are defined in the same way as in Equation 3.6.
Equation 3.8:
$Lottery\_Weight_i = \alpha_i + \beta_1 * Eveningness_i + \beta_2 * Age_i + \beta_3 * Female_i + \beta_4 * Freq_i + \beta_5 * Order\_V_i + \beta_6 * Price_i + \beta_7 * N_i + \beta_8 * RS_i + \epsilon_{it}$.
The dependent variable $Lottery\_Weight_i$ is the average lottery stock weight of account i over the sample period (2010–2012); Other variables are defined as previously.
Student's t-test is performed to test for statistical significance, and p-values are presented; **(*) indicates statistical significance at the 5% (10%) level. R^2 is the adjusted R-squared.

	Trading Freq	Local Bias	Lottery Stock Weight
Intercept	37.6592**	31.6351**	19.4339**
	(<0.0001)	(<0.0001)	(<0.0001)
Eveningness	-1.8613**	-1.5014**	-0.3216**
	(<0.0001)	(<0.0001)	(0.0052)
Age	0.1030**	-0.0168	-0.0605**
	(0.0131)	(0.6904)	(0.0009)
Female	-1.7390	-1.2649	-1.6987**
	(0.1538)	(0.2838)	(0.0009)
Order_V	0.4457**	0.0329	-0.0134
	(<0.0001)	(0.2675)	(0.2983)
Price	-0.3004**	0.0199	-0.2433**
	(<0.0001)	(0.5637)	(<0.0001)
N	0.9925**	-0.6046**	-0.8557**
	(<0.0001)	(0.0060)	(<0.0001)
RS	-16.9204**	0.5765	1.4843**
	(<0.0001)	(0.6102)	(0.0025)
Freq		-0.0777**	-0.0041
		(0.0013)	(0.6971)
Observations	14359	4563	4563
R^2	0.0396	0.0125	0.0970

For local bias, we find that when tested jointly, people holding more stocks are significantly less local-biased, which is consistent with portfolio diversification theory. More importantly, as Eveningness Score increases, account holders become less local-biased, on average. That is, M-type investors are generally more local-biased, and this effect is statistically significant. Age and gender are unrelated factors according the regression results.

In terms of investors' preference for lottery stocks, it can be inferred that M-type, younger and male investors generally hold more lottery stocks in their portfolios compared to E-type, older and female investors, and these effects are statistically significant. In addition, the negative coefficients for average trade order value, average stock price traded and average number of stocks—the three variables that can proxy investors' wealth level (Frino, Lepone & Wright, 2015)—indicate that wealthier investors have less preference for stock market speculation.

The correlation between account holders' behavioural biases, their Eveningness Score and characteristics is presented in Table 3.8. Panel A of Table 3.8 indicates that trading frequency is significantly affected by investors' M-E. E-type investors tend to trade less frequently. Panel B of Table 3.8 shows that Eveningness Score and number of stocks held by account holders are significantly negatively correlated with local bias, confirming that M-type investors are more local-biased on average, and investors with more stocks in their portfolios are generally less local-biased. Finally, Panel C of Table 3.8 provides evidence that as Eveningness Score increases, preference for lottery stocks decreases. Female and older people also have less preference for lottery stocks. All the above correlations are statistically significant.

The comparison of M- and E-types' trading frequency, local bias and preference for lottery stocks under the categorical M-E definition is presented in Table 3.9.

Table 3.8 Correlation matrix of investors' behavioural biases, Eveningness Score, gender and age

This table reports the correlation matrix of investors' trading frequency, local bias and preference for lottery stocks against their continuous Eveningness Score and characteristics. The *Eveningness Score* for each account is calculated as the average score of the order submission hours of this account over the sample period of 2004–2011; *Gender* is a dummy variable that takes the value of one for female and zero for male. For Panel A, *Age* is the age of the account owner at the last day of the sample period (31 August 2012); *Freq* is the total number of trades by the account over the sample period of 2010-2012; *Order_V* is the average order value by the account; *Price* is the average stock price traded by the account; *N* is the daily average number of stocks held by this account; *RS* is another dummy variable that equals one if the account holder always trades in round volumes (multiples of ten), and zero otherwise. For Panel B, the *local bias* for each account is calculated as the difference between the actual local investments and corresponding market portfolio during 2010–2012; Other variables are defined in the same way as in Panel A. For Panel C, the *lottery stocks holding weight* for each account is calculated as the daily average during the sample period of 2010–2012. Lottery stocks are defined as in Kumar (2009), as stocks with an above-average idiosyncratic volatility, idiosyncratic skewness and below average stock price in the previous six months. Other variables are defined in the same way as in Panel A. P-values are presented and **(*) indicates statistical significance at the 5% (10%) level.

Panel A	**Freq**	**Eveningness**	**Age**	**Gender**	**Order_V**	**Price**	**N**	**RS**
Freq	1							
Eveningness	-0.0629** (<0.0001)	1						
Age	0.0352** (<0.0001)	-0.0241** (0.0041)	1					
Gender	-0.0202** (0.0156)	0.0021 (0.8010)	0.1012** (<0.0001)	1				
Order_V	0.0863** (<0.0001)	-0.0586** (<0.0001)	0.1064** (<0.0001)	-0.0138* (0.0981)	1			
Price	-0.0381** (<0.0001)	0.0412** (<0.0001)	0.0057 (0.4990)	0.0902** (<0.0001)	0.1753** (<0.0001)	1		
N	0.1019** (<0.0001)	0.0380** (<0.0001)	0.2038** (<0.0001)	0.0256** (0.0021)	-0.0323** (0.0001)	-0.0001 (0.9930)	1	
RS	-0.1253** (<0.0001)	0.0025 (0.7640)	0.1137** (<0.0001)	0.0411** (<0.0001)	0.0026 (0.7530)	-0.0946** (<0.0001)	-0.0972** (<0.0001)	1

Table 5.17 Continued

Panel B	Local Bias	Eveningness	Age	Gender	Order_V	Price	N	RS	Freq
Local Bias	1								
Eveningness	-0.0857** (<0.0001)	1							
Age	-0.0057 (0.7018)	-0.0486** (0.0010)	1						
Gender	-0.0145 (0.3284)	-0.0118 (0.4263)	0.0712** (<0.0001)	1					
Order_V	0.0230 (0.1196)	-0.0620** (<0.0001)	0.1075** (<0.0001)	-0.0169 (0.2546)	1				
Price	0.0023 (0.8770)	0.0233 (0.1162)	0.0026 (0.8589)	0.0789** (<0.0001)	0.1487** (<0.0001)	1			
N	-0.0552** (0.0002)	0.0931** (<0.0001)	0.0942** (<0.0001)	0.0602** (<0.0001)	-0.0678** (<0.0001)	0.0921** (<0.0001)	1		
RS	0.0134 (0.3668)	-0.0015 (0.9212)	0.1722** (<0.0001)	0.0213 (0.1507)	0.0342** (0.0209)	-0.1497** (<0.0001)	-0.0640** (<0.0001)	1	
Freq	-0.0456** (0.0021)	-0.0452** (0.0022)	0.0384** (0.0097)	-0.0292** (0.0489)	0.0752** (<0.0001)	0.0182 (0.2202)	0.0482** (0.0011)	-0.0979** (<0.0001)	1

Table 5.17 Continued

Panel C	Lottery Stocks	Eveningness	Age	Gender	Order_V	Price	N	RS	Freq
Lottery Stocks	1								
Eveningness	-0.0538** (0.0003)	1							
Age	-0.0568** (0.0001)	-0.0486** (0.0010)	1						
Gender	-0.0756** (<0.0001)	-0.0118 (0.4263)	0.0712** (<0.0001)	1					
Order_V	-0.0431** (0.0036)	-0.0620** (<0.0001)	0.1075** (<0.0001)	-0.0169 (0.2546)	1				
Price	-0.2641** (<0.0001)	0.0233 (0.1162)	0.0026 (0.8589)	0.0789** (<0.0001)	0.1487** (<0.0001)	1			
N	-0.1648** (<0.0001)	0.0931** (<0.0001)	0.0942** (<0.0001)	0.0602** (<0.0001)	-0.0678** (<0.0001)	0.0921** (<0.0001)	1		
RS	0.0788** (<0.0001)	-0.0015 (0.9212)	0.1722** (<0.0001)	0.0213 (0.1507)	0.0342** (0.0209)	-0.1497** (<0.0001)	-0.0640** (<0.0001)	1	
Freq	-0.0200 (0.1758)	-0.0452** (0.0022)	0.0384** (0.0097)	-0.0292** (0.0489)	0.0752** (<0.0001)	0.0182 (0.2202)	0.0482** (0.0011)	-0.0979** (<0.0001)	1

Table 3.9 Trading frequency, tendency towards local bias and preference for lottery stocks under categorical M-E definition

This table reports the differences in the levels of three investment biases between M-types and E-types under the categorial M-E definition. The account holder is an M-type if more than 50% of all the orders submitted by the account during the sample period fall between 5 and 9 am, or an E-type if over 50% of the account orders fall between 8 pm and midnight. *Trading Frequency* for each account is calculated as the total number of trades of the account during the sample period. The *local bias* for each account is calculated as the difference between the actual local investments and corresponding market portfolio. *Lottery Stock Weight* for each account is calculated as the daily average weight of lottery stocks in the account portfolio during the sample period. M-type and E-type investors are classified by each account's order submission time during the day. Student's t-test is performed to test for statistical significance, and p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

Panel A	**No. of accounts**	**Trading Frequency**	**t-statistics**	**p-value**
M-types	516	19.15	8.8552**	<0.0001
E-types	386	7.25	13.8970**	<0.0001
M-E type group difference		11.90	5.3510**	<0.0001
Panel B	**No. of accounts**	**Local Bias**	**t-statistics**	**p-value**
M-types	354	28.10%	12.6640**	<0.0001
E-types	330	11.01%	5.6315**	<0.0001
M-E type group difference		17.09%	5.7813**	<0.0001
Panel C	**No. of accounts**	**Lottery Stock Weight**	**t-statistics**	**p-value**
M-types	354	7.59%	7.8913**	<0.0001
E-types	330	3.59%	5.7480**	<0.0001
M-E type group difference		4.00%	3.4842**	0.0005

Panel A in Table 3.9 shows that on average, M-type investors have approximately 20 trades executed over the sample period, while E-type investors executed less than 10 trades. This difference is statistically significant. Panel B of Table 3.9 indicates that both M-type and E-type investors present a local bias tendency, with the local investment in their portfolio exceeding the proportion of local firms in the market portfolio by 28.10% and 11.01%, respectively. M-type investors' excess local stock weight is more than twice that of E-type investors, and the difference is statistically significant. For the categorical M-E definitions, the comparison of the preference of M- and E-types for lottery stocks is presented in Panel C of Table 3.9. It shows that, on average, M-type investors hold 7.59% lottery stocks in their portfolios, while E-types only hold 3.59%. The difference between these two groups of 4% is both statistically and economically significant.

To summarise, the results indicate that, in general, M-type investors are more frequent traders in the stock market. Although E-type investors are more sensation-seeking (Adan et al., 2010; Tonetti et al., 2010) and this can lead them to trade more frequently according to Grinblatt and Keloharju (2009), the activeness and positiveness of M-type investors (Antúnez et al., 2015; Muro et al., 2009) seem to outweigh in the trading frequency effect.

Further, M-type investors have a greater tendency to be local-biased. Therefore, M-types' greater conscientiousness and goal-orientation (Randler, 2008; Tonetti et al., 2009) seem to have a greater effect in motivating them to tilt their portfolio towards local stocks if they are in possession of advantageous information about these stocks than examining more parts of the stock market beyond their familiar or local stocks to diversify their portfolios. Another explanation is that M-types are less novelty-seeking (Adan et al., 2010) and tend to avoid ambiguity, which leads to investment in stocks with which they are familiar even when they don't have advantageous information about these stocks.

M-type investors also have a greater preference for lottery stocks. According to Han and Kumar (2013), higher lottery stock holding indicates that an investor is more speculative. Therefore, M-type investors generally participate more in stock market speculation activity than do E-types. This observation can be explained by that M-types are more positive, optimistic (Antúnez et al., 2015) and active in general activities (Muro et al., 2009).

3.5 Robustness tests

As discussed in Section 3.3, there are two main methods to define the categorical M-type and E-type. The first, for which the results were presented in Section 3.4, is based around ensuring comparable sample sizes of M- and E-types, conditional on confirming that the sample allocations do not conflict with clinical study findings for the peak-performance periods of each type. The second method follows Smith et al. (2002), who find that M-types' alertness peaks between 8 am and midday, while for E-types, peak alertness is between 8 pm and midnight. Therefore, Robustness Test 1 is based on Smith et al. (2002) and defines that if more than 60% of an investors' orders are submitted between 8 am and midday, then this investor is an M-type; if over 60% of the account orders are submitted between 8 pm and midnight, then the investor is an E-type. Another two robustness tests are conducted, with the definitions of M-type and E-type made more stringent by narrowing the timeslots to 5–8 am and 9 pm to midnight (Robustness Test 2), and 8–10 am and 8–10 pm (Robustness Test 3), respectively. The narrower timeslots of 5–8 am and 9 pm to midnight in Robustness Test 2 are used to ensure that Western Australian M-type (E-type) investors also have more than 50% of trades submitted before market opens (after market closes). Due to the narrower timeslots, the sample sizes for M- and E-type investors in Robustness Test 2 are considerably reduced, and we use bootstrapping–the process of resampling with replacement–to increase the sample sizes to 100 times of the original ones. The definition of M-type and E-type under each robustness test are as follows.

Robustness Test 1: If more than 60% of all orders submitted by an account during the sample period fall between 8 am and midday then the account holder is an

M-type, and if over 60% of the account orders fall between 8 pm and midnight then the account holder is an E-type.

Robustness Test 2: If more than 50% of all orders submitted by an account during the sample period fall within 5–8 am then the account holder is an M-type, and if over 50% of the account orders fall between 9 pm and midnight then the account holder is an E-type.

Robustness Test 3: If more than 50% of all orders submitted by an account during the sample period fall within 8–10 am then the account holder is an M-type, and if over 50% of the account orders fall within 8–10 pm then the account holder is an E-type.

For each M-E definition, investor characteristics are examined, and the comparison between the M-type and E-type investors' trading frequency, local bias and preference for lottery stocks is examined. The investors' characteristic summary statistics for all three robustness tests are presented in Table 3.10, the trading frequency results across the three tests are presented in Table 3.11, the local bias results are presented in Table 3.12, and the preference for lottery stocks results are presented in Table 3.13. The bootstrapping results for Robustness Test 2 are also presented.

The results from these robustness tests are consistent with those presented in Section 3.4. The age effect is still present but is not statistically significant. In terms of trading frequency, M-types are still frequent traders compared to E-types, with the number of trades by a typical M-type investor being more than three times higher than for E-type investors (the difference is statistically significant). As for local bias, M-types have a greater tendency to invest in local companies than do E-type investors (again, the difference is statistically significant). M-type investors have a significantly higher preference for stock market speculation, having a greater weight of lottery stocks in their portfolios.

Table 3.10 Robustness tests: Account holders' age and gender under categorical M-E definition

This table presents the comparison between the categorical M-E types under three robustness tests. In Robustness Test 1, an investor in defined as an M-type if more than 60% of his/her orders are submitted between 8 am and midday; if over 60% of the account orders are submitted between 8 pm and midnight, then the investor is an E-type. In Robustness Test 2, if more than 50% of all the orders submitted by an account during the sample period fall between 5–8 am then the account holder is an M-type, and if over 50% of the account orders fall between 9 pm and midnight, then the account holder is an E-type. For Robustness Test 3, if more than 50% of all the orders submitted by an account during the sample period fall within 8–10 am then the account holder is an M-type; if over 50% of the account orders fall between 8–10 pm then the account holder is an E-type. *Age* is the account holder's age at the last day of the sample period (in years). Student's t-test is performed to test for the statistical significance of group difference, and p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	No. of accounts	**Gender (% of females)**	**Age (years)**
Robustness Test 1			
M-types	7957	30.94	44.98
E-types	570	35.44	44.68
M-E type group difference		-4.50**	0.30
(p-value)		(0.0303)	(0.5886)
Robustness Test 2			
M-types	271	34.32	44.42
E-types	506	32.41	44.08
M-E type group difference		1.91	0.34
(p-value)		(0.5927)	(0.719)
Robustness Test 3			
M-types	1277	33.91	46.00
E-types	409	38.63	44.68
M-E type group difference		-4.72*	1.32*
(p-value)		(0.0864)	(0.0932)

Table 3.11 Robustness tests: Trading frequency under categorical M-E definition

This table presents the comparison between the categorical M-E types under three robustness tests. In Robustness Test 1, an investor in defined as an M-type if more than 60% of his/her orders are submitted between 8 am and midday; if over 60% of the account orders are submitted between 8 pm and midnight, then the investor is an E-type. In Robustness Test 2, if more than 50% of all the orders submitted by an account during the sample period fall between 5–8 am then the account holder is an M-type, and if over 50% of the account orders fall between 9 pm and midnight, then the account holder is an E-type. For Robustness Test 3, if more than 50% of all the orders submitted by an account during the sample period fall within 8–10 am then the account holder is an M-type; if over 50% of the account orders fall between 8–10 pm then the account holder is an E-type. *Trading frequency* is defined as the number of trades by the account holder during the sample period. M-type and E-type investors are classified by each account's order submission time during the day. Student's t-test is performed to test for statistical significance, and p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	No. of accounts	Trading frequency	t-statistic	p-value
Robustness Test 1				
M-types	3090	21.23	15.1760**	<0.0001
E-types	211	6.09	12.8230**	<0.0001
M-E type group difference		15.14	10.2490**	<0.0001
Robustness Test 2				
M-types	89	10.92	5.7508**	<0.0001
E-types	179	6.95	9.1746**	<0.0001
M-E type group difference		3.97	1.9424*	0.0545
Robustness Test 2 (bootstrap resampling)				
M-types	8900	10.78	57.185**	<0.0001
E-types	17900	7.06	90.799**	<0.0001
M-E type group difference		3.72	18.246**	<0.0001
Robustness Test 3				
M-types	478	11.89	9.5318**	<0.0001
E-types	140	5.71	7.9491**	<0.0001
M-E type group difference		6.18	4.2946**	<0.0001

Table 3.12 Robustness tests: Local Bias under Categorical M-E Definition

This table presents the comparison between the categorical M-E types under three robustness tests. In Robustness Test 1, an investor in defined as an M-type if more than 60% of his/her orders are submitted between 8 am and midday; if over 60% of the account orders are submitted between 8 pm and midnight, then the investor is an E-type. In Robustness Test 2, if more than 50% of all the orders submitted by an account during the sample period fall between 5–8 am then the account holder is an M-type, and if over 50% of the account orders fall between 9 pm and midnight, then the account holder is an E-type. For Robustness Test 3, if more than 50% of all the orders submitted by an account during the sample period fall within 8–10 am then the account holder is an M-type; if over 50% of the account orders fall between 8–10 pm then the account holder is an E-type. The *local bias* for each account is calculated as the difference between the actual local investments and corresponding market portfolio. M-type and E-type investors are classified by each account's order submission time during the day. Student's t-test is performed to test for statistical significance, and p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	No. of accounts	Local bias (%)	t-statistics	p-value
Robustness Test 1				
M-types	2045	14.22	16.9260**	<0.0001
E-types	194	11.23	4.4125**	<0.0001
M-E type group difference		2.99	1.1183	0.2646
Robustness Test 2				
M-types	83	24.07	5.5460**	<0.0001
E-types	173	11.22	4.1879**	<0.0001
M-E type group difference		12.85	2.5200**	0.0128
Robustness Test 2 (bootstrap resampling)				
M-types	8300	24.73	57.180**	<0.0001
E-types	17300	11.35	42.367**	<0.0001
M-E type group difference		13.38	26.289**	<0.0001
Robustness Test 3				
M-types	372	24.76	11.9340**	<0.0001
E-types	134	14.00	4.4284**	<0.0001
M-E type group difference		10.76	2.8465**	0.0048

Table 3.13 Robustness tests: Preference for lottery stocks under categorical M-E definition

This table presents the comparison between the categorical M-E types under three robustness tests. In Robustness Test 1, an investor in defined as an M-type if more than 60% of his/her orders are submitted between 8 am and midday; if over 60% of the account orders are submitted between 8 pm and midnight, then the investor is an E-type. In Robustness Test 2, if more than 50% of all the orders submitted by an account during the sample period fall between 5–8 am then the account holder is an M-type, and if over 50% of the account orders fall between 9 pm and midnight, then the account holder is an E-type. For Robustness Test 3, if more than 50% of all the orders submitted by an account during the sample period fall within 8–10 am then the account holder is an M-type; if over 50% of the account orders fall between 8–10 pm then the account holder is an E-type. *Lottery Stock Weight* for each account is calculated as the daily average weight of lottery stocks in the account portfolio during the sample period. M-type and E-type investors are classified by each account's order submission time during the day. Student's t-test is performed to test for statistical significance, and p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	No. of accounts	**Lottery Stock Weight (%)**	**t-statistics**	**p-value**
Robustness Test 1				
M-types	2045	6.62	17.3290**	<0.0001
E-types	194	3.61	4.6869**	<0.0001
M-E type group difference		3.01	3.5120**	0.0005
Robustness Test 2				
M-types	83	7.31	3.7364**	0.0003
E-types	173	3.54	4.1785**	<0.0001
M-E type group difference		3.77	1.7658*	0.0801
Robustness Test 2 (bootstrap resampling)				
M-types	8300	7.20	37.710**	<0.0001
E-types	17300	3.47	41.878**	<0.0001
M-E type group difference		3.73	17.933**	<0.0001
Robustness Test 3				
M-types	372	6.97	7.9862**	<0.0001
E-types	134	3.29	3.4632**	<0.0001
M-E type group difference		3.68	2.8496**	0.0046

Following the robustness tests using the categorical M-E definition, the state in which investors reside is further added to the OLS regressions of Equations 3.6, 3.7 and 3.8 as one explanatory variable to examine the robustness of OLS regression findings when controlling for location information. The results are presented in Table 3.14.

Table 3.14 Impact of eveningness on trading frequency, local bias and preference for lottery stocks (with state effect)

This table reports the estimates from the ordinary linear regressions: $Freq_i = \alpha_i + \beta_1 Eveningness_i + \beta_2 Age_i + \beta_3 Female_i + \beta_4 Order\_V_i + \beta_5 Price_i + \beta_6 N_i + \beta_7 RS_i + \beta_8 State_i + \beta_9 Eveningness_i * State_i + \epsilon_{it}$. The dependent variable $Freq_i$ is the total number of trades of account i over the sample period (2010–2012); Age_i is the account holder's age at the last day of the sample period (in years); $Female_i$ is a dummy variable that equals one if the account holder is female and zero for male; $Order\_V_i$ indicates the average order value (in thousands of AUD) by account i; $Price_i$ stands for the average stock price traded by account i; N_i is the daily average number of stocks held by account i; RS_i is another dummy variable that equals one if the account holder always trades in round volumes (multiples of ten), and zero otherwise; $State_i$ is the state of the account holder's residential address; and $Eveningness_i$ is the average Eveningness Score for account i over the period 2004–2011.

$Local\_Bias_i = \alpha_i + \beta_1 Eveningness_i + \beta_2 Age_i + \beta_3 Female_i + \beta_4 Freq_i + \beta_5 Order\_V_i + \beta_6 Price_i + \beta_7 N_i + \beta_8 RS_i + \beta_9 State_i + \beta_{10} Eveningness_i * State_i + \epsilon_{it}$.
The dependent variable $Local\_Bias_i$ is the average local bias for account i over the sample period (2010–2012), in unit of percentage; $Age_i, Female_i, Freq_i, Order\_V_i, Price_i, N_i$, $Eveningness_i$ are defined in the same way as in Equation 3.6.

$Lottery\_Weight_i = \alpha_i + \beta_1 Eveningness_i + \beta_2 Age_i + \beta_3 Female_i + \beta_4 Freq_i + \beta_5 Order\_V_i + \beta_6 Price_i + \beta_7 N_i + \beta_8 RS_i + \beta_9 State_i + \beta_{10} Eveningness_i * State_i + \epsilon_{it}$.
The dependent variable $Lottery\_Weight_i$ is the average lottery stock weight of account i over the sample period (2010–2012); Other variables are defined as previously.
Student's t-test is performed to test for statistical significance, and **(*) indicates statistical significance at the 5% (10%) level. R^2 is the adjusted R-squared.

	Trading Freq	**Local Bias**	**Lottery Stock Weight**
Intercept	22.3750	-1.6766	19.6100*
Eveningness	-1.0708	0.1814	-0.2562
Age	0.1005*	0.0116	-0.0618**
Female	-1.8534	-1.6578	-1.6570**
Order_V	0.4387**	0.0392	-0.0110
Price	-0.3218**	0.0722**	-0.2365**
N	0.9943**	-0.6436**	-0.8696**
RS	-16.9236**	0.3572	1.5050**
Freq	-	-0.0594**	-0.0024
State_NSW	27.1995	11.4070	-7.5870
State_NT	20.8587	57.7797	-25.0400
State_QLD	12.0028	11.6293	2.6140
State_SA	23.4612	2.5636	-4.9470
State_TAS	-9.7845	13.0791	-2.0470
State_VIC	28.1838	-3.8567	-1.6170
State_WA	12.2167	39.6499	3.8690
Eveningness*NSW	-1.4696	-0.4771	0.4070
Eveningness*NT	-1.3155	-4.3720	1.7110
Eveningness*QLD	-0.7229	-0.4257	-0.2590
Eveningness*SA	-1.2669	0.4388	0.3307
Eveningness*TAS	0.9506	-0.6350	0.3895
Eveningness*VIC	-1.6106	0.5197	0.0249
Eveningness*WA	-0.8377	-0.1611	-0.2555
Observations	14359	4563	4563
R^2	0.0418	0.1196	0.1040

The baseline for the OLS regressions with the categorical variable indicating the state in which investors reside is the state of Australian Capital Territory (ACT). Here we take the regression results for trading frequency as an example to illustrate the interpretation of the coefficients: the coefficient of -1.0708 for the variable *Eveningness* is for ACT, meaning that a typical investor residing in ACT executes 10 less trades as the Eveningness Score increases by 10 points; the coefficient of 27.1995 for the variable *State_NSW* indicates that on average, the investors residing in New South Wales (NSW) trade 27 more trades times than those in ACT; and the coefficient of -1.4696 for the interaction term *Eveningness*NSW* indicates that for investors residing in NSW, every 10 points increase in the Eveningness Score is associated with a change of (-1.0708-1.4696)*10 in the number of trades executed.

The regression results indicate that as Eveningness Score increases, the investors' trading frequency decreases for all states, and the account holders in NSW, North Territory (NT), Queensland (QLD), and Tasmania (TAS) become less local-biased while those residing in ACT, Southern Australia (SA), Victoria (VIC), and Western Australia (WA) become more local-biased. As for investors' preference for lottery stocks, investors residing in ACT, QLD, VIC, and WA generally hold less lottery stocks in their portfolios as their Eveningness Score increases, while investors in the other states have the opposite tendency. Therefore, when controlling for residential location, E-type investors tend to trade less frequently across all states, while the impact of M-E on investors' local bias and preference for lottery stocks varies across states. The results also indicate that time zone is not a significant factor because ACT, VIC, and TAS are in the same time zone as ASX which is located in NSW, however, M-E does not present the same effect on the behavioural biases of investors residing in ACT, VIC, TAS and NSW.

3.6 Conclusion

This chapter is the first paper introducing a new behavioural trait, M-E, to the behavioural finance literature, especially to Australian finance literature. Using data obtained from a leading Australian brokerage house, we were able to distinguish M-type investors (‘early birds’) from E-type investors (‘night owls’) based on their order submission time in stock markets. We examined M-E against different investor demographic groups, and investigated M-E’s effect on investors’ trading frequency, proneness to local bias and preference for market speculation, controlling for other known contributors to these biases.

Two methods were used to define the investors’ M-E: a continuous Eveningness Score and a discrete M-E type. We reached the same conclusions using both methods: older people tend to be M-type investors, which is consistent with prevailing evidence in medical research (Adan, 1992; Chelminski et al., 1997; Merikanto et al., 2012; Paine et al., 2006). In addition, our analysis provides further evidence that M-E type can predict different behavioural preferences; that is, M-type investors trade more frequently in the stock market than do E-types, invest more heavily in local stocks and are more prone to market speculation. Although the existing literature has shown that frequent trading and investment in lottery stocks can result in inferior portfolio performance, the findings regarding the wealth effect of local bias are not consistent among the literature. In that sense, this study has pioneered a new direction in behavioural finance that future studies can investigate further how M-E is linked to investors’ account performance, as well as the linkage between investors’ natural habits and their stock market behaviours.

Chapter 4: Does it pay to invest responsibly? A study of retail investors' ESG preference

4.1 Introduction

As reviewed in Section 2.2, although socially responsible investing (SRI) has been explored extensively in terms of its impact on the financial performance of packaged products, formed portfolios and individual companies, its linkage with the demographic characteristics, trading features and portfolio performance of individual investors trading in the stock market has been studied far less. This study is a pioneering one in its application of SRI to the behavioural finance field, especially in the Australian finance literature. Taking advantage of data from a leading Australian retail brokerage house, we can obtain an objective Account ESG Score measurement for each individual investor account, as a proxy for their preference for SRI, and to examine the linkage between the investors' Account ESG Scores, demographic characteristics and trading features. We find that older and female investors have a greater preference for stocks with higher ESG ratings, as do wealthier (or more sophisticated) investors. In contrast, investors who are less risk-averse and prefer mental shortcuts are more likely to hold stocks with lower ESG ratings. Research Question 4.1 is thus answered. In addition, we find that Account ESG Score positively correlates with investors' account performance. Regarding the impact of companies' ESG rating on their stock market performance, weak evidence of a positive impact is established. The findings provide answers to Research Questions 4.2 and 4.3, and also suggest that SRI can be a beneficial investment opportunity for market participants.

This chapter is organised as follows. Section 4.2 presents the data employed; Section 4.3 discusses the methodology; Section 4.4 reports and interprets the findings; Section 4.5 provides robustness test results; and Section 4.6 concludes this chapter.

4.2 Data

As discussed in Section 2.2, the ESG rating scores provided by specialised rating agencies can provide a comprehensive and direct measurement of social performance at the company level. Therefore, to examine our research questions, here we employ a well-established ESG rating database, Thomson Reuters ESG Scores, which enhances and replaces the Thomson Reuters ASSET4 ratings used in existing literature (e.g., Eccles et al., 2014; Halbritter & Dorfleitner, 2015; Lee et al., 2018). According to Thomson Reuters (2018), the ESG Scores database is formed by collecting over 400 company-based ESG measures from publicly available information, such as company websites and annual reports, non-governmental organisations' websites, stock exchange filings, CSR reports and news sources. The 178 critical measures are further combined into 10 groups—resource use, emissions and innovation groups under the pillar 'Environmental'; management, shareholder and CSR strategy groups under the pillar 'Governance' and workforce, human rights, community and product responsibility groups under the pillar 'Social'—to calculate the overall ESG scores (ranging between 0 and 100) for over 7,000 public companies across the world with histories dating back to 2002.

Here, we use the overall ESG Score rather than the distinctive ESG attributes, keeping in mind that investors will often consider a firm's overall ESG performance rather than each dimension of it (Lee et al., 2018), which is also consistent with prior studies (e.g., Humphrey et al., 2012; Lee et al., 2018). Further, Thomson Reuters also provides the ESG Combined Score, which is a discounted score that takes into consideration the significant ESG controversies that materially affect companies. Considering that these ESG controversies can harm the financial performance of companies (Aouadi & Marsat, 2018; Johnson, 2003; Kang & Kim 2014), the Thomson Reuters ESG Combined Score is used in this study. The industry sector to which each company belongs is also downloaded from Thomson Reuters Datastream.

We obtain three datasets from a leading retail brokerage firm in Australia. The first dataset contains the daily portfolio holding for over 10,000 accounts from 2010 to 2013, including the date, stock identifier in the Australian Securities Exchange (ASX) and the number of stocks held in each account. The second dataset provides the transaction records (i.e., the stock identifier, transaction price and volume) for more than 40,000 accounts between October 2010 and August 2012. The third dataset contains account information, including the account holder's gender, salutation (which also helps to verify the gender information), date of birth, address, and if the holder is the primary account holder.

The information required to calculate account and stock performance is obtained from the following sources: the close prices of the stocks held and traded by the sample accounts are downloaded from the Thomson Reuters Tick History (TRTH) database, which is maintained by the Securities Industry Research Centre of Asia-Pacific (SIRCA); the risk-free interest rate (here, the 90-day Bank Accepted Bill rate) is obtained from the official website of the RBA; the stock market capitalisation and book-to-market ratio are extracted from the Market Quality Dashboard, developed by RoZetta Technology (formerly Capital Market CRC); and the market return proxy is calculated from the ASX All Ordinaries Accumulation Index close prices, downloaded from Yahoo Finance.

4.3 Methodology

We develop a new measurement, Account ESG Score, as a proxy for investors' preference for SRI. The Thomson Reuters ESG Combined Scores are employed and weighted by the daily stock-holding weight in the portfolios of each investor. The rationale is that an investor with a higher Account ESG Score will have a greater proportion of their portfolio invested in stocks with higher ESG Combined Scores during the sample period, and thus be more likely to have a greater preference for SRI.

Specifically, for an account i, the weight of stock s in its portfolio on day t is represented by $Stock\_Weight_{it}$:

$$Stock\_Weight_{ist} = \frac{n_{i,s,t} * P_{s,t}}{\sum_{s=1}^{N_{it}} n_{i,s,t}\, P_{s,t}} * 100\% \, , \tag{4.1}$$

where N_{it} is the number of stocks held by account i on day t; $n_{i,s,t}$ is the number of shares of stock s held by account i on day t; and $P_{s,t}$ is the close price of stock s on day t.

Further, the weighted average ESG score for account i on day t is defined as:

$$Acct\_ESG_{it} = \sum_{s=1}^{S_{it}} Stock\_Weight_{ist} * ESG_{st} \, , \tag{4.2}$$

where S_{it} is the stocks held by account i on day t; and ESG_{st} is the Thomson Reuters ESG Combined Score for company s on day t.

Finally, the average daily ESG Score for account i over the sample period is calculated as:

$$Acct\_ESG_{i} = \frac{\sum_{t=1}^{T} Acct\_ESG_{it}}{\mathrm{T}} \, , \tag{4.3}$$

where T is the total number of days for which account i has portfolio records during the sample period.

To align the sample periods of our datasets, we truncate the first dataset, the accounts' daily portfolio holdings, into the same period as our second dataset: October 2012 to August 2012. During the sample period of 2010–2012, Thomson Reuters have ESG Combined Score records for over 400 publicly listed companies in Australia for each year, while the total number of sample stocks held by the sample accounts is over 2,000. In this case, we substitute missing ESG Combined Scores using the matched firm approach, matching to firms in the same industry sector and of comparable market capitalisation (see Schmidt et al., 2012). For example, for a sample firm with an ESG Combined Score record (firm A) in a sample year (e.g., 2010), its average daily market capitalisation over 2010 is calculated. If firm B belongs to the same industry sector as firm A, but does not have an ESG Combined Score in 2010, then we compare its average daily market capitalisation in 2010 to that of firm A. If firm B's average daily market capitalisation in 2010 falls within 70% to 130% of the market capitalisation of firm A, then firm B will take the same ESG Combined Score as firm A in 2010. If no corresponding firm can be found for firm B, it will take the average ESG Combined Score for the industry to which it belongs for the year.

With the above in mind, the data are cleaned first by deleting any accounts holding stocks that changed industry sector over the sample period, followed by excluding any accounts holding stocks whose industry sector is undefined (e.g., exchange-traded funds [ETFs]). After this process, 102,987 accounts remain, with their average daily ESG Combined Score ranging between 9.49 and 90.52, with a mean (median) of 62.68 (66.27).

4.3.1 Account ESG Score against investors' characteristics and trading features

With the Account ESG Score for the sample accounts established, we proceed to investigate its linkage to account holders' demographic characteristics (i.e., age and gender) and trading features, including trading frequency, average order value and stock price traded by the account, average number of stocks held by the account, and whether the account holder always trades in round sizes.

The rationale for choosing these variables for investigation comes from the existing literature. Considering that SRI products appeal to risk-averse investors (e.g., Nofsinger & Varma, 2014), the investor characteristics related to risk-aversion level are expected to be influential. Gender may be an influencing factor, as women tend to be more risk-averse (Barsky, Juster, Kimball & Shapiro, 1997; Barber & Odean, 2001). In addition, as Dorn and Huberman (2005) pointed out, less risk-averse investors trade more aggressively; therefore, there may be a linkage between trading frequency and Account ESG Score.

Income or wealth level can also be an explanatory variable, as Hood et al. (2014), Sultana et al. (2018) and Ruggie and Middleton (2019) find that higher income investors shy away from low-ESG stocks, and that investors with greater stock market investment amounts tend to prefer ESG attributes. Here, we take three variables to proxy investors' wealth level, based on Frino et al. (2015)—average trade order value, average stock price traded and average number of stocks held by the account—with the expectation of a link between these three variables and Account ESG Score. Finally, the round-size trading pattern is used as the proxy for preferring to take mental shortcuts rather than engage in more involved analytical processing (Frino et al., 2015). Because companies' ESG practices are additional information to stock market participants, which requires extra cognitive processing work, such as information acquisition and analysis, we expect a linkage between this round-size trading pattern and Account ESG Score.

The account holders' characteristics and trading features are extracted and calculated from the second dataset. Before merging the second dataset with the Account ESG Scores, data-cleaning is conducted as follows: first, only those accounts with a single owner and no other holders are kept; second, accounts with missing information, such gender or date-of-birth, are excluded; and third, accounts with extreme values for total number of trades, average order value and average stock price being traded are eliminated. As a result, our final sample contained the Account ESG Score, demographic characteristics and trading features for 35,877 investors.

With these final sample accounts, we first check the pair-wise correlations between Account ESG Score, investor demographic characteristics and trading features. Then, a multivariate regression as stated in Equation 4.4 is established to examine the joint effects of investor characteristics and trading features on Account ESG Score:

$$Acct\_ESG_i = \alpha + \beta_1 Age_i + \beta_2 Female_i + \beta_3 Freq_i + \beta_4 Order\_V_i + \beta_5 Price_i + \beta_5 N_i + \beta_6 RS_i + \varepsilon_i \text{ ,}$$

$$\text{with E } [\epsilon_{it}] = 0 \text{ and VAR } [\epsilon_i] = \sigma_i^2, \qquad (4.4)$$

where Age_i is the age of the account holder on the last day of the sample period (in years); $Female_i$ is a dummy variable that equals one if the account holder is female, and zero if male; $Freq_i$ indicates the total number of trades of account i during the sample period; $Order\_V_i$ stands for the average order value by account i; $Price_i$ is the average stock price traded by account i; N_i is the daily average number of stocks held by account i; RS_i is another dummy variable that equals one if the account holder always trades in round volumes (multiples of ten), and zero otherwise.

The Student's t-test is carried out for both the correlation analysis and the multivariate regression, to examine the statistical significance. Notably, for the multivariate regression, while we could have scaled the independent variables so that they were on a similar scale to the estimated coefficients, considering that variable scaling would not affect the significance or interpretation of the estimation (Hocking, 1976), we keep the original format of the independent variables to make interpretation of the results more straightforward.

4.3.2 Account performance and its linkage to Account ESG Score

To investigate the linkage between individual investors' account performance and their Account ESG Score, we refer to the method employed in the existing literature examining the relation between corporate social performance (CSP) and corporate financial performance (CFP) in terms of ESG portfolios (e.g., Bauer et al., 2005; Derwall et al., 2005; Galema et al., 2008; Halbritter & Dorfleitner, 2015; Kempf & Osthoff, 2007; Lee et al., 2018; Statman & Glushkov, 2009). In these studies, portfolios are formed according to ESG ratings in year y, with one portfolio typically comprising stocks with high ESG ratings and the other low ESG-ranked stocks; the performance of these two constructed portfolios in year $y + 1$ is estimated with the Carhart (1997) four-factor model, as presented in Equation 4.5. The alphas, α in Equation 4.5, of the high- and low-rated ESG portfolios are then taken as the performance proxy and compared, to infer the return difference between these portfolios.

Here, we apply the Carhart model to the portfolio of individual investors and get the account alpha for each account:

$$R_{it} - R_{ft} = \alpha_{it} + \beta_1(R_{mt} - R_{ft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_{it} ,$$

$$\text{with E } [\epsilon_{it}] = 0 \text{ and VAR } [\epsilon_i] = \sigma_i^2 \qquad (4.5)$$

where R_{it} is the monthly return of account i in month t, calculated as the weighted average monthly return of all the stocks held by account i based on the start-of-month portfolio holdings; R_{ft} is the risk-free rate in month t (here, the 90-day Bank Accepted Bill rate); R_{mt} is the market portfolio return in this month, using the ASX All Ordinaries Accumulation Index as the market proxy); SMB_t indicates the monthly return difference between a small- and large-cap portfolio in month t; HML_t denotes the difference in return between a high book-to-market ratio portfolio and low book-to-market ratio portfolio in this month; MOM_t is the momentum for month t, calculated as the return difference between a portfolio with high-return stocks and one with low-return stocks in the previous 12 months; and α_{it} indicates the excess account performance (here, account alpha). Note that SMB_t, HML_t and MOM_t are extracted from French (2019), and are for the Asia Pacific, excluding Japan.

The linkage between the Account ESG Score and account alpha is firstly analysed with quantile analysis, in the spirit of the existing literature, by dividing the sample accounts into two and four quantiles according to their Account ESG Scores, and comparing the mean monthly alpha for the accounts in each quantile. The account performance difference between the top-ESG quantile and the bottom one is tested using the Student's t-test for statistical significance.

In addition, Ordinary Least Squares (OLS) regression, as in Equation 4.6, is performed to examine the correlation between the account alpha and the Account ESG Score:

$$Acct\_alpha_i = \alpha + \beta * Acct\_ESG_i + \varepsilon_i,$$

$$\text{with E } [\epsilon_{it}] = 0 \text{ and VAR } [\epsilon_i] = \sigma_i^2 \qquad (4.6)$$

where $Acct\_alpha_i$ is the average monthly alpha for account i during the sample period; and $Acct\_ESG_i$ stands for the Account ESG Score calculated with the lagged ESG

Combined Score for the stocks held by account i. The analysis results are presented and discussed in Section 4.4.2.

4.3.3 Stock performance and its linkage to company ESG score

To investigate the linkage between companies' ESG scores and their stock performance, the Carhart (1997) four-factor model is used to calculate stock performance (i.e., stock alpha), controlling for market risk, market capitalisation, book-to-market ratio and stock return momentum. Quantile analysis is first carried out, to divide the sample stocks into two and four quantiles according to their firms' ESG Combined Scores. The mean monthly alpha in the subsequent year for the stocks in each quantile is calculated, with the performance difference between the top-ESG quantile and the bottom one tested for statistical significance using the Student's t-test. The OLS regression, as stated in Equation 4.7, is then performed to examine the influence of a company's ESG Combined Score on their stock performance in the next year:

$$Stock\_alpha_{it} = \alpha + \beta * ESG_{it-1} + \varepsilon_{it},$$

$$\text{with E } [\epsilon_{it}] = 0 \text{ and VAR } [\epsilon_i] = \sigma_i^2, \tag{4.7}$$

where the $Stock\_alpha_{it}$ stands for the average monthly alpha of firm i ' s stock in year t; and ESG_{it-1} is the ESG Combined Score for firm i in year $t-1$.

As indicated in meta-analysis studies (e.g., Margolis et al., 2007; Orlitzky et al., 2003), there is a positive concurrent correlation between CFP and CSP. Therefore, we examine the impact of companies' ESG Combined Scores on their stock returns in the same year, along with the quantile analysis and OLS regression. The analysis results are presented in Section 4.4.3.

4.4 Results

4.4.1 Account ESG score against investors' characteristics and trading features

This section presents the results for the linkage between individual investors' Account ESG Scores, demographic characteristics and trading features. The correlation table and multivariate linear regression results for Equation 4.4 are presented.

Table 4.1 provides the summary information for the 35,877 sample accounts, showing the minimum, maximum, mean and median of the Account ESG Scores and the continuous variables for investors' characteristics (age), together with their trading features (trading frequency, average order value, average price of the stocks being traded and number of stocks held).

Table 4.1 Descriptive statistics for investors' Account ESG Score, demographic characteristics and trading features

This table reports the statistics summary for the 35,877 sample accounts with their Account ESG Scores, investor characteristics and trading features over the sample period of October 2010 to August 2012. The *Account ESG Score* is calculated as the weighted average of the ESG Combined Scores of the stocks held by each account; *Age* is the age of the account holder on the last day of the sample period (in years); *Trading Frequency* indicates the total number of trades of the accounts during the sample period.

	Account ESG Score	Age	Trading Frequency	Average Order Value	Average Stock Price Traded	Number of Stocks Held
Minimum	10.36	18.00	1.00	66.44	0.003	1.00
Median	60.33	44.25	4.00	4592.16	5.336	3.00
Mean	59.67	45.12	12.77	8473.26	11.470	4.74
Maximum	90.52	83.99	700.00	186836.50	158.649	77.80

As shown, Account ESG Score ranges between 10.36 and 90.52, with an average of 59.67. The youngest account holder is 18 years old and the oldest is 84. On average, a typical investor trades around 13 times, with the average trade value being AUD 8,473 and the average stock price traded being AUD 11.47. They hold about five stocks per day over the sample period on average. Among the 35,877 account holders, 11,011 are female, and there are 15,043 investors who always trade in round volumes (multiples of ten).

Table 4.2 shows the pair-wise correlations of Account ESG Score, investors' characteristics and their trading features. It is clear that Account ESG Score is positively correlated with the investor's age, and that the effect is statistically significant; that is, older investors are more likely to hold stocks with higher ESG scores in their portfolios. Female investors also tend to have higher Account ESG Scores, and the effect is statistically significant. In terms of the trading features, Account ESG Score is positively correlated with average order value, average stock price being traded and average number of stocks held by the account, with all the correlations being statistically significant. Considering that these three variables together indicate investor wealth (Frino et al., 2015), which further indicates sophistication (Calvet, Campbell & Sodini, 2009; Kacperczyk, Nosal & Stevens, 2018), we can say that wealthier (or more sophisticated) investors are more likely to hold stocks with higher ESG scores in their portfolios. Two variables are negatively correlated with Account ESG Score, with statistical significance: trading frequency and the dummy variable for round-size trading. Thus, frequent-trading investors are more likely to have stocks with lower ESG scores in their portfolios, as are investors who always trade in round sizes.

Table 4.2 The correlation matrix of investors' Account ESG Score, demographic characteristics and trading features

This table reports the correlation matrix of the investors' Account ESG Score, demographic characteristics and trading features. The *Account ESG Score* is calculated for each account as the weighted average of the ESG Combined Scores of the stocks held over the sample period; *Age* is the age of the account owner at the last day of the sample period. *Female* is a dummy variable that takes the value of one for female and zero for male; *Trading Frequency* is the total number of trades by one account over the sample period; *Number of Stocks* is the average number of stocks held by the account over the sample period; *Round Size* is a dummy variable that equals one if the account holder always trades in round volumes (multiples of ten) or zero otherwise. P-values are presented in parentheses and **(*) indicates statistical significance at the 5% (10%) level.

	Account ESG Score	**Age**	**Female**	**Trading Frequency**	**Average Order Value**	**Average Stock Price Traded**	**Number of Stocks**	**Round Size**
Account ESG Score	1.0000							
Age	0.1046** (<0.0001)	1.0000						
Female	0.1247** (<0.0001)	0.0815** (<0.0001)	1.0000					
Trading Frequency	-0.0977** (<0.0001)	0.0331** (<0.0001)	-0.0479** (<0.0001)	1.0000				
Average Order Value	0.1120** (<0.0001)	0.1372** (<0.0001)	-0.0187** (0.0004)	0.1042** (<0.0001)	1.0000			
Average Stock Price Traded[2]	0.5451** (<0.0001)	0.0186** (0.0004)	0.0939** (<0.0001)	-0.0470** (<0.0001)	0.1920** (<0.0001)	1.0000		
Number of Stocks	0.0670** (<0.0001)	0.1881** (<0.0001)	0.0221** (<0.0001)	0.1530** (<0.0001)	-0.0246** (<0.0001)	-0.0088* (0.0957)	1.0000	
Round Size	-0.0645** (<0.0001)	0.1012** (<0.0001)	0.0281** (<0.0001)	-0.1753** (<0.0001)	0.0092* (0.0828)	-0.0893** (<0.0001)	-0.1173** (<0.0001)	1.0000

[2] Note here that the correlation between companies' ESG Combined Score and their stock price is a statistically significant 0.22 during 2010–2012, however, it does not impact the interpretation of the analysis results.

Table 4.3 Impact of the investors' characteristics and trading features on the Account ESG Score

This table reports the estimates from the multivariate linear regression of Equation 4.4: $Acct\_ESG_i = \alpha + \beta_1 Age_i + \beta_2 Female_i + \beta_3 Freq_i + \beta_4 Order\_V_i + \beta_5 Price_i + \beta_5 N_i + \beta_6 RS_i + \varepsilon_i$. The dependent variable $Acct\_ESG_i$ is calculated for account i as the value-weighted average of the ESG Combined Scores of the stocks held over the sample period; Age_i is the age of the account holder at the last day of the sample period (in years); $Female_i$ is a dummy variable that equals one if the account holder is female, and zero otherwise; $Freq_i$ indicates the total number of trades of account i during the sample period; $Order\_V_i$ stands for the average order value (in thousands of AUD) traded by account i; $Price_i$ is the average stock price traded by this account; N_i is the average daily number of stocks held by account i; RS_i is another dummy variable that equals one if the account holder always trades in round volumes (multiples of ten), and zero otherwise. Student's t-test is performed to check the statistical significance, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level. R^2 is the adjusted R-squared.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
Intercept	47.3243	0.2586	183.0070	<0.0001**
Age	0.0982	0.0054	18.2040	<0.0001**
Female	2.2938	0.1579	14.5300	<0.0001**
Freq	-0.0434	0.0022	-19.9470	<0.0001**
Order_V ('000)	0.0147	0.0057	2.5830	0.0098*
Price	0.6258	0.0053	117.6790	<0.0001**
N	0.2042	0.0143	14.2910	<0.0001**
RS	-1.1997	0.1511	-7.9380	<0.0001**
Number of Observations = 35,877, R^2=0.3212				

The regression results of Equation 4.4 are presented in Table 4.3. They show findings consistent with the correlation analysis when considering the joint impact of investors' characteristics and trading features on Account ESG Score. We can see that Account ESG Score increases with age, and that female account holders tend to have a higher Account ESG Score. The 2.2938 coefficient of the dummy variable *Female* indicates that the average Account ESG Score of the accounts owned by female investors exceeds that of the male investors' accounts by more than 2 points. In addition, investors trading in larger order values with higher stock prices and who hold more stocks over the sample period are more likely to hold stocks with higher ESG scores in their portfolios. In comparison, investors who trade more frequently and always in round volumes tend to hold lower ESG-ranked stocks. All these effects are statistically significant at the 5% level.

To summarise, the results indicate that, in general, older investors and female investors are more likely to hold stocks with a higher ESG Combined Score, indicating that they consider ESG attributes when investing. The age effect is consistent with another Australian study (i.e., Beal & Goyen, 1998), and the gender effect also echoes the existing literature (e.g., Beal & Goyen, 1998; Hood et al., 2014). Investors who have greater wealth invested in the stock market (and are thus more sophisticated) also tend to hold stocks with higher ESG ratings, concurring with the empirical evidence that wealthier investors have a greater preference for ESG attributes (Hood et al., 2014; Ruggie & Middleton, 2019; Sultana et al., 2018). In general, frequent-trading investors and those who always trade in round sizes hold lower ESG-rated stocks, reflecting the tendency for less risk-averse market participants and those who prefer mental shortcuts to be less likely to take ESG attributes into consideration when constructing their portfolios.

4.4.2 Account ESG score's impact on account performance

This section answers the question of whether the investors' Account ESG Scores affect their account performance. As discussed in Section 4.3, the existing literature that has used the constructed portfolio method to investigate the CSP–CFP relation normally compares the difference between the estimated alphas from the Carhart (1997) four-factor model of high- and low-ESG portfolios. Similarly, for our sample individual investors' portfolios, the Carhart model is first used to obtain the estimated monthly alpha for each account, with the extreme values of alpha (0.1% at each end) then deleted to minimise the outlier issue. The Account ESG Score is calculated based on the lagged

ESG Combined Score for stocks (i.e., ESG score in the previous year) held by the investors.

The quantile analysis is then conducted by dividing the sample accounts into two and four quantiles according to their Account ESG Score, and the average account alpha of the accounts in each quantile is calculated. The account performance between the top-ESG quantile and bottom one is further compared, with the statistical significance of the difference tested by the Student's t-test. The results are presented in Table 4.4.

Table 4.4 Account performance under each Account ESG Score quantile

This table reports the average account performance under each Account ESG quantile. The sample accounts are divided into two and four quantiles according to the Account ESG Score. The mean account alpha is presented for each ESG quantile. For each account, the account monthly alpha is estimated using the Carhart four-factor model, controlling for market performance, size, book-to-market ratio and momentum on returns, and is in basis-points. Student's t-test is performed to check the statistical significance of the account performance difference between the top and bottom ESG quantiles, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Mean account alpha (bps) for each ESG quantile	
Quantile	Divided into Two Quantiles	Divided into Four Quantiles
1 (lowest-ESG)	100.1350	101.8928
2	106.1429	98.3773
3		104.4242
4 (highest-ESG)		107.8613
Top-Bottom quantile difference (t-statistics)	6.0078** (4.9972)	5.9685** (3.2361)

It is clear that, on average, when the accounts are divided into four quantiles by Account ESG Score, the accounts in the top 25% ESG quantile (Quantile 4) outperform the accounts in the bottom 25% ESG quantile (Quantile 1) by around six basis-points per month. Similar results are obtained when the sample accounts are divided into two quantiles according to Account ESG Score.

Table 4.5 presents the OLS regression results of Equation 4.6. The intercept indicates that the average monthly alpha of the sample accounts is around 92 basis-points. The positive coefficient of $Account\_ESG$ confirms that, in general, the account alpha increases with Account ESG Score, and the effect is statistically significant. Specifically, if an investor's Account ESG Score increases by 10 points, the average monthly return of the portfolio is expected to increase by almost 1.9 basis-points.

Table 4.5 Impact of the Account ESG Score on account performance

This table reports the estimates from the OLS regression of Equation 4.6: $Acct\_alpha_i = \alpha + \beta * Acct\_ESG_i + \varepsilon_i$.The dependent variable $Acct\_alpha_i$ is calculated for account i using the Carhart (1997) four-factor model, controlling for market performance, size, book-to-market ratio and momentum on returns, and is in basis-points; $Acct\_ESG_i$ is calculated as the weighted average of the ESG Combined Scores of the stocks held by account i over the sample period. Student's t-test is performed to check the statistical significance, and the p-values are presented in parentheses; **(*) indicates statistical significance at the 5% (10%) level.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
Intercept	92.0701	2.3374	39.3899	<0.0001**
ESG	0.1898	0.0387	4.9004	<0.0001**
Number of Observations = 35,877, R^2=0.0007				

Thus, to summarise Section 4.4.2, the quantile comparison and OLS regression consistently suggest that investor portfolios with higher ESG scores perform significantly better, both economically and statistically. Investing responsibly does not come with a cost; quite the opposite, it is financially beneficial.

4.4.3 Company ESG score's impact on stock performance

This section presents the analysis results for the linkage between companies' ESG Combined Score and their stock performance. Quantile analysis is first carried out by dividing the sample stocks into two and four quantiles according to their firms' ESG Combined Scores. The mean monthly alpha (estimated using the Carhart four-factor model) in the subsequent year for the stocks in each quantile is then calculated, with the performance difference between the top-ESG quantile and the bottom one tested for statistical significance using the Student's t-test. The results are presented in Table 4.6.

Table 4.6 Stock performance under each ESG Combined Score (lagged year) quantile

This table reports the quantile analysis results when the sample stocks are divided into two and four quantiles according to their lagged ESG Combined Score. The mean stock alpha is presented for each ESG quantile. The stock monthly alpha is calculated using the Carhart (1997) four-factor model, controlling for market performance, size, book-to-market ratio and momentum on returns, and is in basis-points. Student's t-test is performed to check the statistical significance of the stock performance difference between the top and bottom ESG quantiles, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Mean stock alpha (bps) for each ESG quantile	
Quantile	**Divided into Two Quantiles**	**Divided into Four Quantiles**
1 (lowest-ESG)	-8.1003	-7.4746
2	-7.2167	-8.7287
3		-14.7320
4 (highest-ESG)		0.2354
Top-Bottom quantile difference (t-statistics)	0.8836 (0.15303)	7.7101** (2.7441)

This table indicates that when the sample stocks are divided into four quantiles according to their companies' ESG Combined Score, the ones belonging to the top 25% ESG quantile (Quantile 4) outperform those in the bottom 25% ESG quantile (Quantile 1) in the subsequent year by more than seven basis-points per month on average, with that outperformance being statistically significant.

Table 4.7 presents the OLS regression results of Equation 4.7. It confirms that, in general, the ESG Combined Score of firms is positively correlated with their stock performance in the next year. However, the correlation is not statistically significant.

Table 4.7 Impact of company ESG Combined Score on the stock performance in the subsequent year

This table reports the estimates of the OLS regression of Equation 4.8: $Stock\_alpha_{it} = \alpha + \beta * ESG_{it-1} + \varepsilon_{it}$. The dependent variable $Stock\_alpha_{it}$ indicates the average monthly alpha of stock for firm i (in basis-points) in year t, and is calculated using the Carhart (1997) four-factor model, controlling for market performance, size, book-to-market ratio and momentum on returns. ESG_{it-1} is the Thomson Reuters ESG Combined Score for firm i in the previous year. Student's t-test is performed to check the statistical significance, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-12.2350	8.4137	-1.4542	0.1462
ESG	0.1003	0.1732	0.5794	0.5625
Number of Observations = 945, R^2=0.0004				

According to the meta-analysis studies by Orlitzky et al. (2003) and Margolis et al. (2007), there is a positive concurrent linkage between CFP and CSP. Therefore, we also examine the impact of companies' ESG Combined Scores on their stock performance in the same year. The quantile comparison and OLS regression results are presented in Tables 4.8 and 4.9, respectively.

Table 4.8 Stock performance under each ESG Combined Score (current year) quantile

This table reports the quantile analysis results when the sample stocks are divided into two and four quantiles according to their current-year ESG Combined Score. The mean stock alpha is presented for each ESG quantile. The stock monthly alpha is calculated using the Carhart (1997) four-factor model, controlling for market performance, size, book-to-market ratio and momentum on returns, and is in basis-points. Student's t-test is performed to check the statistical significance of the stock performance difference between the top and bottom ESG quantiles, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Mean stock alpha (bps) for each ESG quantile	
Quantile	Divided into Two Quantiles	Divided into Four Quantiles
1 (lowest-ESG)	-2.6533	-3.1320
2	-7.4986	-2.1692
3		-4.0228
4 (highest-ESG)		-10.9482
Top-Bottom quantile difference (t-statistics)	-4.8453 (-0.9920)	-7.8162 (-0.8312)

Table 4.8 shows that, in terms of the contemporaneous relation, the stocks in the top-ESG quantile underperform those in the bottom quantile, but the effect is not statistically significant. The OLS regression results in Table 4.9 indicate a consistent finding that a company's ESG Combined Score is negatively correlated with their stock performance in the same year.

Table 4.9 Impact of company ESG Combined Score on the stock performance in the same year

This table reports the estimates of the OLS regression: $Stock\_alpha_{it} = \alpha + \beta * ESG_{it} + \varepsilon_{it}$. The dependent variable $Stock\_alpha_{it}$ indicates the average monthly alpha of stock for firm i (in basis-points) in year t, and is calculated using the Carhart (1997) four-factor model, controlling for market performance, size, book-to-market ratio and momentum on returns. ESG_{it-1} is the Thomson Reuters ESG Combined Score for firm i in the same year. Student's t-test is performed to check the statistical significance, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	0.1270	7.1395	0.0178	0.9858
ESG	-0.1160	0.1491	-0.7777	0.4369
Number of Observations = 1051, R^2=0.0006				

To summarise Section 4.4.3, the analysis results indicate weak evidence that a company's ESG Combined Score has a positive influence on their stock performance in the subsequent year, which is in line with the findings of Galema et al. (2008) and Halbritter and Dorfleitner (2015). The concurrent relation between ESG Combined Score and stock performance is negative, suggesting that the effect of ESG may take time to emerge, as has been pointed out by Mănescu (2011).

4.5 Robustness test

In Section 4.3, when calculating the Account ESG Score, stocks without Thomson Reuters Combined Scores are given the scores of the firms matched to them. Ideally, for robustness checking, we would only keep those accounts holding stocks that have a Thomson Reuters ESG Combined Score. However, because all the sample accounts hold at least some stocks without Thomson Reuters ESG Scores on some days during the sample period, we need to use another method to deal with stocks without ESG Combined Scores; that is, the industry average.

After calculating the Account ESG Score with the industry average method, we proceed to investigate its linkage with investors' demographic characteristics and trading features. The pair-wise correlations and regression results of Equation 4.4 are presented in Tables 4.10 and 4.11, respectively.

It provides findings consistent with those presented in Section 4.4.1. The age and gender effects are still present and statistically significant, with older and female investors having a greater preference for stocks with higher ESG scores. Investors trading in larger average order values and higher average stock prices and who hold more stocks in their portfolios also have higher Account ESG Scores, indicating that wealthier (more sophisticated) investors are more likely to hold stocks with higher ESG scores. In comparison, frequent-trading investors and those who always trade in round volumes tend to hold stocks with lower ESG scores.

Table 4.10 Robustness test: Correlation matrix of investors' Account ESG Score, demographic characteristics and trading features

This table reports the correlation matrix of the investors' Account ESG Score, demographic characteristics and trading features under the robustness test. The *Account ESG Score* is calculated for each account as the weighted average of the ESG Combined Scores of the stocks held over the sample period, with missing ESG Scores substituted with the industry average; *Age* is the age of the account owner at the last day of the sample period. *Female* is a dummy variable that takes the value of one for female and zero for male; *Trading Frequency* is the total number of trades by one account over the sample period; *Number of Stocks* is the average number of stocks held by the account over the sample period. *Round Size* is a dummy variable that equals one if the account holder always trades in round volumes (multiples of ten), and zero otherwise. P-values are presented in parentheses and **(*) indicates statistical significance at the 5% (10%) level.

	Account ESG Score	**Age**	**Female**	**Trading Frequency**	**Average Order Value**	**Average Stock Price Traded**	**Number of Stocks**	**Round Size**
Account ESG Score	1							
Age	0.1059** (<0.0001)	1						
Female	0.1262** (<0.0001)	0.0815** (<0.0001)	1					
Trading Frequency	-0.0979** (<0.0001)	0.0331** (<0.0001)	-0.0479** (<0.0001)	1				
Average Order Value	0.1132** (<0.0001)	0.1372** (<0.0001)	-0.0187** (0.0004)	0.1042** (<0.0001)	1			
Average Stock Price Traded	0.5522** (<0.0001)	0.0186** (0.0004)	0.0939** (<0.0001)	-0.0470** (<0.0001)	0.1920** (<0.0001)	1		
Number of Stocks	0.0668** (<0.0001)	0.1881** (<0.0001)	0.0221** (<0.0001)	0.1530** (<0.0001)	-0.0246** (<0.0001)	-0.0088* (0.0957)	1	
Round Size	-0.0616** (<0.0001)	0.1012** (<0.0001)	0.0281** (<0.0001)	-0.1753** (<0.0001)	0.0092* (0.0828)	-0.0893** (<0.0001)	-0.1173** (<0.0001)	1

Table 4.11 Robustness test: Impact of the investors' characteristics and trading features on the Account ESG Score

This table reports the estimates from the multivariate linear regression of Equation 4.4 under the robustness test:
$Acct\_ESG_i = \alpha + \beta_1 Age_i + \beta_2 Female_i + \beta_3 Freq_i + \beta_4 Order\_V_i + \beta_5 Price_i + \beta_5 N_i + \beta_6 RS_i + \varepsilon_i$. The dependent variable $Acct\_ESG_i$ is calculated for account i as the value-weighted average of the ESG Combined Scores of the stocks held over the sample period, with missing ESG Scores substituted with the industry average; Age_i is the age of the account holder on the last day of the sample period (in years); $Female_i$ is a dummy variable that equals one if the account holder is female, and zero otherwise; $Freq_i$ indicates the total number of trades of account i during the sample period; $Order\_V_i$ stands for the average order value (in thousands of AUD) traded by account i; $Price_i$ is the average stock price traded by this account; N_i is the average daily number of stocks held by account i; RS_i is another dummy variable that equals one if the account holder always trades in round volumes (multiples of ten), and zero otherwise. Student's t-test is performed to check the statistical significance, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
Intercept	48.4601	0.2413	200.8667	<0.0001**
Age	0.0931	0.0050	18.4892	<0.0001**
Female	2.1758	0.1473	14.7727	<0.0001**
Freq	-0.0403	0.0020	-19.8769	<0.0001**
Order_V ('000)	0.0134	0.0053	2.5134	0.0120
Price	0.5955	0.0050	120.0328	<0.0001**
N	0.1914	0.0133	14.3571	<0.0001**
RS	-1.0131	0.1410	-7.1850	<0.0001**
Number of Observations = 35,877, R^2=0.3292				

For the linkage between Account ESG Score and account performance, quantile analysis is performed, with the results presented in Tables 4.12. It is clear that when the investor accounts are divided into four quantiles according to their Account ESG Scores, the accounts in the top 25% ESG quantile (Quantile 4) outperform those in the bottom 25% quantile (Quantile 1) by 19.7 basis-points, and the difference is statistically significant. Therefore, the robustness test confirms the finding in Section 4.4.2 that investors holding stocks with higher ESG scores in their portfolios achieve better performance. Taking ESG attributes into consideration can thus be beneficial for the investment outcome.

Table 4.12 Robustness test: Account performance under each Account ESG Score quantile

This table reports the average account performance under each Account ESG quantile under the robustness test. The sample accounts are divided into two and four quantiles according to the Account ESG Score. For each account, the account monthly alpha of account *i* is estimated using the Carhart four-factor model, controlling for market performance, size, book-to-market ratio and momentum on returns, and is in basis-points. The mean account alpha is presented for each ESG quantile. Student's t-test is performed to check the statistical significance of the account performance difference between the top and bottom ESG quantiles, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Mean account alpha (bps) for each ESG quantile	
Quantile	**Divided into Two Quantiles**	**Divided into Four Quantiles**
1 (lowest-ESG)	101.0622	82.1540
2	103.6993	102.9484
3		104.2660
4 (highest-ESG)		101.8435
Top-Bottom quantile difference (t-statistics)	2.6371 (1.5830)	19.6895** (3.2241)

In terms of the linkage between companies' ESG Combined Score and their stock performance, the industry sector to which each company belongs is further added to the OLS regression of Equation 4.7 as one explanatory variable. The results are presented in Table 4.13.

The baseline for the OLS regression with the categorical variable indicating GICS sectors is Energy sector. Here we provide three examples for the interpretation of the coefficients: the coefficient of 0.0806 for the variable *ESG* is for Energy sector, meaning that a company in Energy sector is expected to have 0.8 basic-point increase in its stock alpha when its ESG Combined Score increases by 10 points; the coefficient of -3.6523 for the variable *GICS_Materials* indicates that on average, firms belonging to Materials sector underperform the ones in Energy sector by 3.65 basic-points; and the coefficient of -0.4200 for the interaction term *ESG*Materials* indicates that for a typical firm in Materials sector, every 10 points increase in the ESG Combined Score is associated with a change of (0.0806-0.4200)*10 basic-points in its monthly alpha.

Therefore, we can see that the impact of ESG Combined Score varies across industries and is not statistically significant for any industry. Specifically, for companies in Energy, Industries, Consumer Staples, Health Care, Financials, IT, and Utilities, their ESG Combined Score is positively correlated with stock performance in the next year, while companies in Materials, Consumer Discretionary, Telecommunication Services and Real Estate have the opposite tendency.

Table 4.13 Impact of company ESG Combined Score on the stock performance in the subsequent year (with industry effect)

This table reports the estimates of the OLS regression:
$Stock\_alpha_{it} = \alpha + \beta_1 * ESG_{it-1} + \beta_2 GICS_i + \beta_3 ESG_{it-1} * GICS_i + \varepsilon_{it}$.
The dependent variable $Stock\_alpha_{it}$ indicates the average monthly alpha of stock for firm i (in basis-points) in year t, and is calculated using the Carhart (1997) four-factor model, controlling for market performance, size, book-to-market ratio and momentum on returns. ESG_{it-1} is the Thomson Reuters ESG Combined Score for firm i in the previous year; and $GICS_i$ is the industry sector of firm i according to Thomson Reuters Datastream. Student's t-test is performed to check the statistical significance, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
Intercept	-5.4714	23.5390	-0.2320	0.8160
ESG	0.0806	0.4796	0.1680	0.8670
GICS_Materials	-3.6523	29.1973	-0.1250	0.9000
GICS_Industrials	-12.6756	33.3002	-0.3810	0.7040
GICS_Consumer Discretionary	16.4798	40.2584	0.4090	0.6820
GICS_Consumer Staples	-2.6231	57.3043	-0.0460	0.9630
GICS_Health Care	-11.9404	50.9955	-0.2340	0.8150
GICS_Financials	-0.1186	32.1403	-0.0040	0.9970
GICS_IT	-14.3191	56.2991	-0.2540	0.7990
GICS_Telecommuniation Services	11.4213	85.4965	0.1340	0.8940
GICS_Utilities	1.0202	52.3354	0.0190	0.9840
GICS_Real Estate	10.8081	42.7472	0.2530	0.8000
ESG * Materials	-0.4200	0.6194	-0.6780	0.4980
ESG * Industrials	0.1537	0.6766	0.2270	0.8200
ESG * Consumer Discretionary	-0.3996	0.8822	-0.4530	0.6510
ESG * Consumer Staples	0.0637	1.0726	0.0590	0.9530
ESG * Health Care	0.1784	1.0097	0.1770	0.8600
ESG * Financials	0.0321	0.6217	0.0520	0.9590
ESG * IT	0.5097	1.4250	0.3580	0.7210
ESG * Telecommuniation Services	-0.1037	1.9992	-0.0520	0.9590
ESG * Utilities	0.0394	1.3011	0.0300	0.9760
ESG * Real Estate	-0.0887	0.7961	-0.1110	0.9110
Number of Observations = 945, R^2=0.0145				

In addition to the OLS regression, quantile analysis is conducted to examine the industry effect. We divide firms in each industry sector into four quantiles according their ESG Combined Scores and compare the mean monthly alpha in the subsequent year for the stocks in each quantile in that sector. The results are presented in Table 4.14.

This table indicates that when firms in each industry sector are divided into four quantiles according to their ESG Combined Score, the ones belonging to the top 25% ESG quantile outperform those in the bottom 25% ESG quantile in the subsequent year for more than half of the industry sectors except for Materials, Consumer Discretionary, Telecommunication Services, Utilities, and Real Estate, which is consistent to the findings in Table 4.13. Altogether, the robustness test confirms that the impact of ESG Combined Score varies across industries and it has a positive influence on stock performance in the subsequent year for more than half of the industry sectors.

Table 4.14 Stock performance under each ESG Combined Score (lagged year) quantile with industry effect

This table reports the quantile analysis results when the sample stocks are divided into four quantiles in each industry according to their lagged ESG Combined Score. The mean stock alpha is presented for each ESG quantile. The stock monthly alpha is calculated using the Carhart (1997) four-factor model, controlling for market performance, size, book-to-market ratio and momentum on returns, and is in basis-points. The stock performance difference between the top and bottom ESG quantiles is presented.

Quantile	Energy	Materials	Industrials	Consumer Discretion -ary	Consumer Staples	Health Care	Financials	IT	Telecom. Services	Utilities	Real Estate
1 (lowest-ESG)	-11.2462	-16.5540	-7.9780	5.1366	-4.0538	-4.4194	-5.4181	-3.5689	9.1484	5.5643	6.8347
2	3.7959	-3.9386	-12.5542	-7.2462	3.3802	-8.0967	4.1996	-8.4247	-6.2716	-20.4749	2.1098
3	0.8761	-17.0946	-7.3162	1.2324	-5.4381	-7.7867	1.7214	4.9826	6.2857	6.1637	5.6034
4 (highest-ESG)	-0.4138	-54.9977	-1.6559	-8.3185	4.1351	-0.0613	0.9405	11.4738	7.1809	5.2833	4.9293
Top-Bottom quantile difference	10.8323	-38.4437	6.3222	-13.4551	8.1889	4.3582	6.3587	15.0427	-1.9674	-0.2811	-1.9054

4.6 Conclusion

The human element is one of the emerging themes in ESG investing that has yet to be explored (Daugaard, 2019); this essay contributes to extending SRI into the behavioural finance field, especially in the Australian finance literature. Using data from a leading brokerage house in Australia between 2010 and 2012, we are able to directly measure investors' preference for SRI by obtaining their Account ESG Scores using daily portfolio holdings and Thomson Reuters ESG ratings. We analysed the relationships between the investors' Account ESG Scores, demographic characteristics and trading features, examined the impact of Account ESG Score on individual investors' account performance, and investigated the influence of companies' ESG ratings on their stock market performance.

We found that female and older investors have a greater preference for stocks with higher ESG ratings, which is consistent with the prevailing evidence (e.g., Beal & Goyen, 1998; Hood et al., 2014). It is the same case with wealthier or more sophisticated investors, echoing the findings in Hood et al. (2014), Sultana et al. (2018) and Ruggie and Middleton (2019). In comparison, frequent-trading investors and those who always trade in round sizes are less likely to consider ESG attributes when constructing their portfolios. Considering that trading frequency can reflect risk-aversion level and that trading in round sizes is a proxy for taking mental shortcuts, we conclude that risk-averse investors prefer stocks with higher ESG ratings and so are the more sophisticated investors.

Our analysis reveals that SRI can be beneficial for account performance. We found that those accounts with a higher Account ESG Score tended to outperform those with lower Account ESG Scores by achieving higher Carhart (1997) four-factor alphas.

This has practical significance for investors, who in addition to choosing an ethical investment fund or superannuation option, can choose to make their investment decisions based on companies' ESG ratings, which can now be accessed from a variety of sources. For example, many of the companies listed on the ASX publish their sustainability reports on their own official websites following the ESG reporting guidelines provided by the ASX; Yahoo Finance offers publicly available ESG scores, provided by Sustainalytics; BT Financial Group launched their ESG ratings in 2017, covering over 200 Australian-managed funds and ASX 200-listed companies; and the Interactive Brokers Group started to provide Thomson Reuters ESG scores for their clients in late 2018.

In terms of the linkage between a company's ESG rating and their stock performance, we found weak evidence that companies with higher ESG Combined Scores are more likely to outperform in the subsequent year even when controlling for the industry effect, which is consistent with the findings of Galema et al. (2008) and Halbritter and Dorfleitner (2015). Together with the negative concurrent relation between a company's ESG Combined Score and their stock performance, we conclude that the influence of ESG takes time to emerge, as previously observed by Mănescu (2011).

In summary, this essay adds to the research on the CSP–CFP relation in the behavioural finance field, an underdeveloped area particularly in the Australian finance literature, by identifying the demographic characteristics of investors with a greater preference for ESG investing. Further, it provides evidence that SRI based on ESG ratings can be an investment opportunity for stock market participants.

Chapter 5: Index Rebalancing Effects of S&P/ASX 200

5.1 Introduction

The existing literature has extensively explored the index rebalancing events of indices domiciled in North America, the European regions and Asia. While in comparison, far fewer papers have focused on Australian market indices and the findings are inconsistent, with the liquidity effects unexplored. Only one publication, Schmidt et al. (2012), has investigated the S&P/ASX 200, the index covering 80% of Australian equities market capitalisation. Further, that study used data only up to 2009, leaving a gap to fill for future studies.

In addition, the announcement day (AD)– effective day (ED) interval length during the event has been found to be influential for the price effects of the S&P 500 index revision (Beneish & Whaley, 1996), but the impact has never been examined in the Australian finance literature. Considering that Standard and Poor's (S&P) usually gives the S&P/ASX 200 index a longer AD–ED interval (two weeks) compared to that of the S&P 500 index (up to five days), and that the S&P/ASX 200 revision AD–ED interval has been changed from two weeks to only one week for the March, June and December quarters since 2016, it is necessary to examine the index rebalancing effects of the S&P/ASX 200 systematically, and investigate the impact of the AD–ED interval length with more recent data.

With this motivation, this chapter first examines the price, volume, volatility and liquidity effects of the S&P/ASX 200 index rebalancing event during the period 2011–2016, using well-established methods from the existing literature and ensuring the sample stocks are free from other price-sensitive information release and corporate actions. We find that the announcement and revision effects exist for both additions to and deletions from the S&P/ASX 200 index. Moreover, the index rebalancing event more strongly effects additions than deletions. The price discovery for additions mainly occurs on AD, while for the sample deletions, it mainly happens on ED. The event also increases (decreases) the liquidity of the sample additions (deletions). Research Question 5.1 is thus answered.

The key finding of this study is a negative correlation between the cumulative abnormal returns of S&P/ASX 200 additions during the AD–ED interval and the interval length. The correlation is in the opposite direction to that for S&P 500 index additions, indicating that the longer rebalancing interval of the S&P/ASX 200 can provide market participants enough time to build their positions on announcement and then unwind them before ED. In comparison, the correlation for the S&P/ASX 200 deletions is positive. The S&P/ASX 200 additions (deletions) with a shorter AD–ED interval (one week) are found to have more intense price and volume effects upon announcement compared to those with a longer interval. These findings not only provide answers for Research Question 5.2, but also indicate a potentially profitable trading strategy for market participants; that is, buying (selling) the S&P/ASX 200 additions (deletions) with shorter AD–ED intervals (one week) on AD and selling (buying) on the day before ED can bring an excess return of up to 2.67% (4.48%).

Finally, the impact of the growth of index exchange-traded funds (ETFs) over the years is investigated and a weak positive (negative) correlation between the price effects of S&P/ASX 200 additions (deletions) and the market capitalisation of the index ETFs tracking the index is established. Research Question 5.3 is thus answered.

This chapter is organised as follows: Section 5.2 provides the sample additions and deletions of the S&P/ASX 200 index rebalancing event and data; Section 5.3

presents the methodology used; Section 5.4 reports the analysis results; and Section 5.5 discusses the findings and concludes this chapter.

5.2 Data

5.2.1 Index methodology review

The S&P/ASX 200 is a float-adjusted index that covers about 80% of Australian equities market capitalisation, representing the 200 largest eligible ASX-listed stocks (S&P Dow Jones Indices, 2017). Since its introduction in 2000, it has replaced the Australian All Ordinaries index as the premier benchmark index for the Australian equity market. The eligibility of stocks listed on the Australian Securities Exchange (ASX) to be included in the S&P/ASX 200 is primarily measured by market capitalisation and liquidity (S&P Dow Jones Indices, 2017). That is, if a stock's daily average float-adjusted market capitalisation over the previous six months failed to meet the minimum ranking, or its relative liquidity (i.e., the stock's average daily liquidity during the previous six months as a percentage of the market liquidity) dropped below 50%, then it may be considered for removal during a quarterly review.

The quarterly review is conducted by the S&P/ASX Index Committee, which is responsible for reviewing the eligibility of stocks and making decisions about index inclusions and exclusions. S&P/ASX 200 rebalancing occurs on a quarterly basis, and the changes occur on the third Friday of March, June, September and December, after market close. Before March 2016, two weeks' notice was given of revisions; that is, the announcement of any changes was made on the first Friday of the above-mentioned months, before market open. As of March 2016, only one week's notice is given in March, June and December (i.e., the announcement of any changes is made on the second Friday of these months), while for September two weeks' notice continues to be given. Intra-quarter revisions can take place because of removals resulting from mergers, acquisitions, spin-offs, suspensions or bankruptcy. The effective day is whenever the possible completion of such corporate actions can be supported by enough evidence; the announcement is then made two to five business days before the index revision.

5.2.2 Sample additions and deletions

This study covers the period from April 2011 to December 2016. The index revision announcements during the sample period, together with their ADs and EDs, are taken from the *Market Index* website and have been confirmed against the *S&P Dow Jones Indices* official website. Altogether, there were 124 additions to and 126 deletions from the S&P/ASX 200 during the sample period.

Based on the existing literature, a five-step refinement of the sample list is carried out. Following Beneish and Whaley (1996), Lynch and Mendenhall (1997) and Chen et al. (2004), the first step taken to refine the sample list is to remove the stocks of firms added to the index because of spin-offs or mergers and acquisitions, and firms deleted from the index because of corporate actions such as spin-offs, mergers and acquisitions, bankruptcy, delisting and change of share type. In total, eight additions and 37 deletions are excluded in the first step.

The second step is to go through the companies' corporate operational history using Morningstar's *DatAnalysis Premium* database, to identify firms that entered the index within three months of IPO or merger and acquisition. This requirement is similar to the criteria in Elliott and Warr (2003) and Qiu and Pinfold (2007). At this step, a further 24 additions and one deletion are excluded from the sample.

The third step is to go through the companies' corporate operational history using Morningstar's *DatAnalysis Premium* database, to exclude the firms that had announcements that could have possibly impacted the stock prices within a certain number of days of the AD and ED. Such price-sensitive announcements include earnings reports or earnings forecasts, initial dividends or dividends increases, mergers and acquisitions (e.g., projects and assets), completion of replacement, recapitalisation, capital raising (or reduction) and trading halts. Chan and Howard (2002) and Qiu and Pinfold (2007) defined the period to be -5/+5 days of AD and ED, while Beneish and Whaley (1996) used -2/+2 days. To ensure that the final sample size remain above 50% of the original sample size, we used the date range of Beneish and Whaley (1996), excluding a further 16 additions and 11 deletions.

The fourth data-cleaning step involves requiring the additions (deletions) to have trading records (i.e., price and volume data) for 90 days before and 60 days after ED. This requirement is similar to those presented in Hegde and McDermott (2003), Elliott and Warr (2003) and Green and Jame (2011), and aims to eliminate any firms that could be subject to mergers and acquisitions or delisting within this period. Applying this criterion to the sample list resulted in the exclusion of a further eight deletions.

The final step is to exclude the stocks with less than five trading days between AD and ED, excluding one more addition. The resulting final sample list comprises 75 additions to and 69 deletions from the S&P/ASX 200 index during April 2011 to December 2016.

5.2.3 Data

We extract end-of-day, intraday trade and quote data from the Thomson Reuters Tick History (TRTH) database. The end-of-day data contains the stock code, date, prices (open, high, low, last price) and volume; the intraday trade and quote data contains the information for each trade and quote, including the bid price (size), ask price (size), trade price (size) and identifier, timestamped to the millisecond. The data is then processed into the Market Quality Dashboard platform, to calculate the market quality matrices, including quoted spread, effective spread, realised spread, best depth and trade size.

5.3 Methodology

5.3.1 Abnormal returns calculation

For price effects, two methods are used in this study to calculate abnormal returns: the market-adjusted return method and the market model method. The market-adjusted return method has been used in Lynch and Mendenhall (1997), Elliott and Warr (2003), Chen et al. (2004) and Chan and Howard (2002). The abnormal return AR_{it} of stock i on day t is defined as the stock return's deviation from a market benchmark's return, calculated as follows:

$$AR_{it} = R_{it} - R_{mt}, \tag{5.1}$$

where R_{it} is the price return of stock i on day t; and R_{mt} is the return of the market benchmark on day t (here, the S&P/ASX 200 index return).

The second method, the market model, has been used in Hegde and McDermott (2003) and Qiu and Pinfold (2007). This model assumes that there is a linear relation between stock return and market benchmark return, as presented in Equation 5.2:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it},$$

$$\text{with E } [\epsilon_{it}] = 0 \text{ and VAR } [\epsilon_{it}] = \sigma_{it}^2 \tag{5.2}$$

where R_{it} is the price return of stock i on day t; R_{mt} is the return of the market benchmark on day t; and α_i and β_i are the OLS regression parameters estimated for stock i using historical data R_{it} and R_{mt} in the estimation period. Here, we take 250 days to 30 days before ED as the estimation period, with reference to Hegde and McDermott (2003) and Denis et al. (2003).

The estimated stock return $E[R_{it}]$ of stock i on day t during the event period is then estimated by Equation 5.2 using R_{mt}, the market benchmark's return on day t during the event period. Finally, the abnormal return of stock i on day t during the event, AR_{it} , is calculated as follows:

$$AR_{it} = R_{it} - E[R_{it}] = R_{it} - [\alpha_i + \beta_i R_{mt}] \tag{5.3}$$

As for the comparison of these two methods, the pioneering study on event study methodologies, Brown and Warner (1985), points out that the market-adjusted return method and the OLS market model method have similar effectiveness when analysing daily data. Lynch and Mendenhall (1997) also argued that the market model provides results similar to those of the market-adjusted model and may result in more positive (negative) results. Further, the market-adjusted return model has more practical application compared to the market model, considering that it compares the returns of sample stocks to a benchmark index. In that sense, it provides a straightforward trading strategy for investors; that is, longing (shorting) the index additions (deletions) and shorting (longing) the market index. Therefore, we present the results from both methods: the market-adjusted return model's results are discussed in detail, while the results from the market model serve as the robustness check.

With the abnormal return AR_{it} calculated with either method, the mean abnormal return (MAR) MAR_t on day t across the sample is calculated as:

$$MAR_t = \frac{\sum_{i=1}^{N} AR_{it}}{N}, \tag{5.4}$$

where N is the number of stocks in the additions (deletions) sample.

The cumulative abnormal return CAR_i of stock i across the event period $[t_1, t_2]$ is calculated as:

$$CAR_i = \sum_{t=t_1}^{t_2} AR_{it} \tag{5.5}$$

The mean cumulative abnormal return (MCAR) $MCAR_t$ of year t across the added (deleted) stocks is defined as:

$$MCAR_t = \frac{\sum_{i=1}^{N} CAR_{it}}{N} \tag{5.6}$$

where N is the number of stocks added to (or deleted from) the index in year t.

5.3.2 Abnormal volume calculation

The volume effect is calculated with reference to Harris and Gurel (1986), Elliott and Warr (2003) and Chen et al. (2004), with the volume measure defined as:

$$Volume\_Ratio_{it} = \frac{V_{it}}{V_{mt}} \Big/ \frac{V_i}{V_m} = \frac{V_{it}}{V_{mt}} \cdot \frac{V_m}{V_i} \tag{5.7}$$

where V_{it} is the trading volume of stock i on day t; V_{mt} is the total trading volume of the S&P/ASX 200 constituent stocks on day t; V_i is the 60-day average trading volumes of stock i from 90 days before ED to 31 days before ED; and V_m is the 60-day average of the S&P/ASX 200 constituent stocks' total trading volumes during the same pre-event period [ED-90, ED-31]. If the calculated $Volume\_Ratio_{it}$ is bigger than 1, then the trading volume of stock i on day t is bigger than pre-event level; a less-than-one Volume Ratio indicates a trading volume lower than the pre-event level.

5.3.3 Abnormal volatility calculation

The volatility effect is calculated in a similar way to the volume effect:

$$Volatility\_Ratio_{it} = \frac{Volatility_{it}}{Volatility_{mt}} \Bigg/ \frac{Volatility_i}{Volatility_m} = \frac{Volatility_{it}}{Volatility_{mt}} \cdot \frac{Volatility_m}{Volatility_i}\ , \quad (5.8)$$

where $Volatility_{it}$ is defined as the natural logarithm of the highest price divided by the lowest price of stock i on day t (Gallant, Hsu & Tauchen, 1999); $Volatility_{mt}$ is the natural logarithm of the highest price divided by the lowest price of the S&P/ASX 200 index on day t; $Volatility_i$ is the 60-day average volatility of stock i during [ED-90, ED-31]; and $Volatility_m$ is the 60-day average of the S&P/ASX 200 index's volatility during the same pre-event period. If the calculated Volatility Ratio is bigger than 1, then the stock prices of stock i on day t are more volatile than the pre-event level; a less-than-one Volatility Ratio indicates a volatility lower than pre-event level.

5.3.4 Market liquidity measurements

Following Hendershott, Jones and Menkveld (2011), this study takes quoted spread, effective spread, one-minute realised spread, best depth and trade size as the market liquidity measurements.

First, the prevailing midpoint is calculated:

$$midpoint_{i,t} = \frac{Bid\ Price_{i,t} + Ask\ Price_{i,t}}{2}\ , \quad (5.9)$$

where $Ask\ Price_{i,t}$ ($Bid\ Price_{i,t}$) denotes the best ask (bid) price for stock i at time t.

Quoted spread is defined as the prevailing bid-ask spread over the midpoint price:

$$Quoted\ Spread_{i,t} = \frac{Bid\ Price_{i,t} - Ask\ Price_{i,t}}{midpoint_{i,t}} \quad (5.10)$$

The end-of-day quoted spread for a particular stock is then calculated as the time-weighted average of its quoted spreads over one day.

Effective spread is calculated as the difference between the trade-execution price and the midpoint price prevailing in the trade, measuring the execution cost of a round-trip liquidity-taking trade:

$$Effective\ Spread_{i,t} = 2 * D_{i,t} * \frac{Trade\ Price_{i,t} - midpoint_{i,t}}{midpoint_{i,t}}, \quad (5.11)$$

where $Trade\ Price_{i,t}$ denotes the execution price of the trade for stock i at time t; and $D_{i,t}$ is the trade direction defined as in Lee and Ready (1991) for stock i at time t, taking the value of 1 for buyer-initiated trades and the value of -1 for seller-initiated trades. The end-of-day effective spread for a particular stock is then calculated as the volume-weighted average of the effective spreads for all its trades over the day.

One-minute realised spread, which measures the revenue earned by liquidity providers in one trade, is calculated with the assumption that liquidity providers close their positions one minute after the trade, as follows:

$$Realised\ Spread_{i,t} = 2 * D_{i,t} * \frac{Trade\ Price_{i,t} - midpoint_{i,t+1min}}{midpoint_{i,t}}, \quad (5.12)$$

where $Trade\ Price_{i,t}$ denotes the execution price of the trade for stock i at time t; $midpoint_{i,t+1min}$ denotes the midpoint price for stock i one minute after the time of trade t; and $D_{i,t}$ is the trade direction for stock i at time t and is defined as in Equation 5.11. For a particular stock, the end-of-day realised spread is calculated as the volume-weighted average of the realised spreads for all its trades over the day.

Best depth is taken as the volume of best bid and ask quotes in the limit-order book:

$$Best\ Depth_{i,t} = \frac{bid\ volume_{i,t} + ask\ volume_{i,t}}{2}, \quad (5.13)$$

where $bid\ volume_{i,t}(ask\ volume_{i,t})$ denotes the volume at the best bid (ask) price for stock i at time t. The end-of-day best depth for a particular stock is then calculated as the time-weighted average of its best depths throughout the day.

Trade size measures the daily average trade volume of each trade for a particular stock. The trade size for stock i on day d is calculated as:

$$Trade\ Size_{i,d} = \frac{Total\ Volume_{i,d}}{Number\ of\ trades_{i,d}} \tag{5.14}$$

As noted by Qiu and Pinfold (2007), institutional investors can trade off-market in Australia, which is different from in the US stock market. To be consistent with existing Australian studies, off-market trades are excluded in our analysis.

5.4 Results

5.4.1 Price, volume and volatility effects

This section presents the analysis results of the price, volume and volatility effects in two parts, first for the additions and then for the deletions. In each part, the MCAR from AD to ED and from AD to one trading day before ED (ED-1) for each year is presented. Further, the MAR, Volume Ratio and Volatility Ratio on each day of the -/+5 days period around AD [AD-5, AD+5] and -/+5 days period around ED [ED-5, ED+5] are presented.

The stocks' daily returns are winsorised at the 5% level to reduce the impact of extreme values, and the Student's t-test and the Mann-Whitney-Wilcoxon test are performed to check the statistical significance of the price, volume and volatility effects (with p-values presented). The results from both the market-adjusted return model and the market model are presented. The market-adjusted return model's results are discussed in detail, while those from the market model are used as the robustness check.

5.4.1.1 Price, volume and volatility effects for additions

Table 5.1 provides the MCAR from AD to ED [AD, ED] for additions to the S&P/ASX 200 index each year. According to the market-adjusted return model, the MCARs for 2011, 2014 and 2016 are positive, while those from the other three years are negative. The MCAR across the six-year sample period is insignificant at 0.03%. This is consistent with Qiu and Pinfold's (2007) findings for S&P/ASX 100 additions, but contradicts the existing literature on S&P 500 index additions (e.g., Beneish & Whaley, 1996; Chen et al., 2004). Of the 75 additions, 41 stocks obtained positive cumulative abnormal returns.

Table 5.1 Price effect for S&P/ASX 200 index additions during [AD, ED]

This table reports the MCAR from AD to ED for the S&P/ASX 200 sample additions each year during 2011–2016. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ASX 200 index): $AR_{it} = R_{it} - R_{mt}$; the cumulative abnormal return CAR_i of stock i across [AD, ED] is calculated as: $CAR_i = \sum_{t=AD}^{ED} AR_{it}$; The $MCAR_t$ of year t across the N stocks added in that year is calculated as: $MCAR_t = (\sum_{i=1}^{N} CAR_{it})/N$; *Positive: Negative* gives the number of stocks with a positive CAR versus the number of stocks with a negative CAR. Student's t-test is performed to check the statistical significance of the price effects, and the p-values are presented for the entire additions sample. **(*) indicates statistical significance at the 5% (10%) level.

Year	No. of Stocks	Market Adjusted Return Model: MCAR	Market Adjusted Return Model: Positive: Negative	Market Model: MCAR	Market Model: Positive: Negative
2011	11	0.69%	4:7	-4.30%	2:9
2012	12	-0.66%	8:4	-2.36%	7:5
2013	15	-2.83%	6:9	-4.39%	4:11
2014	7	2.56%	6:1	-0.15%	4:3
2015	17	-0.80%	8:9	-2.00%	8:9
2016	13	2.79%	9:4	-0.16%	8:5
Entire Sample	75	-0.03% (p-value = 0.9670)	41:34	-2.38%** (p-value = 0.0051)	33:42

Table 5.2 presents the MCAR from AD to one trading day prior to ED [AD, ED-1] for additions to the S&P/ASX 200 each year. The market-adjusted return model indicates that four out of the six years generated a positive MCAR: 2.24% in 2011, 3.06%

in 2014, 1.26% in 2015 and 3.01% in 2016. The MCAR across the sample additions over the six years is 1.08%. Of the 75 sample additions, 50 obtained a positive cumulative abnormal return during the interval [AD, ED-1].

Table 5.2 Price effect for S&P/ASX 200 index additions during [AD, ED-1]

This table reports the MCAR from AD to one trading day before ED for the S&P/ASX 200 sample additions each year from 2011–2016. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ASX 200 index): $AR_{it} = R_{it} - R_{mt}$; the cumulative abnormal return CAR_i of stock i across the sample period [AD, ED-1] is calculated as: $CAR_i = \sum_{t=AD}^{ED-1} AR_{it}$; The $MCAR_t$ of year t across the N stocks added in that year is calculated as: $MCAR_t = (\sum_{i=1}^{N} CAR_{it})/N$; *Positive: Negative* gives the number of stocks with a positive CAR versus the number of stocks with a negative CAR. Student's t-test is performed to check the statistical significance of the price effects, and the p-values are presented for the entire additions sample. **(*) indicates statistical significance at the 5% (10%) level.

Year	No. of stocks	Market Adjusted Model: MCAR	Market Adjusted Model: Positive: Negative	Market Model: MCAR	Market Model: Positive: Negative
2011	11	2.24%	8:3	-2.16%	2:9
2012	12	-0.19%	9:3	-1.78%	8:4
2013	15	-1.56%	6:9	-3.06%	4:11
2014	7	3.06%	5:2	0.25%	3:4
2015	17	1.26%	12:5	0.03%	9:8
2016	13	3.01%	10:3	0.36%	9:4
Entire Sample	75	1.08%* (p-value = 0.0861)	50:25	-1.12% (p-value = 0.1230)	35:40

Table 5.3 reports the MAR, Volume Ratio and Volatility Ratio for the sample additions to the S&P/ASX 200 on each day within the event window [AD-5, AD+5] (five trading days before to five trading days after AD). According to the market-adjusted return model, the average abnormal return across the sample additions on AD is a statistically significant 1.10%. The abnormal returns on one trading day prior to and after AD are 0.83% and 0.84%, respectively, and are also statistically significant. Volume-wise, the trading volume peaks on AD, at 85% higher than pre-event level. The volume effect persists for five days after AD at a statistically significant level. The trading volume on the trading day prior to announcement is 32% higher than pre-event

level. The stock price volatility peaks on AD, at 47% higher than pre-event level, which is statistically significant. The price volatility effect persists for three trading days after announcement. The price and volume effects around AD are in line with the existing S&P 500 literature and the Australian paper by Schmidt et al. (2012). It is worth noting that an abnormal return and abnormal trading volume the day before announcement may indicate speculators' anticipation of the index rebalancing announcement, or information leakage.

The daily MAR, Volume Ratio and Volatility Ratio of the sample additions during the event window [ED-5, ED+5] are presented in Table 5.4. According to the market-adjusted return model, on average, the sample additions obtain a -1.16% abnormal return on ED and a -0.50% abnormal return on the trading day prior to ED, with both effects being statistically significant. The negative abnormal return is partially reversed after ED.

Volume-wise, the trading volume within the event window [ED-5, ED+5] is universally above the pre-event level, and peaks on ED with a Volume Ratio more than 10 times higher than the pre-event level. In terms of volatility, the stock price volatility on ED is 45% higher than the pre-event level, and this volatility effect persists for almost five trading days after ED.

Our finding of price effect results around ED contradict the S&P 500 literature but are in line with the Australian findings of Chan and Howard (2002), on the All Ordinaries index; Schmidt et al. (2012) on the S&P/ASX 200 index; and Qiu and Pinfold (2007) on the S&P/ASX 100 index.

Table 5.3 Price, volume and volatility effects for S&P/ASX 200 index additions during [AD-5, AD+5]

This table reports the MAR, Volume Ratio and Volatility Ratio for the S&P/ASX 200 sample additions each day within the event window of five trading days before to five trading days after AD. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ASX 200 index): AR_{it} = $R_{it} - R_{mt}$; The MAR_t on day t across the sample stocks is calculated as: MAR_t = $(\sum_{i=1}^{N} AR_{it})/N$; Volume Ratio is calculated as $\frac{V_{it}}{V_{mt}} \cdot \frac{V_m}{V_i}$, representing the trading volume of stock i as a percentage of the total trading volume of the S&P/ASX 200 constituent stocks on day t, compared to the pre-event ratio; Volatility Ratio is calculated in the same manner as Volume Ratio, with volatility defined as the natural logarithm of the daily highest price divided by the daily lowest price. Student's t-test is performed to check the statistical significance of the price, volume and volatility effects, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Price Effect				**Volume Effect**		**Volatility Effect**	
	Market Adjusted Return Model		**Market Model**					
Timeline	**MAR**	**p-value**	**MAR**	**p-value**	**Volume Ratio**	**p-value**	**Volatility Ratio**	**p-value**
AD-5	0.43%	0.0603	0.17%	0.4501	1.14	0.3575	1.39	0.0005**
AD-4	-0.12%	0.6004	-0.49%	0.0363**	1.31	0.0430**	1.19	0.0140**
AD-3	0.25%	0.2465	-0.10%	0.6454	1.33	0.0138**	1.13	0.2187
AD-2	0.24%	0.2986	-0.14%	0.5719	1.14	0.0489**	1.32	0.0054**
AD-1	0.83%	0.0003**	0.30%	0.1718	1.32	0.0056**	1.23	0.0047**
AD	1.10%	<0.0001**	0.71%	0.0075**	1.85	<0.0001**	1.47	0.0062**
AD+1	0.84%	0.0009**	0.44%	0.0865*	1.67	<0.0001**	1.24	0.0044**
AD+2	0.04%	0.8327	-0.27%	0.1832	1.59	<0.0001**	1.32	0.0008**
AD+3	-0.01%	0.9695	-0.27%	0.2296	1.42	0.0013**	1.15	0.0571*
AD+4	0.21%	0.2616	0.04%	0.8489	1.33	0.0060**	0.99	0.9390
AD+5	-0.16%	0.4123	-0.45%	0.0213**	3.38	0.0001**	1.05	0.5086

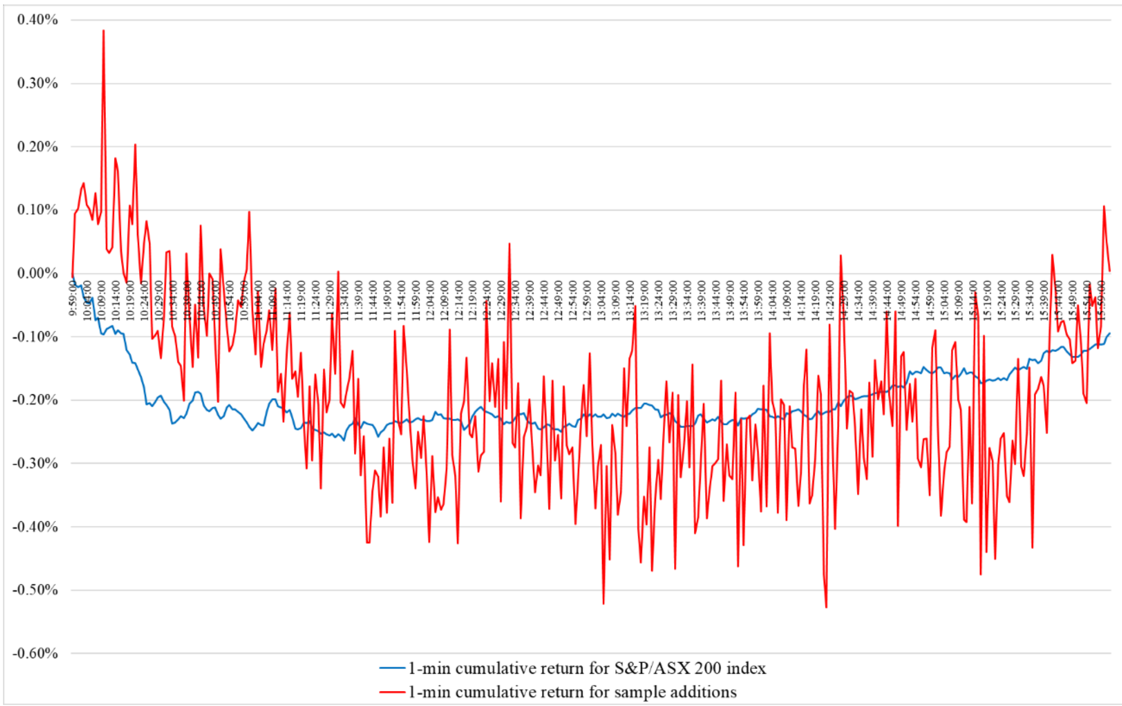
Table 5.4 Price, volume and volatility effects for S&P/ASX 200 index additions during [ED-5, ED+5]

This table reports the MAR, Volume Ratio and Volatility Ratio for the S&P/ASX 200 sample additions each day within the event window of five trading days before to five trading days after ED. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ASX 200 index): $AR_{it} = R_{it} - R_{mt}$; The MAR_t on day t across the sample stocks is calculated as: $MAR_t = (\sum_{i=1}^{N} AR_{it})/N$; Volume Ratio is calculated as $\frac{V_{it}}{V_{mt}} \cdot \frac{V_m}{V_i}$, representing the trading volume of stock i as a percentage of the total trading volume of the S&P/ASX 200 constituent stocks on day t, compared to the pre-event ratio; Volatility Ratio is calculated in the same manner as Volume Ratio, with volatility defined as the natural logarithm of the daily highest price divided by the daily lowest price. Student's t-test is performed to check the statistical significance of the price, volume and volatility effects, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Price Effect				**Volume Effect**		**Volatility Effect**	
	Market Adjusted Return Model		**Market Model**					
Timeline	**MAR**	**p-value**	**MAR**	**p-value**	**Volume Ratio**	**p-value**	**Volatility Ratio**	**p-value**
ED-5	0.25%	0.2749	0.01%	0.9752	1.53	0.0007**	1.10	0.1295
ED-4	0.39%	0.1257	0.01%	0.9605	1.64	0.0002**	1.09	0.2152
ED-3	-0.01%	0.9673	-0.38%	0.0882	1.68	0.0001**	1.07	0.3854
ED-2	-0.01%	0.9765	-0.10%	0.6632	1.60	0.0001**	1.30	0.0074**
ED-1	-0.50%	0.0441**	-0.61%	0.0228**	1.33	0.0023**	0.88	0.1005
ED	-1.16%	<0.0001**	-1.30%	<0.0001**	10.31	<0.0001**	1.45	0.0001**
ED+1	0.18%	0.4941	-0.15%	0.5653	2.77	0.0001**	1.26	0.0045**
ED+2	0.14%	0.5713	-0.06%	0.8040	2.20	<0.0001**	1.68	0.0001**
ED+3	0.25%	0.2718	-0.07%	0.7659	2.03	<0.0001**	1.28	0.0090**
ED+4	-0.35%	0.1575	-0.49%	0.0784	1.62	<0.0001**	1.14	0.1588
ED+5	0.02%	0.9455	-0.33%	0.2372	1.88	0.0008**	1.28	0.0047**

We further investigate the intraday price movement on AD and ED by checking the one-minute intraday price returns and cumulative price returns within the day. Figures 5.1 and 5.2 present the intraday one-minute cumulative price returns of the sample additions compared to the S&P/ASX 200 index on AD and ED, respectively.

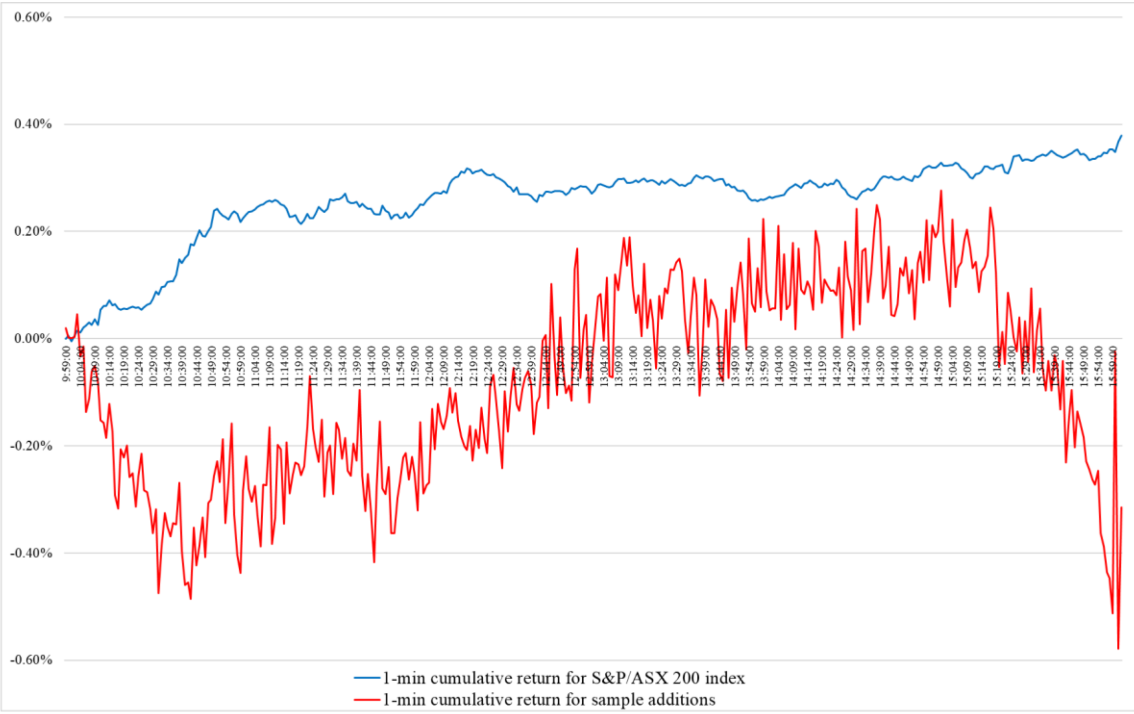
Figure 5.1 AD one-minute cumulative returns of sample additions and S&P/ASX 200 index



Figures 5.1 and 5.2 indicate that for the S&P/ASX 200 additions sample, the average intraday price return increases upon the rebalancing announcement released before market open; however, there is no such pattern on ED. Moreover, we find that the average overnight price return for the sample additions from market close on the day before the announcement (AD-1) to market open of AD is 1.02%, while AD intraday price return from market open to close is only 0.15%. In comparison, the average overnight price return from market close on the day before ED (ED-1) to market open of ED is -0.1%, and ED intraday price return from market open to close is -1.2%.

Therefore, the analysis results in this section reveal that the index revision event has a greater AD effect than ED effect for the S&P/ASX additions. Possible explanations are provided in Section 5.5.

Figure 5.2 ED one-minute cumulative returns of sample additions and S&P/ASX 200 index



5.4.1.2 Price, volume and volatility effects for deletions

The same analysis as for the sample additions is carried out for the sample deletions. Table 5.5 presents the MCAR from AD to ED for each year for the sample deletions. According to the market-adjusted return model, the average cumulative abnormal returns in 2011 and 2013–2016 are all negative. The average cumulative abnormal return across the six-year sample period amounts to -3.44% and is statistically significant. Of the 69 sample deletions, 46 stocks obtained a negative cumulative abnormal return during [AD, ED]. The results agree with existing studies, such as Lynch and Mendenhall (1997), Chen et al. (2004) and Chan and Howard (2002).

Table 5.5 Price effect for S&P/ASX 200 index deletions during [AD, ED]

This table reports the MCAR from AD to ED for the S&P/ASX 200 sample deletions each year from 2011 to 2016. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ASX 200 index): $AR_{it} = R_{it} - R_{mt}$; the cumulative abnormal return CAR_i of stock i during [AD, ED] is calculated as: $CAR_i = \sum_{t=AD}^{ED} AR_{it}$; The $MCAR_t$ of year t across the N stocks deleted in that year is calculated as: $MCAR_t = (\sum_{i=1}^{N} CAR_{it})/N$; *Positive: Negative* gives the number of stocks with a positive CAR versus the number of stocks with a negative CAR. Student's t-test is performed to check the statistical significance of the price effects, and the p-values are presented for the entire deletions sample. **(*) indicates statistical significance at the 5% (10%) level.

Year	No. of stocks	Market Adjusted Model		Market Model	
		MCAR	Positive: Negative	MCAR	Positive: Negative
2011	8	-8.29%	1:7	-4.45%	2:6
2012	9	1.71%	4:5	4.12%	4:5
2013	18	-3.49%	7:11	0.18%	9:9
2014	11	-0.33%	4:7	2.59%	7:4
2015	14	-6.24%	4:10	-2.62%	4:10
2016	9	-3.60%	3:6	-4.67%	3:6
Entire Sample	69	-3.44%** (p-value = 0.0222)	23:46	-0.66% (p-value = 0.6609)	29:40

Table 5.6 reports the MCAR from AD to one trading day before ED each year for the sample deletions. According to the market-adjusted return model, the sample deletions obtained a cumulative abnormal return of -1.94% on average. Of the 69 deletions, 42 experienced a negative abnormal return during [AD, ED-1].

Table 5.6 Price effect for S&P/ASX 200 index deletions during [AD, ED-1]

This table reports the MCAR during AD to one trading day before ED for the S&P/ASX 200 sample deletions each year from 2011 to 2016. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ASX 200 index): $AR_{it} = R_{it} - R_{mt}$; the cumulative abnormal return CAR_i of stock i across the sample period [AD, ED-1] is calculated as: $CAR_i = \sum_{t=AD}^{ED-1} AR_{it}$; The $MCAR_t$ of year t across the N stocks deleted in that year is calculated as: $MCAR_t = (\sum_{i=1}^{N} CAR_{it})/N$; *Positive: Negative* gives the number of stocks with a positive CAR versus the number of stocks with a negative CAR. Student's t-test is performed to check the significance of the price effects, and the p-values are presented for the entire deletions sample. **(*) indicates statistical significance at the 5% (10%) level.

		Market Adjusted Model		Market Model	
Year	**No. of stocks**	**MCAR**	**Positive: Negative**	**MCAR**	**Positive: Negative**
2011	8	-7.18%	1:7	-3.24%	2:6
2012	9	5.20%	5:4	7.26%	5:4
2013	18	-0.35%	8:10	3.54%	10:8
2014	11	0.67%	6:5	3.48%	7:4
2015	14	-6.30%	4:10	-2.75%	4:10
2016	9	-4.03%	3:6	-4.59%	3:6
Entire Sample	69	-1.94% (p-value = 0.1970)	27:42	0.89% (p-value = 0.5520)	31:38

The MAR, Volume Ratio and Volatility Ratio for the sample deletions on each day within the event window [AD-5, AD+5] are presented in Table 5.7. We can see that, on average, the sample deletions obtained a -1.13% abnormal return on AD, which is statistically significant. The negative abnormal return persists for two days after AD before starting to reverse.

As for trading volume, the Volume Ratio on AD is 46% higher than pre-event level, which is statistically significant. This volume effect persists for three trading days after AD. The volatility of stock prices on AD is 47% higher than pre-event level and is uniformly above pre-event level for five trading days after AD. The price and volume effects are consistent with existing studies (e.g., Chen et al., 2004; Hegde & McDermott, 2003; Schmidt et al., 2012).

Table 5.7 Price, volume and volatility effects for S&P/ASX 200 index deletions during [AD-5, AD+5]

This table reports the MAR, Volume Ratio and Volatility Ratio for the S&P/ASX 200 sample deletions each day within the event window of five trading days before to five trading days after AD. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ASX 200 index): AR_{it} = $R_{it} - R_{mt}$; The MAR_t on day t across the sample stocks is calculated as: MAR_t = $(\sum_{i=1}^{N} AR_{it})/N$; *Volume Ratio* is calculated as $\frac{V_{it}}{V_{mt}} \cdot \frac{V_m}{V_i}$, representing the trading volume of stock i as a percentage of the total trading volume of the S&P/ASX 200 constituent stocks on day t, compared to the pre-event ratio; *Volatility Ratio* is calculated in the same manner as *Volume Ratio*, with volatility defined as the natural logarithm of the daily highest price divided by the daily lowest price. Student's t-test is performed to check the significance of the price, volume and volatility effects, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Price Effect				Volume Effect		Volatility Effect	
	Market Adjusted Return Model		Market Model					
Timeline	MAR	p-value	MAR	p-value	Volume Ratio	p-value	Volatility Ratio	p-value
AD-5	-0.07%	0.8457	0.03%	0.9441	1.06	0.5837	1.43	0.0028**
AD-4	0.07%	0.8935	0.11%	0.8205	1.22	0.0376**	1.23	0.0338**
AD-3	-0.50%	0.2158	-0.04%	0.9261	1.21	0.0820*	1.17	0.1689
AD-2	-0.27%	0.4897	-0.02%	0.9543	1.16	0.3542	1.25	0.0497**
AD-1	-0.53%	0.1819	-0.15%	0.7181	1.15	0.2802	1.24	0.0265**
AD	-1.13%	0.0128**	-0.93%	0.0478**	1.46	0.0014**	1.47	0.0028**
AD+1	-0.65%	0.1562	-0.10%	0.8319	1.32	0.0076**	1.56	0.0151**
AD+2	-0.50%	0.3044	-0.17%	0.7315	1.28	0.0134**	1.61	0.0001**
AD+3	0.79%	0.0828*	0.99%	0.0418**	1.28	0.0138**	1.32	0.0065**
AD+4	0.05%	0.9061	0.27%	0.5722	1.11	0.3249	1.41	0.0198**
AD+5	0.85%	0.0799*	1.10%	0.0327**	1.34	0.0081**	1.22	0.0377**

Table 5.8 presents the MAR, Volume Ratio and Volatility Ratio for the sample deletions on each day within the event window [ED-5, ED+5]. According to the market-adjusted return model, on average, the stocks deleted from the index obtained an abnormal return of -1.49% on ED, and the effect is statistically significant. The average abnormal return for the sample deletions on the two days before ED is also negative, at -0.76% and -0.48%, respectively. The price effect partially reverses on the day after ED and then keeps on dropping for another two days. Volume-wise, the trading volume peaks on ED, with Volume Ratio being more than five times higher than pre-event level. The day after ED sees a 50% larger trading volume, after which trading volume fluctuates for the next four days. Stock price volatility is 45% higher than pre-event level on ED and reaches even higher over the next five days. These price and volume effects around ED agree with existing S&P 500 studies and Schmidt et al.'s (2012) study on the S&P/ASX 200 index.

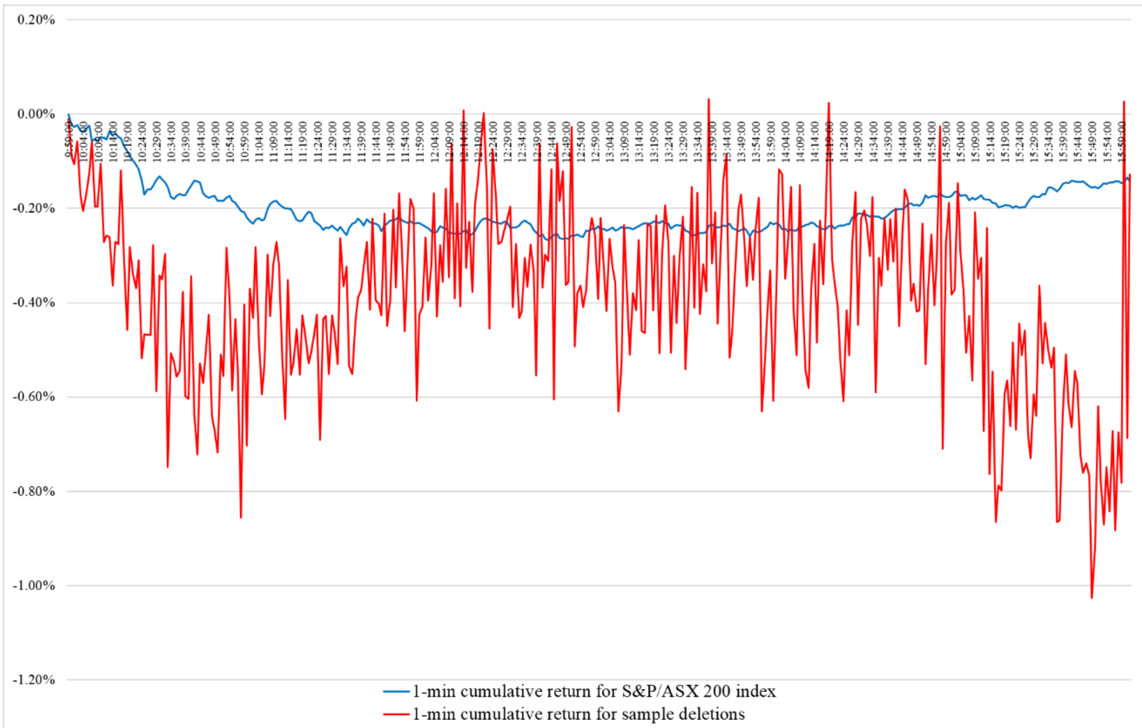
Table 5.8 Price, volume and volatility effects for S&P/ASX 200 index deletions during [ED-5, ED+5]

This table reports the MAR, Volume Ratio and Volatility Ratio for the S&P/ASX 200 sample deletions each day within the event window of five trading days before to five trading days after ED. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ASX 200 index): $AR_{it} = R_{it} - R_{mt}$; The MAR_t on day t across the sample stocks is calculated as: $MAR_t = (\sum_{i=1}^{N} AR_{it})/N$; *Volume Ratio* is calculated as $\frac{V_{it}}{V_{mt}} \cdot \frac{V_m}{V_i}$, representing the trading volume of stock i as a percentage of the total trading volume of the S&P/ASX 200 constituent stocks on day t, compared to the pre-event ratio; *Volatility Ratio* is calculated in the same manner as *Volume Ratio*, with volatility defined as the natural logarithm of the daily highest price divided by the daily lowest price. Student's t-test is performed to check the significance of the price, volume and volatility effects, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Price Effect				**Volume Effect**		**Volatility Effect**	
	Market Adjusted Return Model		**Market Model**					
Timeline	**MAR**	**p-value**	**MAR**	**p-value**	**Volume Ratio**	**p-value**	**Volatility Ratio**	**p-value**
ED-5	0.44%	0.3097	0.63%	0.1716	1.33	0.0476**	1.25	0.0371**
ED-4	-0.36%	0.4553	-0.10%	0.8348	1.34	0.0158**	1.44	0.0006**
ED-3	0.08%	0.8447	0.44%	0.2746	1.17	0.0464**	1.16	0.1492
ED-2	-0.76%	0.0813*	-0.58%	0.1771	1.08	0.3096	1.57	0.0010**
ED-1	-0.48%	0.2896	-0.24%	0.6154	1.04	0.5243	0.82	0.0099**
ED	-1.49%	0.0011**	-1.56%	0.0005**	5.02	<0.0001**	1.45	0.0030**
ED+1	0.16%	0.7229	0.68%	0.1420	1.52	0.0005**	1.19	0.0217**
ED+2	-1.06%	0.0060**	-0.87%	0.0243**	1.18	0.1701	2.86	0.1983
ED+3	-1.02%	0.0229**	-0.77%	0.0817*	1.42	0.2232	1.45	0.0622*
ED+4	0.36%	0.3741	0.91%	0.0302**	1.15	0.4232	1.76	0.3617
ED+5	0.00%	0.9951	0.41%	0.3313	1.26	0.2043	2.05	0.2502

We further investigate the sample deletions' intraday price movement on AD and ED. The intraday one-minute cumulative price returns of the sample deletions and the S&P/ASX 200 index on AD and ED are presented in Figures 5.3 and 5.4, respectively.

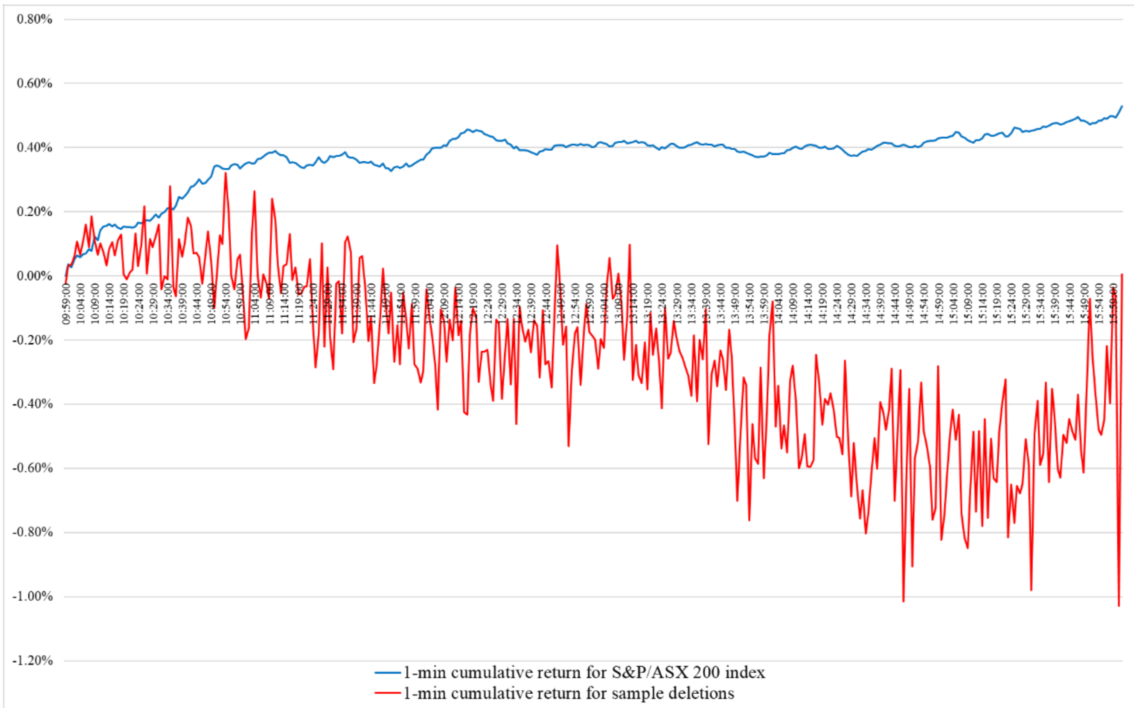
Figure 5.3 AD one-minute cumulative returns of sample deletions and S&P/ASX 200 index



We can see that, on AD, the sample deletions' prices decrease upon the rebalancing announcement and also near market close; on ED, the price drops throughout the day. In addition, we find that the average overnight price return from market close of the day before announcement to market open of AD is -0.73%, and that the AD intraday price return from market open to close is -0.61%. In comparison, the average overnight price return from market close of the day before ED to market open of ED is 0.1%, and the ED intraday price return from market open to close is -1.69%.

Therefore, the results together indicate that the S&P/ASX 200 index rebalancing event has a greater ED effect than AD effect for deletions, which differs from the findings for the index additions.

Figure 5.4 ED one-minute cumulative returns of sample deletions and S&P/ASX 200 index



5.4.2 Impact of AD–ED interval length

Beneish and Whaley (1996) examine whether abnormal returns are correlated with the number of days between AD and ED, and find a positive correlation. They conclude that the positive correlation indicates arbitragers' participation in the index revision, with their demand pushing up stock prices more than do index funds. Thus, a longer AD–ED interval could give arbitragers more time to play the 'S&P 500 game'.

To examine the impact of interval length between AD and ED on the S&P/ASX 200 rebalancing effect, we design an OLS regression model, as in Equation 5.15:

$CAR_i = \alpha + \beta\, N_i + \epsilon_{it}$,

with E $[\epsilon_{it}] = 0$ and VAR $[\epsilon_{it}] = \sigma_{it}^2$ (5.15) where CAR_i is the cumulative abnormal return for stock i over [AD, ED]; and N_i is the number of days between AD and ED for stock i.

5.4.2.1 Analysis results for additions

The regression results of Equation 5.15 are presented in the first column of Table 5.9. They show that for the sample additions, the cumulative abnormal return from AD to ED is negatively correlated with the numbers of days during [AD, ED], with this negative correlation being statistically significant.

Table 5.9 Impact of AD–ED interval length on the price effect for additions

This table reports the estimates from the OLS regression of Equation 5.15: $CAR_i = \alpha + \beta\ N_i + \epsilon_{it}$. The dependent variable CAR_i is the cumulative abnormal return for stock i over [AD, ED], [AD, ED-1] and ED, respectively. N_i is the number of days between announcement to ED for stock i . Student's t-test is performed to check the statistical significance, and the t-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	CAR during [AD, ED]	CAR during [AD, ED-1]	AR on ED
Intercept	0.0670** (2.144)	0.0704** (2.591)	-0.0048 (-0.380)
N	-0.0071** (-2.208)	-0.0063** (-2.250)	-0.0009 (-0.712)

An interpretation of this negative correlation is that an addition with a 10-trading-day interval between AD and ED is expected to obtain a cumulative abnormal return of -0.4% (0.0670 – 0.0071*10 = -0.004); while an addition with only five trading days in this interval is expected to obtain a cumulative abnormal return of 3.15% (0.0670 – 0.0071*5 = 0.0315). This negative correlation contradicts the positive one established in Beneish and Whaley (1996).

Noting that the MAR for additions on ED is -1.16%, as presented in Table 5.4, another two regressions are performed to examine if the negative correlation between cumulative abnormal return and AD–ED interval length is mainly affected by the negative MAR on ED itself, with the dependent variable of Equation 5.15 taken as the stock's cumulative abnormal returns during [AD, ED-1] and the abnormal return on ED, respectively. The regression results are presented in the last two columns of Table 5.9.

The regression results provide a consistent finding that the cumulative abnormal returns of the sample additions during [AD, ED] and [AD, ED-1] are both negatively correlated with AD–ED interval length. The different finding from that in Beneish and Whaley (1996) indicates that either little arbitraging behaviour is occurring during the index rebalancing period and the price pressure mainly comes from the index funds, or that arbitragers participating in the index rebalancing event start to trade once announcement is made and are able to unwind their positions before ED rather than continuing to push up the price until ED.

It is worth noting here that the average length of the S&P 500 AD–ED interval in Beneish and Whaley (1996) is 4.15 days, compared to the longer 9.44-day average interval of our S&P/ASX 200 additions sample. A longer rebalancing interval would provide arbitragers enough time to build their position upon the S&P/ASX 200 rebalancing announcement and then unwind it before ED, which may explain the negative cumulative abnormal returns for the S&P/ASX 200 additions (as shown in Table 5.1).

To further investigate the impact of AD–ED interval length, the MCAR of the sample additions according to their AD–ED interval lengths are presented in Table 5.10.

According to the market-adjusted return model, the 21 additions with a five-, six- or seven-trading-day AD–ED interval obtained a positive MCAR of 9.84%, 1.97% and 6.59%, respectively; while 16 of them obtained a positive cumulative abnormal return. In comparison, the additions with a 10- or 11-trading-day AD–ED interval experienced a negative MCAR of -3.39% and -0.41%, respectively. In general, the S&P/ASX200 additions with shorter AD–ED intervals have positive cumulative abnormal returns over the rebalancing period. This agrees with the literature focusing on the S&P 500 index, such as Beneish and Whaley (1996), Lynch and Mendenhall (1997), Elliott and Warr (2003) and Chen et al. (2004).

Table 5.10 Price effect for S&P/ASX 200 index additions with different AD–ED intervals

This table reports the MCAR during [AD, ED] for the S&P/ASX 200 sample additions with different AD–ED interval lengths. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ASX 200 index): $AR_{it} = R_{it} - R_{mt}$; the cumulative abnormal return CAR_i of stock i across the sample period [AD, ED] is calculated as: $CAR_i = \sum_{t=AD}^{ED} AR_{it}$; The $MCAR_t$ of year t across the N stocks added in that year is calculated as: $MCAR_t = (\sum_{i=1}^{N} CAR_{it})/N$; *Positive: Negative* gives the number of stocks with a positive CAR versus the number of stocks with a negative CAR. Student's t-test is performed to check the significance of the price effects, and the p-values are presented for the entire 75-stock sample. **(*) indicates statistical significance at the 5% (10%) level.

Interval Length	No. of Stocks	Market Adjusted Return Model		Market Model	
		MCAR	Positive: Negative	MCAR	Positive: Negative
5	1	9.84%	1:0	7.85%	1:0
6	18	1.97%	13:5	0.70%	12:6
7	2	6.59%	2:0	-3.93%	0:2
10	13	-3.39%	5:8	-6.37%	4:9
11	41	-0.41%	20:21	-2.65%	16:25
Entire Sample	75	-0.03% (p-value = 0.9670)	41:34	-2.38%** (p-value = 0.0051)	33:42

To further illustrate this perspective, the MAR, Volume Ratio and Volatility Ratio for each trading day during [AD-5, ED+5] are presented for the two larger subgroups of the sample additions: 18 stocks with a six-trading-day AD–ED interval and 41 stocks with an 11-trading-day AD–ED interval (see Tables 5.11 and 5.12).

Considering the smaller sample size of the 18 stocks with a six-trading-day AD–ED interval, the Mann-Whitney-Wilcoxon test is used instead of the Student's t-test to check the probability that the distribution on a day during the event period is the same as the distribution in the pre-test period.

Table 5.11 indicates that for the additions with a six-trading-day AD–ED interval, the stock prices outrun the S&P/ASX 200 index from the day before announcement until four days after announcement (the day before ED). The abnormal return on ED is -1.02% on average, which is statistically significant. Conversely, the additions with an 11-trading-day AD–ED interval, according to Table 5.12, experience positive abnormal returns from the day before announcement until five days after announcement. After that, the price starts to drop until ED. On average, the additions obtain an abnormal return of -1.11% and -1.17% on ED and the day before ED, respectively, with the effects being statistically significant.

Table 5.11 Price, volume and volatility effects during [AD-5, ED+5]: S&P/ASX 200 index additions with a six-trading-day AD–ED interval

This table reports the MAR, Volume Ratio and Volatility Ratio for the S&P/ASX 200 additions with a six-trading-day AD–ED interval on each day within [AD-5, ED+5]. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ ASX 200 index): $AR_{it} = R_{it} - R_{mt}$; The MAR_t on day t across the sample stocks is calculated as: $MAR_t = (\sum_{i=1}^{N} AR_{it})/N$; Volume Ratio is calculated as $\frac{V_{it}}{V_{mt}} \cdot \frac{V_m}{V_i}$, representing the trading volume of stock i as a percentage of the total trading volume of the S&P/ ASX 200 constituent stocks on trading day t, compared to the pre-event ratio; Volatility Ratio is calculated in the same manner as Volume Ratio, with volatility defined as the natural logarithm of the daily highest price divided by the daily lowest price. Mann-Whitney-Wilcoxon test is performed to check the probability that the distribution on a test day is the same as the distribution in the pre-test period, with p-values presented; **(*) indicates statistical significance at the 5% (10%) level.

	Price Effect		**Volume Effect**		**Volatility Effect**	
Timeline	**MAR**	**Mann-Whitney p-value**	**Volume Ratio**	**Mann-Whitney p-value**	**Volatility Ratio**	**Mann-Whitney p-value**
AD-5	0.28%	0.1232	1.14	0.9264	1.74	0.0935*
AD-4	-0.72%	0.2870	1.17	0.8192	1.37	0.0548*
AD-3	-0.25%	0.0083**	1.35	0.9110	1.27	0.4688
AD-2	0.46%	0.7081	1.17	0.9187	1.66	0.0226**
AD-1	1.27%	0.0536*	1.27	0.6097	1.56	0.0116**
AD	1.42%	0.2260	2.03	0.1097	1.31	0.1658
AD+1	2.09%	0.0022**	2.44	0.0548*	1.30	0.0283**
AD+2	-0.12%	0.2782	2.04	0.1600	1.31	0.1658
AD+3	0.28%	0.3684	2.02	0.2260	1.12	0.7226
AD+4	0.42%	0.3581	1.79	0.2655	0.81	0.0416**
AD+5(ED)	-1.02%	0.0001**	10.31	<0.0001**	1.39	0.1719
ED+1	0.71%	0.5498	2.26	0.0397**	1.25	0.5694
ED+2	0.67%	0.4628	2.29	0.0388**	1.51	0.7154
ED+3	-0.87%	0.0032**	2.30	0.0843*	1.36	0.6511
ED+4	-0.13%	0.5563	2.23	0.1355	1.63	0.4337
ED+5	0.65%	0.3841	2.32	0.1433	1.35	0.1942

Table 5.12 Price, volume and volatility effects during [AD-5, ED+5]: S&P/ASX 200 index additions with an 11-trading-day AD–ED interval

This table reports the MAR, Volume Ratio and Volatility Ratio for the S&P/ASX 200 additions with an 11-trading-day AD–ED interval on each day within [AD-5, ED+5]. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ ASX 200 index): $AR_{it} = R_{it} - R_{mt}$; The MAR_t on day t across the sample stocks is calculated as: $MAR_t = (\sum_{i=1}^{N} AR_{it})/N$; Volume Ratio is calculated as $\frac{V_{it}}{V_{mt}} \cdot \frac{V_m}{V_i}$, representing the trading volume of stock i as a percentage of the total trading volume of the S&P/ ASX 200 constituent stocks on trading day t, compared to the pre-event ratio; Volatility Ratio is calculated in the same manner as Volume Ratio, with volatility defined as the natural logarithm of the daily highest price divided by the daily lowest price. Student's t-test is performed to check the statistical significance, and the p-values are presented. **(*) indicates statistical significance at the 5% (10%) level.

	Price Effect		Volume Effect		Volatility Effect	
Timeline	MAR	t-test p-value	Volume Ratio	t-test p-value	Volatility Ratio	t-test p-value
AD-5	0.70%	0.0071*	0.91	0.4285	1.25	0.0093**
AD-4	0.03%	0.9340	1.49	0.0641*	1.18	0.0590*
AD-3	0.71%	0.0279**	1.43	0.0369**	1.02	0.8479
AD-2	-0.24%	0.3793	1.09	0.3909	1.22	0.0349**
AD-1	0.73%	0.0265**	1.44	0.0159**	1.22	0.0178**
AD	1.32%	0.0001**	1.76	<0.0001**	1.41	0.0130**
AD+1	0.94%	0.0043**	1.38	0.0157**	1.18	0.0535*
AD+2	-0.07%	0.8022	1.45	0.0133**	1.39	0.0054**
AD+3	0.12%	0.7268	1.27	0.0984*	1.26	0.0186**
AD+4	0.22%	0.3644	1.08	0.6182	1.06	0.6265
AD+5	0.02%	0.9478	1.29	0.1505	1.07	0.4027
AD+6	-0.31%	0.4439	1.50	0.0476**	1.16	0.1547
AD+7	-0.33%	0.3337	1.69	0.0183**	1.06	0.6482
AD+8	-0.27%	0.5219	1.42	0.0358**	1.47	0.0078**
AD+9	-1.17%	0.0013**	1.22	0.1056	0.98	0.8693
AD+10(ED)	-1.11%	0.0051*	10.52	<0.0001**	1.62	0.0003**
ED+1	0.54%	0.1816	2.97	0.0124**	1.29	0.0237**
ED+2	0.28%	0.4988	2.27	<0.0001**	1.92	0.0010**
ED+3	0.08%	0.8408	2.10	0.0031**	1.31	0.0260**
ED+4	-0.49%	0.1579	1.52	0.0009**	0.99	0.9253
ED+5	0.34%	0.2561	2.00	0.0223**	1.33	0.0148**

Together, Tables 5.11 and 5.12 show that for both subsamples, the additions have announcement effects that can last for four days after announcement. The subgroup with a six-trading-day AD–ED interval obtains average abnormal returns of 1.42% and 2.09% on AD and the day after, respectively, accompanied by trading volumes of more than double pre-event level. Buying the additions with a six-trading-day rebalancing interval at AD end and selling on the fourth day end would bring an excess return of 2.67%.

In comparison, the stocks with an 11-trading-day interval obtain average abnormal returns of 1.32% and 0.94% on AD and AD+1, respectively, with trading volumes of 76% and 38% higher than pre-event level. Similarly, buying the additions with an 11-trading-day rebalancing interval at AD end and then selling on the fourth day end would generate an excess return of 1.21%. Therefore, we can see that the shorter event window can lead to more intense price and volume effects upon announcement, and greater excess returns. The trading volumes on ED for both groups are 10 times larger than pre-event level, suggesting that index ETFs and other institutional investors are buying in.

The negative abnormal returns on ED contrast with the positive abnormal returns on AD and indicate that most of the price discovery happens around announcement. The reason for this could be that AD is the time when new information is released into the market, while no further information is released on ED.

To summarise, we find that the difference in the index rebalancing effects for the S&P/ASX 200 and S&P 500 is related to the different AD–ED rebalancing interval lengths of these two indices. The longer average revision interval for the S&P/ASX 200 gives any participating arbitragers enough time to buy upon announcement and unwind their positions and take a profit before ED. When the interval is shorter, arbitragers have limited time to unwind their position before ED, keeping the price up until the day before ED.

5.4.2.2 Analysis results for deletions

We now extend the rebalancing interval analysis to the S&P/ASX 200 sample deletions. Table 5.13 provides the MCAR for the sample deletions with different AD–ED interval lengths.

Table 5.13 Price effect for S&P/ASX 200 index deletions with different AD–ED interval lengths

This table reports the MCAR during [AD, ED] for the S&P/ASX 200 sample deletions with different AD–ED interval lengths. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ASX 200 index): $AR_{it} = R_{it} - R_{mt}$; the cumulative abnormal return CAR_i of stock i across the sample period [AD, ED] is calculated as: $CAR_i = \sum_{t=AD}^{ED} AR_{it}$; The $MCAR_t$ of year t across the N stocks deleted in that year is calculated as: $MCAR_t = (\sum_{i=1}^{N} CAR_{it})/N$; *Positive: Negative* gives the number of stocks with a positive CAR versus the number of stocks with a negative CAR. Student's t-test is performed to check the significance of the price effects, and the p-values are presented for the entire 69-stock sample. **(*) indicates statistical significance at the 5% (10%) level.

		Market Adjusted Return Model		Market Model	
Interval Length	**No. of Stocks**	**MCAR**	**Positive: Negative**	**MCAR**	**Positive: Negative**
5	1	-11.58%	0:1	-9.11%	0:1
6	5	-4.88%	1:4	-8.03%	1:4
9	1	-12.39%	0:1	-8.89%	0:1
10	14	-4.08%	5:9	-1.40%	4:10
11	48	-2.74%	17:31	0.67%	24:24
Entire Sample	69	-3.44%** (p-value = 0.0222)	23:46	-0.66% (p-value = 0.6609)	29:40

According to the market-adjusted return model, deletions with shorter rebalancing intervals (five to seven trading days) experience more negative average abnormal returns (-11.58%, -4.88% and -12.39%, respectively) compared to those with longer rebalancing intervals (-4.08% for the 10-day interval subgroup and -2.72% for the 11-day interval subgroup).

The regression results of Equation 5.15 provide a consistent finding, as presented in Table 5.14. It suggests that for the sample deletions, the cumulative abnormal returns during [AD, ED] are slightly positively correlated with the number of days between AD and ED, but this correlation is not statistically significant.

Table 5.14 Impact of AD–ED interval length on the price effect for deletions

This table reports the estimates from the OLS regression of Equation 5.15: $CAR_i = \alpha + \beta N_i + \epsilon_{it}$. The dependent variable CAR_i is the cumulative abnormal return for stock i over [AD, ED]. N_i is the number of days between announcement to ED for stock i . Student's t-test is performed to check the statistical significance, and the t-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-0.1129	0.1052	-1.073	0.287
N	0.0076	0.0101	0.753	0.454

Further, we again select the two subgroups with six- and 11-trading-day rebalancing intervals, to examine closely the price, volume and volatility effects on each day during [AD-5, ED+5]. The results are presented in Tables 5.15 and 5.16.

Table 5.15 shows that, on average, the deletions with a six-trading-day AD–ED interval experience a negative abnormal return of -2.76% upon the announcement, which is statistically significant. The negative abnormal return persists for the next four days, until the price reverses on ED. On average, the stocks obtain an abnormal return of 1.97% on ED, accompanied by a trading volume of more than twice pre-event level. Selling the deletions with a six-trading-day AD–ED interval at AD end and buying on the fourth day end would bring an excess return of 4.48%.

Table 5.15 Price, volume and volatility effects during [AD-5, ED+5]: S&P/ASX 200 index deletions with a six-trading-day AD–ED interval

This table reports the MAR, Volume Ratio and Volatility Ratio for the S&P/ASX 200 deletions with a six-trading-day AD–ED interval on each day within [AD-5, ED+5]. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ASX 200 index): $AR_{it} = R_{it} - R_{mt}$; The MAR_t on day t across the sample stocks is calculated as: $MAR_t = (\sum_{i=1}^{N} AR_{it})/N$; Volume Ratio is calculated as $\frac{V_{it}}{V_{mt}} \cdot \frac{V_m}{V_i}$, representing the trading volume of stock i as a percentage of the total trading volume of the S&P/ ASX 200 constituent stocks on trading day t, compared to the pre-event ratio; Volatility Ratio is calculated in the same manner as Volume Ratio, with volatility defined as the natural logarithm of the daily highest price divided by the daily lowest price. Mann-Whitney-Wilcoxon test is performed to check the probability that the distribution on a test day is the same as the distribution in the pre-test period, with p-values presented; **(*) indicates statistical significance at the 5% (10%) level.

	Price Effect		Volume Effect		Volatility Effect	
Timeline	**MAR**	**Mann-Whitney p-value**	**Volume Ratio**	**Mann-Whitney p-value**	**Volatility Ratio**	**Mann-Whitney p-value**
AD-5	4.91%	0.0012**	1.23	0.8127	3.49	0.0012**
AD-4	5.69%	0.0237**	1.63	0.8463	1.92	0.1963
AD-3	-1.24%	0.4382	1.10	0.6824	1.11	0.3657
AD-2	-0.69%	0.9656	0.97	0.6511	1.18	0.3434
AD-1	-1.33%	0.1210	1.00	0.6357	2.70	0.0081**
AD	-2.76%	0.0024**	0.99	0.8632	1.19	0.1890
AD+1	-3.52%	0.0251**	0.85	0.6204	2.08	0.0296**
AD+2	-0.91%	0.4382	0.63	0.3657	0.87	0.0429**
AD+3	-0.01%	0.0739*	1.14	0.9314	2.26	0.0811*
AD+4	-0.04%	0.4907	0.85	0.7304	0.98	0.1491
AD+5(ED)	1.97%	0.0034**	2.35	0.0889*	1.25	0.6053
ED+1	-1.78%	0.0296**	1.15	0.9828	1.57	0.4132
ED+2	0.20%	1.0000	0.93	0.7630	2.37	0.0367**
ED+3	-1.74%	0.0251**	0.70	0.4382	1.36	0.9143
ED+4	-1.41%	0.0889*	0.65	0.2039	0.54	0.0024**
ED+5	-1.32%	0.1063	0.99	0.8802	0.77	0.0076**

In comparison, the deletions with an 11-trading-day AD–ED interval, as shown in Table 5.16, obtain an insignificant abnormal return of -0.12% upon announcement. The MAR maintains a similar level for the next two days, after which it starts to fluctuate until three days before ED. On ED, the MAR is -1.76%, which is statistically significant, and the trading volume is five times pre-event level. The price reverses on the day after ED, accompanied by a trading volume of 50% higher than pre-event level.

Following the strategy of selling the deletions with an 11-trading-day AD–ED interval three days before ED and buying on ED would bring an excess return of 4.27%.

The results show that the deletions with a shorter event window have stronger AD effects, while the deletion with a longer event window have stronger ED effects, indicating that market participants tend to build their position and start selling as ED approaches.

Table 5.16 Price, volume and volatility effects during [AD-5, ED+5]: S&P/ASX 200 index deletions with an 11-trading-day AD–ED interval

This table reports the MAR, Volume Ratio and Volatility Ratio for the S&P/ASX 200 deletions with an 11-trading-day AD–ED interval on each day within [AD-5, ED+5]. For the market-adjusted return model, Abnormal Return AR_{it} of stock i on day t is defined as the stock return's deviation from the market benchmark return (here, the S&P/ASX 200 index): $AR_{it} = R_{it} - R_{mt}$; The MAR_t on day t across the sample stocks is calculated as: $MAR_t = (\sum_{i=1}^{N} AR_{it})/N$; Volume Ratio is calculated as $\frac{V_{it}}{V_{mt}} \cdot \frac{V_m}{V_i}$, representing the trading volume of stock i as a percentage of the total trading volume of the S&P/ ASX 200 constituent stocks on trading day t, compared to the pre-event ratio; Volatility Ratio is calculated in the same manner as Volume Ratio, with volatility defined as the natural logarithm of the daily highest price divided by the daily lowest price. Student's t-test is performed to check the statistical significance, and the p-values are presented. **(*) indicates statistical significance at the 5% (10%) level.

	Price Effect		Volume Effect		Volatility Effect	
Timeline	**MAR**	**t-test p-value**	**Volume Ratio**	**t-test p-value**	**Volatility Ratio**	**t-test p-value**
AD-5	-0.23%	0.5638	0.91	0.3812	1.17	0.1528
AD-4	-0.59%	0.3586	1.17	0.1188	1.01	0.9206
AD-3	-0.95%	0.1122	1.16	0.2162	1.10	0.4124
AD-2	-0.15%	0.7797	0.90	0.2421	1.13	0.1439
AD-1	-0.61%	0.2232	1.02	0.7906	1.08	0.3441
AD	-0.12%	0.8512	1.30	0.0135**	1.35	0.0095**
AD+1	-0.27%	0.6623	1.17	0.1708	1.16	0.2489
AD+2	-0.85%	0.2593	1.24	0.0538*	1.65	0.0007**
AD+3	2.31%	0.0111**	1.26	0.0833*	1.22	0.0970*
AD+4	-0.05%	0.9526	1.08	0.5957	1.49	0.0438**
AD+5	0.88%	0.1856	1.26	0.0957*	1.20	0.1581
AD+6	-0.07%	0.8866	1.27	0.0319**	1.38	0.0211**
AD+7	0.68%	0.2156	1.11	0.2075	1.09	0.4673
AD+8	-1.38%	0.0111**	1.01	0.8714	1.31	0.0133**
AD+9	-1.13%	0.0716*	1.02	0.8399	0.81	0.0277**
AD+10(ED)	-1.76%	0.0029**	5.11	<0.0001**	1.45	0.0162**
ED+1	1.05%	0.0885*	1.56	0.0056**	1.11	0.2839
ED+2	-0.86%	0.0330**	1.06	0.5334	1.44	0.0013**
ED+3	-1.37%	0.0066**	1.00	0.9620	1.22	0.1285
ED+4	1.51%	0.0579*	0.95	0.7455	0.91	0.1380
ED+5	0.19%	0.7517	1.18	0.4536	1.12	0.2554

5.4.3 Market liquidity effects

This section examines the market liquidity effects of the S&P/ASX 200 rebalancing event. Beneish and Whaley (1996) measures the abnormal quoted spread (trade size) for a particular stock by computing the ratio of its average-quoted spread (trade size) over the event period to the 60-day pre-event average level. Therefore, a larger than 1 ratio indicates the quoted spread (trade size) over the event window is bigger than the pre-event level, while a smaller than 1 ratio indicates the opposite. A similar method is used by Hegde and McDermott (2003) in investigating the short-term market liquidity effects of S&P 500 additions.

The OLS regression as presented in Equation 5.16 is employed to examine the market liquidity effects of the S&P/ASX 200 index rebalancing:

$$Liquidty_{it} = \alpha_i + \beta_i Event_{it} + \epsilon_{it},$$

$$\text{with E } [\epsilon_{it}] = 0 \text{ and VAR } [\epsilon_{it}] = \sigma_{it}^2 \qquad (5.16)$$

where $Liquidity_{it}$ is the end-of-day market liquidity measurements—quoted spread, effective spread, realised spread, best depth and trade size—for stock i on day t; and $Event_{it}$ takes a value of 1 if day t falls in the event period, or 0 if it falls in the pre-event window [ED-90, ED-31]. This OLS regression functions in the same way as the ratio method in Beneish and Whaley (1996) and Hegde and McDermott (2003): a positive β_i indicates a ratio bigger than 1, while a negative β_i suggests otherwise.

Based on the effect found for the AD–ED interval in Section 5.4.2, we first analyse the subgroups of additions and deletions with six- and 11-trading-day intervals. The event window is taken as [AD-5, ED+5], and the estimated α, β and corresponding Student's t-test p-values are presented for each day during the event period.

5.4.3.1 Analysis results for additions

The OLS regression results of Equation 5.16 for the additions with six- and 11-trading-day AD–ED intervals are presented in Tables 5.17 and 5.18, respectively.

Table 5.17 shows that for the additions with a six-trading-day AD–ED interval, the coefficients of the dummy variable Event for the quoted spread, effective spread and realised spread on each day are uniformly negative, indicating the spreads decrease during [AD-5, ED+5]. The statistically significant narrower spreads appear from the day after announcement until four to five days after ED.

The coefficients of the dummy variable Event for best depth are positive during the study period, indicating that the average volume of best bid-ask prices is larger than the pre-event level. The statistically significant larger best depth appears on the day after AD, and from the day before ED to three days after ED.

As for trade size, the coefficients for the dummy variable Event are negative across the event window [AD-5, ED+5] except for on ED. This indicates that the trade size is smaller than the pre-event level during the event, but on ED the average trade size is three times larger than in the pre-event period.

The regression results for the additions with an 11-trading-day AD–ED interval are similar, as presented in Table 5.18. The spreads are uniformly narrower, best depth is larger, and trade size is smaller than the pre-event level, with the largest trade size appearing on ED. The OLS regression of Equation 5.16 is also performed for the additions with a 10-trading-day AD–ED interval, and the results are presented in *Appendix 2* and are similar to those for the additions with an 11-trading-day interval.

Table 5.17 Liquidity effects during [AD-5, ED+5]: S&P/ASX 200 index additions with a six-trading-day AD–ED interval

This table reports the estimates for the OLS regression of Equation 5.16: $Liquidity_{it} = \alpha_i + \beta_i Event_{it} + \epsilon_{it}$ for the additions with a six-trading-day AD–ED interval. The dependent variable $Liquidity_{it}$ is the end-of-day market liquidity measurements—quoted spread, effective spread, realised spread, best depth and trade size—for stock i on day t; $Event_{it}$ takes a value of 1 if day t is within the event period, or 0 if it is pre-event. Student's t-test is performed to check the statistical significance, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Quoted Spread (bps)		Effective Spread (bps)		Realised Spread (bps)		Best Depth ('000 shares)		Trade Size ('000 shares)	
Timeline	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**
AD-5	41.28 (<0.0001)**	-5.74 (0.2505)	33.11 (<0.0001)**	-2.17 (0.6449)	22.53 (<0.0001)**	-4.58 (0.3120)	25.83 (<0.0001)**	0.16 (0.9855)	0.97 (<0.0001)**	-0.37 (0.3246)
AD-4	41.28 (<0.0001)**	-4.85 (0.3321)	33.11 (<0.0001)**	-4.71 (0.3142)	22.53 (<0.0001)**	-0.70 (0.8762)	25.83 (<0.0001)**	1.06 (0.9062)	0.97 (<0.0001)**	-0.31 (0.4107)
AD-3	41.28 (<0.0001)**	-5.28 (0.2907)	33.11 (<0.0001)**	-4.11 (0.3796)	22.53 (<0.0001)**	-1.67 (0.7119)	25.83 (<0.0001)**	0.57 (0.9492)	0.97 (<0.0001)**	-0.30 (0.4283)
AD-2	41.28 (<0.0001)**	-4.86 (0.3313)	33.11 (<0.0001)**	-4.36 (0.3522)	22.53 (<0.0001)**	-6.69 (0.1392)	25.83 (<0.0001)**	1.37 (0.8785)	0.97 (<0.0001)**	-0.16 (0.6812)
AD-1	41.28 (<0.0001)**	-5.03 (0.3140)	33.11 (<0.0001)**	-8.54 (0.0688)	22.53 (<0.0001)**	-8.44 (0.0619)*	25.83 (<0.0001)**	2.51 (0.7802)	0.97 (<0.0001)**	-0.13 (0.7285)
AD	41.28 (<0.0001)**	-5.83 (0.2438)	33.11 (<0.0001)**	-7.64 (0.1032)	22.53 (<0.0001)**	-4.46 (0.3236)	25.83 (<0.0001)**	6.85 (0.4473)	0.97 (<0.0001)**	-0.08 (0.8384)
AD+1	41.28 (<0.0001)**	-9.63 (0.0540)*	33.11 (<0.0001)**	-8.34 (0.0752)*	22.53 (<0.0001)**	-9.44 (0.0370)**	25.83 (<0.0001)**	18.04 (0.0478)*	0.97 (<0.0001)**	-0.19 (0.6109)
AD+2	41.28 (<0.0001)**	-9.75 (0.0510)*	33.11 (<0.0001)**	-10.37 (0.0268)**	22.53 (<0.0001)**	-6.22 (0.1688)	25.83 (<0.0001)**	10.46 (0.2460)	0.97 (<0.0001)**	-0.30 (0.4286)
AD+3	41.28 (<0.0001)**	-9.00 (0.0716)*	33.11 (<0.0001)**	-9.92 (0.0340)**	22.53 (<0.0001)**	-7.80 (0.0842)*	25.83 (<0.0001)**	11.85 (0.1905)	0.97 (<0.0001)**	-0.16 (0.6749)
AD+4	41.28 (<0.0001)**	-10.34 (0.0384)**	33.11 (<0.0001)**	-9.90 (0.0345)**	22.53 (<0.0001)**	-8.99 (0.0468)**	25.83 (<0.0001)**	29.39 (0.0016)**	0.97 (<0.0001)**	-0.25 (0.5025)
AD+5 (ED)	41.28 (<0.0001)**	-10.29 (0.0394)**	33.11 (<0.0001)**	-10.94 (0.0195)**	22.53 (<0.0001)**	-7.97 (0.0779)*	25.83 (<0.0001)**	37.53 (0.0001)**	0.97 (<0.0001)**	3.43 (<0.0001)**

Table 5.17 Continued

	Quoted Spread (bps)		Effective Spread (bps)		Realised Spread (bps)		Best Depth ('000 shares)		Trade Size ('000 shares)	
Timeline	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**
ED+1	41.28 (<0.0001)**	-11.19 (0.0251)**	33.11 (<0.0001)**	-12.48 (0.0077)**	22.53 (<0.0001)**	-8.33 (0.0655)*	25.83 (<0.0001)**	12.82 (0.1567)	0.97 (<0.0001)**	-0.21 (0.5881)
ED+2	41.28 (<0.0001)**	-11.74 (0.0188)**	33.11 (<0.0001)**	-12.67 (0.0068)**	22.53 (<0.0001)**	-7.63 (0.0913)*	25.83 (<0.0001)**	23.24 (0.0107)**	0.97 (<0.0001)**	-0.17 (0.6611)
ED+3	41.28 (<0.0001)**	-10.55 (0.0347)**	33.11 (<0.0001)**	-10.67 (0.0227)**	22.53 (<0.0001)**	-8.52 (0.0595)*	25.83 (<0.0001)**	17.03 (0.0614)*	0.97 (<0.0001)**	-0.13 (0.7312)
ED+4	41.28 (<0.0001)**	-9.78 (0.0504)*	33.11 (<0.0001)**	-11.57 (0.0135)**	22.53 (<0.0001)**	-7.76 (0.0861)*	25.83 (<0.0001)**	9.47 (0.2948)	0.97 (<0.0001)**	0.29 (0.4595)
ED+5	41.28 (<0.0001)**	-10.21 (0.0410)**	33.11 (<0.0001)**	-10.83 (0.0208)**	22.53 (<0.0001)**	-6.23 (0.1689)	25.83 (<0.0001)**	4.72 (0.5993)	0.97 (<0.0001)**	-0.13 (0.7264)

Table 5.18 Liquidity effects during [AD-5, ED+5]: S&P/ASX 200 index additions with 11-trading-day AD–ED interval

This table reports the estimates for the OLS regression of Equation 5.16: $Liquidity_{it} = \alpha_i + \beta_i Event_{it} + \epsilon_{it}$ for the additions with an 11-trading-day AD–ED interval. The dependent variable $Liquidity_{it}$ is the end-of-day market liquidity measurements—quoted spread, effective spread, realised spread, best depth and trade size—for stock i on day t; $Event_{it}$ takes a value of 1 if day t is within the event period, or 0 if it is pre-event. Student's t-test is performed to check the statistical significance, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Quoted Spread (bps)		Effective Spread (bps)		Realised Spread (bps)		Best Depth ('000 shares)		Trade Size ('000 shares)	
Timeline	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**
AD-5	46.20 (<0.0001)**	-5.07 (0.1744)	36.18 (<0.0001)**	-4.29 (0.1977)	24.46 (<0.0001)**	-1.09 (0.7440)	48.11 (<0.0001)**	-6.65 (0.7297)	1.13 (<0.0001)**	-0.16 (0.6310)
AD-4	46.20 (<0.0001)**	-4.61 (0.2169)	36.18 (<0.0001)**	-4.04 (0.2250)	24.46 (<0.0001)**	-2.34 (0.4841)	48.11 (<0.0001)**	-3.49 (0.8565)	1.13 (<0.0001)**	-0.03 (0.9379)
AD-3	46.20 (<0.0001)**	-6.39 (0.0873)*	36.18 (<0.0001)**	-5.52 (0.0973)*	24.46 (<0.0001)**	-2.61 (0.4347)	48.11 (<0.0001)**	-3.39 (0.8605)	1.13 (<0.0001)**	-0.20 (0.5422)
AD-2	46.20 (<0.0001)**	-7.01 (0.0608)*	36.18 (<0.0001)**	-5.65 (0.0902)*	24.46 (<0.0001)**	-2.55 (0.4454)	48.11 (<0.0001)**	4.69 (0.8086)	1.13 (<0.0001)**	-0.35 (0.2805)
AD-1	46.20 (<0.0001)**	-6.57 (0.0790)*	36.18 (<0.0001)**	-4.85 (0.1458)	24.46 (<0.0001)**	-1.63 (0.6250)	48.11 (<0.0001)**	9.64 (0.6206)	1.13 (<0.0001)**	-0.13 (0.6999)
AD	46.20 (<0.0001)**	-8.17 (0.0286)**	36.18 (<0.0001)**	-6.49 (0.0513)*	24.46 (<0.0001)**	-6.05 (0.0702)*	48.11 (<0.0001)**	35.64 (0.0694)*	1.13 (<0.0001)**	-0.02 (0.9593)
AD+1	46.20 (<0.0001)**	-6.10 (0.1026)	36.18 (<0.0001)**	-7.18 (0.0308)**	24.46 (<0.0001)**	-4.70 (0.1588)	48.11 (<0.0001)**	26.13 (0.1809)	1.13 (<0.0001)**	-0.19 (0.5577)
AD+2	46.20 (<0.0001)**	-8.11 (0.0299)**	36.18 (<0.0001)**	-6.78 (0.0419)**	24.46 (<0.0001)**	-1.96 (0.5562)	48.11 (<0.0001)**	16.46 (0.3960)	1.13 (<0.0001)**	-0.13 (0.6859)
AD+3	46.20 (<0.0001)**	-5.65 (0.1304)	36.18 (<0.0001)**	-6.78 (0.0414)**	24.46 (<0.0001)**	-3.49 (0.2953)	48.11 (<0.0001)**	18.95 (0.3300)	1.13 (<0.0001)**	-0.25 (0.4346)
AD+4	46.20 (<0.0001)**	-5.21 (0.1628)	36.18 (<0.0001)**	-5.62 (0.0915)*	24.46 (<0.0001)**	-1.97 (0.5556)	48.11 (<0.0001)**	10.43 (0.5912)	1.13 (<0.0001)**	-0.31 (0.3363)
AD+5	46.20 (<0.0001)**	-5.40 (0.1480)	36.18 (<0.0001)**	-7.29 (0.0286)**	24.46 (<0.0001)**	-1.66 (0.6199)	48.11 (<0.0001)**	2.86 (0.8821)	1.13 (<0.0001)**	-0.38 (0.2481)

Table 5.18 Continued

	Quoted Spread (bps)		Effective Spread (bps)		Realised Spread (bps)		Best Depth ('000 shares)		Trade Size ('000 shares)	
Timeline	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**
AD+6	46.20 (<0.0001)**	-4.58 (0.2204)	36.18 (<0.0001)**	-7.59 (0.0226)**	24.46 (<0.0001)**	-4.97 (0.1355)	48.11 (<0.0001)**	-5.77 (0.7645)	1.13 (<0.0001)**	-0.41 (0.2069)
AD+7	46.20 (<0.0001)**	-6.45 (0.0846)*	36.18 (<0.0001)**	-7.85 (0.0182)**	24.46 (<0.0001)**	-2.92 (0.3825)	48.11 (<0.0001)**	17.37 (0.3715)	1.13 (<0.0001)**	-0.32 (0.3213)
AD+8	46.20 (<0.0001)**	-6.13 (0.1015)	36.18 (<0.0001)**	-7.71 (0.0204)**	24.46 (<0.0001)**	-1.07 (0.7484)	48.11 (<0.0001)**	9.81 (0.6118)	1.13 (<0.0001)**	-0.30 (0.3622)
AD+9	46.20 (<0.0001)**	-5.58 (0.1358)	36.18 (<0.0001)**	-6.81 (0.0410)*	24.46 (<0.0001)**	-4.28 (0.1990)	48.11 (<0.0001)**	19.86 (0.3070)	1.13 (<0.0001)**	-0.27 (0.4094)
AD+10(ED)	46.20 (<0.0001)**	-6.41 (0.0866)*	36.18 (<0.0001)**	-7.88 (0.0179)**	24.46 (<0.0001)**	-3.36 (0.3139)	48.11 (<0.0001)**	25.34 (0.1916)	1.13 (<0.0001)**	3.58 (<0.0001)**
ED+1	46.20 (<0.0001)**	-6.49 (0.0828)*	36.18 (<0.0001)**	-8.89 (0.0075)**	24.46 (<0.0001)**	-3.00 (0.3701)	48.11 (<0.0001)**	2.80 (0.8847)	1.13 (<0.0001)**	-0.15 (0.6423)
ED+2	46.20 (<0.0001)**	-6.14 (0.1006)	36.18 (<0.0001)**	-8.34 (0.0124)**	24.46 (<0.0001)**	-6.00 (0.0718)*	48.11 (<0.0001)**	7.37 (0.7027)	1.13 (<0.0001)**	-0.27 (0.4104)
ED+3	46.20 (<0.0001)**	-4.89 (0.1937)	36.18 (<0.0001)**	-10.10 (0.0024)**	24.46 (<0.0001)**	-9.02 (0.0068)**	48.11 (<0.0001)**	21.32 (0.2719)	1.13 (<0.0001)**	-0.25 (0.4409)
ED+4	46.20 (<0.0001)**	-2.89 (0.4407)	36.18 (<0.0001)**	-8.02 (0.0160)**	24.46 (<0.0001)**	-3.61 (0.2799)	48.11 (<0.0001)**	29.3 (0.1365)	1.13 (<0.0001)**	-0.14 (0.6632)
ED+5	46.20 (<0.0001)**	-7.38 (0.0485)**	36.18 (<0.0001)**	-9.02 (0.0068)**	24.46 (<0.0001)**	-5.95 (0.0747)*	48.11 (<0.0001)**	0.67 (0.9722)	1.13 (<0.0001)**	-0.28 (0.3870)

We then take one step further to run the OLS regression of Equation 5.16 for all the sample additions, with each stock-day observation during the period [AD, ED] and the 60-day pre-event period [ED-90, ED-31]. The results are presented in Table 5.19. It is worth noting that trade size is not analysed, because as presented in Tables 5.17 and 5.18, a significantly larger trade size is only observed on ED, while it is smaller on other event days.

Table 5.19 Liquidity effects for S&P/ASX 200 index sample additions during [AD, ED]

This table reports the estimates for the OLS regression of Equation 5.16: $Liquidity_{it} = \alpha_i + \beta_i Event_{it} + \epsilon_{it}$. The dependent variable $Liquidity_{it}$ is the end-of-day market liquidity measurements—quoted spread, effective spread, realised spread, best depth−for stock i on day t; $Event_{it}$ takes a value of 1 if day t is within the event period [AD, ED], or 0 if it is pre-event. Student's t-test is performed to check the statistical significance and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Market Liquidity Measurement			
	Quoted Spread (bps)	**Effective Spread (bps)**	**Realised Spread (bps)**	**Best Depth ('000 shares)**
Intercept	42.25** (<0.0001)	33.67** (<0.0001)	22.15** (<0.0001)	38.14** (<0.0001)
Event	-5.62** (<0.0001)	-6.43** (<0.0001)	-3.17** (<0.0001)	15.21** (<0.0001)

Table 5.19 shows that for quoted spread, effective spread and realised spread, the coefficients of the dummy variable Event are significantly negative, meaning that the spreads for the entire sample of additions decrease during [AD, ED]. Conversely, best depth increased significantly during the event period.

The analysis results in Tables 5.17 to 5.19 reveal that during the S&P/ASX 200 index rebalancing event, the stocks added to the index experienced liquidity improvement in terms of quoted spread, effective spread, realised spread and best depth. The significantly larger trade size on ED indicates that index funds and institutional investors buy newly added stocks on that day.

Finally, the long-run market liquidity effects are investigated by running the OLS regression of Equation 5.17 for all the sample additions with each stock-day observation during the post-event period of [ED+31, ED+90] (31 days after ED to 90 day after it) and the 60-day pre-event period [ED-90, ED-31]:

$$Liquidity_{it} = \alpha_i + \beta_i Post\_Event_{it} + \epsilon_{it},$$

$$\text{with E } [\epsilon_{it}] = 0 \text{ and VAR } [\epsilon_{it}] = \sigma_{it}^2, \quad (5.17)$$

where $Liquidity_{it}$ is the end-of-day market liquidity measurements—quoted spread, effective spread, realised spread, best depth and trade size—for stock i on day t. $Post\_Event_{it}$ takes a value of 1 if day t falls in the post-event period [ED+31, ED+90], or 0 if it falls in the pre-event window [ED-90, ED-31]. The results are presented in Table 5.20.

Table 5.20 Liquidity effects for S&P/ASX 200 index sample additions during [ED+31, ED+90]

This table reports the estimates for the OLS regression of Equation 5.17: $Liquidity_{it} = \alpha_i + \beta_i Post\_Event_{it} + \epsilon_{it}$. The dependent variable $Liquidity_{it}$ is the end-of-day market liquidity measurements—quoted spread, effective spread, realised spread, best depth and trade size—for stock i on day t; $Post\_Event_{it}$ takes a value of 1 if day t is within the post-event period [ED+31, ED+90], or 0 if it is pre-event. Student's t-test is performed to check the statistical significance and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Market Liquidity Measurement				
	Quoted Spread (bps)	**Effective Spread (bps)**	**Realised Spread (bps)**	**Best Depth ('000 shares)**	**Trade Size ('000 shares)**
Intercept	42.25** (<0.0001)	33.67** (<0.0001)	22.15** (<0.0001)	38.14** (<0.0001)	1.04** (<0.0001)
Event	-6.88** (<0.0001)	-8.32** (<0.0001)	-5.27** (<0.0001)	9.90** (<0.0001)	-0.21** (<0.0001)

Table 5.20 shows that for quoted spread, effective spread, realised spread and trade size, the coefficients of the dummy variable Post_Event are significantly negative, indicating that the stocks added to the S&P/ASX 200 experienced a decrease in quoted

spread, effective spread, realised spread and trade size after the index rebalancing event. Conversely, best depth increased significantly after the event. Thus, the long-run liquidity of the additions to the S&P/ASX 200 increased after the index rebalancing event.

To summarise the liquidity effects for the index additions, the short-term market liquidity effects in terms of quoted spread and best depth are consistent with the findings in Beneish and Whaley (1996) and Hegde and McDermott (2003); that is, the spreads are narrower and depth is thicker during the index rebalancing event. In terms of trade size, we find that a significantly larger trade size appears only on ED. As for the long-term market liquidity, we find that the stocks added to the S&P/ASX 200 index have experienced a significant decrease in quoted spread, effective spread and relative spread, and a significant increase in best depth, which suggests a sustained market liquidity improvement for the additions. These findings are consistent with those in Hegde and McDermott (2003).

5.4.3.2 Analysis results for deletions

The same analysis as for the sample additions is now performed for the S&P/ASX 200 deletions sample. First, the OLS regression of Equation 5.16 is carried out for the deletions with six- and 11-trading-day AD–ED intervals, respectively, with the results presented in Tables 5.21 and 5.22.

Table 5.21 Liquidity effects during [AD-5, ED+5]: S&P/ASX 200 index deletions with a six-trading-day AD–ED interval

This table reports the estimates for the OLS regression of Equation 5.16: $Liquidity_{it} = \alpha_i + \beta_i Event_{it} + \epsilon_{it}$ for the deletions with a six-trading-day AD–ED interval. The dependent variable $Liquidity_{it}$ is the end-of-day market liquidity measurements—quoted spread, effective spread, realised spread, best depth and trade size—for stock i on day t; $Event_{it}$ takes a value of 1 if day t is within the event period, or 0 if it is pre-event. Student's t-test is performed to check the statistical significance, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Quoted Spread (bps)		Effective Spread (bps)		Realised Spread (bps)		Best Depth ('000 shares)		Trade Size ('000 shares)	
Timeline	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**
AD-5	102.24 (<0.0001)**	-29.73 (0.4754)	66.39 (<0.0001)**	-13.95 (0.6219)	67.1 (<0.0001)**	-39.61 (0.3669)	432.4 (<0.0001)**	-291.39 (0.4782)	2.28 (<0.0001)**	0.89 (0.4643)
AD-4	102.24 (<0.0001)**	-32.65 (0.4330)	66.39 (<0.0001)**	-18.24 (0.519)	67.1 (<0.0001)**	-44.04 (0.3155)	432.4 (<0.0001)**	-307.35 (0.4544)	2.28 (<0.0001)**	1.51 (0.2195)
AD-3	102.24 (<0.0001)**	-29.47 (0.4794)	66.39 (<0.0001)**	-10.72 (0.7052)	67.1 (<0.0001)**	-40.87 (0.3516)	432.4 (<0.0001)**	-333.54 (0.4169)	2.28 (<0.0001)**	0.19 (0.8777)
AD-2	102.24 (<0.0001)**	-28.25 (0.4978)	66.39 (<0.0001)**	-12.76 (0.6522)	67.1 (<0.0001)**	-40.85 (0.3518)	432.4 (<0.0001)**	-322.99 (0.4318)	2.28 (<0.0001)**	0.24 (0.8453)
AD-1	102.24 (<0.0001)**	-31.00 (0.4568)	66.39 (<0.0001)**	-13.32 (0.6380)	67.1 (<0.0001)**	-32.49 (0.4591)	432.4 (<0.0001)**	-355.23 (0.3872)	2.28 (<0.0001)**	-0.74 (0.5383)
AD	102.24 (<0.0001)**	-28.94 (0.4873)	66.39 (<0.0001)**	-10.49 (0.7111)	67.1 (<0.0001)**	-36.53 (0.4051)	432.4 (<0.0001)**	-311.00 (0.4491)	2.28 (<0.0001)**	-0.22 (0.8574)
AD+1	102.24 (<0.0001)**	-26.54 (0.5242)	66.39 (<0.0001)**	-10.21 (0.7185)	67.1 (<0.0001)**	-38.40 (0.3815)	432.4 (<0.0001)**	-334.39 (0.4157)	2.28 (<0.0001)**	-0.54 (0.6538)
AD+2	102.24 (<0.0001)**	-27.26 (0.5133)	66.39 (<0.0001)**	-7.07 (0.8029)	67.1 (<0.0001)**	-25.69 (0.5581)	432.4 (<0.0001)**	-308.37 (0.4529)	2.28 (<0.0001)**	-0.65 (0.5871)
AD+3	102.24 (<0.0001)**	-23.99 (0.5651)	66.39 (<0.0001)**	-13.34 (0.6383)	67.1 (<0.0001)**	-28.85 (0.5108)	432.4 (<0.0001)**	-328.58 (0.4238)	2.28 (<0.0001)**	-0.17 (0.8853)
AD+4	102.24 (<0.0001)**	-20.53 (0.6228)	66.39 (<0.0001)**	6.95 (0.8065)	67.1 (<0.0001)**	-2.21 (0.9599)	432.4 (<0.0001)**	-294.31 (0.4738)	2.28 (<0.0001)**	-0.2 (0.8666)
AD+5 (ED)	102.24 (<0.0001)**	-23.04 (0.5805)	66.39 (<0.0001)**	-10.18 (0.7200)	67.1 (<0.0001)**	-28.88 (0.5104)	432.4 (<0.0001)**	-239.85 (0.5594)	2.28 (<0.0001)**	2.51 (0.0394)

Table 5.21 Continued

	Quoted Spread (bps)		Effective Spread (bps)		Realised Spread (bps)		Best Depth ('000 shares)		Trade Size ('000 shares)	
Timeline	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**
ED+1	102.24 (<0.0001)**	-23.22 (0.5774)	66.39 (<0.0001)**	-3.00 (0.9157)	67.1 (<0.0001)**	-38.54 (0.3798)	432.4 (<0.0001)**	-294.22 (0.4739)	2.28 (<0.0001)**	0.1 (0.9332)
ED+2	102.24 (<0.0001)**	-21.15 (0.6121)	66.39 (<0.0001)**	-3.55 (0.9004)	67.1 (<0.0001)**	-36.31 (0.4079)	432.4 (<0.0001)**	-319.74 (0.4364)	2.28 (<0.0001)**	0.41 (0.7385)
ED+3	102.24 (<0.0001)**	-13.57 (0.7449)	66.39 (<0.0001)**	-3.57 (0.9001)	67.1 (<0.0001)**	-25.47 (0.5619)	432.4 (<0.0001)**	-239.48 (0.5601)	2.28 (<0.0001)**	-0.04 (0.9710)
ED+4	102.24 (<0.0001)**	-12.91 (0.7570)	66.39 (<0.0001)**	-5.43 (0.8483)	67.1 (<0.0001)**	-28.39 (0.5177)	432.4 (<0.0001)**	-269.69 (0.5116)	2.28 (<0.0001)**	-0.71 (0.5545)
ED+5	102.24 (<0.0001)**	-12.77 (0.7596)	66.39 (<0.0001)**	-6.70 (0.8133)	67.1 (<0.0001)**	-41.20 (0.3478)	432.4 (<0.0001)**	-299.57 (0.4659)	2.28 (<0.0001)**	-0.69 (0.5645)

Table 5.22 Liquidity effects during [AD-5, ED+5]: S&P/ASX 200 index deletions with an 11-trading-day AD–ED interval

This table reports the estimates for the OLS regression of Equation 5.16: $Liquidity_{it} = \alpha_i + \beta_i Event_{it} + \epsilon_{it}$ for the deletions with an 11-trading-day AD–ED interval. The dependent variable $Liquidity_{it}$ is the end-of-day market liquidity measurements—quoted spread, effective spread, realised spread, best depth and trade size—for stock i on day t; $Event_{it}$ takes a value of 1 if day t is within the event period, or 0 if it is pre-event. Student's t-test is performed to check the statistical significance, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Quoted Spread (bps)		Effective Spread (bps)		Realised Spread (bps)		Best Depth ('000 shares)		Trade Size ('000 shares)	
Timeline	Intercept	Event	Intercept	Event	Intercept	Event	Intercept	Event	Intercept	Event
AD-5	113.98 (<0.0001)**	20.78 (0.0802)	87.89 (<0.0001)**	14.99 (0.1210)	62.85 (<0.0001)**	17.12 (0.0810)	542.97 (<0.0001)**	384.14 (0.0346)	4.77 (<0.0001)**	2.31 (0.0397)**
AD-4	113.98 (<0.0001)**	21.49 (0.0704)	87.89 (<0.0001)**	16.06 (0.0971)	62.85 (<0.0001)**	21.92 (0.0253)	542.97 (<0.0001)**	399.14 (0.0298)	4.77 (<0.0001)**	1.67 (0.1368)
AD-3	113.98 (<0.0001)**	22.09 (0.063)	87.89 (<0.0001)**	4.60 (0.6324)	62.85 (<0.0001)**	28.51 (0.0037)	542.97 (<0.0001)**	646.03 (0.0005)	4.77 (<0.0001)**	2.03 (0.0712)*
AD-2	113.98 (<0.0001)**	21.87 (0.0656)	87.89 (<0.0001)**	19.43 (0.0452)	62.85 (<0.0001)**	14.52 (0.1362)	542.97 (<0.0001)**	479.3 (0.0088)	4.77 (<0.0001)**	1.04 (0.3525)
AD-1	113.98 (<0.0001)**	21.70 (0.0678)	87.89 (<0.0001)**	18.79 (0.0523)	62.85 (<0.0001)**	1.02 (0.9174)	542.97 (<0.0001)**	321.21 (0.0743)	4.77 (<0.0001)**	1.16 (0.3000)
AD	113.98 (<0.0001)**	24.53 (0.0390)	87.89 (<0.0001)**	4.86 (0.6140)	62.85 (<0.0001)**	25.44 (0.0097)	542.97 (<0.0001)**	424.84 (0.0193)	4.77 (<0.0001)**	1.43 (0.2015)
AD+1	113.98 (<0.0001)**	26.58 (0.0254)	87.89 (<0.0001)**	16.49 (0.0887)	62.85 (<0.0001)**	21.47 (0.0280)	542.97 (<0.0001)**	158.94 (0.3738)	4.77 (<0.0001)**	0.27 (0.8113)
AD+2	113.98 (<0.0001)**	28.24 (0.0176)	87.89 (<0.0001)**	18.33 (0.0589)	62.85 (<0.0001)**	21.18 (0.0310)	542.97 (<0.0001)**	336.78 (0.0643)	4.77 (<0.0001)**	1.5 (0.1798)
AD+3	113.98 (<0.0001)**	29.71 (0.0126)	87.89 (<0.0001)**	18.38 (0.0573)	62.85 (<0.0001)**	28.61 (0.0035)	542.97 (<0.0001)**	215.21 (0.2300)	4.77 (<0.0001)**	0.64 (0.5675)
AD+4	113.98 (<0.0001)**	22.03 (0.0633)	87.89 (<0.0001)**	13.48 (0.1630)	62.85 (<0.0001)**	20.68 (0.0344)	542.97 (<0.0001)**	60.88 (0.7319)	4.77 (<0.0001)**	0.76 (0.4950)
AD+5	113.98 (<0.0001)**	19.11 (0.1070)	87.89 (<0.0001)**	13.51 (0.1621)	62.85 (<0.0001)**	20.32 (0.0380)	542.97 (<0.0001)**	46.95 (0.7914)	4.77 (<0.0001)**	0.02 (0.9878)

Table 5.22 Continued

	Quoted Spread (bps)		Effective Spread (bps)		Realised Spread (bps)		Best Depth ('000 shares)		Trade Size ('000 shares)	
Timeline	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**
AD+6	113.98 (<0.0001)**	18.93 (0.1105)	87.89 (<0.0001)**	11.64 (0.2280)	62.85 (<0.0001)**	14.21 (0.1459)	542.97 (<0.0001)**	2.31 (0.9896)	4.77 (<0.0001)**	0.67 (0.5480)
AD+7	113.98 (<0.0001)**	19.14 (0.1068)	87.89 (<0.0001)**	11.41 (0.2374)	62.85 (<0.0001)**	22.39 (0.0224)	542.97 (<0.0001)**	111.05 (0.5315)	4.77 (<0.0001)**	-0.04 (0.9735)
AD+8	113.98 (<0.0001)**	25.29 (0.0335)	87.89 (<0.0001)**	22.65 (0.0195)	62.85 (<0.0001)**	18.28 (0.0616)	542.97 (<0.0001)**	292.23 (0.1027)	4.77 (<0.0001)**	0.1 (0.9267)
AD+9	113.98 (<0.0001)**	27.25 (0.0221)	87.89 (<0.0001)**	25.85 (0.0078)	62.85 (<0.0001)**	29.68 (0.0026)	542.97 (<0.0001)**	332.32 (0.0628)	4.77 (<0.0001)**	1.06 (0.3431)
AD+10(ED)	113.98 (<0.0001)**	30.97 (0.0094)	87.89 (<0.0001)**	19.31 (0.0465)	62.85 (<0.0001)**	22.65 (0.0210)	542.97 (<0.0001)**	539.42 (0.0029)	4.77 (<0.0001)**	14.03 (<0.0001)**
ED+1	113.98 (<0.0001)**	24.96 (0.0355)	87.89 (<0.0001)**	18.25 (0.0594)	62.85 (<0.0001)**	17.34 (0.0767)	542.97 (<0.0001)**	61.75 (0.7279)	4.77 (<0.0001)**	1.84 (0.1018)
ED+2	113.98 (<0.0001)**	23.94 (0.0438)	87.89 (<0.0001)**	21.34 (0.0278)	62.85 (<0.0001)**	10.65 (0.2749)	542.97 (<0.0001)**	89.47 (0.6145)	4.77 (<0.0001)**	0.60 (0.5923)
ED+3	113.98 (<0.0001)**	27.86 (0.0191)	87.89 (<0.0001)**	22.43 (0.0207)	62.85 (<0.0001)**	12.76 (0.1927)	542.97 (<0.0001)**	151.11 (0.3959)	4.77 (<0.0001)**	1.02 (0.3641)
ED+4	113.98 (<0.0001)**	22.76 (0.0552)	87.89 (<0.0001)**	21.46 (0.0266)	62.85 (<0.0001)**	29.23 (0.0029)	542.97 (<0.0001)**	67.49 (0.7039)	4.77 (<0.0001)**	1.76 (0.1188)
ED+5	113.98 (<0.0001)**	25.15 (0.0341)	87.89 (<0.0001)**	22.46 (0.0205)	62.85 (<0.0001)**	18.74 (0.0554)	542.97 (<0.0001)**	94.24 (0.5957)	4.77 (<0.0001)**	1.31 (0.2394)

Table 5.21 shows that for the deletions with a six-trading-day AD–ED interval, the coefficients of the dummy variable Event for quoted spread, effective spread and realised spread on each day during [AD-5, ED+5] are uniformly negative. That is, the spreads decrease during the event period. The coefficients of the dummy variable Event for best depth are also negative, indicating that the average volume of best bid-ask prices is smaller than the pre-event level. In terms of trade size, the coefficients of Event are negative for most of the days during the period but stay positive from ED to two days after that, which indicates that the trade size is larger around ED than during the pre-event period.

As for the deletions with an 11-trading-day AD–ED interval, the spreads are uniformly wider, best depth is larger, and trade size is larger than the pre-event level across the event period, as shown in Table 5.22. (Similar results are obtained for the deletions with a 10-trading-day interval, as reported in *Appendix 3.*)

The OLS regression of Equation 5.16 is next conducted for all the sample deletions, with each stock-day observation during the period [AD, ED] and the 60-day pre-event period [ED-31, ED+90]. The results are presented in Table 5.23. Because trade size is significantly larger only on ED, while on other event days it is smaller, the OLS regression is not performed for trade size.

Table 5.23 shows that the coefficients of the dummy variable Event are significantly positive, indicating that the quoted spread, effective spread, realised spread and best depth all increase for the sample deletions during the period [AD, ED].

Table 5.23 Liquidity effects for S&P/ASX 200 index sample deletions during [AD, ED]

This table reports the estimates for the OLS regression of Equation 5.16: $Liquidity_{it} = \alpha_i + \beta_i Event_{it} + \epsilon_{it}$. The dependent variable $Liquidity_{it}$ is the end-of-day market liquidity measurements—quoted spread, effective spread, realised spread and best depth—for stock i on day t; $Event_{it}$ takes a value of 1 if day t is within the event period [AD, ED], or 0 if it is pre-event. Student's t-test is performed to check the statistical significance and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Liquidity Measurement			
	Quoted Spread (bps)	**Effective Spread (bps)**	**Realised Spread (bps)**	**Best Depth ('000 shares)**
Intercept	105.99** (<0.0001)	81.47** (<0.0001)	58.62** (<0.0001)	495.28** (<0.0001)
Event	31.89** (<0.0001)	23.46** (<0.0001)	26.92** (<0.0001)	924.86** (<0.0001)

Linking the results from Tables 5.21 to 5.23, we can infer that the liquidity decreases in terms of quoted spread, effective spread and realised spread for the S&P/ASX 200 deletions from AD to ED. The significantly larger trade size on ED indicates index funds and institutional investors sell the deleted stocks on this day.

To investigate the long-run market liquidity effects, the OLS regression of Equation 5.17 is conducted for all the sample deletions with each stock-day observation during the post-event period of [ED+31, ED+90] and the 60-day pre-event period. The results are presented in Table 5.24.

It is clear that the coefficients of the dummy variable *Post_Event* are positive, and that this is statistically significant. That is, the quoted spread, effective spread, realised spread, best depth and trade size all increase for the stock deleted from the S&P/ASX 200 after the index rebalancing event.

To sum up this section, the S&P/ASX 200 additions experienced an increase in market liquidity during and after the index rebalancing event, while in comparison, the liquidity of the deletions deteriorated.

Table 5.24 Liquidity effects for S&P/ASX 200 index sample deletions during [ED+31, ED+90]

This table reports the estimates for OLS regression of Equation 5.17: $Liquidity_{it} = \alpha_i + \beta_i Post\_Event_{it} + \epsilon_{it}$. The dependent variable $Liquidity_{it}$ is the end-of-day market liquidity measurements—quoted spread, effective spread, realised spread, best depth and trade size—for stock i on day t; $Post\_Event_{it}$ takes a value of 1 if day t is within the post-event period [ED+31, ED+90], or 0 if it is pre-event. Student's t-test is performed to check the statistical significance and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Liquidity Measurement				
	Quoted Spread (bps)	**Effective Spread (bps)**	**Realised Spread (bps)**	**Best Depth ('000 shares)**	**Trade Size ('000 shares)**
Intercept	105.99** (<0.0001)	81.47** (<0.0001)	58.62** (<0.0001)	495.28** (<0.0001)	4.18** (<0.0001)
Event	45.11** (<0.0001)	36.35** (<0.0001)	31.33** (<0.0001)	436.31** (<0.0001)	3.66** (<0.0001)

5.4.4 Impact of index funds growth

This section investigates the impact of the growth of index funds. Theoretically, given the index ETFs' mandate to replicate the index holdings and minimise their tracking errors, the growth of index ETFs means that there would be greater demand around the index revision period and therefore more opportunities for arbitragers. Beneish and Whaley (1996) and Wurgler and Zhuravskaya (2002) point out that the growth of index funds is one of the contributing factors to abnormal stock returns, while Edmister et al. (1996) and Elliott and Warr (2003) hold a contradictory opinion.

In Australia, ETFs were introduced in 2001 (Stockspot, 2016), and the ETF market experienced considerable growth during our study period of 2011–2016. According to Cunningham (2017), by the end of 2016, the assets under management (AUM) of the Australian ETF market had reached almost AUD 25 billion, tripling in size compared to 2012. Among these ETFs, 44% are domestic equity ETFs. Of these domestic equity ETFs, index funds—which track market indices—take up 31% of the total AUM (AUD 7.6 billion).

We obtain a full list of exchange-traded products from the official website of the ASX. Among these ETFs, six funds provide investors with exposure to the S&P/ASX 200 index: SPDR S&P 200 Fund (ASX code: STW), iShares Core S&P/ASX 200 ETF (ASX code: IOZ), BetaShares Geared Australian Equity Fund (ASX code: GEAR), BetaShares Managed Risk Australian Share Fund (ASX code: AUST), BetaShares Australian Equities Bear (ASX code: BEAR) and BetaShares Australian Equities Strong Bear (ASX code: BBOZ). (Hereafter, these funds are referred to by their ASX codes.) BEAR and BBOZ are excluded from our study sample, as they both state their objective as to provide investors with the opportunity to 'short' the market and profit from the declining market.

The fact sheets of the remaining four index funds indicate that the objective of both STW and IOZ is to track or provide investors the performance of the S&P/ASX 200 index (before fees and expenses); the objective of AUST is to provide investors with exposure to the largest 200 Australian shares, while mitigating the volatility of investment returns and losses in the case of market drawdowns; and the objective of GEAR is to provide investors with geared exposure to the largest 200 Australian shares using both investor and borrowed funds. In contrast to STW and IOZ, GEAR and AUST do not track the holdings of the S&P/ASX 200 as closely (Stockspot, 2016).

To examine the correlation between the index funds' AUM and the index revision effects, the total market capitalisation of these four ETFs during each stock's rebalancing period—five trading days before announcement to five trading days after ED [AD-5, ED+5]—is calculated, and the yearly average is presented in Table 5.25.

Table 5.25 Total market capitalisation of selected index ETFs during the S&P/ASX200 sample additions (deletions) event period [AD-5, ED+5]

Year	Total market capitalisation of selected index ETFs (millions)	
	Additions event period [AD-5, ED+5] (as a % of total ASX market capitalisation)	Deletions event period [AD-5, ED+5] (as a % of total ASX market capitalisation)
2011	2190.03 (0.17%)	2167.26 (0.16%)
2012	2178.63 (0.16%)	2166.74 (0.16%)
2013	2385.70 (0.18%)	2381.43 (0.18%)
2014	2640.49 (0.20%)	2639.06 (0.20%)
2015	3265.00 (0.25%)	3193.18 (0.24%)
2016	3492.50 (0.26%)	3448.86 (0.26%)

We can see that the total market capitalisation of these four index funds has grown from 2.2 billion to almost 3.5 billion from 2011 to 2016. However, as presented in Tables 5.1 and 5.5, the cumulative abnormal returns of the S&P/ASX 200 additions (deletions) have not increased (decreased) accordingly over the years.

The OLS regression of Equation 5.18 is performed for the cumulative abnormal returns of the S&P/ASX 200 additions (deletions) and the market capitalisations of the sample index funds (AUM in billions):

$$CAR_{it} = \alpha + \beta\ AUM_{it} + \epsilon_{it},$$

$$\text{with E}\ [\epsilon_{it}] = 0 \text{ and VAR}\ [\epsilon_{it}] = \sigma_{it}^{2} \tag{5.18}$$

where CAR_{it} is the cumulative abnormal return for stock i added to (deleted from) the S&P/ASX 200 index in year t; and AUM_{it} is the total market capitalisation of the selected index funds over the event period [AD-5, ED+5] of stock i in year t.

Table 5.26 presents the regression results for the sample additions and deletions. The results show that the index funds' growth in Australia has a positive (negative) effect on the cumulative abnormal returns of the S&P/ASX 200 additions (deletions) between AD and ED. However, the correlations are not statistically significant and do not provide strong evidence that index fund growth is correlated with the S&P/ASX 200 rebalancing effects.

Table 5.26 Impact of index funds' growth on the price effect for the S&P/ASX 200 sample additions (deletions)

This table reports the estimates from the linear regression of Equation 5.18: $CAR_{it} = \alpha + \beta\ AUM_{it} + \epsilon_{it}$. The dependent variable CAR_{it} is the cumulative abnormal return for the stock i added to (deleted from) the S&P/ASX 200 index in year t, AUM_{it} is the total market capitalisation of the selected index funds over the event period [AD-5, ED+5] of stock i in year t. Student's t-test is performed to check the statistical significance and the t-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	CAR for additions	CAR for deletions
Intercept	-0.0397 (-0.8263)	-0.0007 (-0.0075)
AUM	0.0158 (0.9030)	-0.0124 (-0.3721)

5.5 Conclusion

This chapter investigated the S&P/ASX 200 index rebalancing effects by systematically examining the price, volume, volatility and market liquidity effects for stocks both added to and deleted from the index during April 2011 to December 2016. The study contributes to the existing Australian finance literature in the following ways: it employs well-established methods from the existing literature and ensured that the sample stocks are free from corporate actions and price-sensitive information; and the impacts of the AD–ED interval length and the growth of index funds are investigated. The analysis helped establish the following findings.

There are announcement effects for the S&P/ASX 200 additions. That is, when the additions are announced, there are statistically significant positive average abnormal returns on AD (1.10%) and the day after AD (0.84%), with these positive abnormal returns supported by abnormal volumes (85% and 67% higher than pre-event level, respectively).

On average, the sample additions obtained a negative average abnormal return on ED (-1.16%) and the day prior to ED (-0.50%), with the price partially reversed after ED. There are abnormal volumes around ED. The negative price effect on ED contradicts the literature focusing on the S&P 500 but is in line with the Australian literature (e.g., Chan & Howard, 2002; Schmidt et al., 2012; Qiu & Pinfold, 2007). The analysis of intraday price returns also showed that the price discovery mainly occurs on AD rather than ED.

These results suggest that most buying occurs on the first several days after AD, when new information is released into the market. ETFs and institutional investors buy mandatorily on ED; however, there is little price discovery on this day as no new information is being released. We also found that the S&P/ASX 200 rebalancing event improved the stock market liquidity of the additions over the rebalancing period and in the long run.

For the deletions from the S&P/ASX 200 index, there are also announcement effects. That is, there is a statistically significant negative abnormal return on AD (-1.13%) accompanied by significant abnormal volume. The abnormal returns on the following two days are also negative, with trading volumes of about 30% higher than in the pre-event period.

There are also ED effects for the sample deletions, with negative abnormal returns leading up to ED. The ED sees a statistically significant negative average abnormal return (-1.49%) accompanied by abnormal volume. The day after ED sees an insignificant price reversal with abnormal volume. The overall cumulative abnormal return from AD to ED for the S&P/ASX 200 deletions is -3.44%, which is statistically significant. The AD and ED effects for the S&P/ASX 200 deletions are in line with the existing literature (e.g., Schmidt et al., 2012). Intraday price return analysis confirmed the finding that the price discovery for the S&P/ASX 200 deletions mainly happens around AD market open and close, and throughout ED. In addition, the S&P/ASX 200 rebalancing event deteriorates the deleted stocks' market liquidity over the rebalancing period and in the long run.

Overall, the S&P/ASX 200 index revisions have a more powerful impact on additions compared to deletions in terms of price and volume effects. The S&P/ASX 200 sample additions have greater abnormal volumes on both AD and ED than do the deleted stocks. This suggests a rush to buy stocks added to the index, perhaps due to the mandate of the index funds and possible buying from other market participants; conversely, holders of deleted stocks do not rush out, or there may be a lock on shorting activities.

Our key finding is that there is a negative correlation between the cumulative abnormal return of S&P/ASX 200 additions during the AD–ED interval and the interval length. This finding is in the opposite direction to findings for S&P 500 index additions, which may be explained by the longer 9.44-day average interval length for our S&P/ASX 200 sample, compared to the 4.15-day average interval length for the S&P 500 index in Beneish and Whaley (1996). This longer interval length would give arbitragers more time to build their positions upon announcement and unwind them before ED to take profits, generating negative abnormal returns on ED.

Further analysis focusing on two subgroups of additions with different AD–ED interval lengths (i.e., six and 11 trading days) indicated that sample additions with a shorter AD–ED interval have more intense price and volume effects upon announcement compared to those with a longer interval. Moreover, both subgroups have announcement effects that last for four days and obtained negative abnormal returns on ED, accompanied by large trading volumes.

As for the deletions, the correlation between the abnormal returns during the AD–ED interval and the interval length is positive. The deletions with a shorter event interval had stronger announcement effects, while deletions with a longer event interval had stronger ED effects, indicating that market participants tend to start selling the deletions as ED approaches.

Given that the additions (deletions) with a one-week AD–ED interval have price effects of greater magnitude, a profitable trading strategy for market participants would be to buy (sell) the additions (deletions) on AD end and sell (buy) on the day before revision, which could result in an excess return of up to 2.67% (4.48%).

The effect of index funds' growth was also examined, and a weak positive (negative) correlation was established between the index funds' market capitalisation and the cumulative abnormal return within the AD–ED interval for the sample additions (deletions).

Chapter 6: Conclusion

Individual investors in reality behave differently from completely rational decision-makers in the assumptions of traditional economic models. Given their behavioural biases and the fact that they are often the uninformed party in the stock market, individual investors underperform the market benchmark on many occasions. The importance of understanding the behaviours of individual investors, investigating the contributors to their behavioural biases and identifying possible opportunities in the stock market is underscored by the increasing numbers of investors making direct investments in recent years, and their impact on stock price movement. Each essay presented in this dissertation explores one area for which there are limited prior research findings. The findings of this dissertation thus provide insights for investors themselves, academic researchers, financial institutions and regulators.

To develop a better understanding of investor behaviour, research in behavioural finance has adopted techniques generally applied in other science fields. Many potential contributors have been examined for their possible impact on some well-documented behavioural biases. These factors include age, gender, education level and emotions, to name a few. However, until the present study, morningness–eveningness (M-E) —that is, one's diurnal rhythm preference—had gone unexplored in behavioural finance research.

Given the documented influence of M-E on individual behaviour, we propose that it also affects investor proneness to commonly observed behavioural biases. The first essay (Chapter 3) thus aims to introduce M-E into the field of behavioural finance. Employing proprietary stock trading data from a leading retail brokerage house in Australia, we are able to group investors into morning-types (M-types) and evening-types (E-types), based on their order submission time in stock markets. To ensure robustness, we use both a continuous Eveningness Score and a categorical M-type and E-type classification, to test whether certain demographic groups are more likely to be a particular M-E type, and whether M-E affects investors' proneness to commonly observed stock market behavioural biases. Ordinary Least Squares regression, multivariate regression, correlation analysis and categorical comparison analysis are employed.

Both methods of M-E classification reveal that older investors are more likely to be M-types and that gender has no significant effect on the likelihood of being a certain M-E type. More importantly, we find that M-E predicts proneness to stock market behavioural biases. After controlling for demographic and trading characteristics, M-type investors are found to trade more frequently, and have a greater tendency towards home bias and a stronger preference for stock market speculation.

Understanding this additional driver of common investor behavioural biases provides insights for stock market participants and helps to identify investors who are more at risk of these biases. A new direction in behavioural finance is also pioneered by this study. Future studies can investigate further how investors' behaviour in the stock market can be influenced by their natural habits.

The second essay, which is presented as Chapter 4, extended socially responsible investing (SRI) into the behavioural finance field. This chapter investigates the linkage between individual investors' environmental, social and governance (ESG) preference, their demographic and trading characteristics, and their account performance. In addition, the impact of companies' ESG rating on their stock performance is examined.

First of all, using individual investors' daily portfolio holding data, obtained from a leading brokerage house in Australia, we are able to measure investors' preference for SRI through their Account ESG Score, calculated based on the Thomson Reuters ESG Combined Scores of their held stocks. Correlation analysis and multivariate regression analysis are conducted to investigate the linkage between the investors' ESG preference and their demographic and trading characteristics. We find that older, female and wealthier investors have a greater preference for stocks with higher ESG ratings. Conversely, investors who trade more frequently and prefer mental shortcuts, as measured by them always trading in round volumes, tend to hold stocks with lower ESG ratings.

Further, our analysis reveals that ESG investing can be a profitable opportunity for investors. Comparing Carhart (1997) four-factor alphas, we find that accounts with higher ESG scores outperform those with lower ESG scores. Using Carhart (1997) four-factor model, we reveal that ESG beta is significantly positive. As for the impact of the companies' ESG ratings on their stock market performance, we show that companies with a higher ESG ranking are more likely to outperform their lower ranked counterparts in the subsequent year. Therefore, the study not only advances SRI research in the behavioural finance area but also provide further evidence that SRI based on ESG ratings can be an investment opportunity for stock market participants.

The third essay (presented as Chapter 5) proceeds from a market microstructure perspective and identifies another opportunity in the stock market that could be potentially profitable for investors: the S&P/ASX 200 index revision event. Chapter 5 systematically investigates the price, volume, volatility and liquidity effects of the S&P/ASX 200 index rebalancing event.

By calculating the abnormal returns using the market-adjusted return model (and the market model as a robustness test), and comparing the volume, volatility and liquidity measurements to the pre-event level, we find that both announcement day (AD) and effective day (ED) effects exist for the S&P/ASX 200 additions and deletions. The price discovery for the stocks added to the index mainly occurs around AD, while it mainly happens around ED for the stocks deleted. The liquidity of the additions (deletions) increases (deteriorates) in both the short run and the long run.

The study also finds a negative (positive) correlation between the abnormal returns of the stocks added to (deleted from) the S&P/ASX 200 index during the AD–ED interval and the interval length. This finding contrasts with those of the existing S&P 500 study by Beneish and Whaley (1996). Specifically, we find that index additions with one week's notice experienced a price increase from AD until the day before ED, while the additions with two weeks' notice experienced a price increase on AD until the fifth trading day after AD, at which point the price started to drop until ED. For the index deletions with one week's notice, they experience a price drop from AD until the day before ED, while for the deletions with two weeks' notice, the price starts to drop as ED approached: from four days before ED until ED.

The price changes for the additions (deletions) with a shorter AD–ED interval (one week) are of greater magnitude, and constitute an opportunity for investors: buying the additions on AD end and selling on the day before ED could bring an excess return of up to 2.67%, while selling the deletions on AD and buying back on the day before ED could bring an excess return of up to 4.48%.

Altogether, the three essays presented in this dissertation investigate the trading behaviours of investors and the contributors to their behavioural biases, leading to the identification of two potential profitable opportunities for investors in the stock market:

SRI and the opportunities afforded by S&P/ASX 200 index rebalancing events. Each essay deals with an unexplored or underdeveloped area, or one without a consensus in the existing literature, particularly in Australian finance literature. The evidence provided in this dissertation not only pioneers new directions in behavioural finance but also presents practical investment opportunities for investors. The findings are meaningful for investors themselves, researchers, financial practitioners and regulators alike, especially considering the increasing number of investors making direct investments and their influence on stock market price movement.

Some limitations of the studies should be noted. First, the datasets of investors' transaction records and portfolio holdings employed in Chapter 3 and 4 are over the sample period of 2010–2012 and 2010–2013. Therefore, in order to generalise the findings in those two chapters, similar datasets with more recent or longer sample periods would be helpful. Second, these proprietary stock trading datasets are provided by a leading retail brokerage house in Australia, which means we are only able to observe a fraction of the entire investor population in Australia. Finally, it is worth noting that there are costs associated with becoming informed, and the process of obtaining the information of companies' ESG rating or the index rebalancing event would have opportunity cost, which means that the potential profits associated with the two opportunities presented in this thesis are not completely cost-free.

The work in this dissertation suggests potential future research directions. The findings in Chapter 3 indicate that M-E has an influence on investors' trading frequency, local bias and preference for market speculation. Future research could further examine M-E's influence on other investor behaviours, such as the disposition effect which is the investors' propensity to sell stocks that have made profits in their portfolios than to sell those that have made losses (Brown, Chappel, Da Silva Rosa & Walter, 2006; Odean, 1998; Shefrin & Statman, 1985). In addition, the existing literature has shown that frequent trading and investment in lottery stocks are associated with inferior portfolio performance, however, the findings regarding the wealth effect of local bias are not consistent among the literature. In that sense, future studies can investigate the linkage between M-E and investors' account performance. The results in Chapter 4 suggest that companies' ESG ratings can predict their future performance in the stock market. Future research could extend the current study by examining this trend further with each ESG attribute in the rating system, to see which aspects of ESG are of the greatest influence. Moreover, sample firms can be selected from the constituents in environmentally friendly ETFs or indices that are listed on ASX to compare their stock performance to market benchmarks, which method is employed by Chan and Walter (2014) in their examination on the stocks listed in the US. Chapter 5 investigates the rebalancing effects of the S&P/ASX 200 index. Given that Standard and Poor's has changed the AD–ED interval from two weeks to only one week for the March, June and December quarters since 2016, and more stocks have since become available for inclusion in a sample for the announcement scheme change, an event study could be conducted to examine the impact of the announcement scheme change. Further, other metrics such as price discovery metrics and measures of information asymmetry, and the investors' wealth effect together with their trading decisions during the index rebalancing event could be explored. These potential directions could be topics for future research.

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Appendices

Appendix 1 Contribution statement

The contribution statement has been agreed upon by Grace Lepone, Andrew Lepone and Jin Boon Wong, the co-authors of the working papers listed in the Preface.

Lepone, G. and Yang, Z. (2019). Do early birds behave differently from night owls in stock markets.							
	Project supervisor	Literature review	Methodology	Data collection	Data analysis	Results interpretation	Manuscript
Grace Lepone	√	10%	30%	80%	50%	20%	15%
Zhini Yang		90%	70%	20%	50%	80%	85%

Lepone, G. and Yang, Z (2019). Does it pay to invest responsibly? A study of retail investors' ESG preference							
	Project supervisor	Literature review	Methodology	Data collection	Data analysis	Results interpretation	Manuscript
Grace Lepone	√	5%	70%	80%	50%	30%	5%
Zhini Yang		95%	30%	20%	50%	70%	95%

Lepone, A., Wong, J., and Yang, Z (2017). Index rebalance effects of S&P/ASX 200.							
	Project supervisor	Literature review	Methodology	Data collection	Data analysis	Results interpretation	Manuscript
Jin Boon Wong	√	5%	20%			20%	
Andrew Lepone	√		10%			20%	
Zhini Yang		95%	70%	100%	100%	60%	100%

Appendix 2 Liquidity effects during [AD-5, ED+5]: S&P/ASX 200 index additions with 10-trading-day AD–ED interval

This table reports the estimates for the OLS regression of Equation 5.16: $Liquidity_{it} = \alpha_i + \beta_i Event_{it} + \epsilon_{it}$ for the additions with an 10-trading-day AD–ED interval. The dependent variable $Liquidity_{it}$ is the end-of-day market liquidity measurements—quoted spread, effective spread, realised spread, best depth and trade size—for stock i on day t; $Event_{it}$ takes a value of 1 if day t is within the event period, or 0 if it is pre-event. Student's t-test is performed to check the statistical significance, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Quoted Spread (bps)		**Effective Spread (bps)**		**Realised Spread (bps)**		**Best Depth ('000 shares)**		**Trade Size ('000 shares)**	
Timeline	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**
AD-5	31.68 (<0.0001)**	-0.87 (0.8528)	26.42 (<0.0001)**	-1.74 (0.6841)	15.46 (<0.0001)**	-0.50 (0.8955)	17.80 (<0.0001)**	2.26 (0.7638)	0.76 (<0.0001)**	-0.03 (0.9221)
AD-4	31.68 (<0.0001)**	-2.28 (0.6254)	26.42 (<0.0001)**	-3.85 (0.3699)	15.46 (<0.0001)**	-3.27 (0.3892)	17.80 (<0.0001)**	-0.34 (0.9634)	0.76 (<0.0001)**	-0.24 (0.4638)
AD-3	31.68 (<0.0001)**	-4.58 (0.3271)	26.42 (<0.0001)**	-3.72 (0.3865)	15.46 (<0.0001)**	-3.22 (0.3969)	17.80 (<0.0001)**	4.02 (0.5937)	0.76 (<0.0001)**	0.08 (0.8191)
AD-2	31.68 (<0.0001)**	-0.95 (0.8390)	26.42 (<0.0001)**	-3.39 (0.4304)	15.46 (<0.0001)**	-3.33 (0.3830)	17.80 (<0.0001)**	1.63 (0.8277)	0.76 (<0.0001)**	-0.07 (0.8234)
AD-1	31.68 (<0.0001)**	-4.44 (0.3429)	26.42 (<0.0001)**	-7.49 (0.0814)*	15.46 (<0.0001)**	-1.85 (0.6258)	17.80 (<0.0001)**	-1.16 (0.8759)	0.76 (<0.0001)**	-0.17 (0.6158)
AD	31.68 (<0.0001)**	-4.71 (0.3139)	26.42 (<0.0001)**	-1.25 (0.7708)	15.46 (<0.0001)**	-1.46 (0.7012)	17.80 (<0.0001)**	6.15 (0.4121)	0.76 (<0.0001)**	-0.02 (0.9577)
AD+1	31.68 (<0.0001)**	-2.95 (0.5284)	26.42 (<0.0001)**	-4.18 (0.3301)	15.46 (<0.0001)**	-3.06 (0.4204)	17.80 (<0.0001)**	1.72 (0.8187)	0.76 (<0.0001)**	-0.26 (0.4387)
AD+2	31.68 (<0.0001)**	-4.20 (0.3695)	26.42 (<0.0001)**	-4.3 (0.3184)	15.46 (<0.0001)**	-3.49 (0.3595)	17.80 (<0.0001)**	-0.53 (0.9434)	0.76 (<0.0001)**	-0.3 (0.3725)
AD+3	31.68 (<0.0001)**	-1.90 (0.6847)	26.42 (<0.0001)**	-0.68 (0.8748)	15.46 (<0.0001)**	-3.20 (0.4009)	17.80 (<0.0001)**	4.15 (0.5788)	0.76 (<0.0001)**	-0.15 (0.6474)
AD+4	31.68 (<0.0001)**	-4.45 (0.3420)	26.42 (<0.0001)**	-3.44 (0.4242)	15.46 (<0.0001)**	-1.16 (0.7601)	17.80 (<0.0001)**	5.39 (0.4701)	0.76 (<0.0001)**	-0.03 (0.9327)

Appendix 2 Continued

	Quoted Spread (bps)		Effective Spread (bps)		Realised Spread (bps)		Best Depth ('000 shares)		Trade Size ('000 shares)	
Timeline	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**
AD+5	31.68 (<0.0001)**	-5.02 (0.2839)	26.42 (<0.0001)**	-5.02 (0.2434)	15.46 (<0.0001)**	-2.20 (0.5640)	17.80 (<0.0001)**	-0.83 (0.9117)	0.76 (<0.0001)**	-0.2 (0.5451)
AD+6	31.68 (<0.0001)**	-5.32 (0.2557)	26.42 (<0.0001)**	-3.57 (0.4063)	15.46 (<0.0001)**	-0.92 (0.8089)	17.80 (<0.0001)**	7.28 (0.3319)	0.76 (<0.0001)**	-0.15 (0.6547)
AD+7	31.68 (<0.0001)**	-5.90 (0.2076)	26.42 (<0.0001)**	-7.24 (0.0922)*	15.46 (<0.0001)**	0.03 (0.9940)	17.80 (<0.0001)**	10.25 (0.1733)	0.76 (<0.0001)**	-0.25 (0.4438)
AD+8	31.68 (<0.0001)**	-2.39 (0.6090)	26.42 (<0.0001)**	-1.12 (0.7946)	15.46 (<0.0001)**	2.55 (0.5049)	17.80 (<0.0001)**	6.35 (0.3961)	0.76 (<0.0001)**	-0.07 (0.8258)
AD+9(ED)	31.68 (<0.0001)**	-0.97 (0.8368)	26.42 (<0.0001)**	-3.12 (0.4675)	15.46 (<0.0001)**	-0.67 (0.8601)	17.80 (<0.0001)**	17.87 (0.0188)**	0.76 (<0.0001)**	2.01 (<0.0001)**
ED+1	31.68 (<0.0001)**	-3.66 (0.4362)	26.42 (<0.0001)**	-5.24 (0.2247)	15.46 (<0.0001)**	-3.48 (0.3606)	17.80 (<0.0001)**	9.5 (0.2074)	0.76 (<0.0001)**	0.15 (0.6464)
ED+2	31.68 (<0.0001)**	-2.30 (0.6249)	26.42 (<0.0001)**	-5.87 (0.1732)	15.46 (<0.0001)**	-4.31 (0.2568)	17.80 (<0.0001)**	8.59 (0.2523)	0.76 (<0.0001)**	0.13 (0.6917)
ED+3	31.68 (<0.0001)**	-2.37 (0.6145)	26.42 (<0.0001)**	-6.14 (0.1542)	15.46 (<0.0001)**	-4.48 (0.2399)	17.80 (<0.0001)**	7.95 (0.2890)	0.76 (<0.0001)**	-0.01 (0.9727)
ED+4	31.68 (<0.0001)**	-3.90 (0.4059)	26.42 (<0.0001)**	-6.29 (0.1438)	15.46 (<0.0001)**	-3.32 (0.3837)	17.80 (<0.0001)**	0.14 (0.9853)	0.76 (<0.0001)**	-0.14 (0.6830)
ED+5	31.68 (<0.0001)**	-2.36 (0.6148)	26.42 (<0.0001)**	-3.42 (0.4288)	15.46 (<0.0001)**	-3.43 (0.3669)	17.80 (<0.0001)**	8.36 (0.2675)	0.76 (<0.0001)**	-0.003 (0.9931)

Appendix 3 Liquidity effects during [AD-5, ED+5]: S&P/ASX 200 index deletions with 10-trading-day AD–ED interval

This table reports the estimates for the OLS regression of Equation 5.16: $Liquidity_{it} = \alpha_i + \beta_i Event_{it} + \epsilon_{it}$ for the deletions with an 10-trading-day AD–ED interval. The dependent variable $Liquidity_{it}$ is the end-of-day market liquidity measurements—quoted spread, effective spread, realised spread, best depth and trade size—for stock i on day t; $Event_{it}$ takes a value of 1 if day t is within the event period, or 0 if it is pre-event. Student's t-test is performed to check the statistical significance, and the p-values are presented; **(*) indicates statistical significance at the 5% (10%) level.

	Quoted Spread (bps)		Effective Spread (bps)		Realised Spread (bps)		Best Depth ('000 shares)		Trade Size ('000 shares)	
Timeline	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**	**Intercept**	**Event**
AD-5	81.42 (<0.0001)**	52.03 (0.0014)**	67.13 (<0.0001)**	33.07 (0.0242)**	44.91 (<0.0001)**	49.32 (<0.0001)**	397.7 (<0.0001)**	5348.63 (<0.0001)**	2.91 (<0.0001)**	1.67 (0.0576)*
AD-4	81.42 (<0.0001)**	54.15 (0.0009)**	67.13 (<0.0001)**	28.79 (0.0495)**	44.91 (<0.0001)**	38.33 (0.0007)**	397.7 (<0.0001)**	5463.07 (<0.0001)**	2.91 (<0.0001)**	1.16 (0.1938)
AD-3	81.42 (<0.0001)**	48.2 (0.0031)**	67.13 (<0.0001)**	39.47 (0.0072)**	44.91 (<0.0001)**	36.03 (0.0014)**	397.7 (<0.0001)**	5692.02 (<0.0001)**	2.91 (<0.0001)**	1.47 (0.0984)*
AD-2	81.42 (<0.0001)**	50.32 (0.002)**	67.13 (<0.0001)**	34.34 (0.0193)**	44.91 (<0.0001)**	36.28 (0.0015)**	397.7 (<0.0001)**	5951.79 (<0.0001)**	2.91 (<0.0001)**	6.13 (<0.0001)**
AD-1	81.42 (<0.0001)**	56.40 (0.0005)**	67.13 (<0.0001)**	47.67 (0.0012)**	44.91 (<0.0001)**	45.37 (0.0001)**	397.7 (<0.0001)**	4878.96 (<0.0001)**	2.91 (<0.0001)**	1.17 (0.1849)
AD	81.42 (<0.0001)**	61.36 (0.0002)**	67.13 (<0.0001)**	34.18 (0.0197)**	44.91 (<0.0001)**	37.93 (0.0007)**	397.7 (<0.0001)**	3561.38 (<0.0001)**	2.91 (<0.0001)**	0.86 (0.3272)
AD+1	81.42 (<0.0001)**	62.79 (0.0001)**	67.13 (<0.0001)**	48.84 (0.0009)**	44.91 (<0.0001)**	60.26 (<0.0001)**	397.7 (<0.0001)**	4405.32 (<0.0001)**	2.91 (<0.0001)**	1.38 (0.1156)
AD+2	81.42 (<0.0001)**	63.12 (0.0001)**	67.13 (<0.0001)**	37.79 (0.0103)**	44.91 (<0.0001)**	36.60 (0.0012)**	397.7 (<0.0001)**	4789.28 (<0.0001)**	2.91 (<0.0001)**	1.67 (0.0571)*
AD+3	81.42 (<0.0001)**	62.19 (0.0001)**	67.13 (<0.0001)**	50.77 (0.0006)**	44.91 (<0.0001)**	57.68 (<0.0001)**	397.7 (<0.0001)**	4954.82 (<0.0001)**	2.91 (<0.0001)**	1.52 (0.0860)*
AD+4	81.42 (<0.0001)**	62.79 (0.0001)**	67.13 (<0.0001)**	56.32 (0.0001)**	44.91 (<0.0001)**	47.25 (<0.0001)**	397.7 (<0.0001)**	4478.12 (<0.0001)**	2.91 (<0.0001)**	1.09 (0.2156)
AD+5	81.42 (<0.0001)**	64.81 (0.0001)**	67.13 (<0.0001)**	55.90 (0.0002)**	44.91 (<0.0001)**	66.49 (<0.0001)**	397.7 (<0.0001)**	4373.96 (<0.0001)**	2.91 (<0.0001)**	0.46 (0.5998)

Appendix 3 Continued

Timeline	Quoted Spread (bps) Intercept	Quoted Spread (bps) Event	Effective Spread (bps) Intercept	Effective Spread (bps) Event	Realised Spread (bps) Intercept	Realised Spread (bps) Event	Best Depth ('000 shares) Intercept	Best Depth ('000 shares) Event	Trade Size ('000 shares) Intercept	Trade Size ('000 shares) Event
AD+6	81.42 (<0.0001)**	63.08 (0.0001)**	67.13 (<0.0001)**	49.16 (0.0009)**	44.91 (<0.0001)**	48.50 (<0.0001)**	397.7 (<0.0001)**	4169.8 (<0.0001)**	2.91 (<0.0001)**	0.73 (0.4094)
AD+7	81.42 (<0.0001)**	63.89 (0.0001)**	67.13 (<0.0001)**	57.15 (0.0001)**	44.91 (<0.0001)**	74.54 (<0.0001)**	397.7 (<0.0001)**	4427.3 (<0.0001)**	2.91 (<0.0001)**	0.7 (0.4238)
AD+8	81.42 (<0.0001)**	62.90 (0.0001)**	67.13 (<0.0001)**	62.77 (<0.0001)**	44.91 (<0.0001)**	70.39 (<0.0001)**	397.7 (<0.0001)**	1087.96 (<0.0001)**	2.91 (<0.0001)**	0.42 (0.6341)
AD+9(ED)	81.42 (<0.0001)**	70.30 (<0.0001)**	67.13 (<0.0001)**	52.51 (0.0004)**	44.91 (<0.0001)**	46.82 (<0.0001)**	397.7 (<0.0001)**	2082.76 (<0.0001)**	2.91 (<0.0001)**	11.49 (<0.0001)**
ED+1	81.42 (<0.0001)**	70.18 (<0.0001)**	67.13 (<0.0001)**	57.63 (0.0001)**	44.91 (<0.0001)**	54.94 (<0.0001)**	397.7 (<0.0001)**	4775.44 (<0.0001)**	2.91 (<0.0001)**	2.79 (0.0019)**
ED+2	81.42 (<0.0001)**	221.63 (<0.0001)**	67.13 (<0.0001)**	190.73 (<0.0001)**	44.91 (<0.0001)**	158.83 (<0.0001)**	397.7 (<0.0001)**	689.32 (0.0007)**	2.91 (<0.0001)**	7.75 (<0.0001)**
ED+3	81.42 (<0.0001)**	165.49 (<0.0001)**	67.13 (<0.0001)**	149.5 (<0.0001)**	44.91 (<0.0001)**	144.54 (<0.0001)**	397.7 (<0.0001)**	2278.32 (<0.0001)**	2.91 (<0.0001)**	18.14 (<0.0001)**
ED+4	81.42 (<0.0001)**	126.93 (<0.0001)**	67.13 (<0.0001)**	108.69 (<0.0001)**	44.91 (<0.0001)**	67.12 (<0.0001)**	397.7 (<0.0001)**	925.03 (<0.0001)**	2.91 (<0.0001)**	12.28 (<0.0001)**
ED+5	81.42 (<0.0001)**	99.63 (<0.0001)**	67.13 (<0.0001)**	75.17 (<0.0001)**	44.91 (<0.0001)**	38.49 (0.0010)**	397.7 (<0.0001)**	1009.68 (<0.0001)**	2.91 (<0.0001)**	6.38 (<0.0001)**