Retail Investor Behavioural Biases, the Causes and Impacts - Evidence from Equity Markets

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of the requirements for the degree of

Doctor of Philosophy

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Certificate

I certify that this thesis has not already been submitted for any degree and is not being submitted as part of candidature for any other degree.

I also certify that the thesis has been written by me and that any help that I have received in preparing this thesis, and all sources used, have been acknowledged in this thesis.

Signature of Candidate

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Grace Lepone

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Preface

Some of the work presented in this thesis is published/presented as joint work.

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Synopsis

This dissertation examines the trading behaviour of retail investors. The research provides empirical evidence on an increasingly important issue, the behaviour of retail investors, possible causes for their sub-optimal behaviour, and the impact of their biases. Given the high proportion of trades executed by retail investors in equity markets and their impact on price movements, the behaviour of retail investors is of interest to themselves, academics, financial institutions, market operators and regulators. Each chapter in this dissertation addresses a research question with limited or conflicting prior research findings to provide evidence and insights to help researchers, businesses, investors and regulators understand investors' behavioural biases.

The first issue examined is a bias displayed in investors' selling behaviour. Existing research finds that investors are more willing to sell for a gain than to sell at a loss, representing a bias known as the disposition effect. The disposition effect analysis uses investment account records from a leading retail brokerage house in Australia. The research examines the extent to which the disposition effect exists across a large set of investor characteristics, including ethnicity, in a multicultural host country market setting. Chinese investors in the sample are identified using a surname flag from a comprehensive surname list tested to be valid for predicting Chinese ethnicity in medical research, and the degree of loss aversion among this group is examined. Strong evidence of the disposition effect is found across the whole sample. The results show that investors are, on average, approximately twice as likely to realise a gain as to realise a loss, broadly supporting the findings of Odean (1998). This bias holds across all investor characteristic groups, although the level of bias differs depending on investor sophistication, gender, age and ethnicity.

The second chapter examines bias in investors purchasing behaviour; the purchase of lottery stocks which symbolises risk seeking. The research first defines lottery stocks using different approaches including Kumar (2009), Bali, Cakici and Whitelaw (2011) and an improved version of Bali, Cakici and Whitelaw (2011), and confirms that lottery stocks are risky investments with inferior returns. Brokerage data set is then employed to analyse the investment in lottery stocks. Lottery stocks attract mainly retail investors. Among the sample investors, those who distribute a great portion of their portfolio on lottery stocks obtain significantly lower risk adjusted returns compared to the rest of the investors in the sample and the overall market. Investigation on triggers of the tendency to gamble in the stock market reveals that investors are more prone to risk seeking behaviour following previous portfolio gains, supporting the behavioural theory of the house money effect. This finding is robust across all investors, including those who are considered non-gambling-preferred investors based on their overall low lottery stock holding weight. Consistent with previous findings, certain investor groups are found to be more likely to invest in lottery stocks. Specifically, women are less likely to gamble with lottery stocks, and the increase of age reduces the tendency to gamble.

Having examined Australian investors using samples over a relatively short time period, the third chapter uses an overseas market sample over two decades to test the same biases. There are two motivations for this; (i) to test that biases observed in previous studies are not unique to Australian investors, and (ii) to test that the observed biases exist over a longer horizon, i.e., they are not driven by specific sample periods. It is found that a person’s lifetime experience, as reflected by the time he/she is born, influences their behaviour. In addition, overall economic and stock market conditions at the time when an investor forms decisions, such as the unemployment rate and the number of corporate bankruptcies, affect the likelihood of behavioural biases. Evidence of interactions between different behavioural biases is also found; specifically, investors who are more risk seeking are at the same time more likely to be affected by the disposition effect.

The final chapter examines the trading of stocks by listed companies' directors and the announcements of their trading. Company directors, when they invest in the stock market, are trading individuals. As such, they are expected to behave similarly to other investors. However, when they trade stocks of their own companies, they are insiders with privileged (superior) information. By analysing the trading of 'the informed', we are able to test whether having superior information subdues behavioural biases. Both director purchases and sales of companies listed on the ASX are examined, and results indicate that directors do use their superior information to time their trades, making these trades free from behavioural bias. There is also evidence that other traders in the market watch director trading and collect their trading information. However, retail investors cannot make superior returns by piggybacking directors' trades, after considering transaction costs and the speed of response of other more sophisticated investors. Given this, the following of directors' trades can be considered a form of biased behaviour, namely herding.

Chapter 1 Introduction

The growth of online trading, which has enabled retail investors to trade more actively than ever before,[1] has broadened the opportunities to study the cause and effect of the seemingly countless market anomalies that contradict neoclassical finance theory by bringing to stock market more retail investors with limited experience in trading. According to the Australian Share Ownership Study,[2] close to 40% of the entire population invest in shares directly.[3] Retail traders are found to move the market, especially among small stocks (e.g., Barber, Odean and Zhu, 2009; Han and Kumar, 2013). Therefore, individual decisions involving financial risks affect all market participants, with direct impacts on market efficiency and, as a consequence, portfolio optimisation, asset pricing, trading strategies, policy-making and regulation.

As important as the matter of retail investor behaviour is, the study of behavioural finance has gained greater attention and recognition just over the last two decades. For a very long time traditional finance theory is the only widely accepted framework, which is based on the model that assumes all investors are rational and make decisions with the sole purpose to maximise their final wealth. These assumptions have been found to not accurately reflect real market behaviour, thanks to the development of behavioural finance theory from both academic research and market practice. Now it is generally accepted by academia that investors, especially individual retail investors, make investment decisions that are not always rational, and the purpose or reason behind their investment decision making is not

[1] See, for example, Barber and Odean (2001b).
[2] *Australian Share Ownership Study 2013*, Report produced by the Australian Securities Exchange. See http://www.asx.com.au/documents/resources/asx-sos-2012.pdf.
[3] Retail investors represent an important portion of trading on stock exchanges worldwide. According to an ASX Australian Share Ownership Study in 2012, as of late 2012, 34% of the adult Australian population (5.98 million people) directly participated in the Australian share market, with an average of 22 trades over a 12 month period.

always wealth maximisation. The research in behavioural finance, as a new discipline in finance study, has also been given more credit and attention from both industry and academia.

1.1 Investor Characteristics and the Disposition Effect

The first topic examined is an investor behavioural bias known as the Disposition Effect. This bias has been named so because it refers to an investor disposition when they make sale decisions; when they have more than one stock in their portfolio to choose from for a sale, they tend to prefer to sell the stocks whose prices have gone up since purchase, and keep holding stocks whose prices have gone down since purchase, even when the preference does not maximise their portfolio wealth.

Shefrin and Statman (1985) were the first to define the ‘disposition effect’. They note that according to Kahneman and Tversky’s (1979) prospect theory, investors want to avoid losses with all means because losses hurt more than gains of similar scale please. This suggests that investors will hold losing stocks as long as they can, so that the loss is not realised. Having established the theoretical explanation, Shefrin and Statman show that, on average, investors’ trades exhibit the disposition effect. Using individual trading data from an existing study, where transaction costs are considered, as well as mutual funds transaction data from Investment Company Institute, for which the transaction costs are ignorable, Shefrin and Statman show that the ratio of redemption to purchases associated with gains is generally higher than the ratio associated with losses.

Since Shefrin and Statman (1985), the disposition effect has been tested in many markets and contexts. Odean (1998) builds on this work to formally test whether investors are more reluctant to realise losses than gains. Using transaction data for a sample of discount brokerage accounts in the U.S. for the period 1987 to 1993, Odean finds that, on average, a significantly higher proportion of gains are realised than losses. The use of a discount broker data rules out the possibility that the disposition effect is created by broker influence on the clients, since discount brokerage clients do not get advice. He shows that this observation persists even after considering portfolio rebalancing, the effect of low price and low-return stocks in a portfolio, and a rational contrarian investment strategy under which today's losers are expected to be tomorrow's winners, and vice versa. The only exception to loss aversion behaviour occurs in December, when a higher proportion of losses are realised than gains. This is attributed to tax-loss selling behaviour in the U.S. market. Further, Odean (1998) demonstrates that the disposition effect holds for frequent and infrequent traders, although it is less pronounced in investors who trade more.

The above mentioned studies use empirical data. Weber and Camerer (1998) design experiments to test whether subjects exhibit the disposition effect and provide additional insights into this behavioural bias. Two insights are derived regarding the reference point; (i) the disposition effect only arises when the original purchase price, or another price of a previous period, is used as the reference; and (ii) the disposition effect exists both when the purchase price is the reference point, and when the price of the previous period is the reference point.

Subsequent studies have further developed the linkages between behavioural biases and the category of investors. More sophisticated investors, for example, are shown to demonstrate lower levels of loss aversion than relatively unsophisticated investors in studies by Shapira and Venezia (2001) and Locke and Mann (2005). Brown, Chappel, da Silva Rosa and Walter

(2006) show that the disposition effect is observable across retail, institutional and foreign investors in the Australian equities market.

This investor behavioural bias is found to exist in the majority of studies, and indeed has been commented as ‘one of the most robust facts about the trading of individual investors’.[4] The disposition effect is also found in settings other than stock markets. Shiller and Case (1988) interviewed home buyers in areas where homes had risen in price (or remained flat). They find evidence of the disposition effect from their interviews; homeowners are keener to sell at a profit than at a loss. Genesove and Mayer (2001) also find real estate market evidence. Further, Heath, Huddart and Lang (1999) document the disposition effect in the exercise of executive stock options.

As often as the disposition effect has been documented, the underlying reasons for this bias are not clear. Barberis and Xiong (2009) show that realisation utility, with no time discounting but with a functional form for utility that, as in prospect theory, is concave over gains and convex over losses, can predict the disposition effect. Kaustia (2010) shows, contrary to other studies, that the S-shaped value functions of prospect theory are not likely to explain the disposition effect. The study also shows that portfolio rebalancing, a belief in mean–reversion, or acting on targeting price, can explain the observed empirical patterns. Kaustia (2010) suggests that psychological motives such as avoiding regret and self-deception could offer a simple explanation to disposition for now, until new preference, or information-based theories, are developed.

[4] Barberis and Xiong (2009).

Given the evidence that the disposition effect results in sub-optimal investment returns, one important question is 'who is more likely to suffer from this bias'. Some studies find the following factors affect investment decision making and biases: gender (Olsen and Cox, 2001; Barber and Odean, 2001; Brooks and Zank, 2005), age (Goyal, 2004; Ang and Maddaloni, 2005; Feng and Seasholes, 2005), and cultural factors (e.g., Yates, Lee and Bush, 1997; Chen, Kim, Nofsinger and Rui, 2007). However, one criticism of these studies is the limited diversity of investor characteristics in their samples. For example, Brooks and Zank (2005) analyse data from an experiment of 49 university economics students. Odean (1998) suggests that given his evidence is from discount brokerage accounts, 'it would be illuminating to repeat this study with data … from a retail brokerage house' (Odean, 1998: 1796). Brown, Chappel, da Silva Rosa and Walter (2006) have access to large samples, yet the study is largely restricted to investment in IPO and index stocks. Feng and Seasholes (2005) note that their results are consistent with Grinblatt and Keloharju (2001), but contradict the findings in Barber and Odean (2001) in terms of gender's role in the propensity to sell. They suggest that nationality be a possible reason for the differences in the findings across the three studies; Feng and Seasholes (2005) are not able to test this conjecture. Finally, Yates, Lee and Bush (1997) and Chen, Kim, Nofsinger and Rui (2007) compare cultural effects using cross-country data, assuming investors in each country are of a homogenous ethnic background, and that market conditions are identical and static.

This dissertation aims to help better answer the question with more detailed information. In the third chapter, we replicate the non-parametric approach of Odean (1998), as well as developing a model to jointly consider the effect of investor characteristics on the presence of loss aversion. Investment account records from a leading retail brokerage house in Australia are examined. All on-market equity trades and holdings data are included to form a sample of over 2 million observations. We examine the extent to which the disposition effect exists across a large set of investor trading characteristics and demographic features, including ethnicity, in a multicultural host country market. Using a surname flag from a comprehensive surname list tested to be valid for predicting Chinese ethnicity in medical research, we are able to identify Chinese investors in the sample and test for the degree of loss aversion among this group.

Examining loss aversion in individuals with Chinese heritage is of importance for three reasons. First, studies of the disposition effect across investor classes have not considered investor's origins. However, there is a strong reason to investigate the effect of an investor's cultural background, as it is shown in the broader behavioural psychology research to have a significant effect on individuals' decision-making. The findings presented in this dissertation have potential implications for the way financial literacy is approached in a multicultural economy like Australia.

This issue of cultural background in a multicultural society has not been considered in studies of behavioural bias. This is the second motivation for this study. While previous studies provide valuable insights to the activity in the markets involved, it is difficult to differentiate between the influence of ethnic background and the unique market features of these emerging markets (for example, Chen, Kim, Nofsinger and Rui, 2007). By examining the behaviour of Chinese-background investors in Australia, we are able to overcome these issues and isolate the effect of Chinese ethnicity. Chinese ethnicity contributes to 4.6% of the total population in Australia. It is ranked 7th of all ethnic groups, and the top non-Caucasian ethnic group in

Australia.[5] In addition, according to Huang (2012), China has become the world's fifth largest overseas investor, with an outward direct investment of USD 68 billion. In this trend, 'Australia has been among the top recipients of Chinese overseas direct investment (ODI) in recent years… between January 2005 and December 2010 Chinese ODI to Australia was around USD 34 billion, the largest single destination for Chinese direct investment overseas' (Hurst and Wang, 2012: 32). Therefore, an understanding of investors with Chinese heritage is of crucial importance to the Australian market given the increasing amount of business Australia has with both China and investors with Chinese heritage in other parts of the world.

Finally, it is in itself particularly compelling to study the trading behaviour of individuals of a Chinese background. Chinese financial markets are rapidly evolving, and a large diaspora lives around the world. The analysis presented in this dissertation can assist in understanding the future world economy, as it helps to understand the mentality of this ethnicity that has an already great and ever increasing impact, on the global economy, from both their homeland market and around the world.

We find strong evidence of the disposition effect across the sample. The results in Chapter 3 indicate that investors are, on average, approximately twice as likely to realise a gain as to realise a loss, broadly supporting the findings of Odean (1998). This bias holds across all investor characteristic groups considered, although the level of bias differs depending on investor sophistication, gender, age and ethnicity. More sophisticated investors demonstrate a lower degree of loss aversion than unsophisticated investors. Adding to the conclusions of Brooks and Zank (2005), Chapter 3 documents difference in the levels of loss aversion between genders, with women demonstrating a higher level of loss aversion than men. The

[5] Reflecting a Nation: Stories from the 2011 Census, 2012–2013, Australian Bureau of Statistics, 21 June 2012; Retrieved 22 January 2013.

age of an investor also appears to be related to their level of loss aversion. Older investors are more likely to demonstrate loss aversion, and to demonstrate a higher level of loss aversion than their younger counterparts. Results indicate that loss aversion differs by ethnicity, with investors of Chinese heritage more disposed to sell winners than losers relative to non-Chinese investors. After controlling for other investor characteristics, including age and gender, the Chinese background investors' disposition bias is approximately 5% larger than the rest of the sample.

1.2 Stock Market Gambling when Investors Make Paper Gains

In Chapter 3, investor behavioural bias when making a sale decision is examined. Under the influence of the disposition effect, investors treat winning and losing stocks with different principles. On the one hand, for winning stocks, investors' willingness to sell comparatively quickly indicates risk aversion. On the other hand, for losing stocks, investors display strong loss aversion by holding onto the stocks for too long. Given investments involve both buy and sell decisions, a question that arises is whether investors, when making purchase decisions, act in a biased manner. Chapter 4 deals with investor behavioural bias incurred when they acquire new stocks: stock market gambling.

Polkovnichenko (2005) observes that, "Investors not only want protection from risk but also want to have a 'shot at riches' " (2005: 1469). As a result, they "attempt to 'get ahead' by hoping to capture large but unlikely extreme gains, gains which are only possible in a relatively undiversified portfolio" (2005:1469). In trying to achieve a big win that has a very small possibility, investors effectively engage themselves in an activity that is similar to gambling. In this instance, risk seeking exists at the same time as loss aversion. This cognitive dissonance can be seen to manifest as otherwise risk averse individuals engaging in gambling behaviour.

Research into stock market gambling has received more attention recently. Barberis and Huang (2008) observe that certain investors synthetically create lottery-like portfolios by taking large and undiversified positions in securities with positive skew. Kumar (2009) formalises the general notion of ‘being lottery-like’ and defines lottery stocks as stocks with a small probability of a high reward, but a negative expected payoff. Specifically, lottery stocks are identified as stocks that have high idiosyncratic volatility, high idiosyncratic positive skew and low price. Kumar (2009) finds that lottery stocks underperform, and investors who prefer lottery stocks suffer from lower portfolio returns.

Bali, Cakici and Whitelaw (2011) define lottery stocks based on the maximum daily return of each security during the previous month. Stocks with extreme returns in the highest decile are classified as lottery stocks for the given month. The authors show that stocks ‘maxed out’ this way underperform when compared to non-lottery stocks, and the market more generally. The use of an extreme return criterion, albeit relatively simple, is consistent with the approach investors are found to take in making investment decisions. Odean (1998) finds that the market under-reacts to highly relevant and reliable information when it is abstract or statistic, and overreacts to information that is extreme and salient; maximum stock return is information both salient and extreme in nature. Grinblatt and Keloharju (2001) present empirical evidence that investors rely on relatively simple trading rules, showing that trading activity is affected following monthly high or low records. Barber and Odean (2008) find that stocks that are considered “attention-grabbing” by exhibiting extreme daily returns are attractive to individual investors.

In Chapter 4, three definitions of lottery stocks are employed in the examination of stock market gambling. The first two methods used are the methods used in Kumar (2009) and Bali, Cakici and Whitelaw (2011), while the third method is an improved approach of Bali, Cakici and Whitelaw (2011). All three definitions lead to qualitatively similar results – lottery stocks represent inferior investment in terms of the returns they produce. Investors portfolio returns are compared in the attempt to investigate whether high proportions of lottery stocks in the portfolio result in sub-optimal portfolio returns. The results show that investors who invest in lottery stocks heavily underperform their peers who do not have a high weight of lottery stocks in their portfolio. These results are robust to portfolio size and alternative behavioural explanations, including over-confidence.

Having established the harm of gambling with lottery stocks, the next part of Chapter 4 is on the investor characteristics and triggers that contribute to proneness to stock market gambling. This comprises two aspects of investor behavioural biases; on the one hand, different investors are subject to behavioural biases to different extents (e.g., Frino, Lepone and Wright 2015); on the other hand, the same investor, under different scenarios, make decisions with different risk preferences. Thaler and Johnson (1990) note that most decision makers are influenced by prior outcomes. Similar to Kahneman and Tversky (1979), Thaler and Johnston (1990) assert that prior events are measured against a reference point and coded and edited as either gains or losses relative to the reference point. They use a series of two-option choices to test preferences under the effect of prior outcomes, and find that decisions after a loss are less biased, often being risk averse, and occasionally risk seeking when there is a chance to break-even. However, when faced with choices after a prior gain, decision makers are more likely to 'accept gambles', and this observed phenomenon is labelled the 'house money effect’. In Chapter 4, we test for the house money effect by examining whether investors are more likely to gamble with lottery stocks after they have achieved a portfolio gain.

Existing literature has included house money effect examination using real market data. Taking advantage of the setting of futures trades by locals in the Sydney Futures Exchange, which includes a lunch break that serves as an unambiguous divide within the daily trading cycle, and the fact that futures trades are almost always closed out by the end of trading day, Frino, Grant and Johnstone (2008) investigate the existence of the house money effect in a real market setting. They find that traders who make money in the morning session take higher total dollar risk, trade larger sizes, and trade more frequently. This is consistent when both realised and unrealised morning profits are considered in aggregate, and when realised morning profits are considered alone. These findings support the house money effect. The authors also find that the house money effect, when in its most severe manifestation, reduces the profits made by the traders.

Hsu and Chow (2013) examine the existence of the house money effect by analysing trade data of individual investors in Taiwan between 1 January 1995 and 31 December 1999. The authors find that the average component of volatility in an investors account has strong correlation with the gains in the previous sale period. They conclude that individual investors display the house money effect in share trading. Huang and Chan (2014) analyse trading of the most active futures contracts on the Taiwan Futures Exchange, TX futures contracts, by all types of traders. They find that active individual traders tend to take greater risk in the afternoon session when they have large morning gains, supporting the house money effect.

Previous research use realised gains in their analysis of the house money effect. Barberis and Xiong (2009) find that 'utility from realised gains and losses may… be a useful way of thinking about certain aspects of individual investor trading.'[6] However, the aspect Barberis and Xiong (2009) examine is a different bias, the disposition effect. When it comes to the examination of the house money effect, although it is not a problem in a laboratory experiment when an action is required as part of the experiment design, nor in Frino, Grant and Johnstone (2008), where most traders have to close their positions by the end of the day in the futures market, it does raise issues for studies of retail investors in the stock market.

First, not having realised a gain by way of selling does not mean that an investor is not 'winning' in the game. If an investor knows that his/her investment is doing well, this knowledge may create joy and cushion for possible loss just as a realised gain does, and thus will affect later decisions, just as a realised gain will. Second, unlike in the futures market when one is more likely to close the position by the end of the day, in the stock market a sale is a voluntary decision that can be reflected upon. An investor will still know about, and may still follow a stock's price movement after he/she has closed the position. If the stock's price continues to increase after the sale, the investor may regret selling too early. The later risk-seeking behaviour, if observed, may be driven by the preference to generate a large gain to compensate for the profit not made, instead of originating from the urge to use 'house money'.

Third, retail investors trade less frequently, and there is generally the advice for retail investors to 'buy and hold'. To analyse the house money effect using realised gains limits the sample to only those transactions after a (recent) sale, and effectively only analyse investors who trade comparatively frequently (e.g., Hsu and Chow, 2013). Using paper gains, which

[6] Barberis and Xiong (2009: 751).

have not been examined previously, will avoid the above mentioned problems. Finally, whether paper gains trigger the house money effect is an interesting topic with its own merit. In Chapter 4, unrealised paper gains are used in the examination of the house money effect in the Australian share market. Investors' gambling in the stock market is a novel signal of the risk seeking preference used in the research. The current study also adds to the existing literature by employing a comprehensive set of explanatory variables, including trading characteristics, and actual rather than inferred demographic features.

Results of this study indicate that there is significant investment in lottery stocks among retail investors, which is consistent with the prediction by Prospect Theory. Retail investors are more attracted to lottery stocks as evidenced by the holding weight of lottery stocks among the sample investors; however, investors who trade greater values, or hold a greater number of stocks, and older and female investors, are less likely to invest in lottery stocks. In testing the behaviour of investors following prior outcomes, we find that retail investors gamble significantly more following portfolio gains regardless of their innate risk preference, consistent with the house money effect.

1.3 Life Experience Impact on Investing Behaviour and Investor Biases Over A Long Time Horizon

Chapters 3 and 4 provide helpful insights about the link between investors' behavioural biases and their investment performance. However, they are based on comparatively short time periods post-GFC, which may not necessarily reflect long-term market conditions. For example, the disposition effect analysis is based on a predominantly bearish market, when there are many stocks that are 'losers' that investors prefer to hold till market conditions change. To answer the question of how robust the findings are, the analysis is repeated in Chapter 5 using data from the Finland stock market over the previous two decades.

The Finland market is used for a number of reasons. First, there is the attempt to find evidence that the existence of investment behavioural biases and their impacts on investment returns are universal, not just restricted to the Australian market. Second, similar to Australia, Finland is a country with high living standards; both countries enjoy high per capita GDP rankings. Finland also has good social welfare, similar to Australia. These comparable living and social welfare standards ensure that the mindset in relation to economic matters is similar between citizens, and thus investors, in both countries.

Another reason is that previous studies find people with certain cultural backgrounds are more (or less) prone to certain behavioural biases. For example, Yates, Lee and Bush (1997) find that people raised in Asian cultures exhibit more behavioural biases than people from the United States. Chen, Kim, Nofsinger and Rui (2007) find evidence that Chinese investors are more overconfident than U.S. individuals. Frino, Lepone and Wright (2015) find that investors of Chinese background are more affected by the disposition effect. Osili and Paulson (2008) find that the effect of home-country institutions affects immigrants for at least the first 28 years that they live in the United States, and is present in all but the youngest group of migrants that arrive in the United States before they are 16. Finland, being predominantly a non-immigrant country that is much less culturally diversified than Australia, provides a natural filter of results driven by part of the investor population that is associated with a particular ethnic background.

While Chapter 5 examines the disposition effect and lottery stock investment as with the previous two chapters, it is not just a repetition of the same analysis with different data. In Chapter 5 a number of new issues are addressed, and additional tests are conducted. One matter examined is whether there is any interaction between different behavioural biases. Specifically, are investors who are loss averse more risk seeking? This question has important implications because if investors are not willing to realise losses, and are prone to invest in riskier and on-average losing lottery stocks, then the aggregated effect will be a market where the majority of retail investors hold onto depreciated stocks which are low in liquidity. For the investors themselves, they are not only suffering from inferior returns as a result of holding their capital in existing poor investments, but they are also exposed to greater losses as they replace winning stocks with low-return lottery stocks.

Previous studies focus on factors that are more endogenous and individual specific, be it investors' gender, or age, or ethnic background, or their prior investment outcome. Chapter 5 employs exogenous factors that are not controlled by, or affected by, investors themselves, namely macroeconomic conditions. Doran, Jiang and Peterson (2011) find that there is a new-year effect for lottery stocks – people hold more lottery stocks in January than other months of the year. In Chapter 4 this cannot be examined because the sample period only covers a relatively short time. In Chapter 5, this issue is investigated by examining the holding weight of lottery stocks across months.

A relatively new direction for investor behavioural research is the link between the (early) life experience and the investors risk preference. Recent literature in economics suggests that the cultural and political environment in which individuals grow up affects their preference and belief formation, such as their trust in financial institutions, stock market participation, and preferences over social policies.

Guiso, Sapienza and Zingales (2003) document that difference in religious upbringing can create considerable differences in levels of trust across individuals, regions, and countries. Guiso, Sapienza and Zingales (2004) find that investment in stocks is related to people's trust in others, whose level is typical of the place where they grow up. Guiso, Sapienza and Zingales (2008) also find that differences in trust across individuals and countries can help explain the difference in stock market participation.

Alesina and Fuchs-Schündeln (2007) utilise the split of Germany between 1945 and 1990 to investigate whether living under certain political regimes has an influence on people's preference. Since West Germans have experienced the same political and economic system as East Germans before 1945 and after 1990, and have not experienced the communist regime as East Germans did, West Germans are used as a meaningful control group for the East Germans in the analysis of communism's impact on individual's beliefs, attitudes, and preferences. Alesina and Fuchs-Schündeln find that the communist regime instils in people the view that the state is essential for individual well-being. Further, not only is this effect strong, but it is also long-lasting. Alesina and Fuchs-Schündeln conclude that it will take 20 to 40 years for the communism's impact on people's attitudes and preference to finally fade, even when the former East Germans are now living in the same political environment as the West Germans.

Osili and Paulson (2008) examine the link between the quality of U.S. immigrant's home country institutions and the immigrants' financial decision making; in particular, participation in the stock market. They find that immigrants from countries with institutions that more effectively protect private property and provide incentives for investment are more likely to participate in U.S. financial markets. For example, they find if Argentina's institutions increased in quality by one standard deviation, then stock market participation among Argentine immigrants in the United States would increase by 2.8 percentage points, a 29% increase. The effect of home-country institutions affects immigrants for at least the first 28 years that they live in the U.S., and is present in all but the youngest migrant who arrived in the U.S. before they are 16 years of age. Another interesting finding is that for immigrants who left their birth countries when they were 16 to 20 years old, institutions play an important role in their financial decisions. Because this group is unlikely to have had much direct experience with financial institutions, this suggests that important lessons about institutions are absorbed in the family and at school.

More recently, Malmendier and Nagel (2011) find that people who have experienced low stock market returns throughout their lives are less likely to take financial risks. In addition, younger people with shorter life experiences are more sensitive to recent returns than older people. Malmendier, Tate and Yan (2011) also find that CEOs who are ‘depression babies’ (growing up during the time of Great Depression) are averse to debt and lean excessively on internal finance. In Chapter 5, the hypothesis of whether people who lived through the depression are less risk seeking is examined through the lottery stock holding weights grouped by generation.

Chapter 5 also examines the impact of the overall economy’s impact on retail investors’ risk preference. We find that an increase of unemployment rate, for example, reduces the disposition effect, but increase the likelihood of stock market gambling. The number of corporate bankruptcies reduces both the disposition effect and the house money effect. While stock market performance does not have a significant impact on the prevalence of the disposition effect, it does reduce the investment in lottery stocks.

1.4 Investing Behaviour of Informed Investors and Their Followers

Biases observed in investment decision making, as discussed in Chapters 3 to 5, arise when investors face uncertainty. For example, the disposition effect is largely due to the individuals' unwillingness to accept that the purchase was wrong – if they had known for certain this would be a losing investment, they would not have purchased the stock to start with. Similarly, the house money effect reflects the individuals increased level of preference to take risks for 'a shot at the riches', which quite often lead to inferior investments – if they knew for certain lottery stocks will underperform, they would not buy the stocks even with 'house money'. Indeed, the framework of prospect theory, which is central in behavioural finance, is a framework of decisions under risk and uncertainty. Therefore, one reason that the discussed biases exist is that individuals who are affected by them lack sufficient 'correct' information that they can rely on, and their interpretation of the information they have is incorrect due to their biases. In the absence of uncertainty, the presence of many behavioural biases will be questioned.

Because of the above mentioned reasons, it is likely that behavioural biases will not affect investors when they have information that 'guarantees' the outcome of an investment. Say, for example, if a person knows with certainty that a stock will double in value in the next week, then this person, whether he/she is prone to biases or not, will attempt to secure any finance possible to invest in this stock before the price increases[7]. Investors with information that is superior do exist in the real market; one such group are “corporate insiders”. In Chapter 6, we investigate whether informed traders trade at the right time and obtain superior returns, which is not achievable by traders with biases. While the behaviour of informed traders is an interesting topic, informed insiders represent a small proportion of the market. The majority of individual investors do not have the luxury of ‘knowing for sure’. Because they do not have all the information they need, many investors attempt to derive information by observing how others, especially the so-called insiders, behave. In Chapter 6, an examination is also undertaken on whether followers of insider traders are rewarded with increased profits, or whether their piggybacking actions are nothing more than another bias, herding.

The trading of corporate insiders in this analysis is trading that meets the legal requirements for insiders. In most developed countries, trading based on insider information is illegal. In Australia and the U.K., insider trading rules apply to company non-executive directors and executives, both referred to as ‘directors’. In the U.S., insider trading regulations apply to a larger group which includes non-executive directors, referred to as ‘directors’, executives referred to as ‘officers’, and large shareholders who own at least 10% of outstanding shares. Several U.S. studies exclude from their samples large shareholders with the belief that they have less access to information than directors and officers of the company (e.g., Garfinkel and Nimalendran, 2003; Brochet, 2010); other studies include large shareholders, but partition different insider groups, and examine results separately, (e.g., Inci, Lu and Seyhun, 2010).

[7] In saying this, we assume that investors do want to take the opportunity to make large profits when they can, as long as it is legitimate.

Historically, the timeframes for director trading disclosure vary significantly across the three regions. Requirements relating to the reporting timeframe are critical in insider trading/announcement studies, as the delay in reporting can lead to information leakage and reduced reaction in the market. In addition, the announcement time is required to accurately measure price effects associated with the event. In the U.S., prior to 2002 when improvements in processing electronic filings led to greater accuracy, there was no precise timestamp on filings. Currently, only EDGAR subscribers are able to obtain trade information concurrent with filings submitted to the SEC; there are often processing delays associated with publishing on the SEC website.[8] Therefore, studies using U.S. data prior to 2002 generally suffer from incorrect announcement times, using filing time as a proxy.

The majority of literature finds that legal insider trading is based on information which enables abnormal profit over a longer-time horizon.[9] Specifically, there is evidence that director trading differs from a simple contrarian strategy.[10] Further, insiders often wait to trade after information releases, selling after releases that drive prices up, and buying after releases that drive prices down.[11] For the short-term, which is probably more of interest to the market, however, there are conflicts in both whether and how much the market captures the signals when they are released. While there is no need to doubt that previous studies use the 'best available' data at their times, these studies still suffer from the limitation of data being infrequent or imprecise. While using infrequent data may fail to capture the speed of response, Friederich, Gregory, Matatko and Tonks (2002) note that using imprecise signalling time may cause bias. No matter whether the release date is assumed, such as in

[8] EDGAR is the electronic filing system used by the SEC.
[9] See Jaffe (1974), Finnerty (1976), Seyhun (1986, 1998), Rozeff and Zaman (1988), Lin and Howe (1990), Jeng, Metrick and Zeckhauser (1999), Lakonashok and Lee (2001), Piotroski and Roulstone (2005), and Ke, Huddart and Petroni (2003) for the U.S.; Gregory, Matatko and Tonks (1997), Hillier and Marshall (2002b), Friederich, Gregory, Matatko and Tonks (2002), and Fidrmuc, Goergen and Renneboog (2006) for the U.K.
[10] For example, Lakonishok and Lee (2001), Piotroski and Roulstone (2005).
[11] For example, Seyhun (1986), Noe (1999).

Jaffe (1974) and Seyhun (1986), or is defaulted to be the 'filing date' as in Chang and Suk (1998) and Lakonoshok and Lee (2001), it is simply not the actual release date. In other words, the above mentioned studies do not have the actual event date in their event analysis.

Studies equipped with precise event time still have no consensus about exactly when and how the knowledge of insider trades become public, although it is generally considered that the time is either of the two events; trade time or the official announcement time.[12] In Australia, according to discussions with an ASX officer, due to the human work involved, the time between electronic submission of Appendix 3Y and the actual release of the report vary with factors including time of the year, staff on post over the period etc. Therefore, release time is a more reliable measure on when the information reaches the market, and Chapter 6 uses the release time as the time when the market learns about directors' trades.

Using a sample of director trades executed between 2005 and 2010, we find that over longer time periods of 120-trading days, director purchases are associated with significantly negative returns before the trade, and significantly positive returns after the trade. Sales are not associated with significant price movements after the trade. However, directors are able to sell at prices sufficiently close to the highest level over the 120-day trading period, and thus realise maximum profit by selling at the 'optimal' time. Larger trade size reflects director's greater confidence in their superior information. This provides strong evidence that directors exhibit significant market timing, executing both their purchases and sales and adjusting their trade size to make significant abnormal profits.

[12] Garfinkel and Nimalendran (2003) give evidence that the information is released even before the trade is executed. They measure the difference between effective spreads on insider trading days and non-insider trading days in 1998 on the NYSE specialist system, and on the NASDAQ dealer system. The documented larger effective spread changes on the NYSE compared to the NASDAQ support the conclusion that specialists are better able to use their relationship with floor brokers to elicit more information about the orders, including whether there is potential insider information.

Evidence is also found that the market believes director's purchases contain information, and reacts to the knowledge of director purchases. Announcements of director purchases have immediate and significant price impact, especially when the announcements relate to trades with possible information not already incorporated in the price (i.e., the price at the time of announcement is lower than the directors trade price). The market does not react significantly to the announcement of directors disposing of shares; however, if the announcement contains some 'surprise' component (i.e., the price at the time of announcement is higher than the directors trade price), there is some evidence of a negative price reaction to the close of trading. Announcements of director purchasing of less liquid stocks attract greater market attention and reaction.

While the above findings suggest that in theory, following director trading can be a way of obtaining information, in reality it is difficult to make a profit out of this practice, as these adjustments occur quickly – as fast as the immediate next quote after the announcement of director trading, which can be less than a second. For the majority of individual investors, even if they learn about the announcement at the same time as it is made, it is not possible for them to place the order and execute it before the information is incorporated into the price. Quite often investors realise there has been a director trade by observing others trade, or learn the news from other traders who have already acted. Considering the transaction costs associated with the trade, piggybacking director's trades is not a way to improve portfolio wealth. Further, if investors just follow director trades blindly, they might be engaging in an activity that is nothing more than herding.

1.5 Summary

This dissertation provides evidence regarding the existence of retail investors' behavioural biases, the triggers and causes of such biases, and the impact of the biases on investors' performance and the overall market. Trading with superior insider knowledge, and market reaction to insiders' trading are also examined in this dissertation in an attempt to explore the role of information in counteracting behavioural biases. This chapter motivates each issue by illustrating the importance of the evidence to both academics and practitioners faced with a litany of inconclusive literature in the area.

The remainder of this dissertation is organised as follows. Chapter 2 provides a review of prior literature pertaining to investor behavioural biases, and the subsequent methodological issues. Chapters 3, 4, 5 and 6 examine the four issues discussed in this chapter. Each chapter contains sections describing the data and sample, research design, empirical results, additional tests and conclusions reached. Chapter 7 concludes by highlighting how the evidence presented in this dissertation can be used to help avoid the negative influence of behavioural biases and improve investor performance and the overall quality of the market.

Chapter 2 Literature Review

The main objective of this dissertation is to examine retail investors trading behaviour and identify specific biases in investment decision making. Rational, risk averse utility maximising behaviour underpins neoclassical finance theory, yet seemingly countless market anomalies contradicting this expectation are identified. In the stock market, what has been challenged over the last two decades is not just the traditional finance theory, but also the traditional way of trading. The internet has facilitated retail investor's ability to trade actively more than ever before[13], and among the investors are those who are not necessarily expected theory practitioners, and have limited experience in trading. According to The Australian Share Ownership Study 2013 by the ASX, [14] during sample periods covered in this dissertation, close to 40% of the entire population invested in shares directly. Retail traders are found to move the market, especially among small stocks. [15] Therefore, individual decisions involving financial risks affect all market participants, with direct impacts on portfolio optimisation, trading strategies, asset pricing, market efficiency, policy-making and regulation.

This dissertation attempts to investigate the following major issues: are retail investors rational in their trading? If not, why do they trade? How do they construct their portfolios? How do they perform? Are there ways to help retail investors make better decisions?

[13] See, for example, Barber and Odean (2001b).
[14] Australian Share Ownership Study 2013, Report produced by the Australian Securities Exchange. See http://www.asx.com.au/documents/resources/asx-sos-2012.pdf
[15] See, for example, Barber, Nicholas and Xiong (2009), Han and Kumar (2013).

The first two sections of this chapter review literature concerned with all these issues. Section 2.1 focuses on literature concerned with choice under uncertainty and the application of relevant theories in the context of investment decision making. Section 2.2 concentrates on literature concerned with the behaviour of informed traders whose uncertainty is reduced, and how the market responds to the news of the trading by investors advantaged with superior information. Section 2.3 utilises the literature reviewed to develop several theories and hypotheses that are tested in this dissertation. Section 2.4 summarises and concludes this chapter.

2.1 Investor Behaviour

Neoclassic finance models have their roots in expected utility theory, which dates back to as early as the 18th century. First initiated by Daniel Bernoulli, expected utility theory was formalised in von Neumann and Morgenstern (1944). Until near the end of the 20th century, the expected utility theory was the main (if not only) framework for models of investors' financial decision making. The traditional finance models based on expected utility theory are prescriptive models rather than descriptive models and they assume: investors are rational and unconditionally risk averse; people make investment decisions that will maximise their final wealth based on expected returns and the probabilities of outcomes.

Being risk averse, investors are expected to prefer lower risk investments to higher risk investments, all else being equal. To take an investment that is risky, a risk averse investor requires a premium over a riskless investment. As the risk of the investment or the degree of risk aversion of the investor increases, so does the required premium. Alternative risk preferences include risk neutrality (an indifference to risk) and risk seeking (a preference *for* risk), which do not exist in the neoclassic finance models.

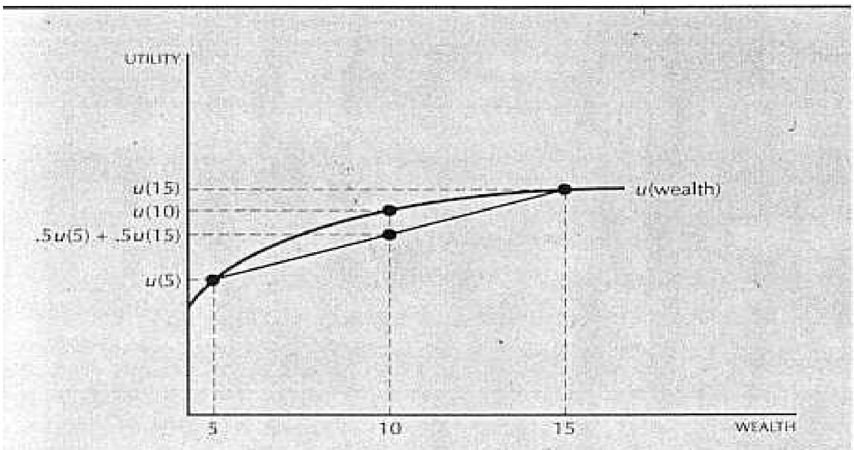
Expected utility theory, which has been widely accepted and applied as the dominant model of economic behaviour analysis, also predicts that people weight outcomes by their probabilities. Therefore, the expected utility of an action is defined as:

$$\text{EU (A)} = \sum_{o \in O} P_A(o) U\,(o) \qquad (2\text{-}1)$$

In the above equation, O is the set of outcomes, $P_A(o)$ is the probability of outcome conditioned on action A, and $U\,(o)$ is the utility of (o). Another critical assumption of traditional finance theory is that utility or value is derived from the final position of wealth.

With the above mentioned principles, the expected utility function graph takes a concave shape curve, because of utility derived from a sure value in total wealth is higher than the utility from a fair gamble. It is as illustrated in the graph below –

Figure 2-1
Concave Curve of Expected Utility Function[16]



Risk aversion. For a risk-averse consumer the utility of the expected value of wealth, $u(10)$, is greater than the expected utility of wealth, $.5u(5) + .5u(15)$.

[16] Source: http://www.econ.ucsb.edu/~tedb/Courses/Ec100C/VarianExpectedUtility.pdf, accessed 14 January 2016.

Traditional finance theories have their strength and are widely applied. However, seemingly countless market anomalies contradicting the assumptions of these economic models have been identified. These anomalies can be summarised as following: investors are not always risk averse; investors do not measure utility simply by their final wealth; investors do not necessarily have wealth maximisation as the purpose of investment decisions making.

2.1.1 Not Necessarily Risk Averse

Friedman and Savage (1948) propose a special shape for an individual's utility-of-wealth function. They suggest that people are risk averse for low and high wealth ranges, and risk-seeking in between. Markowitz (1952) states that risk seeking occurs when choices are between negative prospects, when the amount is considered significant enough to matter to the individual's wealth level. Summarising 'typical answers (of my middle-income acquaintances)' (1952: 154), he notes that individuals will prefer one chance in ten of owing $10,000,000 rather than owing $1,000,000 for sure. According to him, the utility of wealth is carried by the change in wealth, rather than level of wealth. Allais (1953) uses two-gamble choices, later famously known as the Allais Paradox, to demonstrate inconsistencies with the predictions of expected utility theory. His results show that individual decision makers prefer a sure outcome over a gamble that has greater expected value.

Williams (1966) uses more formally conducted surveys to test attitudes towards risk. In one test, participants were asked to indicate the lowest probability of loss that would have to be present before they would pay a stated amount to avoid potential losses. Subjects are found to be risk seeking when there is no potential for gain. As shown in the re-constructed table below, in all 12 scenarios, subjects will only pay a fee to avoid loss when its probability is much greater than the probability of loss whose expected value equals the fee required to transfer the loss.

Table 2-1
Reconstruction of Test Construction Table and Table 1 in Williams (1966)

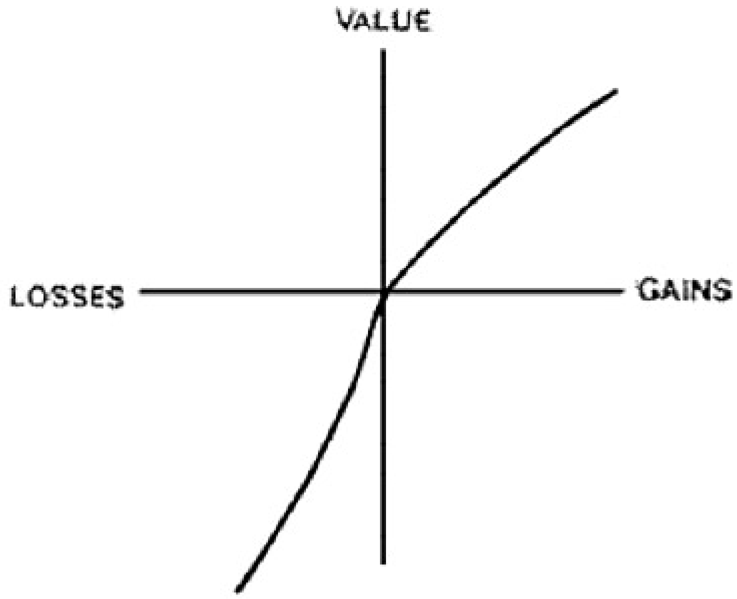
Loss	Potential Dollar Loss	Fee to Avoid Loss	Probability of Loss for which Expected Dollar Loss =Fee	Average Probability Subjects Indicated
1	5000	100	0.02	0.10
2	1,000	500	0.50	0.72
3	5,000	4,000	0.80	0.93
4	25,000	12,500	0.50	0.72
5	200	4	0.02	0.31
6	5,000	2,500	0.50	0.67
7	25,000	20,000	0.80	0.92
8	1,000	20	0.02	0.15
9	200	100	0.50	0.80
10	200	160	0.80	0.94
11	25,000	500	0.02	0.14
12	1,000	800	0.80	0.94

Using data from 5 published studies, Fishburn and Kochenberger (1979) divide all 30 data sets into below-target data and above-target data, and fit functions for each subset. In the majority of cases, the target was at the zero-gain point. They find that about two-thirds of the below-target functions (where prospects are negative) are convex or risk-seeking, and in essentially all cases, below-target utility is steeper than above-target utility.

Kahneman and Tversky (1979) provide a decision framework alternative to the expected utility theory, which has subsequently been used as the corner stone of behavioural finance. Using responses of students and university faculty to a series of hypothetical choice problems, this seminal paper established 3 concepts which explain the observed discrepancies from optimal rational behaviour: (i) risk seeking exists in the value function, (ii) value functions are carried by changes in wealth rather than absolute wealth, and (iii) investors assign decision weights to outcomes, rather than merely probabilities.

Kahneman and Tversky (1979) find several pervasive effects that violate the axioms of expected utility theory. The two main effects found are the certainty effect and the isolation effect. The certainty effect describes people's tendency to assign a higher weight to outcomes that are certain. This tendency leads to risk aversion with the prospect of gains, which are illustrated by a concave curve in the domain of gains. When faced with the prospect of losses, people become risk seeking as illustrated by a convex curve in the value function. The authors also conclude that losses hurt much more than the gains of the same scale please, therefore the convex curve drops much steeper than the convex curve rises. The authors name this theory the prospect theory, in that risk preference differs when facing different prospects (i.e., gain versus loss). The prospect theory value function, illustrated in Figure 2-2, is an 'S' shaped curve, kinked at the origin which is the reference point for the change in wealth. To the left of the origin is the loss domain, and to the right of the origin is the domain for gains. The risk-seeking prediction when people are facing a sure loss contradicts the unconditional risk-averse tenet in descriptive finance models. However, it is not difficult to comprehend and is very common is reality. Because of the fear of pain caused by a sure loss, people take extra risk to avoid it.

Figure 2-2
Reproduction of Value Function of Kahneman and Tversky (1979)



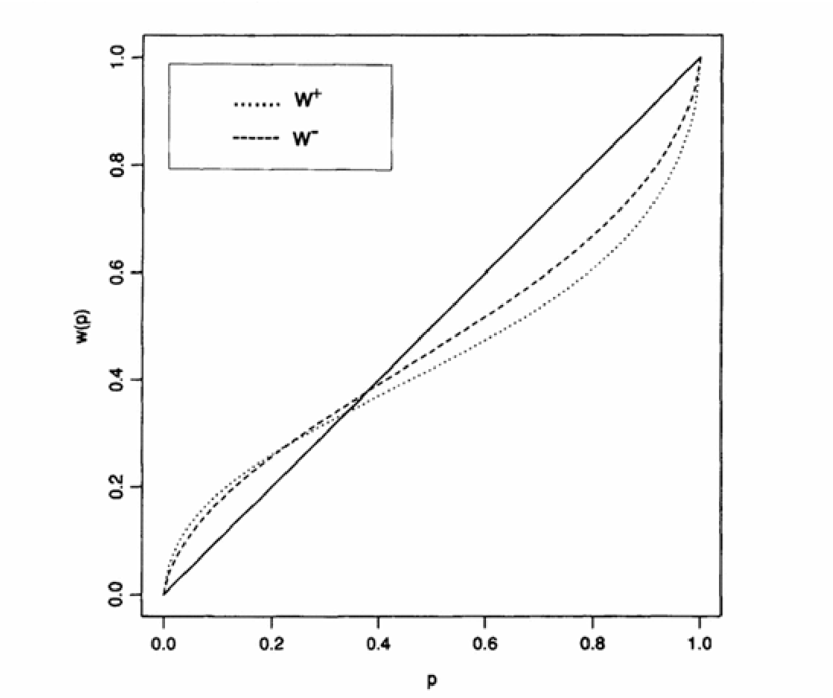
According to Kahneman and Tversky (1979), another instance of risk seeking occurs when there is a shift of the reference point. Specifically, the authors show that "incomplete adaptation of recent losses increases risk seeking in some situations" (1979: 287). The authors also observe that people overweight low probabilities, which explains risk seeking gambling behaviour. Another effect shown in the paper is the isolation effect, which refers to the inconsistency of preferences when the same option is presented in different forms.

Prospect theory distinguishes two phases in the choice process: an early editing phase, where prospects are simplified and a subsequent phase, where the edited prospects are evaluated and choice is made based on the value of the prospects. Kahneman and Tversky (1979) note that many anomalies in preferences result from the editing stage. In addition, in the evaluation phase, people allocate decision weights that are different from probabilities. In particular, people may overweight a small chance event, even if they do not over-estimate the probability of the event actually occurring.

Thaler and Johnson (1990) provide an extension to the prospect theory. They note that most decision makers are influenced by prior outcomes. Like Kahneman and Tversky (1979), Thaler and Johnston (1990) assert that prior events are measured against a reference point, and coded and edited outcomes as either gains or losses relative to the reference point. They use a series of two-option choices for participants to indicate their preferences. Particularly, these choices include those after a known gain or a loss. Using the data from real money experiments, Thaler and Johnston (1990) find that decision makers are more likely to 'accept gambles' in the following two situations. First, when there is a prior gain, and this observed phenomenon is labelled the 'house money effect'. The authors note that in this case, the 'integration' rule in the editing phase applies. Because 'after a gain, subsequent losses that are smaller than the original gain can be integrated with the prior gain, mitigating the influence of loss aversion and facilitating risk-seeking.'(1990: 657). The second is when break-even is possible following a previous loss. Notably, a long-shot is more appealing as it does not risk losing significantly more money, yet still offers the opportunity to break-even.

Tversky and Kahneman (1992) extend the prospect theory to uncertainty as well as to risky prospects with any number of outcomes, while preserving most of the features of the prospect theory. Employing cumulative rather than separable decision weights, the new version is named the cumulative prospect theory. In this framework, risk aversion and risk seeking are determined jointly by the value function and by the cumulative weighting functions. The value function is S-shaped as in Figure 2-2, while the cumulative weighting functions are inverse S-shaped, as illustrated in Figure 2-3. For the value function, the shape indicates two things; (i) diminishing sensitivity – the impact of a change diminishes with the distance from the reference point, and (ii) loss aversion – losses loom larger than corresponding gains. The asymmetry of the function also explains the reluctance to accept mixed prospects. For the weighting functions, diminishing sensitivity also applies.

Figure 2-3
Reproduction of Weighting Function of Tversky and Kahneman (1992)



As can be seen in Figure 2-3, the impact (weight) of a given change in probability (X axis) diminishes with its distance from the boundary, which is impossibility in the case of zero probability on the X-axis, or certainty in the case of 100% probability (1) on the X-axis. The weighting functions are concave near 0 and convex near 1, reflecting the fact that people overweight events with small probabilities, which contributes to the purchase of both lotteries and insurance; underweight events with median to high probabilities, which can be seen in the risk-averse preference for sure things over probable gains; and risk seeking preference for probable over sure losses. In addition, the weighting function shape also suggests relative insensitivity to probability difference in the middle of the range. Therefore, risk attitudes under the combined value and weighting functions have a four-fold pattern; risk aversion for gains and risk seeking for losses of moderate or high probability; risk seeking for gains and risk aversion for losses of low probability. The authors note that 'prospect theory does not imply perfect reflection in the sense that the preference between any two positive prospects is reversed when gains are replaced by losses.' (1992: 306)

Polkovnichenko (2005) observes, "Investors not only want protection from risk but also want to have a 'shot at riches' " (2005: 1469). As a result of this desire, investors either gamble in the stock market (Kumar, 2009), or "attempt to 'get ahead' by trying to capture large but unlikely extreme gains, gains which are only possible in a relatively undiversified portfolio" (Polkovnichenko, 2005:1469). In this instance, risk seeking exists at the same time as loss aversion. This cognitive dissonance can be seen to manifest as otherwise risk averse individuals engaging in gambling behaviour.

Brown, Chappel, da Silva Rosa and Walter (2006) provide empirical evidence in support of the house money effect. Using 5-years of daily exchange data, the authors find that when existing gains and losses are measured by the same stock, and risk seeking is represented by holding onto winning stocks, investors are more risk seeking after prior gains. The evidence from Brown, Chappel, da Silva Rosa and Walter (2006) is strong; however, it does not distinguish between a change in risk preference and a change in the degree of disposition effect. That is, the authors cannot identify whether their results are the effect of a shift to risk seeking behaviour, or are reflective of milder 'less loss averse' behaviour.

Taking advantage of the setting of futures trades by locals in the Sydney Futures Exchange, which includes a lunch break that serves as an unambiguous divide within the daily trading cycle, and the fact that futures trades are almost always closed out by the end of trading day, Frino, Grant and Johnstone (2008) investigate the existence of the house money effect in a real market setting. They find that traders who make money in the morning session take higher total dollar risk, trade larger size and trade more frequently. This is consistent when both realised and unrealised morning profits are considered in aggregate, and when realised morning profits are considered alone. These findings support the house money effect. The authors also find that the house money effect, when in its most severe manifestation, reduces the profits made by the traders.

Hsu and Chow (2013) investigate the existence of the house money effect by analysing intra-day transaction data of individual investors in Taiwan between 1 January 1995 and 31 December 1999. The authors examine the average component volatility in an investor's account and its correlation with the gains in the previous sale period. They find that individual investors tend to buy stocks with higher volatility after having sold them for a gain, supporting the house money effect with empirical evidence from the stock market. They further look into the role of the size of the gain and the time-frame for the house money effect, and find that the house money effect is generally observable for every size quintile over different horizons of risk taking. However, the house money effect is strongest among the large gain groups, and within a short period of time when a prior gain is made. Whether the same stocks sold are re-invested does not appear to affect the house money effect.

Huang and Chan (2014) analyse trading of the most active futures contracts on the Taiwan Futures Exchange, TX futures contracts, by all types of traders. They find that active individual traders tend to take greater risk in the afternoon session when they have large morning gains, supporting the house money effect.

Existing studies all use realised gains in the analysis of the house money effect. This is not a problem in a laboratory experiment when action is required, nor in Frino, Grant and Johnstone (2008), where most traders have to close their positions by the end of the day in the futures market, but it does raise issues for studies of retail investors in equity markets. First, not having realised a gain by way of selling does not mean that an investor is not 'winning' in the game. If an investor knows that his/her investment is performing well, this knowledge may bring joy just as a realised gain does, and thus will affect later decisions, just as a realised gain will. Second, unlike in futures markets when one generally closes the position by the end of the day, and therefore cannot 'blame' themselves for the decisions to sell the position, in equity markets a sale is a voluntary decision that can be reflected upon. An investor will still know about, and may still follow a stock's price movement after he/she has closed the position. If the stock's price keeps increasing after the sale, the investor may regret selling too early. Many studies find that in equity markets, investors suffer from disposition effect, which is the tendency to sell winners too soon (see Frino, Lepone and Wright, 2015). In this case, the later risk-seeking behaviour, if observed, may be due to the wish to have a large gain to compensate for the profit not made, instead of originating from the urge to use house money. Third, retail investors do not trade very frequently and there is often the advice for retail investors to 'buy and hold'. To analyse the house money effect using realised gains limits the sample to only those transactions after a (recent) sale (e.g., Hsu and Chow, 2013). Using paper gains, which have not been examined previously, will avoid the above mentioned problems.

2.1.2 Investors do not measure utility simply by their final wealth

Conlisk (1993) argues that 'economists do not model food preferences solely in terms of nutritional consequences for health … similarly, economists need not model gambling solely in terms of consequences for wealth.' (1993: 256). While acknowledging the risk-seeking factor in gambling behaviour, he suggests that people obtain utility from gambling merely from the 'pleasure of participation', and proposes a model of the utility of gambling. Although, in this work, the word gamble takes a narrow sense.

Statman (2002) observes that gambling is evident in the investment context, and states that we 'impoverish our understanding of investment behaviour when we exclude from it aspects such as hope, camaraderie, and fun.' (2002: 14). He suggests that stock trading, like buying a lottery, can be motivated by (i) an aspiration for riches for those whose only way to become wealthy is lottery or day-trading; (ii) emotions such as aversion to regret – for example, regret to have sold the stock whose value has bounced back up again; and (iii) the joy of winning and seeing peers win. He also points out that 'the equity premium depends on people's attitudes toward risk as much as it depends on the level of risk… the equity premium might turn negative if many people were to place great weight on their upside potential goals. Indeed, preferred securities in such situations are like lotteries.' (2002: 18).

Assuming that investors apply cumulative prospect theory to gains and losses in overall wealth, Barberis and Huang (2008) predict that a positively skewed security in small supply will earn a low average return, as investors exhibit a preference for skewness. They observe that investors favour and synthetically create lottery-like positions in their portfolios by taking large and undiversified positions in securities with positive skew. This behaviour can be explained by the fact that lottery-like positions give an investor a chance, albeit a small chance, of a very large return; the investor values this chance highly, and is willing to accept a low return.

Using a large and comprehensive data set from Finland, Grinblatt and Keloharju (2009) find that the behavioural trait of sensation seeking (as measured by number of speeding tickets received and sports car ownership) explains some of the trading volumes that cannot be fully explained by rational reasons such as portfolio rebalancing. Combining survey results and transaction records of over 1,000 clients at one of the top three discount brokers in Germany, Dorn and Sengmueller (2009) find that some investors trade for entertainment purposes. They suggest that some investors derive non-pecuniary benefits from trading that offsets the costs of churning, stating ‘for people who trade because they like to do so, the monetary cost of trading is offset by non-pecuniary benefits from researching, executing, talking about, anticipating the outcome of, or experiencing the outcome of a trade’ (2009, p592). Carpentier, Cumming and Suret (2012) also find lottery preferences for small stocks in IPO subscription in Canada.

Kumar (2009) formalises the general notion of ‘being lottery-like’ and defines lottery stocks as stocks with a small probability of a high reward, but a negative expected payoff. Lottery stocks feature high variance and positive skew. Specifically, lottery stocks are identified as the joint set of stocks that have high idiosyncratic volatility, high idiosyncratic positive skew and low stock price. He further defines investors as holding either ‘lottery-preferred’ accounts or non-lottery-preferred accounts using the weighting of lottery stocks in the portfolio. Kumar (2009) finds that lottery stocks underperform, and investors who prefer lottery stocks suffer from lower portfolio returns.

In a more recent study, Bali, Cakici and Whitelaw (2011) define lottery stocks based on the maximum daily return of each security during the previous month. Those stocks with extreme returns in the highest decile are classified as lottery stocks for the given month. The authors show that stocks 'maxed out' this way underperform non-lottery stocks, and the market more generally.

The use of an extreme return criterion, albeit relatively simple, is consistent with the approach investors are found to take in making investment decisions in existing studies. Odean (1998) finds that the market under-reacts to highly relevant and reliable information when it is abstract or statistic, and overreacts to information that is extreme and salient. Maximum stock return is information that is salient and has extreme nature. Grinblatt and Keloharju (2001) find further empirical evidence that investors rely on relatively simple trading rules, showing that trading activity is affected following monthly high or low records. Further, Barber and Odean (2008) show that stocks that are considered "attention-grabbing" by exhibiting extreme daily returns are attractive to individual investors.

Barberis and Xiong (2012) present a model of realisation utility. The realisation utility is triggered by the act of selling. According to this model, investors measure their investment not by how much it improves total wealth, but by whether they can have investment episodes where there is positive realisation utility. If the selling price is higher than the purchase price, investors enjoy positive realisation utility; if the selling price is lower than the purchase price, investors suffer from negative realisation utility. Barberis and Xiong (2012) believe that the realisation utility model predicts risk seeking, especially among unsophisticated retail investors; volatile stocks will offer the chance of selling at a higher gain, and although the stock may have a negative expected excess return and the stock value may fall significantly, the investor "will simply postpone selling the stock until he is forced to sell by a liquidity shock. Any realized loss therefore lies in the distant, discounted future and does not scare the investor very much at the time of purchase. Overall, then, the investor may prefer more volatility to less" (2012: 252).

Doran, Jiang and Peterson (2011) investigates the seasonality of investment into lottery-type stocks. The authors list the following reasons for expecting investors to favour lottery-type stocks in January: (i) new money coming in the form of bonuses; (ii) investors' tendency to rebalance their portfolios as evidenced in existing literature; (iii) findings in psychology suggest that investors' risk preference is affected by framing, therefore if the new year is perceived to be the starting point for a new round of events, investors are expected to be more risk seeking at the start of the year and; (iv) anecdotal evidence suggests that people gamble more at the start of the new year. To test the theory's application, the authors examine the seasonality in Las Vegas gambling and Mega-Million/Powerball lottery playing. They document higher per capita gaming revenue in January than all other months in every year between 1997 and 2007, as well as higher sales of lottery tickets in January. In their stock market analysis, the authors find that in the U.S., retail investors are more bullish towards lottery-type stocks in early January than other times of the year. Further, lottery-type stocks in China outperform in the Chinese New Year's month, but not in January.

Han and Kumar (2013) identify retail investors with speculative propensity, who are attracted to stocks with strong lottery features. These investors not only hold a greater proportion of highly speculative stocks, they also trade them more actively. The speculative trading is more evident in regions where people exhibit stronger gambling propensity. The authors also note that stocks with high idiosyncratic volatility appeal to risk-seeking investors who derive an extra non-wealth utility when they realise gains, because these highly volatile stocks offer a greater chance of experiencing a large gain.

2.1.3 Investors do not necessarily make investment decisions that maximise their wealth

A very good example for this discrepancy from the traditional theory is what is known as the Disposition Effect. One outstanding feature of the prospect theory curve is that the drop in the loss domain is steeper than the increase in the gain domain. This depicts the well accepted fact that losses hurt more than gains of the same scale please. Derived from this is the behaviour of loss aversion, which can be observed as trying to avoid losses with all efforts, even if it is against the rational wealth maximisation rule. Concerned with this feature, Shefrin and Statman (1985) were the first to define the 'disposition effect' – the disposition to hold losing stocks too long, even when the precepts of standard theory prescribe closing the position by sale; and selling winning stocks too soon, even when the rational decision should be keeping them.

According to Shefrin and Statman (1985), when an investor sells a stock, he/she is closing a mental account that was opened when he/she first bought the stock. When the closure is done at a gain, pride is induced; when the closure is at a loss, the investor suffers from regret, because it is now evident that he/she has made the wrong decision at the time of the purchase. In their view, 'investors ride losers to postpone regret, and sell winners "too quickly" because they want to hasten the feeling of pride at having chosen correctly in the past.' (1985: 782) Shefrin and Statman (1985) provide empirical evidence of the proposed disposition effect. Using individual trading data from an existing study, where transaction costs are considered, as well as mutual funds transaction data from Investment Company Institute, for which the transaction costs are ignorable, Shefrin and Statman show that the ratio of redemption to purchases associated with gains is higher than the ratio associated with losses in the majority of cases. They conclude that on average investors' trades exhibit the disposition effect. The authors acknowledge that 'our conclusion can be taken only as tentative. There is a clear need to analyse more detailed data on loss and gain realisation… (and) to look at other reasons for realisation: examples include consumption and trading on information (public or private)." (1985: 788 – 789).

While the definition of the disposition effect is regarding the holding and disposing of stocks, the observed behaviour is essentially reluctance to realise losses compared to eagerness to substantiate wins. As such, one would expect that the disposition effect could be observed in other markets where individuals are subject to losses and profits, rather than just the stock market. Shiller and Case (1988) interviewed home buyers in areas where homes had risen in price, or remained flat. They find evidence of the disposition effect from their interviews: homeowners are keener to sell at a profit than at a loss. Heath, Huddart and Lang (1999) document the disposition effect in the exercise of executive stock options. Further, Genesove and Mayer (2001) find real estate market evidence.

Odean (1998) builds on this work to formally test whether investors are more reluctant to realise losses than gains. Using transaction data for a sample of discount brokerage accounts in the U.S. for the period 1987 to 1993, Odean finds that, on average, a significantly higher proportion of gains are realised than losses. The use of discount broker data rules out the possibility that the disposition effect is created by the brokers influence on the clients, since discount brokerage clients do not receive advice. He shows that this observation persists even after considering portfolio rebalancing, the effect of low price and low-return stocks in a portfolio, and a rational contrarian investment strategy under which today's losers are expected to be tomorrow’s winners, and vice versa. The only exception to loss aversion behaviour occurs in December, when a higher proportion of losses are realised than gains. This is attributed to tax-loss selling behaviour in the U.S. Further, Odean (1998) demonstrates that the disposition effect holds for frequent and infrequent traders, although it is less pronounced for investors that trade more.

Odean’s (1998) findings have the following implications. First, the disposition effect may stabilise the market at near prices at which substantial trading has previously occurred. ‘If many investors buy a stock at a particular price, that price may become their reference point. If the stock falls below this reference point, these investors will be averse to selling for a loss, reducing the supply of potential sellers. A reduced supply of potential sellers could slow further price decreases. On the other hand, if the stock rises above the reference point, these investors will be more willing to sell, increasing the supply of potential sellers, and possibly slowing further price increases. If these investors have private information about the future prospects of a company whose stock they hold, the disposition effect may slow the rate at which this information is incorporated into prices. For example, investors with negative information may be unwilling to sell a stock if its price is below their reference point. In not selling the stock, these investors will fail to signal their negative information to the market, and there could be a delay before that information is reflected in prices.’ (1998: 1975 – 1976). However, the most significant impact the disposition effect has shall be on individual investors. Odean (1998) provides strong evidence that due to the disposition effect, an investor suffers substantial underperformance compared to trading without this bias.

Weber and Camerer (1998) design experiments to test whether subjects exhibit the disposition effect, and provide additional insights into this behavioural bias. Two insights are documented on the reference point: (i) the disposition effect will only arise when the original purchase price or another price of a previous period is the reference point; and (ii) the disposition effect exists both when the purchase price is the reference point and when the price of the previous period is the reference point.

Assuming an investor purchases a stock at the price P. Later the stock will either fall by L (so the price becomes $P - L$), or gain by G (so the price becomes $P + G$). In case that the stock depreciates, after the first loss of L, the price will either rebound to the same as the purchase price P, or falls by a further L (so the price becomes $P - 2L$). In the case that the stock appreciates, the price later will either gain by another G (so the price becomes $P + 2G$), or falls back to the previous purchase price P. Fig 2-4(a) illustrates what happens when the investor's reference is the original purchase price P according to prospect theory. When the current state is a loss, then the stock is worth $P - L$ if sold, and either P or $P - 2L$ if held. Given it's in the loss domain which predicts risk seeking, and the chances of breaking even or losing another L are equal, the investor will keep the stock. When the current state is a win, the stock is worth $P + G$ if sold, and either P or $P + 2G$ if held. Given it's in the domain of gains which predicts risk-averse behaviour, and the chances of making a further gain and making no profit are the same, an investor will sell the stock to realise the gain as soon as possible.

Figure 2-4(a)
Prospect Theory Function when Original Purchase Price is Reference Point
Reproduction from Weber and Camerer (1998)

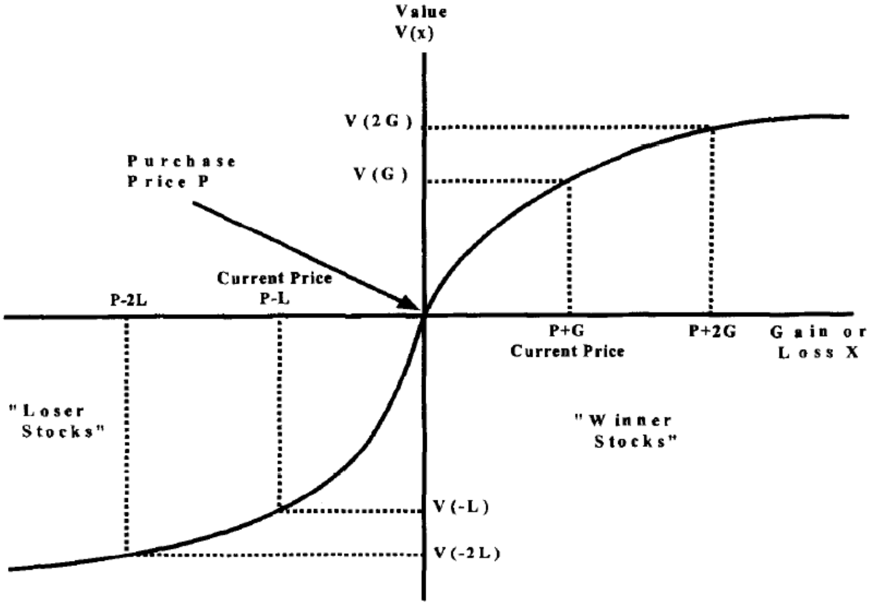
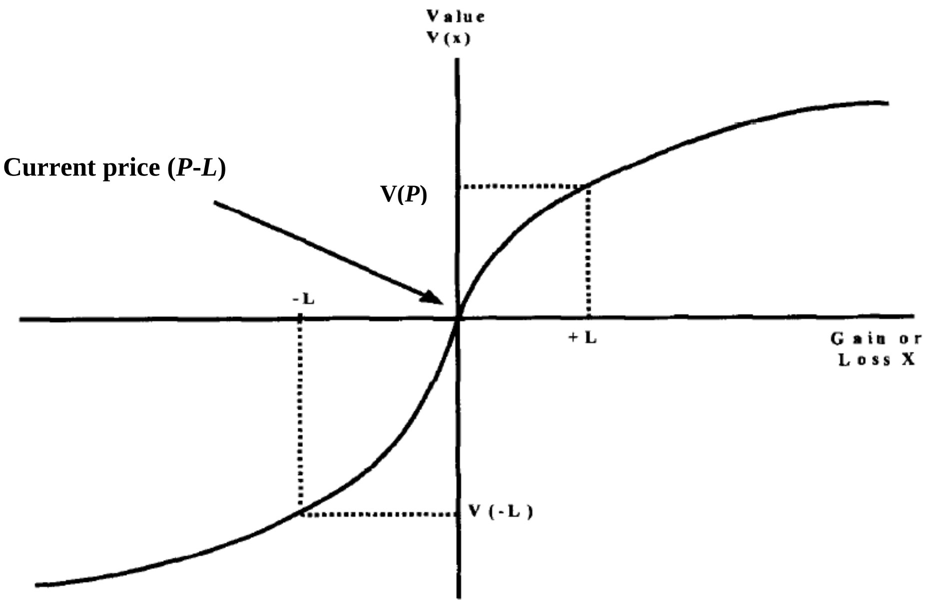


Figure 2-4(b) illustrates what happens if the current price is the reference point and the current price is a loss of *L* from the purchase price *P*. The investor will then face a gamble of either having the price rebound with the amount of *L*, so that the price becomes *P*, or having the price fall by another *L* such that the price becomes *P*- 2*L*. The investor will choose to sell the stock as the current state is better than the prospects of the gamble. If the reference point is the current price which is a gain of *G* from the purchase price *P* (which is not shown in the figure), for the same reason the investor will still choose to sell. Because a value function which exhibits loss aversion ($v(x) < -v(-x)$ for $x > 0$) predicts that for equal chance gambles, the investor will always sell the lottery if the reference point is the current price – there will be no disposition effect.

Figure 2-4(b)
Prospect Theory Function When Current Price is Reference Point
Reproduction from Weber and Camerer (1998)



In testing the existence of the disposition effect, Weber and Camerer (1998) define gains and losses using two reference points; the purchase price and the price of the previous period. They find that investors are more likely to realise gains than losses in both cases. To understand the source of the effect, they conduct an additional experimental condition in which subjects' holdings are automatically sold at the end of the period, and the subjects are told they are free to reinvest the proceeds into any stock. If subjects were holding on to their losing stocks because they thought that these stocks would rebound, then they are expected to re-establish their positions in the losing stocks automatically sold. However, subjects do not re-establish these positions. This casts doubt on the mean-reversion view of the disposition effect, and lends support to the realisation utility view, namely that subjects were refusing to sell their losers simply because it would have been painful to do so.

Further, one important design characteristic of the experiment is that stock price changes are positively auto-correlated across all stocks. That is, stocks that rise are more likely to be positive-trend stocks and are more likely to rise again; similarly, losing stocks are more likely to continue losing. The fixed probabilities of appreciating for all stocks are given to subjects at the start of the experiments, but they are not told which probability is for which stock. However, after having been given the stock prices for several periods, subjects, who are statistically well-trained university students in engineering and business and economic graduates, should be able identify from the historical prices the trends of each stock. A test on this shows that the subjects indeed had a good idea of which stocks had upward and downward trends. In this case, subjects are holding onto losing stocks even when they know the stocks are more likely to lose again than to rebound, which again supports the loss aversion interpretation and cannot be explained by the mean-reversion view.

Thaler (1999) offers another reason why individuals might want to avoid and delay realising a loss; “one clear intuition is that a realised loss is more painful than a paper loss. When a stock is sold, the gain or loss has to be ‘declared’ both to the tax authorities and to the investor (and spouse).” (1999: 189)

Subsequent studies further develop the linkages between behavioural biases and the category of investors. More sophisticated investors, for example, are shown to demonstrate lower levels of loss aversion than relatively unsophisticated investors in studies by Shapira and Venezia (2001) and Locke and Mann (2005). Brown, Chappel, da Silva Rosa and Walter

(2006) show that the disposition effect is observable across retail, institutional and foreign investors in the Australian equity market. Although the disposition effect has been clearly documented, the reasons for its existence are not clear. Barberis and Xiong (2009) show that realisation utility, with no time discounting but with a functional form for utility that, as in prospect theory, is concave over gains and convex over losses, can predict the disposition effect.

Kaustia (2010) shows, contrary to previous studies, that the S-shaped value function of the prospect theory is not likely to explain the disposition effect. The study also shows that portfolio rebalancing, a belief in mean-reversion, or acting on targeting price can explain the observed empirical pattern. Kaustia (2010) suggests that psychological motives, such as avoiding regret and self-deception, could offer a simple explanation to disposition for now, until new preference or information-based theories are developed.

Barberis and Xiong (2012) propose a realisation utility model, whose most important application is that it helps explain the disposition effect: investors voluntarily sell a stock only when they can sell at a gain relative to the purchase price because they want only the positive realisation utility; as for losing stocks, investors will keep holding them until the stocks' values bounce back to enable positive realisation utility, except for when a liquidity shock forces selling at a loss. The authors believe that buying a stock offers the investor either a short-term realised gain, in the case the stock is a winner, or a long-term realised loss, if the stock is a loser.

Other studies show investor characteristics, such as gender and age, and cultural factors, can affect risk perceptions and investment biases. Many studies show that women, for example, are more risk averse than men in investment situations (Olsen and Cox, 2001). In an experimental study by Brooks and Zank (2005), women are shown to be proportionately more loss averse than men. Men, on the other hand, are shown in the literature to demonstrate higher levels of overconfidence (Barber and Odean, 2001).

Ethnic background is also found to play a very important role in behaviour related to risk. Yates, Lee and Bush (1997) find that people raised in Asian cultures exhibit more behavioural biases than people from the United States. Chen, Kim, Nofsinger and Rui (2007) study the stock investment decisions using data from a brokerage firm in China, finding evidence that Chinese investors are “just as prone to the disposition effect as U.S. individuals’ but ‘more overconfident than U.S. individuals” (2007: 448).

One criticism of previous research which examines the disposition effect across investor classes is the limited diversity of investor characteristics in their samples. Brooks and Zank (2005), for example, analyse data from an experiment of 49 university economics students. Other studies using trading records are limited with the lack of representativeness of the data. Odean (1998) suggests that given his evidence is from discount brokerage accounts, ‘it would be illuminating to repeat this study with data… from a retail brokerage house’ (1998: 1796). Brown, Chappel, da Silva Rosa and Walter (2006) have access to large samples, yet the study is largely restricted to investment in IPO and index stocks. Finally, Yates, Lee and Bush (1997) and Chen, Kim, Nofsinger and Rui (2007) compare cultural effects using cross-country data assuming investors in each country are of a homogenous ethnic background, and that market conditions are identical and static. Therefore, analysis with a more comprehensive set of investor data, as presented in Chapter 3, will help to fill this gap in the current literature.

2.1.4 *Lifetime Experience's Impact*

A relatively new direction for investor behavioural research is the link between the (early) life experience and the investors risk preference. Recent literature in economics suggests that the cultural and political environment in which an individual grows up affects their preference and belief formation. Guiso, Sapienza and Zingales (2003) document that difference in religious upbringing can create considerable differences in levels of trust across individuals, regions, and countries. Guiso, Sapienza and Zingales (2004) find that investment in stocks is related to people's trust in others, whose level is typical of the place where they grow up. Guiso, Sapienza and Zingales (2008) also find that differences in trust across individuals and countries can help explain the difference in stock market participation.

Alesina and Fuchs-Schündeln (2007) utilise the split of Germany between 1945 and 1990 to investigate whether living under certain political regimes has an influence on people's preference. Since West Germans have experienced the same political and economic system as East Germans before 1945 and after 1990, and have not experienced the communist regime as East Germans did, West Germans are used as a meaningful control group for the East Germans in the analysis of communism's impact on individual's beliefs, attitudes, and preferences. Alesina and Fuchs-Schündeln (2007) find that the communist regime instils in people the view that the state is essential for individual well-being. Further, not only is this effect strong, but it is also long-lasting. Alesina and Fuchs-Schündeln conclude that it will take 20 to 40 years for the communism's impact on people's attitudes and preferences to finally fade, even when the former East Germans are now living in the same political environment as the West Germans.

Osili and Paulson (2008) examine the link between the quality of U.S. immigrants' home country institutions and the immigrants' financial decision making; in particular, participation in the stock market. They find that immigrants from countries with institutions that more effectively protect private property and provide incentives for investment are more likely to participate in U.S. financial markets. For example, they find if Argentina's institutions increased in quality by one standard deviation, then stock market participation among Argentine immigrants in the United States would increase by 2.8 percentage points, a 29% increase. The effect of home-country institutions affects immigrants for at least the first 28 years that they live in the U.S., and is present in all but the youngest migrants who arrived in the U.S. before they are 16 years of age. Another interesting finding is that for immigrants who left their birth countries when they were 16 to 20 years old, institutions play an important role in their financial decisions. Because this group is unlikely to have had much direct experience with financial institutions, this suggests that important lessons about institutions are absorbed in the family and at school.

More recently, Malmendier and Nagel (2011) find people who have experienced low stock market returns throughout their lives are less likely to take financial risks. In addition, younger people with shorter life experiences are more sensitive to recent returns than older people are. In addition, Malmendier, Tate and Yan (2011) also find that CEOs who are 'depression babies' (growing up during the Great Depression) are averse to debt and lean excessively on internal finance.

2.2 Director Trading and the Market's Response

The section above discusses in detail many factors that impact on or determine individuals' behaviour in financial decision making, such as age, gender, culture and education. There is yet another factor which might be considered the most important factor that affects decision making. This factor is information. In making investment decisions, individuals attempt to collect information. The information collection efforts include obtaining formal training, studying financial products' price history, discussing in forums, obtaining tips from experts etc. Many investors attempt to acquire some knowledge of the prospect of certain investments by obtaining hints from 'insiders'. Some of these insiders, indeed, are individuals investing in the equity market themselves. Considering the different information hierarchy in financial markets, it is of interest to academia, market participants, and regulators to determine whether investors with inside information trade differently, and whether their behaviour affects the quality of the market.

This section details the way in which literature has contended with director and insider trading, as well as the market's reaction to the news of the trading and followers' investment performance. Policies regulating insider trading and announcement and impacts of regulation changes, as well as various techniques used for measurement, are discussed.

Company directors, when they invest in the stock market, are trading individuals who, as human beings, are not free of behavioural biases. However, when directors trade stocks of their own company, they are insiders equipped with superior information. The study of insider trading and reporting commences with determining whether legally trading insiders trade randomly, and on average, do not outperform the market; or whether they time their trades well, utilising their superior knowledge of the company while trading (at least marginally) legally, and thus making abnormal profits. This is because without evidence of insiders outperforming the market, the interest in reporting insider trading (and the interest in insider trading itself) is senseless. The majority of literature finds that legal insiders' trading is based on information which enables abnormal profit over a long time horizon.[17] Specifically, there is evidence that director trading differs from a simple contrarian strategy;[18] further, insiders often wait to trade after information releases, selling after releases that drive prices up, and buying after releases that drive prices down.[19]

In the examination of insider trading, different studies have used different definitions of 'insiders'. Several U.S. studies exclude from their samples large shareholders with the belief that they have less access to information than directors and officers of the company (e.g., Garfinkel and Nimalendran, 2003; Brochet, 2010); other studies include large shareholders, but partition different insider groups, and examine results separately (e.g., Inci, Lu and Seyhun, 2010).

Market efficiency theory states that in a semi-efficient market, stock prices reflect all publically available information. Given the market anecdotal belief, and vast academic evidence, that insider trading is based on superior knowledge of the firm, and is therefore profitable, in a semi-efficient market like the Australian market[20], any information associated with an insider's trade will be incorporated into stock price once it is public. The question then shifts to when this information becomes 'public'; either at the time of the release of the report by the ASX, or at some earlier time (rendering the ASX release redundant). Existing

[17] See Jaffe (1974), Finnerty (1976), Seyhun (1986, 1998), Rozeff and Zaman (1988), Lin and Howe (1990), Jeng, Metrick and Zeckhauser (1999), Lakonashok and Lee (2001), Piotroski and Roulstone (2005), and Ke, Huddart and Petroni (2003) for the U.S.; Gregory, Matatko and Tonks (1997), Hillier and Marshall (2002b), Friederich, Gregory, Matatko and Tonks (2002), and Fidrmuc, Goergen and Ronneboog (2006) for the U.K.
[18] For example, Lakonashok and Lee (2001), Piotroski and Roulstone (2005).
[19] For example, Seyhun (1986), Noe (1999).
[20] There is rich literature about Australian market efficiency, for example, Aitken and Frino (1996).

literature provides conflicting/inconsistent findings in terms of whether the reporting of insider trading affects prices.[21] Research that concludes that *both* trades and announcements contain information are against the semi-efficient market hypothesis.

Jaffe (1994) examines the 200 largest securities on the Chicago Research in Securities Prices (CRSP) between 1962 and 1968, and calculates cumulative average monthly return residuals after the insider trade event, and 2-months after the trade event, the latter of which is assumed to be the *Official Summary*[22] date. The conclusion from the results is that 'trades of insiders contain information', while 'much information contained in the trades remains undiscounted by the publication date in the *Official Summary*.'

Seyhun (1986) also uses CRSP data, using firms whose daily returns are filed with CRSP from 1975 to 1981. Over a 200-day period centred on the insider trade, both insider purchasers and sellers make a profit of about 4.5%.[23] In market efficiency analysis, Seyhun (1986) uses a sub-sample of reported transactions as of the last day of each month for filing effects, and the date the *Official Summary* was received by the Rush-Rhees Library of the University of Rochester as the date when *Official Summary* is available to the market. Despite the fact that the actual date for *Official Summary* availability may be as much as a week to 10 days earlier[24], Seyhun (1986) documents significant information effects at both the filing date and the *Official Summery* date. No profit is earned for the followers of this information, after taking transaction costs into consideration; therefore, the market is deemed efficient.

[21] Studies concluding that filing/announcements contain information include Jaffe (1974), Seyhun (1986), Chang and Suk (1998) etc. Lakonishok and Lee (2001) conclude that the 'market ignores reporting'.
[22] Official Summary of Insider Trading, a monthly report by SEC.
[23] AR for purchase is -1.4% 100 days before the trade, and 3% 100 days after the trade; AR for sales is 2.5% 100 days before the trade, and -1.7% 100 days after the trade.
[24] Seyhun (1986), page 208, footnote 13.

Lin and Howe (1990) study insider trading on the OTC market from January 1975 to April 1983 by measuring the abnormal returns surrounding the intensive trading month, and find that insiders purchase (sell) after periods of negative (positive) abnormal returns, and their transactions have predictive content. Noe (1999) studies director trades in companies with management earnings announcements that were publicly-traded through 1 July 1979 to 31 December 1987. The results provide evidence that managers increase their trades after 'self-serving' voluntary disclosures which push prices up/down for their sales/purchases. Post trade, these stocks experience abnormal returns and the net insider trading amounts following disclosures are positively related to the company's long-term earnings performance.

Chang and Suk (1998) examine average cumulative abnormal stock returns and cumulative average abnormal trading volume around 3 event times: insider trades, the SEC filing of these trades, as well as the later Wall Street Journal publication of these trades. The sample covers a period between 31 August 1988 and 31 December 1990, and includes both on-exchange and OTC insider trades. Significant price movements, as well as an increase in trading activity, are documented following all 3 events. The findings suggest that the SEC filing attracts only limited attention by the market. One explanation given by the authors is that the 'individual investors consider the expected cost of obtaining new information from the SEC filing to exceed the expected benefits' (1998: 125).

Lakonishok and Lee (2001) provide another possible explanation for Chang and Suk's (1998) findings - 'As soon as insiders file their transactions, any investors can get access to that information. However, in reality, it might take a few days to obtain the information' (2001: 88). Opposite to Chang and Suk's findings of abnormal returns following both trading and release, Lakonishok and Lee (2001) report significant abnormal returns around neither the insider trading day, nor the reporting day. However, long-term performance comparison between firms with extensive insider purchases and extensive insider sales during the prior 6-months shows that insiders' activities predict stock returns for individual firms for a 12-month holding horizon, even after adjusting for a simple contrarian strategy.

A more recent study by Brochet (2010) measures the information content of directors trading announcements, in terms of stock returns and trading volume, both before and after the introduction of Sarbanes – Oxley Act 2001 (SOX). Brochet (2010) documents speedier and greater information content post-SOX than pre-SOX, and this is interpreted as the result of speedier reporting and more strict reporting requirements leading to rapid price reaction. However, filing dates in the post-SOX sample are more likely to be the actual announcement date given the improvement of the filing and releasing system that occurred in 2002[25], therefore the greater and speedier information effects may be a result of having an event date more precise than the pre-SOX event date. Also, another result of speedier reporting is that the filing date is more likely to be, or closer to, the trading date, so part of the greater information effects attributed to filing may in fact be the effects from the trading.

Studies based on U.S. and U.K. data are generally consistent in the conclusion about the information content of insider trades over a long-time horizon. For the short-term, which is probably more of interest to the market, however, there are conflicts in both whether and how much the market captures the signals when they are released. While there is no need to doubt that earlier studies mentioned above use the 'best available' data at their times, these studies still suffer from the limitation of data being infrequent or imprecise. While using infrequent

[25] Inquiries to the SEC about the 'Accepted' time of insider trading report (Form-4), published on the SEC website though EDGAR, reveal that 'the 2002 changes around Filing Date reflect an improvement in process, including greater accuracy.'

data may be unable to capture the more rapid market response to any event, as noted in Friederich, Gregory, Matatko and Tonks (2002), using imprecise signalling time may cause bias. Irrespective of whether the release date is assumed, such as in Jaffe (1974) and Seyhun (1986), or is defaulted to be the 'filing date' as in Chang and Suk (1998) and Lakonishok and Lee (2001), it is simply not the actual release date, at least during the sample periods of the above mentioned studies.

Studies equipped with precise event time still have no consensus about exactly when and how the knowledge of insider trades become public, although it is generally considered that the time is either of the two events; trade time or the official announcement time.[26] Hillier and Marshall (2002b) document price movements in the director's favour for both purchases and sales after directors trade, although purchases are associated with reactions on the day of the trade, while sales have delayed reactions. Friederich, Gregory, Matatko and Tonks (2002) find offsetting patterns in daily returns immediately surrounding insider trades, and conclude that earlier studies using monthly data conceal price effects. Inci, Lu and Seyhun (2010) suggest the possibility of the market being informed of the insiders trades at the time of the trade because 'insiders have to disclose their insider identity to the brokers at the time they open their account' (2010:329).

While the above mentioned studies provide evidence that the market becomes informed at the time of the trade, other researchers find the signal reaches the market at the official announcement time, which is later than the trade time. Fidrmuc, Goergen and Renneboog

[26] Garfinkel and Nimalendran (2003) provide evidence that the information is out even before the trade is executed. They measure the difference between effective spreads on insider trading days and non-insider trading days in 1998 on the NYSE specialist system, and on the NASDAQ dealer system. The document larger effective spread changes on the NYSE compared to the NASDAQ, supporting the conclusion that specialists are better able to use their relationship with floor brokers to elicit more information about the orders, including whether there is potential insider information.

(2006) report significantly positive CARs following the announcement of director purchases, and significantly negative CARs following the announcement of director sales. They also document larger returns than documented in U.S. studies, and attribute the difference to U.K. regulations requiring much speedier reporting during their sample period.

2.3 Hypothesis Development

This section uses the literature reviewed in the previous two sections to develop several hypotheses that are tested in this dissertation. The topics discussed in this dissertation are related to individuals' behaviour surrounding investment decisions. These behaviours are closely associated with their experience, and expected wins and losses – how they weight the outcomes, and how they react to the outcomes once they eventuate. Both wins and losses are possible in the process of investing. The entire field of behavioural finance would not exist if investors simply faced the possibilities associated with investing without any emotional involvement. However, as many researchers have identified, investors view wins and losses with different standards. Further, the way they interpret realised and unrealised gains (or losses) varies considerably.

Shefrin and Statman (1985) note that realising the win may induce the positive feeling of pride. Thaler (1999) notes that paper losses are different from realised losses, with the later more painful because while one might be able to turn a blind eye to a paper loss, they have to declare the realised loss both to the government and the partner. The compounded effect of wanting enjoyment from gains, and dreading pain from losses, is what has been observed as the most robust behavioural effects in equity markets. The disposition effect is the tendency to realise gains too soon, and maintaining positions in losing stocks for too long. There is significant literature on the disposition effect. However, a lack of comprehensiveness of investor characteristics, or a limitation of investment products analysed, have restricted the conclusion of the broadness of this bias. With the aid of a rich data set, this dissertation examines the first hypothesis that the disposition effect exists across all retail investors in the stock market.

Hypothesis$_{3,1}$: *The Disposition Effects exists across all retail investors in the Australian market. In effect, the Proportion of Realised Losses is less than the Proportion of Realised Gains.*

In testing the existence of the disposition effect, Weber and Camerer (1998) conduct an additional experimental condition in which subjects' holdings are automatically sold at the end of the period, and the subjects are told they are free to reinvest the proceeds into any stock. They find subjects do not re-establish these positions, and conclude that subjects were refusing to sell their losers simply because it would have been painful to do so. One might therefore think that if there is no pain involved in selling losers, or if there is even some direct and obvious benefit of selling losers, then the disposition effect will not be as persistent.

Existing literature finds evidence of investors engaging in tax motivated loss selling. Studies using U.S. data (e.g., Dyl, 1977; Lakonishok and Smidt, 1986; Badrinath and Lewellen, 1991) typically find more losing investments are sold near the end of December, because it's also the end of the financial year in the U.S. Odean (1998) finds that the ratio between PGR (proportion of gain realised) and PLR (proportion of loss realised) declines from 2.1 in January to 0.85 in December. In Australia, where June is the end of the financial year, Brown, Chappel, da Silva Rosa and Walter (2006) find that PGR in June is much lower than the rest of year, and PLR in June is much higher than the rest of the year. This leads to the following hypothesis.

Hypothesis$_{3,2}$: *Investors engage in tax selling, resulting in a lower incidence of the Disposition Effect in last month of the financial year (June) in Australia.*

While this dissertation aims to establish the prevalence of the disposition effect, there is no intention from the author to claim that this bias, or any other bias, affects different individuals equally. The fact is actually quite the opposite. It is documented that certain people are more loss averse than others. For example, Brooks and Zank (2005) find that women are more likely to be loss averse than men. It is thus hypothesised that both other behavioural traits and demographic features affect individuals' loss aversion level, which is seen as the difference in the likelihood of exhibiting the disposition effect. Specifically, the following hypothesis is tested in this dissertation.

Hypothesis$_{3,3}$: *Trading characteristics and demographic features affect investors proneness to the Disposition Effect.*

One possible reason that drives the disposition effect to be an important issue is the potential harm it does to retail investors. Some investors think that they are not biased by holding onto losers, rather, they are holding on to what might be tomorrow's winners. If these hopes eventuate, then it is not a bias to hold onto the losers. However, as found in Odean (1998), this belief is not justified. The next hypothesis in this dissertation is that the losing stocks retail investors continue to hold underperform when they are compared to the winning stocks that they sell.

Hypothesis$_{3,4}$: *Average excess returns on paper losers are lower than average excess returns on winning stocks sold.*

In the test of gambling in retail investors, investment in lottery stocks is used as a signal of increased gambling preference. Lottery stocks are stocks that have the features of lottery tickets, which include a very small chance of a large win. For investment in lottery stocks to be a bias, which is why this behaviour is of concern, lottery stocks need to underperform when compared to other stocks. In this dissertation, three different methodologies to define lottery stocks are employed. It is hypothesised that regardless of the difference of the method employed, the lottery stocks defined share similar features and are inferior in terms of risk adjusted returns.

Hypothesis$_{4,1}$: *Lottery Stocks defined using different methods have lower risk adjusted returns compared to non-lottery stocks.*

If it is established that lottery stocks do underperform, the next step is to examine whether investors that invest heavily in lottery stocks suffer from lower portfolio returns as a result of their behavioural bias. This leads to the next hypothesis -

Hypothesis$_{4,2}$: *Investors with portfolios that have a high weight in lottery stocks suffer from lower portfolio returns.*

Given that lottery stocks represent inferior investments, and to an extent attention-grabbing stocks due to their recent extreme returns, they are not likely to appeal to institutional traders who are equipped with more resources, knowledge, skills and trading experiences. We hypothesise that lottery stocks attract mainly retail investors.

Hypothesis$_{4,3}$: *Lottery stocks mainly attract retail investors.*

So far the interpretation of the investment in lottery stocks is viewed as preference of risk. This is because that the high price volatility feature of lottery stocks makes it a risky investment. Further, the high skewness feature of lottery stocks makes the investment in lottery stocks a gamble, and ‘accepting a gamble’ has long been viewed as a sign of seeking more risk in the literature (e.g., Thaler and John, 1990).

However, there can be another way of explaining the investment in lottery stocks. Investors who buy lottery stocks do not like the risk of these stocks any more than other people, nor do they think they are involved with higher risks when they invest in lottery stocks. Rather, they think they are simply going to get the higher (although rare) return because they are good at picking the right stocks at the right time. In other words, investors might be investing in lottery stocks because they are over-confident with their ability to choose speculative stocks. The next hypothesis examined in this dissertation relates to an alternative interpretation of the reason behind lottery stock investment.

Hypothesis$_{4,4}$: *It is a risk-seeking preference, rather than over-confidence, that drives the investment in lottery stocks.*

The study of individual risk preference in investments cannot avoid two important questions: (i) whether each individual’s risk preference is consistent through time and under different scenarios; and (ii) whether risk preferences across individuals is different. With the first question, although traditional finance literature assumes that individuals risk attitude is static, and quite often in practice an investor is given a 'tag' for his or her risk tolerance level after being assessed through a questionnaire, many studies find that the same investor's risk preference changes through time. According to prospect theory (Kahneman and Tversky, 1979), investors' risk preference is affected by changes of wealth. When individuals face the prospects of 'win', they are risk averse; however, when individuals face the prospect of 'loss', they become risk seeking.

While prospect theory predicts people's risk preference when they face winning and losing possibilities in the future, Thaler and Johnson (1990) focus on people's risk preference *after* a win or loss. They note that prior outcomes, just as prospective outcomes, affect individuals risk preference. Their extension of prospect theory is also based on the change of wealth, rather than the final position. When the change that has happened is a loss, investors are less biased in that they are generally risk averse, except for the case when they have a chance of breaking even. However, when the change that has happened is a win, investors become more risk seeking. Thaler and Johnson (1990) name this behavioural pattern as the house money effect.

The house money effect has been examined across both professional and retail investors. However, existing studies have all used realised gains in their definition of a win. This methodology can raise several issues. First, having just sold with a gain does not necessarily mean the investor is winning in the game, and vice-versa. Second, the investor could possibly find out after the realised gain that he/she could have achieved an even larger gain had he/she held the stock for longer, and this regret for having sold too soon might be the driving factor behind any future decision to trade. Third, using realised gains greatly reduces the sample size given retail investors' comparatively low trading frequency and the investors analysed are effectively active traders, which may bias the finding. In this dissertation, paper gains are used as the benchmark for a win from prior investment in the examination of the prevalence of the house money effect. Not only will the use of paper gain avoid the above mentioned issues, but also whether paper gains trigger the house money effect is an interesting topic itself.

Hypothesis$_{4,5}$: *The house money effect exists among retail investors in the Australian stock market. Investors are more likely to gamble with lottery stocks when there is a portfolio gain.*

To answer the second question discussed above, we test the following hypothesis that different investor categories display different levels of house money effect.

Hypothesis$_{4,6}$: *Trading characteristics and demographic features affect investors proneness to stock market gambling.*

Given the sample periods used for the analysis in Chapters 3 and 4 are approximately 2 years, there is the possibility that the results might be influenced, if not completely driven by, the particular sample period chosen. Therefore, a much longer sample period of data from another market is utilised to repeat the tests for the disposition effect and stock market gambling. The following three hypotheses are tested in this dissertation.

Hypothesis$_{5,1}$: *The disposition effect is evident across investors when examined over longer time periods and across different markets.*

Hypothesis$_{5,2}$: *Lottery stocks and lottery preferred accounts underperform when examined over longer time periods and across different markets.*

Hypothesis$_{5,3}$: *The house money effect is evident across investors when examined over longer time periods and across different markets.*

Behavioural finance literature has identified a number of factors that affect investors' behavioural biases, including age, gender, culture etc. More recently, Malmendier and Nagel (2011) find that people who have experienced low stock market returns throughout their lives are less likely to undertake financial risks. In this dissertation we investigate whether people who are born around the time of the Great Depression are less risk seeking and less loss averse. This leads to the following 2 hypotheses.

Hypothesis$_{5,4}$: *Investors born around the time of the Great Depression are less likely to exhibit the disposition effect.*

Hypothesis$_{5,5}$: *Investors born around the time of the Great Depression are less likely to invest in lottery stocks.*

While existing studies examine many possible contributors to individuals' risk preferences and behavioural biases, be it age, gender, culture, pass performance or early life experience, these contributors are all endogenous factors that define an investor – who they are, what they do, and what they have done. In contrast to these factors are exogenous factors that are independent of the individuals, for example, macro-economic conditions. The following hypothesis examines whether macro-economic factors affect investor decision making and potential behavioural biases.

Hypothesis$_{5,6}$: *Macro-economic conditions affect investors decision making and the behavioural biases exhibited by retail investors, such as the disposition effect and stock market gambling.*

This dissertation so far focusses on general individual investors. Among retail investors there is a unique group of individuals, company insiders. They are just like other retail investors in the market when they trade stocks from other companies. However, when they trade stocks from their own companies, which they are legally permitted to do, they are unavoidably equipped with information that is superior to the rest of the market.

There is a very fine line between illegal insider trading, and legal trading by an insider. Even when an insider follows all rules when he/she trades, it doesn't preclude that they have knowledge of their own company's future prospects. This raises an interesting question: when insiders trade in a legally accepted manner, do they use any information that is superior to the rest of the market? If insiders do have information and use it, then it is expected that they do not display the behavioural biases identified throughout this dissertation. This is because the observed biases are necessarily associated with uncertainty, and information regarding future possibilities reduces or eliminates this uncertainty.

We already know that the disposition effect is widely documented across investors in the stock market. Investors sell winners too soon, and keep losers for too long. On making purchase decisions, individuals at times are risk seeking and invest in gambling stocks, which subsequently underperform. Insiders, if using superior information about the company's prospects and future stock price movements, will trade at the 'right' time. They will not sell winners too early, or losers too late. They will also time their trades, purchasing before stock prices rise, and sell before stock prices decline. If there is evidence that company insiders' time their trades, which the general market is not able to do given the prevalence of investor behavioural biases, then it would suggest that company directors utilise their superior information in their trading, and are free from behavioural biases when they do so. This leads to the following hypothesis.

Hypothesis$_{6,1}$: *Company directors time their trades to obtain superior investment returns.*

Evidence from previous research suggests that the market believes that directors' trades convey information. There are people, ranging from professional analysts to online trading individuals in the market, who analyse and closely follow the trading of company insiders with the hope that they will obtain and benefit from superior information themselves. When resources permit, as in institutional traders' case, technologies such as programs are employed to flag and follow company directors' trades. It is to the interests of many to know when and how insiders' trades are known to outsiders. In Australia, company directors are required to report their trades of their own companies' shares to the ASX within 5 days of their trading. The ASX then announces the trade upon receiving the report on its website. If directors' trading is known to the market between trading and the announcement, the requirement for reporting their trades to the ASX will be pointless. However, if the announcement time is when the trading is known to the market, then theoretically it will make observing the announcement an effective way to obtain information. To find out when the market receives the information, an examination is undertaken on when there is a price reaction in the stock traded. If there is a price movement around the trading event, then the trading itself is the release of the information to the market. However, if there is a price movement around the announcement of the trade, then the information of the trading remains unknown until it's published. This leads to the following 2 hypotheses.

Hypothesis$_{6,2}$: *There is price impact around the time when director trading is announced to the market.*

Hypothesis$_{6,3}$: *There is no price impact around the time of the actual director trading.*

Superior information is the luxury that the vast majority of the market does not have. For most retail investors, the only means to information is from public channels, such as the ASX website. If the announcement on the ASX website is timely, and contains new information, then it could be possible that following the ASX director trading announcement is profitable. While this is possible theoretically, on a practical level, the ability to profit depends on how fast the new information is incorporated into the price, and how fast an individual trader can react to the announcement. In a world where trading is dominated by computer algorithms, it is unlikely that human speed can win the contest. Therefore, realistically, the time that it takes for director trading announcements to have a price impact will be so fast that, unless the trader is equipped with institutional technology, he or she is not able to react quickly enough to take advantage of the information. This leads to the following hypothesis.

Hypothesis$_{6,4}$: *The price impact of director trading announcements occurs rapidly in the market.*

2.4 Summary

This chapter reviews the literature concerned with retail investors trading behaviour, the causes and impact of certain investor behavioural biases, and develops several hypotheses that are tested in the following chapters. The next chapter examines the disposition effect in retail investor trading. Following that, lottery stock investment and risk seeking preference and triggers are investigated. Chapter 5 examines the impact of life-time experience on investors behaviours, and how macro-economic conditions affect the aggregated and individual behavioural bias level in the market. The final topic, which is discussed in detail in Chapter 6, examines informed individual traders' behaviours in the market, as well as how investors, in general, react to the news of insider trading.

Chapter 3 Disposition Effect

3.1 Introduction

A large body of work has emerged detailing the presence of so-called 'behavioural biases' in the trading behaviour of stock market participants. These biases include a reluctance to realise losses, a tendency to trade too frequently, and a preference at times for risk-seeking investments. The observation of these trading characteristics contradicts the assumptions of standard economic models, and has given rise to the area of behavioural finance. Cultural background influences an individual's values, judgements and decisions. Yet this factor is not extensively considered in the behavioural finance literature. This chapter examines the relationship between a range of investor characteristics, including trading behaviour, demographic features and whether an individual is of Chinese ethnicity, and the observed disposition effect.

Shefrin and Statman (1985) were the first to define the 'disposition effect' – an extension of Kahneman and Tversky's (1979) prospect theory. The disposition effect describes the tendency of investors to sell stocks which have made gains more readily than those which have experienced losses. In other words, there is a disposition to sell 'winners' and hold 'losers'. Odean (1998) builds on this work to formally test whether investors are more reluctant to realise losses than gains, arguing the cause of the disposition effect is loss aversion, and finds that, on average, a significantly higher proportion of gains are realised than losses. In addition to empirical studies using real market data, experimental analysis such as Weber and Camerer (1998) also provides evidence of the disposition effect in investment decision making.

This prevalent behavioural bias has attracted the interest of many. While some researchers attempt to establish a theoretical function for the underlying reasons for the disposition effect (e.g., Barberis and Xiong, 2009), others focus on the investor characteristics that predict proneness of this bias (e.g., Olsen and Cox, 2001; Feng and Seasholes, 2005; Brown, Chappel, da Silva Rosa and Walter, 2006); this chapter falls into the latter category. Existing literature in this area suffers from the restriction of data used. For example, Odean (1998) suggests that it would be illuminating to repeat his study with data from a retail brokerage house. Feng and Seasholes (2005) suggest that difference in sample investors' nationalities might be the reason of the discrepancy in their findings and earlier literature, yet they are unable to test this conjecture. In Brown, Chappel, da Silva Rosa and Walter (2006), the investments examined are restricted to IPO and index stocks which do not represent the majority of the investments in the stock market. Finally, Yates, Lee and Bush (1997) and Chen, Kim, Nofsinger and Rui (2007) compare cultural effects using cross-country data assuming investors in each country are of a homogenous ethnic background, and that market conditions are identical and static.

This chapter aims to fill the gap in the literature by examining the broadness of this behavioural bias with the aid of a rich data set that includes investor trading and holding records, investor trading characteristics and demographic features, including whether an investor is of Chinese heritage. Specifically, we test $\text{Hypothesis}_{3,1}$ that the disposition effect prevails across retail investors in Australia. While we expect that this loss aversion behaviour to be wide spread, we conjecture if the loss is justified, for example with the benefit of reducing capital gains tax, then investors will be more willing to realise a loss. Therefore we test $\text{Hypothesis}_{3,2}$ that investors engage in tax-purposed loss selling, which leads to a lower incidence of the disposition effect in the last month of the financial year. We also test

Hypothesis$_{3,3}$ that certain investor characteristics predict a greater likelihood of the disposition effect. To rule out the possibility that any observed patterns are due to a contrarian strategy, we test Hypothesis$_{3,4}$ that the average excess returns on paper losers held are lower than on the winners sold.

The remainder of this chapter is presented as follows. The next section outlines the methodology used in this chapter. Section 3.3 describes the data set available, and reports key descriptive statistics. Section 3.4 presents and discusses the results. Section 3.5 contains several robustness checks, and Section 3.6 concludes.

3.2 Sample and Data

Transaction and holding data for 46,289 accounts which have had at least one trade are obtained from a leading Australian retail brokerage house for the period 1 October 2010 to 31 August 2012. This data set contains the recorded transaction prices and volumes of all on-market trades made through these accounts, as well as their aggregate start-of-month portfolio positions. A second data set is obtained which contains information of the accounts in the transaction and holding data set, including account holders' date of birth, name, address, title (from which we obtain gender information), account open date, and the relationship to the account (for example, individual owner, joint owner or account operator). Market data for stock prices, stock splits, dividends and corporate actions, as well as market index (All Ordinaries) adjusted price history, are obtained from the Thomson Reuters Tick History service. Stocks which do not have these data available are excluded.

To measure gains or losses, it is essential to know the purchase price. Only accounts which have had both purchases and sales of the same stock during the sample period are included to obtain the actual purchase price for precise measurement of gains and losses. If none of an account's sales can be matched with a paper gain or a paper loss, this account is removed. Accounts that have users different from the account owner (e.g., accounts having an 'account operator') or accounts that have more than one owner (i.e., jointly owned accounts) are excluded from the final sample, to better match the decisions to the demographic features of the decision maker. Of the original 46,289 accounts, there are 11,886 accounts in the final sample representing 2,053,199 observations. This includes 209,090 sale transactions whose purchase prices are known, and 1,844,109 holding observations on the accounts on the days of the sales. The accounts kept in the final sample had 626,208 transactions during the sample period. In addition to the 209,090 sale transactions described above, all sale transactions which occurred on days when there were no other stocks held on the accounts, and purchase transactions of these accounts, are included. The accounts in the final sample include those that are not active during the entire sample period to overcome survivorship bias. That is, there are accounts which closed before the end of the sample period, or opened after the start of the sample period.

In this chapter, the disposition effect across different investor characteristics is examined. Investor characteristic data available covers age and gender. This is expanded by adding flags for investor trading frequency and Chinese/non-Chinese heritage. An investor is classified as a frequent trader if their number of trades places them in the top decile of traders. This cut-off follows the partition used in Odean (1999). Investors are classified as being of Chinese heritage using a comprehensive list of Chinese surnames adapted from Quan, Wang, Schopflochter, Noris, Galbraith, Faris, Graham, Knudsten and Ghali (2006).

Table 3-1 presents a set of descriptive statistics. Investors in the sample hold, on average, 6.29 stocks in their portfolios. The median number of stocks held is 3.95. Again, although without knowing the betas of the stocks, the number of stocks held does not of itself guarantee diversification. Rather it tells us that investors in our sample generally do not make a single bet on their investment. In terms of trading frequency, the average trade number of the accounts during the 23-month sample period is 51.78, and the median number of trades is 21.

Females hold a marginally more diversified portfolio than their male counterparts.[27] Women trade less frequently than men. Both of these facts support the general belief that men exhibit greater over-confidence compared to women. The number of stocks held increases with age, reflecting increased wealth and risk aversion as investors grow older. If we use the average stocks to divide the average total number of trades, we get an estimation of number of trades per stock across the investors. Using this estimation, we can see that investors under 35 years of age trade nearly twice as often per stock compared to investors over 65, suggesting that trading activity decreases with age. Estimation using the median exhibits the same pattern. Chinese investors have fewer stocks in their portfolio, and trade more often than non-Chinese investors. This relative under-diversification and over-trading is consistent with previous behavioural finance research that has identified greater risk-taking among Chinese investors.[28] Differences in behavioural trading biases between Chinese and non-Chinese investors are examined in further detail in the next section.

[27] The total of male and female holder accounts is smaller than the total account number, because there are accounts whose holders' gender is not available.

[28] For example, many psychology studies find that Chinese people are more vulnerable to problem gambling (Abbot and Volberg, 1994).

Table 3-1
Descriptive Statistics

This table reports summary statistics of the sample. The sample period is 1 October 2010 to 31 August 2012. There are 11,886 accounts in the final sample which had 626,208 on-market transactions. Median (average) stocks is the median (average) number of stocks held at the start of each month by all accounts. The median (average) total trade number is the median (average) of the total trade numbers across all accounts during the 23-month sample period.

	Total Sample	Gender		Age			Ethnic background	
		Male	Female	< 35	35-65	> 65	Chinese	Non-Chinese
Observations	11,886	8,404	2,140	3,014	7,729	1,143	1,410	10,476
Median Number of Stocks	3.95	3.82	4.44	2.75	4.29	6.82	3.29	4.03
Average Stocks	6.29	6.14	6.75	3.90	6.65	10.21	5.32	6.42
t-Statistic	*87.32*	*74.90*	*42.25*	*56.09*	*72.13*	*30.80*	*27.77*	*82.90*
Median Total Trade Numbers	21	22	19	15	23	26	24	21
Average Total Trade Numbers	51.78	52.04	48.47	35.44	58.27	50.96	67.95	49.60
t-Statistic	*39.20*	*35.21*	*16.41*	*13.03*	*34.42*	*21.97*	*16.69*	*35.59*

3.3 Research Design

To measure loss aversion, this study follows the approach of Odean (1998). To calculate loss aversion, investor-level transaction prices and holdings data are matched to market prices for all stocks in the portfolio. A significant advantage of this study over previous research is access to actual transaction prices. Without knowing the transaction prices for all trades in their sample, Brown, Chappel, da Silva Rosa and Walter (2006), for example, limit their study to the behaviour of investors in IPO stocks, or use the volume weighted average trade price on the transaction day in their study of loss aversion in the Australian market.

In measuring the disposition effect, it is not sufficient to measure the number of gains realised to the number of losses. Rather, it is important to measure the relative propensity to realise gains and losses, conditioned on there being gains and losses. If this condition is not included, then the observation of loss aversion may be driven by market conditions (specifically, where many stocks' prices have increased), and not an investor preference to sell winners. Thus the opportunities to sell at a gain or loss need to be calculated.

We calculate the realised gain, *RG*, or realised loss, *RL*, on days with a sale recorded for all stocks sold in the portfolio by comparing the volume weighted average purchase price with the sale price:

$$\frac{s_{j,t}}{s_{j,0}} - 1 \begin{cases} > 0, & RG = 1 \\ < 0, & RL = 1 \end{cases} \tag{3-1}$$

where $S_{j,t}$ is the sale price of stock j on trade date t, and $S_{j,0}$ is the volume weighted average purchase price.[29]

Paper (unrealised) gains or losses for stocks in the portfolio not sold on the trade date are determined using the volume weighted average purchase price and the high and low prices of the day.[30] Following Odean (1998), paper gains, PG, are recorded where the volume weighted average purchase price $S_{j,0}$ is below the low of the day, $P_{j,t}^{L}$, and paper losses, PL, are recorded where $S_{j,0}$ is above the high of the day, $P_{j,t}^{H}$:

$$S_{j,0} < P_{j,t}^{L}, \qquad PG = 1 \tag{3-2}$$

$$S_{j,0} > P_{j,t}^{H}, \qquad PL = 1 \tag{3-3}$$

On days where the average purchase price is between the high and low prices, or there are no trades in the portfolio, neither a gain or loss is recorded. There are days when there is no on-market trade in the stock to be examined for paper gains/losses; to address this, we attempt various approaches. The first is to consider the realised gains/losses as missing values when there is no trading for the other stocks held in the portfolio. The reported results are based on this approach for comparison to previous research. The second method is to use the day's closing bid and ask mid-points as the benchmark to decide whether there is a paper gain or a paper loss. This method enables us to keep more observations, and the results from this are consistent with the reported results. The proportion of gains realised (PGR) is then measured as the ratio of realised gains to all gains, paper and realised. Similarly, the proportion of losses realised (PLR) is the ratio of realised losses to all losses. The difference between these proportions is the indicator of investor disposition to sell winners and hold losers. Following

[29] For example, if the account holder purchased 150 stocks, 50 of the stocks were purchased at $1.00 and 100 of the stocks were purchased at $0.90, then $S_{j,0}$ would be (50*1+100*0.90)/150 ≈ $0.93.

[30] The results are robust to the use of close price, VWAP or intra-day midpoint-price as the comparison value.

Odean (1998), standard errors of the *t*-statistics for the difference between PLR and PGR are calculated as:

$$\sqrt{\frac{PGR(1-PGR)}{n_{rg}+n_{pg}}+\frac{PLR(1-PLR)}{n_{rl}+n_{pl}}} \tag{3-4}$$

where $n_{rg},\ n_{pg},\ n_{rl}, n_{pl}$ are the number of realised gains, paper gains, realised losses and paper losses.

We also use the highest purchase price and the most recent purchase price, respectively, to replace $S_{j,0}$ in the equations above to test for robustness, given that it is possible for an investor to use these more readily available and easily remembered prices, instead of the volume weighted average purchase price as the benchmark. To address the concerns that a historical purchase price may not necessarily be relevant to the investor, we substitute other reference points including the expected values of the stock today based on the market return, as well as the term deposit rate. And finally, we also compare a stocks most recent return with the account holder's previous month's portfolio return. A stock whose return is higher than the investors own portfolio is a winning stock; a stock whose return is lower than the portfolio return is a losing stock; and if the stock's return is the same as the portfolio return, it is set as missing value. The results using different reference points lead to the same conclusions. The first set of results reported in this chapter are those using the volume weighted average purchase price as the benchmark for comparison to existing literature, with remaining robustness results presented later in the chapter.

Having established the metric for loss aversion, we test for its presence and strength across the total sample, and within different investor groups. To examine whether differences in levels of loss aversion exist between different groups of investors, we initially measure the difference in means. The critical t-value for significance of the differences between groups is calculated using the method in Davidson and Faff (1999). For all the partitions reported, the differences between groups are statistically significant.

The analysis in previous studies into loss aversion tends to consider each particular investor characteristic individually. However, there is evidence that certain characteristics tend to be correlated. For example, Barber and Odean (2001) show that trade frequency and investor sophistication differ by gender. Specifically, the authors argue that their results demonstrate a higher level of over-confidence in men drives more frequent trading among male investors. We extend the literature by testing the disposition effect jointly across different investor characteristics. We model the impact of different factors by using the following OLS regression:

$$Acct\_DE_i = \alpha + \beta_1 Freq_i + \beta_2 RS_i + \beta_3 Price_i + \beta_4 D_i + \beta_5 CH_i + \beta_6 Age_i + \beta_7 Female_i + \varepsilon_i \quad (3\text{-}5)$$

In the model, the dependent variable, $Acct\_DE_i$, is the mean difference between PGR and PLR for the i^{th} account (PGR – PLR), measuring each investor's average disposition effect. The first four explanatory variables are related to the trading features of an account. $Freq_i$ is the natural logarithm of the total trade count of account i over the sample period, as a proxy for investor overconfidence.[31] RS_i is a dummy variable taking the value of 1 if account i always trades in round volumes (volumes which are multiples of ten), and 0 otherwise. Trading round size lots in financial markets is raised as a possible human bias that silicon

[31] Barber and Odean (2001) and Chen, Kim, Nofsinger and Rui (2007) show trade frequency can proxy investor overconfidence, with a greater value of trade frequency representing a higher level of overconfidence.

traders take advantage of by Easley, Kiefer, O'Hara and Paperman (2012).[32] According to Chen, Kim, Nofsinger and Rui (2007), behavioural biases such as the disposition effect 'are forms of heuristic simplification, which stem from the brain's tendency to make mental shortcuts rather than engaging in longer analytical processing' (2007: 425). Trading round size lots, regardless of the optimality of the investment decision, is considered a mental shortcut. We find that 81% of our investors' trades are round size lots. Interestingly, we find the trades of Chinese investors have 20% of their volumes ending in number 8, which is considered a lucky number in Chinese culture.

$Price_i$ is the natural logarithm of the average stock price traded by account *i*. This controls for the nominal price range of stocks in the portfolio. D_i is the average number of stocks held in account *i* at the start of each month. This reflects how diversified the portfolio is. While a greater number does not necessarily mean the portfolio is diversified, for example, in the case where the stocks are perfectly positively correlated and have the same beta, a portfolio with few stocks is definitely insufficiently diversified. The remaining explanatory variables reflect the demographic characteristics of the account holder. CH_i is a dummy variable taking the value of 1 if the holder of account *i* is of Chinese ethnicity, and 0 otherwise. Age_i is the age of the holder of account *i* in years as at the last day of the sample period. The dummy variable $Female_i$ takes the value of 1 if the account holder is female, and 0 otherwise. Finally, ε_i is the regression error term assumed to meet standard OLS assumptions.

[32] Easley, Kiefer, O'Hara and Paperman (2012) argue that human investors leave 'footprints' from their behavioural biases which enable silicon traders to identify them as a human traders.

3.4 Empirical Results

3.4.1 Loss Aversion

Table 3-2 reports the loss aversion statistic for the sample and different investor groups. Consistent with previous studies, there is strong evidence that investors display the disposition effect. Overall, investors realise losses 5.96% less often than gains. This is in line with Odean's (1998) finding of a 5% disposition effect. Based on the ratio of realised gains to realised losses, the proportion of gains realised is nearly twice the proportion of losses realised. This provides evidence consistent with Hypothesis$_{3,1}$.

Contrasting with the results of Odean (1998), we find that the disposition effect persists even in the last month of the financial year. Using Australian data, the financial year for tests of tax-loss related trading ends in June. We observe the loss aversion statistic to decrease in June, suggesting some investors do engage in loss selling for tax purposes, although overall, the disposition effect holds. This finding is consistent with Hypothesis$_{3,2}$ that the disposition effect is less prevalent in June.

Table 3-2
PGR and PLR across Different Time of Year and Investor Categories

This table reports the aggregate Realised Gain (RG), Realised Loss (RL), Paper Gain (PG), Paper Loss (PL), Proportion of Gains Realised (PGR) and Proportion of Losses Realised (PLR), difference between PLR and PGR (PLR-PGR), t-statistics for the difference between PLR and PGR, and the PGR to PLR ratio (PGR/PLR). The results are reported cross the entire sample, by different time periods in a year and holding for tax-related selling, by different trading characteristics and by demographic features. The sample period is 1 October 2010 to 31 August 2012.

	RG	PG	RL	PL	PGR (%)	PLR (%)	PLR-PGR (%)	*t*-statistic	PGR/PLR
Panel A: Disposition Effect									
Entire Sample	98,717	600,688	110,373	1,243,421	14.11	8.15	-5.96	*-124.68*	1.73
Panel B: Disposition Effect - Tax Effect									
July - May	94,132	564,266	98,844	1,122,175	14.30	8.10	-6.20	*-124.78*	1.77
June	4,585	36,422	11,529	121,246	11.18	8.68	-2.50	*-14.38*	1.29
Holding < = 12 mths	97,518	558,997	108,537	1,123,878	14.85	8.81	-6.05	*-119.09*	1.69
Holding > 12 mths	1,199	41,691	1,836	119,543	2.80	1.51	-1.28	*-14.75*	1.85
Panel C: Disposition Effect - Trading Characteristics									
Non-Frequent Trader	37,224	110,742	33,671	196,077	25.16	14.66	-10.50	*-77.91*	1.72
Frequent Trader	61,493	489,946	76,702	1,047,344	11.15	6.82	-4.33	*-89.04*	1.63

Table 3-2 (continued)

	RG	PG	RL	PL	PGR (%)	PLR (%)	PLR-PGR (%)	*t*-statistic	PGR/PLR
Not Always round size	86,912	565,115	99,943	1,177,340	13.33	7.82	-5.50	*-113.88*	1.70
Always round size	9,747	28,759	8,571	54,169	25.31	13.66	-11.65	*-44.72*	1.85
Panel D: Disposition Effect - Demographic Features									
Male	75,719	465,461	88,007	964,790	13.99	8.36	-5.63	*-103.67*	1.67
Female	19,214	116,462	18,570	243,064	14.16	7.10	-7.06	*-65.93*	2.00
Non-Chinese	81,400	499,715	91,971	1,043,928	14.01	8.10	-5.91	*-113.17*	1.73
Chinese	17,317	100,973	18,402	199,493	14.64	8.45	-6.19	*-52.14*	1.73
Age < 35	17,460	86,315	19,592	167,146	16.82	10.49	-6.33	*-46.54*	1.60
35 <= Age <= 65	72,885	459,096	82,252	965,029	13.70	7.85	-5.85	*-108.3*	1.74
Age > 65	8,372	55,277	8,529	111,246	13.15	7.12	-6.03	*-39.38*	1.85

Figure 3-1 shows that the PGR/PLR ratio has a tendency to fall over the financial year. We also find higher PGR/PLR ratio for stocks held over 12-months than those held under 12-months, which also provides support of the tax loss hypothesis. However, both PGR and PLR for stocks held over 12-months are much lower than those held for less than a year, which suggests that investors in this sample are not long-term investors in the equities market. The median holding period in the sample is 58 trading days, which is shorter than the median in Odean's (1998) study.

Figure 3-1
Average PGR/PLR Ratio by Month over the Financial Year

PGR is Proportion of Gains Realised, calculated as the number of realised gains divided by the number of realised gains plus the number of paper (unrealised) gains. PLR is Proportion of Losses Realised, calculated as the number of realised losses divided by the number of realised losses plus the number of paper (unrealised) losses. Realised gains, paper gains, realised losses and paper losses are aggregated over the entire sample period (1 October 2010 to 31 August 2012) and across all accounts in the sample.

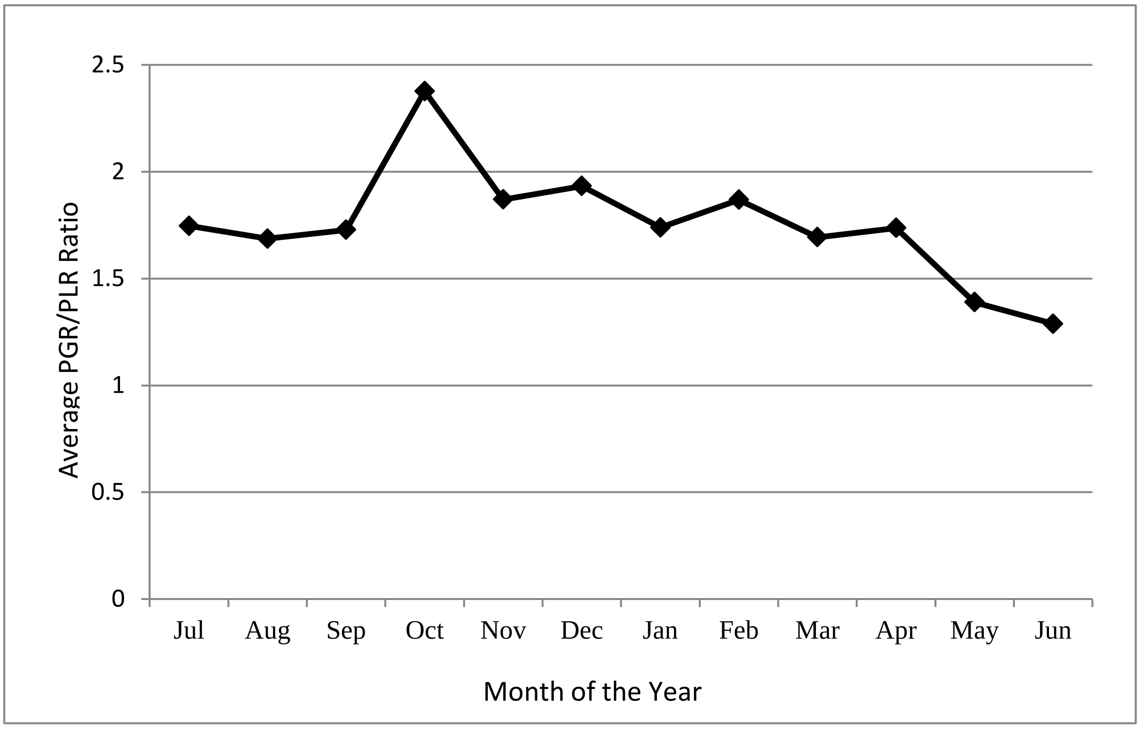


Table 3-3 also suggests that some investors do engage in tax loss selling. In June, the average (median) absolute value of realised losses is greater than for other months, and for the entire year, while the average (median) value of realised gains is smaller than for other months. This indicates that investors are willing to accept greater losses, and will realise gains to a smaller extent in June. This provides some support for Hypothesis$_{3,2}$.

Table 3-3
Mean and Median Returns

This table reports the mean and median realised returns on stocks sold by whether they are realised gains or realised losses. It also reports mean and median returns on stocks that could be sold for a gain or a loss on the days when there was a sale of another stock on the same account. The unrealised returns are classified as paper gains (if positive) and paper losses (if negative). The returns are reported for all accounts over the entire sample period, and for all accounts during the last month of the Australian financial year (June) and the remaining 11 months. PG represents paper gains which are recorded where the volume weighted average purchase price is below the low for the day, $P_{j,t}^{L}$. PL represents paper losses which are recorded where the volume weighted average purchase price is above the high for the day, $P_{j,t}^{H}$. RG represents realised gains which are recorded where the volume weighted average purchase price is lower than the sale price. RL represents realised losses which are recorded where the average volume weighted purchase price is above the sale price. The sample period extends from 1 October 2010 to 31 August 2012.

	Entire Year Returns (%)		June Returns (%)		July – May Returns (%)	
	Mean	Median	Mean	Median	Mean	Median
PG	15.75**	11.18	15.71**	11.42	15.75**	11.16
PL	-22.37**	-19.10	-24.13**	-21.80	-22.18**	-18.83
RG	10.68**	6.15	9.93**	5.03	10.71**	6.20
RL	-13.66**	-9.23	-16.63**	-12.11	-13.31**	-8.96

** indicates statistical significance at the 0.01 level.

While the disposition effects are observed across all groups, some groups are more prone to this bias than others. Investors who trade less frequently suffer more than those who trade frequently. This is consistent with the observations of Chen, Kim, Nofsinger and Rui (2007) who report a negative correlation between over-confidence (defined by high trading frequency) and the disposition effect. This result suggests that an investor is not likely to exhibit both the disposition effect and over-confidence biases, and is supported by the results from the regression analysis. Investors who always trade round size numbers, however, are more subject to the disposition effect.

We find that investors of different demographic groups suffer the disposition effect to different degrees. Consistent with previous findings and general beliefs, women are more likely to suffer from it than men, and older people are more loss averse than younger people. Investors with Chinese ethnic background are more subject to this bias than investors from other ethnic backgrounds, even when they live in the same country and trade on the same market. This shows that the previously observed differences in the degree of loss aversion bias of Chinese (Asian) investors extends beyond trading mechanism inadequacy in the developing market, a conclusion that Chen, Kim, Nofsinger and Rui (2007) could not reach. Given this observation, we posit that trading biases and some market immatureness will persist, even as the emerging market systems of China evolve and become more established.

3.4.2 Impact of Different Investor Characteristics

Table 3-4 reports the linear regression results of fitting the sample to regression model 1 (Equation 3-5). The dependent variable is the average difference between PGR and PLR of an account; the greater this value, the more the account holder is subject to the disposition effect. The independent variables are trading frequency (the logarithm of the account’s total trade number during the sample period), whether the account holder always trades round lot sizes, the logarithm of the average purchase price of the account’s all stock purchases, average number of stocks held in the account at the start of the month, whether the person is of Chinese ethnicity, the account holder's age and the account holder's gender. The regression follows a step-wise procedure, where a variable enters the regression only when its *p*-value is smaller than 5%, and only remains in the equation when its *p*-value is smaller than 5%. The Model's F value is 65.27. Based on the regression results, $\text{Hypothesis}_{3,3}$ is not rejected. Investor trading characteristics and demographic features do affect the likelihood of the disposition effect.

All else equal, investors who trade 1% more often are 8.12% less in the difference of PGR and PLR. Trading frequency has been used as the proxy of overconfidence (e.g., Odean, 2000; Chen, Kim, Nofsinger and Rui, 2007). This result further supports that the two biases, namely overconfidence and loss aversion, counteract. Investors who always trade round sizes are 3.42% more inclined to realise gains than losses. Previously in this chapter, we discuss trading round size being a form of taking mental shortcuts and heuristic simplification. People who always trade round size are more likely to avoid extensive analysis of expected returns and make a decision based on simplifications and prevailing (or historical) market conditions, rather than forward-looking expectations, supporting the finding of the disposition effect.

Table 3-4
OLS Regression Results

OLS regression is estimated using a stepwise method at a 0.05 entry and remain level. In the model, dependent variable $Acct\_DE_i$ is the mean (PGR-PLR) for an account. $Freq_i$ is the logarithm of the total trade count of the account over the sample period. If an account always trades round size (a volume ending 0), dummy RS_i variable takes the value of 1, 0 otherwise. $Price_i$ is the natural logarithm of the average stock price traded by the account. D_i is the average number of stocks an account holds at the start of the month. The first four variables are related to the trading features of an account. The additional variables reflect the accounts' demographic characteristics. Dummy variable CH_i takes the value of 1 if the account holder is of Chinese ethnicity, 0 otherwise. Age_i is the account holders actual age on the last day of the sample period (31 August 2012). The dummy variable $Female_i$ takes the value of 1 if the account holder is female, 0 otherwise. The sample period extends from 1 October 2010 to 31 August 2012.

	Intercept	$\mathrm{Freq_i}$	$\mathrm{RS_i}$	$\mathrm{Price_i}$	$\mathrm{D_i}$	$\mathrm{CH_i}$	$\mathrm{Age_i}$	$\mathrm{Female_i}$
Parameter Estimate	0.4006	-8.12	3.42	-1.48	0.16	5.01	0.08	2.30
t-Statistic	*20.87*	*-18.56*	*3.16*	*-6.15*	*2.67*	*3.76*	*2.51*	*2.12*
Model F-Value	*65.27*							

Table 3-4 also shows that the higher the prices of stocks the investor trades, the less the investor suffers from the disposition effect. One possible explanation is that investors that trade higher-price stocks are more likely to have greater wealth and be experienced and sophisticated, and hence less biased. For each additional stock an investor holds, the investor is 0.16% more likely to display the disposition bias. Investors with more stocks in their portfolio have more choices when making sell decisions. This result might be simply from the fact that those who do not have many stocks in the portfolio do not have the 'opportunity' to display this bias. Chinese investors are 5.01% more exposed to this bias. Chinese people appear to be less willing to accept a past purchase decision as being poor. For each year of age increase, investors are 0.08% more likely to suffer from the disposition effect. This might be because the older an investor becomes, at least in their mind, the less time and fewer opportunities they have to recover from a loss; therefore age increases loss aversion. Women are 2.3% more loss averse than their male counterparts. This is consistent with the previous findings in the literature that men are more prone to the bias of over-confidence (Odean, 2000), and the negative correlation between over-confidence and the disposition effect (Chen, Kim, Nofsinger and Rui, 2007). These results provide support for Hypothesis$_{3,3}$ that trading characteristics and demographic features affect investors proneness to the disposition effect.

3.5 Robustness Tests

3.5.1 Portfolio Re-balancing

One argument against the disposition effect is that investors may choose to sell stocks in the portfolio for rebalancing reasons. Odean (1998) suggests that portfolio rebalancing will most likely *not* result in sales of the whole position, therefore, by removing partial sales, we can (if not completely) rule out the majority of rebalancing motivated transactions. Following Odean

(1998), we only keep realised gains and losses when the sale clears the total holding, and paper gains and losses on days of these sales. Table 3-5 reports the results of this sub-sample. It demonstrates that even after controlling for portfolio rebalancing, the disposition effect persists. Investors are 18.78% less willing to realise losses than gains, or 1.5 times as willing to realise gains than losses.

3.5.2 Cost Concerns

Selling winners instead of losers can be rational if the losing stocks are relatively low-priced and have low absolute returns, as the comparative cost of selling these stocks is too high for the sale to be a wise decision. In other words, brokerage fees and other trading costs make up a relatively larger proportion of the total cost of trading low-priced stocks. This could explain the disposition effect, without necessarily indicating a behavioural bias in the trading activity of market participants. To test whether the disposition effect disappears when low-price and low-absolute return stocks are accounted for, stocks are partitioned into groups following Odean (1998). Specifically, stocks are divided into 4 equally-sized groups by the absolute value of their average returns, and then into 3 approximately equally-sized groups by price.[33] As seen in Table 3-6, the difference of PLR and PGR in all months but June is significant in 11 of the 12 groups after this control is imposed. This result indicates that the disposition effect is not a result of investors holding low-priced 'loser' stocks that are relatively expensive to trade.

[33] The group of stocks priced under \$0.20 represent 29.08% of the sample, the group of stocks priced between \$0.20 and \$2.00 represent 34.31% of the sample, and the group of stocks with prices over \$2.00 represent 36.61% of the sample.

Table 3-5
PGR and PLR When the Entire Position in a Stock Is Sold

This table reports the PGR and PLR over time (1 October 2010 to 31 August 2012) for the sub-sample after PG, PL, RG and RG for partial sales are excluded from the sample. PGR is Proportion of Gains Realised, calculated as the number of realised gains divided by the number of realised gains plus the number of paper (unrealised) gains. PLR is Proportion of Losses Realised, calculated as the number of realised losses divided by the number of realised losses plus the number of paper (unrealised) losses.

	RG	PG	RL	PL	PGR (%)	PLR (%)	PLR-PGR (%)	*t*-Statistic	PGR/PLR
Panel A: Disposition Effect									
Entire Sample	41,847	37,053	212,187	407,151	53.04	34.26	-18.78	*-100.08*	1.55
Panel B: Disposition Effect - Tax Effect									
July - May	40,032	33,500	200,899	371,241	54.44	35.11	-19.33	*-99.53*	1.55
June	1,815	3,553	11,288	35,910	33.81	23.92	-9.90	*-14.66*	1.41
Holding ≤ 12 mths	40,988	35,723	199,444	370,206	53.43	35.01	-18.42	*-96.51*	1.53
Holding > 12 mths	859	1,330	12,743	36,945	39.24	25.65	-13.60	*-12.80*	1.53
Panel C: Disposition Effect - Trading Characteristics									
Non-Frequent Trader	22,242	18,634	64,165	110,144	54.41	36.81	-17.60	*-64.69*	1.48
Frequent Trader	19,605	18,419	148,022	297,007	51.56	33.26	-18.30	*-68.83*	1.55
Not Always round size	35,949	32,549	196,327	378,798	52.48	34.14	-18.35	*-91.37*	1.54
Always round size	5,324	3,862	13,433	24,290	57.96	35.61	-22.35	*-39.14*	1.63

Table 3-5 (Continued)

	RG	PG	RL	PL	PGR (%)	PLR (%)	PLR-PGR (%)	*t*-Statistic	PGR/PLR
Panel D: Disposition Effect - Demographic Features									
Male	31,979	29,397	162,904	311,589	52.10	34.33	-17.77	*-83.39*	1.52
Female	8,430	6,111	40,831	79,792	57.97	33.85	-24.12	*-55.92*	1.71
Non-Chinese	35,433	33,295	183,917	357,305	51.56	33.98	-17.57	*-87.34*	1.52
Chinese	6,414	3,758	28,270	49,846	63.06	36.19	-26.87	*-52.83*	1.74
Age < 35	8,033	7,708	33,281	61,290	51.03	35.19	-15.84	*-37.04*	1.45
35 ≤ Age ≤ 65	29,866	25,604	152,287	293,743	53.84	34.14	-19.70	*-88.23*	1.58
Age > 65	3,948	3,741	26,619	52,118	51.35	33.81	-17.54	*-29.51*	1.52

Table 3-6
PGR and PLR Partitioned by Price and Return

This table reports the PGR and PLR partitioned on stock price and on absolute value of the return to date (R) for all accounts during the entire sample period (1 October 2010 to 31 August 2012). PGR is Proportion of Gains Realised, calculated as the number of realised gains divided by the number of realised gains plus the number of paper (unrealised) gains. PLR is Proportion of Losses Realised, calculated as the number of realised losses divided by the number of realised losses plus the number of paper (unrealised) losses.

	$\|R\| \leq 0.06$ (%)	$0.06 < \|R\| \leq 0.15$ (%)	$0.15 < \|R\| \leq 0.29$ (%)	$0.29 < \|R\|$ (%)
Panel A: Average Purchase Price < $0.20				
PGR	26.61	17.06	12.98	10.68
PLR	16.08	8.55	4.98	2.76
PLR-PGR	-10.52	-8.50	-8.00	-7.92
t-statistic	*-29.94*	*-35.32*	*-39.85*	*-44.12*
Panel B: $0.20 ≤ Average Purchase Price ≤ $2.00				
PGR	22.74	13.04	10.39	8.05
PLR	16.18	9.21	6.79	4.60
PLR-PGR	-6.56	-3.84	-3.60	-3.46
t-statistic	*-29.41*	*-23.45*	*-24.51*	*-25.37*
Panel C: Average Purchase Price > $2.00				
PGR	20.71	10.36	6.91	6.31
PLR	15.84	9.74	7.07	4.15
PLR-PGR	-4.87	-0.62	0.16	-2.15
t-statistic	*-33.33*	*-4.75*	*1.17*	*-11.15*

3.5.3 Contrarian Trading

Another belief investors have when they sell winners and keep losers is that today's loser will be tomorrow's winner. This contrarian trading strategy may explain the tendency of investors to sell winners more readily than losers, without necessarily being a sign of loss aversion. Consistent with the existing literature, including Odean (1998) and Brown, Chappel, da Silva Rosa and Walter (2006), the findings suggest that this belief is mistaken.

Table 3-7 presents results for excess stock returns over various periods post-sale. Specifically, we consider the excess return over 58-trading days (the median holding period in this sample), 84-trading days (the median holding period in the seminal study by Odean (1998)) and 252-trading days (a year). Given the sample period is recent, we do not calculate ex-post returns for 2-years after the sale days, as this will greatly reduce the sample size.[34]

Table 3-7
Ex-Post Returns

This table reports the excess returns for stocks sold for a gain, and stocks that could be, but are not, sold for a loss. The excess returns are calculated as the stocks returns minus the returns of the All Ordinaries Index. Returns are measured over 58-trading days, 84-trading days, and 252-trading days subsequent to the date of a realised gain sale, and subsequent to a date on which there is a sale of another stock in the account of the paper loser. The sample period extends from 1 October 2010 to 31 August 2012.

Excess Returns (%)	Average Excess Return On Winning Stocks Sold	Average Excess Return On Paper Losers
Over the Next 58 Trading Days	-4.44**	-6.19**
Over the Next 84 Trading Days	-6.30**	-8.72**
Over the Next 252 Trading Days	-14.72**	-19.01**

** indicate significance at the 0.01 level.

We find that the returns of the losing stocks investors continue to hold underperform the winning stocks they sell. Excess returns are calculated as the stock returns for the period minus the corresponding return of the All Ordinaries index. Odean (1998) finds that the winning stocks investors sell continue to have positive excess returns. It is not the case in the current sample. The returns for winning stocks, losing stocks, as well as the index itself

[34] Preliminary analysis indicates that the result is consistent over this longer period.

during the sample period are negative, reflecting market conditions of the post-GFC recovery. Nevertheless, the returns of the held current losers have a larger negative return than the winning stocks they sell. Given that the losing stocks held consistently and continuously perform worse than the stocks sold, a rational trader, having a contrarian strategy or not, would acknowledge that such hope for the losing stocks' prices to rebound is unrealistic, and therefore sell the depreciating stocks to prevent further loss. The continuity and scale of riding the loss observed in the study cannot be completely accounted for by a contrarian strategy; rather, it is more likely to represent the behavioural bias known as the disposition effect. This finding is consistent with $\text{Hypothesis}_{3,4}$.

3.6 Summary

This chapter re-examines an investor behavioural bias known as the disposition effect. Adding evidence to existing literature which has limitations in the types of investors studied, we employ equity trading data from a leading Australian retail brokerage house. Using a unique sample with investors' demographic information not previously explored, we extend the existing literature by specifically examining the behaviour of investors of Chinese ethnic background relative to non-Chinese investors. With an aim to determine how cultural factors contribute to the disposition effect, and predict the likelihood of an investor suffering from the disposition effect, we compare this particular behavioural bias across different groups by their trading characteristics and demographic features. Further, a new factor that represents investor trading bias – trading round size lots – is introduced into this study of the disposition effect.

We find that the disposition effect exists in all groups. In the sample period, the preference for selling winners compared to losers prevails even in the last month of the financial year when investors have the last chance to realise a loss for tax benefits. Women, older investors, investors who trade relatively infrequently, investors who do not hold a great number of stocks, investors who tend to invest in low-priced stocks and investors who trade round lot sizes are more prone to behaviour in line with the disposition effect. Investors with a Chinese cultural influence are more subject to the disposition effect, although they are more over-confident than other investors. We also find certain biases such as over-confidence and the disposition effect do not tend to occur together, while some biases such as trading round lot sizes appears to be a predictor of a higher likelihood of the disposition effect.

This research uses trade data in the examination of disposition effect. Linnainmaa (2010) provides evidence that disposition effect observed can be driven by the use of limit orders. This is because sell limit orders are more likely to execute following upward price movements than downward price movements, hence giving the appearance of preferring to sell winners and hold losers. As we do not have order information for the trades, we cannot test whether our results are driven by the use of limit orders, and if yes to what extent. However, there is reason to believe that the observed disposition effect will still persist given the sample of investors examined, being retail, most likely infrequently use limit orders[35]. It will be interesting to do the same analysis with trades executed from market orders only where the data permit.

[35] Kelley and Tetlock (2013) document that ‘the number of retail market orders (178 million) exceeds the numbers of both nonmarketable (115 million) and executed limit orders (47 million)’ (2013: 1235).

Chapter 4 Are Paper Winners Gamblers? Evidence from Australian Retail Investors

4.1 Introduction

Polkovnichenko (2005) observes, “Investors not only want protection from risk but also want to have a ‘shot at riches’ ” (2005: 1469). As such, they “attempt to ‘get ahead’ by hoping to capture large but unlikely extreme gains” (2005:1469). In doing so, investors are seeking pay-offs similar to those from gambling, which has attracted attention in recent research. One concept that has arisen from stock market gambling is ‘lottery like investments’. Barberis and Huang (2008) note that some investors create synthetic lottery like positions in their portfolios as they favour the possibility, albeit small, of a high pay-off. Kumar (2009) formalises the general notion of ‘being lottery-like’ and defines lottery stocks as those with high idiosyncratic volatility, high idiosyncratic positive skew and low price at the same time. Bali, Cakici and Whitelaw (2011) use a more straightforward method to define lottery stocks. Stocks whose extreme returns in the previous month rank in the highest decile are classified as lottery stocks for the given month. In the first part of Chapter 4, we test two hypotheses that lottery stocks underperform (Hypothesis$_{4,1}$), as do the investors that gamble with them (Hypothesis$_{4,2}$).

Having established the harm of investing in lottery stocks, the next part of this chapter focuses on who is more likely to be a ‘victim’ of such investments. We test the hypothesis that lottery stocks appeal mainly to retail investors, who are less sophisticated compared to professional traders (Hypothesis$_{4,3}$). We also test the hypothesis that it is a risk-seeking preference, rather than over-confidence, that is the driver of the investment in lottery stocks ($Hypothesis_{4,4}$). In addition, among retail investors, we hypothesise that certain individuals are more prone to stock market gambling, and investors gambling preference can change; specifically, the house money effect exists and investors are more likely to gamble following portfolio gains ($Hypothesis_{4,5}$ and $Hypothesis_{4,6}$).

Thaler and Johnson (1990) note that most decision makers are influenced by prior outcomes. They find that decisions after a loss are less biased, often being risk averse, and occasionally risk seeking when there is a chance to break-even. However, when faced with choices after a prior gain, decision makers are more likely to 'accept gambles', and this observed phenomenon is labelled the 'house money effect'. In Chapter 4, the existence of the house money effect among retail investors in Australia is examined.

Using empirical data to examine the house money effect is not new. Frino, Grant and Johnstone (2008) find that futures traders who make money in the morning session take higher total dollar risk, trade larger size and trade more frequently. Hsu and Chow (2013) find that average component volatility in an investor's account has strong correlation with the gains in the previous sale period. Huang and Chan (2014) find that active individual traders on the Taiwan Futures Exchange tend to take greater risk in the afternoon session when they have large morning gains.

Existing real-market studies provide strong evidence of the house money effect, however, they all use realised gains in the analysis of house money effect. While it is not a problem in a laboratory experiment when an action is required as part of the experiment design, nor in Frino, Grant and Johnstone (2008), where most traders have to close their positions by the end of the day in the futures market, it does raise issues for studies of retail investors in the stock market. Therefore, in the present chapter, we take a new approach by using paper gains in the examination of the house money effect.

The remainder of the chapter is structured as follows. Section 4.2 discusses the data available, and presents descriptive statistics for lottery stocks and non-lottery stocks. Section 4.3 discusses the methodology by which we identify lottery stocks, investors with a gambling preference, over-confident investors and ex-post investor behaviour following portfolio gains. Section 4.4 reports the results, and Section 4.5 discusses these findings and concludes.

4.2 Sample and Data

This study utilises a rich sample of nearly 60,000 retail online investors from a major Australian retail brokerage house. The data include investor daily holdings and account information, intra-day buy and sell orders, over the sample period 1 February 2010 to 28 February 2013. We also obtain the executed trade data for the period of 1 January 1995 to 28 February 2013. Specifically, a daily portfolio holdings file contains the date, security code (stock ticker used on the Australian Securities Exchange), and the size of the security held in the portfolio. The account information file records the account holder’s date of birth, gender and address. The equity order file contains date and time-stamped order submission details, including the size of the order, limit price in the case of a limit order, and the portion of the order which is filled upon submission. Finally, the trade execution file holds security code, trade price and date records for each account. Holding, order, trade and investor information data sets are linked using a unique investor account identifier which is present across all files.

For this study, it is necessary to know stock prices and company information, as well as market risk-free benchmarks and market portfolio returns. As such, we supplement the order and portfolio data with the following information. Daily stock prices and information on stock splits and dividends (size and date) are sourced from Thompson Reuters Tick History (TRTH). Daily stock market capitalisation and book value per share are obtained from Bloomberg. The rate on the 90-day bank accepted bill (BAB) is assumed to represent the risk free interest rate and is obtained from the RBA website, [36] while the All Ordinaries Accumulation Index proxies for the market portfolio, and daily adjusted prices are obtained from Yahoo Finance.[37]

The following data filtering procedures are applied. Daily stock prices are dividend and split adjusted. Daily returns that are greater than 100% or lower than –50% are removed. On investigation, these outliers are found to be mainly caused by data error (such as inconsistencies in dollar or cent reporting between the data sources). These observations account for less than 1% of the total sample. Only accounts that have had stock holdings for more than 30 days are considered.

Table 4-1 reports statistics of stocks by their lottery categories. While the K Method has multiple criteria, and the other two methods are relatively straightforward, lottery stocks defined by all methods share similar features. Lottery stocks exhibit a low price, low book-to-market ratio and low market capitalisation. Lottery stocks are traded less frequently when measured by the number of days traded per month. However, on the days they trade, their trading volume is higher than other stocks.

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[36] Reserve Bank of Australia, Statistical Tables, Interest Rates and Yields – Money Market – Daily, accessed 17 March 2013, http://www.rba.gov.au/statistics/tables/index.html#interest_rates.
[37] Yahoo Finance, Historical Prices, accessed 17 March, 2013, http://au.finance.yahoo.com/q/hp?s=^AORD.

Table 4-1
Sample Statistics

This table reports statistics for stocks by their lottery categories that have been traded / held by individual investors from a large retail brokerage house during the sample period 1 February 2010 to 28 February 2013. Panel A presents statistics using the K Method to define lottery stocks. Panel B presents statistics using the BCW Method to define lottery stocks. Panel C presents these statistics using the Generalized BCW Method to define lottery stocks.

	Daily Trade Volume	Stock Price ($)	Trade Value ($)	Days Traded Per Month	Book to Market Ratio	Market Capitalisation ($ mil)
Panel A: Definition by K Method						
Non Lottery	1,619,161	6.82	8,514,134	19	2.9	3,745
Other	1,081,723	1.53	1,983,615	16	1.5	2,144
Lottery	1,539,917	0.08	91,005	15	0.11	103
Panel B: Definition by BCW Method						
Least Lottery	986,668	8.22	4,750,667	8	4.25	6,449
2	1,842,193	10.46	14,081,887	18	4.15	7,595
3	1,500,406	4.86	7,708,489	18	2.88	3,690
4	1,337,661	2.68	3,998,417	18	2.05	2,320
5	1,198,994	1.45	1,809,481	18	1.4	1,018
6	1,114,663	0.80	905,036	17	0.87	637
7	1,140,226	0.48	544,049	17	0.72	428
8	1,288,761	0.33	346,066	17	0.49	325
9	1,402,050	0.27	237,342	16	0.44	345
Most Lottery	2,252,276	0.22	307,070	15	0.37	210

Table 4-1 (Continued)

	Daily Trade Volume	Stock Price ($)	Trade Value ($)	Days Traded Per Month	Book to Market Ratio	Market Capitalisation ($ mil)
Panel C: Definition by Generalized BCW Method						
Least Lottery	1,283,047	11.58	9,093,671	14	4.63	7,372
2	1,826,843	8.01	12,534,098	19	3.63	6,491
3	1,511,588	4.45	7,337,009	19	2.65	3,188
4	1,221,132	2.56	3,418,351	19	1.89	1,980
5	1,169,580	1.43	1,843,716	19	1.30	1,026
6	1,096,331	0.78	906,073	18	0.86	607
7	1,064,257	0.51	570,829	18	0.73	525
8	1,212,076	0.31	356,385	17	0.50	344
9	1,353,045	0.28	257,616	17	0.48	331
Most Lottery	2,372,081	0.20	363,575	15	0.38	237

4.3 Research Design

4.3.1 Lottery Stocks

Lottery stocks are identified using 3 methods. We first replicate the Kumar (2009) and Bali, Cakici and Whitelaw (2011) methods, henceforth the "K Method" and the "BCW Method", respectively. We then develop a generalised approach of the BCW Method which relaxes the necessary assumptions of investor trading patterns.

Under the K Method, lottery stocks are initially defined as exhibiting high idiosyncratic volatility, high idiosyncratic skewness and low price. Idiosyncratic volatility is obtained as the variance of residual by fitting a four-factor (Fama-French plus momentum) model using daily data. The four factors are calculated using end-of-day stock prices, stock market capitalisation, stock book value per share and daily All Ordinaries Accumulation Index price. Idiosyncratic skewness is obtained as the third moment of the standardised residual obtained by fitting a two-factor (market excess returns and the squared excess market returns) model to the daily stock returns time series. Each month all stocks are ranked independently by idiosyncratic volatility, idiosyncratic skewness and average end of day stock price for the preceding 6 (-6, -1) months. Lottery stocks for each month are defined as the stocks which *jointly* exhibit idiosyncratic volatility in the top 50%, idiosyncratic skewness in the top 50%, and price in the bottom 50%. Stocks which meet none of these criteria – i.e., are jointly below the median idiosyncratic volatility and skewness and above the median average price – are defined as 'Non-lottery', while stocks which meet some lottery criteria, but not all, are classified as 'Other'.

The second lottery stock definition used in this chapter replicates the BCW Method. Under this definition, lottery stocks are identified as stocks with extreme maximum returns. Specifically, stocks are ranked by their maximum daily return (close-to-close) in the previous calendar month. Those stocks ranked in the top decile are defined as lottery stocks under the BCW definition.

The third lottery stock definition considered in this chapter extends the BCW Method. Underlying the definition of extreme maximum daily return in the BCW Method is the 'availability heuristic'. That is, recent events remain in investors' minds, so recent extreme return stocks appear attractive to a lottery-seeking investor. While intuitively appealing, this effect is inconsistently applied in the BCW Method as a result of the use of past calendar months. That is, a lottery-stock could be identified one-day after its extreme return (on the first day of the prediction month if the maximum was observed on the last day of the previous month) to over 60-days after (on the last day of the prediction month if the maximum was observed on the first day of the previous month). This chapter provides a more robust approach to identifying lottery stocks by using a continuous prior month rolling window for extreme past returns ranking. For each trading day t, we find the maximum daily return for each stock over the previous 20 trading days, and then rank stocks by their maximum return. Stocks ranked in the top decile are defined as lottery stocks for day t.

4.3.2 Lottery Accounts

Accounts that prefer to gamble need to be identified. In the first approach, we adapt the K Method and define gambling preference based on the lottery stocks holding weight. We improve on the K Method's holding weight measure by using daily holding data instead of month-end holding data, capturing a more precise holding weight, and therefore more accurate gambling preference. Specifically, we obtain the weight of an account's lottery stocks for each day; gambling-preferred accounts are defined as those with an average daily lottery stock holding weight during the sample period ranked in the top decile across all accounts. The actual lottery stock weight score, LW_{it} , for an account *i* on day *t* is computed following Equation 4-1:

$$LW_{it} = \frac{\sum_{j \in L_t} n_{ijt} P_{jt}}{\sum_{j=1}^{N_{it}} n_{ijt} P_{jt}} * 100\% \tag{4-1}$$

where L_t is the set of lottery-type stocks defined by K Method on day *t*, N_{it} is the number of stocks in the portfolio of investor *i* on day *t*, n_{ijt} is the number of shares of stock *j* in the portfolio of investor *i* on day *t*, and P_{jt} is the close price of stock *j* on day *t*.

Consistent with Kumar (2009), we take into consideration the portfolio size. This is because an investor may happen to have a larger weight of lottery stocks simply because of his/her large portfolio size. Following the K Method, the second approach of defining gambling-preferred accounts is based on size-adjusted lottery stock holding. For each day, we compute each account's normalised lottery stock holding weight and expected normalised lottery weight, with which we calculate each account's size adjusted lottery weight. Accounts with an average size-adjusted lottery stock holding weight during the entire sample period that is ranked in the top decile are defined as the gambling-preferred accounts. The size-adjusted lottery weight score, $SALW_{it}$, for account *i* on day *t* is given by Equation 4-2:

$$SALW_{it} = \frac{NW_{it} - ENW_{it}}{ENW_{it}} * 100\% \tag{4-2}$$

where NW_{it} and ENW_{it} are account i's normalised and expected normalised lottery stock holding on day *t*. NW_{it} and ENW_{it} are given by Equations 4-3 and 4-4:

$$NW_{it} = \frac{LW_{it} - min(LW_t)}{max(LW_t) - min(LW_t)} \tag{4-3}$$

$$ENW_{it} = \frac{PSize_{it} - min(PSize_t)}{max(PSize_t) - min(PSize_t)} \tag{4-4}$$

where LW_{it} is as defined in Equation 4-1, $min(LW_t)$ is the minimum portfolio lottery-stock holding weight across all accounts on day *t*, $max(LW_t)$ is the maximum portfolio lottery-stock holding weight of all accounts on day *t*, $PSize_{it}$ is the total value of account *i* on day *t* calculated with holding volume and the closing price of the stock, $min(PSize_t)$ is the minimum portfolio size of all accounts on day *t*, and $max(PSize_t)$ is the maximum portfolio size of all accounts on day *t*. Both the simple and size-adjusted methods of defining gambling-preferred accounts give similar results in the account performance examination.

4.3.3 Measuring Account Performance

As in Kumar (2009), to isolate the effect of preferring (or not preferring) gambling on a portfolio's performance, we construct a hypothetical portfolio for each investor's portfolio every day by replacing the non-lottery component with the market portfolio.[38] In other words, the hypothetical portfolios are a combination of a well-diversified market portfolio and lottery-stocks, where the lottery stock weighting is equal to the observed lottery-stock weighting for each account. This method isolates the effect on portfolio performance by investing/holding lottery stocks at the given weight. Monthly four-factor alphas are calculated

[38] The Non-Lottery component of a portfolio are all stocks held in the portfolio which are not defined as lottery-stocks using the three criteria in the K Method.

for all hypothetical accounts. These are then averaged to find the portfolio monthly alphas by gambling preference classification. Any difference across accounts is attributable to the lottery stock component, not the stock selection of the particular investor.

4.3.4 Presence of Other Biases, Portfolio Gain and Investor Gambling Preference

Logit regressions are estimated to investigate whether it is gambling preference or over-confidence that is driving the purchase of lottery stocks. The regression is given by Equation 4-5:

$$Ln\left(\widehat{\frac{BL_{it}}{1-BL_{it}}}\right) = \alpha + \beta_1\, GPA_i + \beta_2\, OCA_i \tag{4-5}$$

where BL_{it} takes the value of 1 when there is a purchase order of lottery stock(s) by account *i* on day *t*, and 0 otherwise; GPA_i takes value of 1 if account *i* is a gambling-preferred account, and 0 otherwise; OCA_i takes the value of 1 if account *i* is defined as an over-confident account, and 0 otherwise.

In the regression above, the purchase order of a lottery stock BL signals a gambling decision. *GPA* represents an account's (investor's) intrinsic gambling preference. We apply 2 methods to identify an overconfident account (OCA). The first adopts Kumar (2009) by defining an over-confident account as one with an average monthly turnover that is ranked in the top 10%, and average risk adjusted monthly return (four-factor alpha) is ranked in the lowest 10%. The average monthly turnover is a parameter representing an account's confidence, and the second criterion reflects the fact that the confidence is not justified; the combination of these parameters represents over-confidence.

In calculating average monthly turnover, we adopt the method in Barber and Odean (2001a). Barber and Odean (2001a) compute the turnover for any month as the sum of the half monthly purchase turnover and half monthly sale turnover using the difference between 2 months' holdings as a proxy for the monthly trade value. This study makes use of actual trade data to obtain a more precise estimate of turnover. Specifically, we calculate purchase turnover as purchase value divided by portfolio value after purchase, and sale turnover as the sale value divided by portfolio value before sale.[39] Using this method, each account's average monthly turnover during the sample period is calculated.

Turnover, however, may be a biased measure of trading frequency for lottery stocks given their typically lower price than non-lottery stocks. If, for example, investors make trading decisions based on volume, not value, then a lottery stock trade will be typically smaller in value and contribute less in value-based turnover than a comparable volume trade of non-lottery stocks. Investors who trade a lot and focus on trading lottery stocks will have a low value-based turnover, and thus will not be identified as over-confident traders. To address this concern, we use a second method to identify over-confident accounts. The measure of trading frequency is defined as the average number of trades per month. In this second measure, accounts with an average monthly trade count ranked in the top 10% are considered as frequent trading accounts. Among these frequent trading accounts, those who also are ranked as the lowest 10% in their risk adjusted performance are considered to be over-confident accounts. Regression results using both methods lead to the same conclusion, and are reported in the next section.

[39] This gives us a purchase of an account with zero holding a turnover value of 1 instead of a missing value, and a sale of the whole position a turnover value of 1 instead of a missing value.

Having obtained results from the regressions above, which show that it is a preference to gamble, rather than over-confidence that leads to a lottery stock purchase, we continue to test whether gambling is predicted by an account's past performance. Given the House Money Effect focuses on directions of the prior outcome, i.e., whether it's a gain or a loss, rather than the actual amount, we start the test on the House Money Effect by designing a logit regression where the variables are binary values. The logit model estimated is given by Equation 4-6:

$$Ln\left(\widehat{\frac{BL_{it}}{1-BL_{it}}}\right) = \alpha + \beta\, Win_{it} \tag{4-6}$$

where BL_{it} takes the value of 1 when there is a purchase order of a lottery stock by account *i* on day *t*, and 0 otherwise; Win_{it} takes value of 1 if the account *i* is having a positive portfolio return, and 0 otherwise for 1-trading day before day *t*, 5-trading days before day *t* and 20-trading days before day *t*, respectively, in 3 independent logistic regressions. Returns are cumulative daily returns using day-end prices.

To further examine whether it is confidence gained from success of previous investment in lottery stocks, rather than the changed risk preference as predicted by the House Money Effect, that is motivating the purchase of lottery stocks, we estimate the above regressions again separating gambling-preferred accounts from other accounts. Because other accounts do not have heavy lottery investment previously, their purchase of a lottery stock is unlikely to be attributed to confidence from previous lottery investment.

So that there is a distinct difference between gambling preferences, we first use only purchase orders of lottery stocks and non-lottery stocks defined in the K Method in the above regression analysis. The same 9 regressions are estimated using all purchase orders, including purchase of the other stocks, as a robustness test. These additional regression results are consistent with the reported results in supporting the House Money Effect, although not as strong in terms of statistical significance.

As a robustness test, we also use account abnormal returns relative to the market. The returns of the All Ordinaries Accumulation Index are used to represent market performance. When account abnormal returns are used, Win_{it} takes value of 1 if the account *i* is having a positive abnormal return, and 0 otherwise, for 1-trading day before day *t*, 5-trading days before day *t* and 20-trading days before day *t* in the 9 regressions described above. Another robustness test is undertaken where we define only the highest 25% of returns as winners, i.e., Win_{it} takes the value of 1 if account *i*'s portfolio return ranks in the top quartile among all the accounts for 1-trading day before day *t*, 5-trading days before day *t* and 20-trading days before day *t*, respectively. Both of these robustness tests generate results similar to the results reported later in the chapter, providing support for the House Money Effect.

According to Lee and Radhakrishna (2000), enquiries into investor behaviour are best achieved by using order-level data. In this analysis, the submission of orders is used to represent the individual investors' decision time for trading, rather than the actual trades. This makes intuitive sense as we are seeking to determine investor gambling preference at the time behaviour is recorded. It is especially the case for thin-trading stocks, and for limit orders with prices far away from the market price that do not execute quickly. Given the sample contains retail investors, cases where there are multiple order submissions for the same stock on the same day are rare. As such, even though the orders in the data set are time-stamped, it is the day of the order submission that is used. We further investigate the decision to trade lottery stocks by separate limit orders and market orders, which reflects the investors' determination and eagerness to trade lottery stocks. When only market orders are used for the above regression, we obtain similar results.

4.3.5 Multiple Possible Contributors for Stock Market Gambling

In the previous section, we focus on which bias is most prevalent in the lottery stock investment decision. Next, we analyse how different factors, when combined, determine an investor's gambling likelihood. A logit regression is estimated, as given in Equation 4-7:

$$Ln\left(\frac{\widehat{BL_{it}}}{1-BL_{it}}\right) = \alpha + \beta_1 AR_{i,t-1} + \beta_2 AR_{i,(t-5,t-1)} + \beta_3 AR_{i,(t-20,t-1)} + \beta_4 NSH_{it} + \beta_5 AOV_i + \beta_6 PW_i + \beta_7 GPA_i + \beta_8 RGD_{it} + \beta_9 F_i + \beta_{10} A_i \tag{4-7}$$

In the above regression, BL_{it} takes the value of 1 when there is a purchase order of a lottery stock by account *i* on day *t*, and 0 otherwise. As with the previous analysis, the order to purchase a lottery stock signals the tendency for gambling. The first 3 explanatory variables are the cumulative daily returns before the lottery stock purchase order by account *i*; specifically, they are returns for 1 day before day *t*, 5 days to 1 day before day *t*, and 20 days to 1 day before day *t*. NSH_{it} is the number of stocks held on the account. Two NSH_{it} definitions are used in the examination; the number of stocks held on day *t*, and the average number of stocks held on account *i* over the sample period. The reported results are obtained using the first NSH_{it} definition, although both methods lead to similar conclusions.

AOV_i is the average value of all the orders account *i* has placed. This variable is designed to capture the normal order size of an account. We conjecture that accounts that tend to place small value orders will be more likely to place lottery stock orders as lottery stocks are typically lower priced. We use AOV_i to test whether this is the case. PW_i represents portfolio wealth, and is defined as the logarithmic value of account i's average portfolio value. For logistic reasons, it is not very likely for a retail investor to have trading accounts with substantial amount of value across different brokerage houses. Therefore, we assume that what an investor has with this brokerage house reasonably represents their total investment in equities. While we do not know how much total wealth an account holder has outside of their stock holdings, the holding information we have at least reflects their wealth disposable in equity investment.

RGD_{it} takes the value of one if on day t account i has a realised gain, and 0 otherwise. In calculating realised gain, we use the weighted average purchase price as the reference point. If the sale price is higher than the weighted average purchase price, then the sale is considered a realised gain. So that we have virtually all purchase prices for all stocks held on the accounts during the main sample period which starts from 2010, we obtain executed trade data starting from 1995. It is very rare that an account still has stocks purchased before 1995 in 2010, and if it does, the long holding period has made the original purchase price unreliable as a benchmark, in which case the observation is not used in the sample. Observations removed for this reason are very few.

F_i takes the value of 1 when account i's holder is female. The last variable in the regression, A_i, is the age of the account holder. Because we only have gender and age information for part of the sample, the above regression uses only the sub-sample for which gender and age information is available. Results for this complete regression are reported in the chapter. We also have estimated a partial regression without gender and age variables for the whole sample. The two regressions lead to the same conclusions for the variables in common.

4.4 Empirical Results

4.3.1 Lottery stock performance

Tables 4-2, 4-3 and 4-4 report stock average monthly four-factor alphas over the sample period by lottery categories defined using the 3 different methods. Under all 3 definitions, lottery stocks underperform. Table 4-2 presents the stock performance when lottery stocks are defined using the K Method. Lottery stocks underperform by 0.28% per month, and 0.75% per month when compared to other stocks and non-lottery stocks, respectively. The difference between lottery stocks and non-lottery stocks is 9% per year, which is both statistically and economically significant. This finding supports Hypothesis$_{4,1}$.

Table 4-2
Stock Performance when Lottery Stocks are Identified Using the K Method

This table presents sample stocks' average monthly weighted four-factor alphas in different categories. Stocks in this sample include all the stocks that have been traded / held by individual investors from a large retail brokerage house during the sample period (1 February 2010 to 28 February 2013). Lottery stocks and non-lottery stocks are defined per Kumar (2009). Stocks are ranked by their idiosyncratic volatility, idiosyncratic skewness and price in the previous month. Each of the three rankings is independent. Stocks in the joint set of highest 50% by ranking of idiosyncratic volatility, highest 50% by ranking of idiosyncratic skewness and lowest 50% by ranking of price are defined as lottery stocks. Stocks in the joint set of lowest 50% by ranking of idiosyncratic volatility, lowest 50% by ranking of idiosyncratic skewness and highest 50% by ranking of price are defined as non-lottery stocks. Stocks that are neither lottery stocks nor non-lottery stocks are classified as 'other'.

Stock Category	Average Monthly Weighted Four-Factor Alpha (%)	*t*-statistic
Non-Lottery Stocks	0.76	25.05
Others	0.29	12.97
Lottery Stocks	0.01	9.14

Table 4-3 reports the performance of lottery stocks using the BCW Method. There is a very distinct pattern displayed in Table 4-3; the more lottery-like the stocks are, the worse the returns. The difference between the most lottery-like stocks and the second least lottery-like stocks using the BCW Method is as much as 0.42% per month, or 5.04% annually. This again is economically significant.

Table 4-3
Stock Performance by the BCW Definition

This table presents stocks' monthly weighted four-factor alpha by their lottery-like ranking. Stocks in this sample include all the stocks that have been traded / held by individual investors from a large retail brokerage house during the sample period (1 February 2010 to 28 February 2013). The ranking follows the BCW definition; each month stocks are ranked by their maximum daily return in the previous calendar month, the decile of stocks whose maximum daily returns in the previous month are highest is defined as the most lottery-like.

Lottery-Like Ranking	Average Monthly Weighted Four-Factor Alpha (%)	*t*-statistic
Least	0.06	5.68
2	0.43	16.30
3	0.25	15.03
4	0.16	10.62
5	0.07	10.53
6	0.04	7.71
7	0.02	3.74
8	0.02	8.76
9	0.01	5.23
Most	0.01	3.82

The results in Table 4-4 using the Generalized BCW Method are not as statistically strong. However, the general pattern suggests that more lottery-like stocks have worse performance. While the most lottery-like stocks have a monthly return that is not significantly different from zero, 7 out of the other 9 groups have positive monthly returns. The stock performance results under all 3 definitions are consistent with existing findings that lottery stocks underperform, again supporting Hypothesis$_{4,1}$.

Table 4-4
Stock Performance by Generalized BCW Method

This table presents stocks' average monthly value weighted return by their rolling lottery-like ranking. Stocks in this sample include all the stocks that have been traded / held by individual investors from a large retail brokerage house during the sample period (1 February 2010 to 28 February 2013). Stocks are ranked by the Generalized BCW Method; each day stocks are ranked by the previous 20 trading days' maximum daily return, the decile of stocks whose maximum daily returns in the previous rolling window are highest is defined as the most lottery-like.

Lottery-like Ranking	Average Monthly Value Weighted Return (%)	*t*-statistic
Least	0.40	2.82
2	-0.03	-0.17
3	0.35	1.29
4	0.53	4.29
5	0.43	4.63
6	0.27	4.27
7	0.36	6.39
8	0.25	7.08
9	0.27	7.77
Most	0.14	0.71

4.3.2 Gambling Preferred Accounts

Table 4-5 reports the performance of retail investor accounts by gambling preference categories. Gambling-preferred accounts are defined as accounts with average lottery stock holding weight during the sample period in the top decile. When we define gambling-preferred accounts by ranking of actual lottery stock holding weight, gambling-preferred accounts underperform other accounts by 0.28% per month, or 3.36% per year. When we define gambling-preferred accounts by ranking of size-adjusted lottery stock holding weight, gambling-preferred accounts underperform other accounts by 1.22% annually. The differences are both statistically and economically significant. Based on these findings, $\text{Hypothesis}_{4,2}$ regarding lottery-preferred investors' inferior performance in terms of account returns is not rejected.

Table 4-5
Account Performance

This table reports the account performance difference between Non-Gambling-preferred accounts and Gambling-preferred accounts. We define gambling-preferred accounts as those whose (size-adjusted) average lottery stock holding weight during the sample period is ranked as the top decile. The lottery weight for account *i* on day *t* is computed as $LW_{it} = \frac{\sum_{j \in L_t} n_{ijt} P_{jt}}{\sum_{j=1}^{N_{it}} n_{ijt} P_{jt}} * 100\%$. The size-adjusted lottery weight score $SALW_{it}$ for account *i* on day *t* is given by $SALW_{it} = \frac{NW_{it} - ENW_{it}}{ENW_{it}} * 100\%$.

	Average Monthly Four-Factor Alpha (%)	Test of Difference Between Means	
		Pooled *t*-test	Satterthwaite *t*
Panel A: Account type defined without size adjustment			
Non-Gambling-preferred Accounts	1.10 ***	9.29 ***	3.54 ***
Gambling-preferred Account	0.82 ***		
Panel B: Account type defined with size adjustment			
Non-Gambling-preferred Accounts	1.08 ***	9.32 ***	3.51 ***
Gambling-preferred Account	0.97 ***		

Statistical significance is denoted as * at the 5% level, ** at the 1% level, and *** at the 0.1% level.

The above analysis clearly attests that lottery stock investment is risky and adversely affects investor wealth. Gambling through lottery stocks represents a behavioural heuristic. It is of interest to know which investors are more prone to stock market gambling. Han and Kumar

(2013) find that lottery stocks attract retail investors. If different types of investors invest in different types of stocks equally, then we expect to see that any type of investors' aggregated holding represents the market portfolio. That is to say, the holding weight of each type of stocks in the investors aggregated portfolio shall be equal to the weight of the stocks in the market. In testing Hypothesis$_{4,3}$, we compare the total market capitalisation of lottery stocks and their proportion in the holdings of investors in the sample, who are retail investors.

Table 4-6 shows that while lottery stocks are only 0.41% by market capitalisation, they represent 6.43% of the total holdings of the investors in the sample. The holding weight is more than 10 times of the lottery stocks value weight, and demonstrates that retail investors are more likely to gamble through low performance lottery stocks compared to more sophisticated institutional investors.[40] These results are consistent with Hypothesis$_{4,3}$.

Table 4-6
Stock Weight by Market Capitalisation and Account Holding

This table reports the weights of lottery stocks compared to the rest of the stocks by market capitalisation and account holding. Stocks examined are all stocks listed on the Australian Securities Exchange during the period of 1 February 2010 to 28 February 2013. Lottery stocks in this table are defined using the K-method. To obtain weights by market capitalisation, for each month we calculate all lottery stocks' market capitalisation; this is then divided by all the stocks' market capitalisation. An average of all months in the sample period is used as the final weight by market capitalisation. To obtain weight of lottery stocks in account holdings, we calculate the holding value of each stock for each investor on each day. The weight of lottery stocks for any investor on any day is calculated as the lottery stock holding value divided by the total holding value of all stocks on the investors' portfolio. The average of all investors on all the days is then obtained as the weight in account holding.

	Lottery Stocks	Other Stocks
Number	417	1674
Weight by Market Capitalisation (%)	0.41	99.59
Weight in Account Holding (%)	6.43	93.57

[40] Lottery stocks in Table 4-6 are defined using the K Method.

Given lotteries are risky, and the chance of winning from a lottery is small, it is possible that investment in lottery stocks is induced by an investor’s over-confidence. Statman (2002) observes that people engage in playing lottery and excessive trading because ‘we think we are above average (2002: 15). Rather than preferring the higher risk associated with lottery stocks, investors who pick lottery stocks may do so simply because they are over-confident with the belief that they are good at choosing the right opportunity for a shot at the riches. A logit regression is designed where the explanatory variables are the two behavioural traits described, and the dependent variable is the decision to acquire a lottery stock.

Table 4-7 reports the regression estimates. Panel A presents the results when average monthly turnover is used to identify over-confident accounts. The negative intercept suggests that after gambling preference and over-confidence are controlled, investors are not likely to purchase lottery stocks. When one of the features are present, an account’s gambling-preferred feature predicts a higher likelihood of purchasing lottery stocks, as indicated by the significantly positive parameter estimate; an over-confident account appears to be less likely, although only to a very small extent, to purchase lottery stocks.

Panel B presents the results when average monthly trade count is used to identify over-confident accounts. The second definition for over-confident accounts is used because of the concern that using value-based turnover may exclude investors that frequently trade lottery stocks with low prices that do not contribute significant value. Results in Panel B rule out the possibility that findings in Panel A are mechanically created results. Conclusions drawn from the results in Panel B are consistent with those in Panel A. Both sets of results provide support for Hypothesis$_{4,4}$.

Table 4-7
Logit Regression Results: Gambling Preference or Over-Confidence

This table reports the estimations of the logit regressions designed to test whether the purchase of lottery stocks (decision to gamble) is predicted by preference to gamble or by the over-confidence bias:

$$Ln(\widehat{\frac{BL_{it}}{1-BL_{it}}}) = \alpha + \beta_1 \, GPA_i + \beta_2 \, OCA_i,$$

where BL_{it} takes the value of 1 when there is a purchase order of lottery stocks by account *i* on day t, and 0 if not; GPA_i takes value of 1 if account i is defined as gambling-preferred account, and 0 if not; OCA_i takes the value of 1 if account *i* is an over-confident account, and 0 if not. Panel A reports the parameter estimates for the regression when account average monthly turnover is used to define an over-confident account. Panel B reports the parameter estimates for the regression when account average monthly trade number is used to define an over-confident account. Lottery stocks and gambling-preferred accounts here are defined using Kumar (2009) definition.

α	β_1	β_2
Panel A: Defining Over-confident Account by Average Monthly Turnover		
-1.883***	2.686***	-0.167***
Panel B: Defining Over-confident Account by Average Monthly Trade Number		
-1.885***	2.683***	-0.055***

Statistical significance is denoted as * at the 5% level, ** at the 1% level, and *** at the 0.1% level.

We now examine whether prior investment outcomes trigger stock market gambling. According to the House Money Effect, investors become more risk seeking after they make profits. Table 4-8 reports the logit regression results, with Panel A presenting the results when the regressions are estimated across all investors.

The results support the conjecture that while investors are generally risk averse and avoid lottery stocks. The negative intercept value indicates that when investors do not have portfolio gains, they are not likely to purchase lottery stocks. A positive account performance predicts a greater risk seeking gambling decision. For example, the odds of having a portfolio gain in the past 20 trading days (win = 1) over not having a portfolio gain (win = 0) is exp(0.217) = 1.24. Results reported in Table 4-8 use both limit and market purchase orders of lottery stocks and non-lottery stocks. Results from using purchase orders of all stocks (which include lottery stocks, non-lottery stocks and other stocks) are consistent with the results reported. Further, the results are quantitatively similar when using abnormal returns or top account performance to define winning, and using only market orders for the regressions as robustness tests.

We have considered that the negative intercept, which is robust, may be caused by the fact that there are fewer lottery stocks. Further investigation rules out this possibility. Of all the stocks in the sample, lottery stocks and non-lottery stocks are approximately 22% and 23%, respectively, with the remaining being the 'other stocks' category which account for approximately 50% of stocks. When only lottery stock and non-lottery stock purchase orders are examined, the purchase orders of lottery stocks are only 25% of all purchases orders. When all purchase orders are examined, the purchase orders of lottery stocks are approximately 10% of all purchase orders, although the number of lottery stocks is nearly one quarter of all stocks in that sample.

Panel B in Table 4-8 follows the same procedure as used in Panel A, however, we separate 'gambling-preferred' investors from other investors. The results are consistent with a-priori expectations. Gambling-preferred accounts have a 'built-in' tendency to buy lottery stocks. In addition to a positive intercept estimate, we find there are more lottery stock purchase orders for this investor group. This tendency, which is a significant effect in the unconditional estimates, becomes even stronger when the prior investment outcome is 'winning money.' This finding supports the House Money Effect, as investors are increasing their risk seeking following prior gains. The results are statistically significant at the 0.1% level over all periods during which prior performance is measured.

Table 4-8
Logit Regressions: Prediction of Gambling Following Gains

This table reports the estimations of the logit regression designed to test whether the purchase of lottery stocks (decision to gamble) is predicted by the accounts' past performance:

$$Ln(\widehat{\frac{BL_{it}}{1-BL_{it}}}) = \alpha + \beta\, Win_{it},$$

where BL_{it} takes the value of 1 when there is a purchase order of a lottery stock by account *i* on day *t*, and 0 otherwise; Win_{it} takes value of 1 if the account *i* is having a positive portfolio return, and 0 otherwise for 1-trading day before day *t*, 5-trading days before day *t* and 20-trading days before day *t*, respectively, in 3 independent logistic regressions. A stepwise procedure is used to only keep explanatory variables with statistical significance greater than the 0.05 level. Panel B presents the results when the same regressions are run separating gambling-preferred accounts from other accounts. Lottery-like stocks and gambling-preferred accounts here are defined using Kumar (2009) definition. In this analysis, only the purchase of lottery-stocks and non-lottery stocks are kept for regression.

Panel A: Across All Accounts

No. of Days Before Purchase Order	α	β
20	-1.185***	0.217***
5	-1.201***	0.170***
1	-1.186***	0.130***

Panel B: By Account Type

No. of Days Before Purchase Order	Account Type	α	β
20	Gambling-preferred	0.782***	0.039***
	Non-gambling-preferred	-1.962***	0.217***
5	Gambling-preferred	0.742***	0.115***
	Non-gambling-preferred	-1.981***	0.203***
1	Gambling-preferred	0.756***	0.082***
	Non-gambling-preferred	-1.986***	0.201***

Statistical significance is denoted as * at the 5% level, ** at the 1% level, and *** at the 0.1% level.

This house-money effect is not confined to the gambling-preferred investors. Investors who do not have a gambling preference are, by definition, less inclined to buy lottery-stocks. Regressions for this group have significantly negative intercept values, and there are fewer lottery stock purchase orders than non-lottery stocks. However, the results show that positive portfolio performance increases the likelihood of lottery stock purchases for this group of investors as well. In fact, the greater values of β estimates for non gambling-preferred accounts suggest that for this group of investors, the House Money Effect plays a larger role than it does for gambling-preferred investors.

Findings for the non-gambling-preferred accounts also rule out the possibility that the observed gambling behaviour following wins across the entire sample is due to confidence gained from previous success in lottery stock investment. This is because the 'winnings' of non-gambling-preferred accounts are not likely to have come from lottery stock investments, given the very low weight of lottery stocks these accounts hold. These findings support $\text{Hypothesis}_{4,5}$ that the house money effect exists among Australian retail investors, who are more likely to gamble in the stock market after portfolio gains.

In one of the robustness tests, the explanatory variable in the regressions takes the value of 1 if the corresponding period performance is in the top quartile, and 0 otherwise. In another robustness test, the explanatory variable takes the value of 1 if the period return is greater than that of the market (All Ordinaries Accumulation Index), and 0 otherwise. The results in these tests are consistent with those reported, only stronger in statistical significance and parameter values, implying that the greater the win, the more prevalent the House Money Effect. These regression results provide strong support for the House Money Effect, unconditional on investor gambling preference.

Having reached a conclusion for the key questions, the last regression is designed to investigate how multiple factors, when considered together, predict investors' gambling behaviour. The results from the logit regressions are reported in Table 4-9. Consistent with previous studies and findings presented earlier in this chapter, the multivariate regression shows that, even when realised gain is controlled, the better the previous portfolio investment returns are, the more likely an investor will be to purchase lottery stocks. This finding adds yet another level of support to the House Money Effect theory. Investors who hold comparatively more stocks are less likely to gamble with lottery stocks. This is probably because those who invest in multiple stocks are more risk averse, as evidenced by the fact that they do not make a single bet in one stock with all their wealth. Accounts whose orders are of higher value are less likely to buy lottery stocks. This finding is as expected as lottery stocks are generally cheaper stocks, so these stocks are not likely to be associated with large orders.

The regression results indicate that wealth does not have a statistically significant impact on investors' risk preference. While wealthy individuals are more capable of absorbing a loss from a risky investment, people with less wealth may be attracted to lottery stocks because they are eager to have a 'shot at the riches'. Gambling-preferred investors are more likely to purchase lottery stocks, even when multiple other contributors are taken into consideration at the same time. On the day when there is a realised gain, the tendency of purchasing lottery stocks is even stronger. Consistent with existing literature and general consensus, female investors are less likely to be stock market gamblers compared to their male peers, and age has a negative impact on a person's tendency to gamble. These findings provide support for

Hypothesis$_{4,6}$ that trading characteristics and demographic features affect investors proneness to stock market gambling.

Table 4-9
Logit Regression: Multivariate Analysis

This table reports the estimations of the logit regression designed to examine different factors that affect an investor's gambling behaviour. Gambling decision is signalled by the purchase of lottery stocks. The dependent variable uses a binary variable which takes the value of 1 when a purchase order of lottery stock is placed, and 0 otherwise. Account returns are accumulative returns of 1-, 5- and 20-trading days before the placing of the order, respectively. Lottery stocks, gambling-preferred accounts and over-confident accounts are defined using method in Kumar (2009).

	Coefficient	Significance Level
Intercept	-0.7215	<.0001
Account Return of 1 Day Before	2.1066	<.0001
Account Return of 5 Days Before	0.3992	<.0001
Account Return of 20 Days Before	1.7457	<.0001
Number of Stocks Held When Placing Buy Order	-0.0064	<.0001
Average Order Value of Account	-0.00003	<.0001
Log (Account Average Value)	0.0094	0.0498
Gambling-prefer Account	2.4660	<.0001
Realised Gain Day	0.0257	0.0774
Female	-0.1927	<.0001
Age	-0.0134	<.0001

4.5 Summary

The impact and causes of investor gambling behaviour are examined in this study. Using a large proprietary database of portfolio holdings, order submissions and trade information, together with investor characteristics, this study is able to identify investors with a gambling preference and examine contributing factors of this preference.

Lottery stocks have characteristics similar to a common speculative lottery, such as high volatility and skew, a low probability of a high positive return, and are cheap to purchase. This lottery-like payoff would not appeal to a rational risk-averse investor, but are favoured by investors with a gambling preference. We find that across a range of different definitions of lottery stocks, such assets significantly underperform on a risk-adjusted basis. Further, investors who tend to overweight their portfolios with these lottery stocks suffer from inferior investment returns. The investigation reveals that retail investors are more likely to hold lottery stocks compared to more sophisticated institutional investors.

This study provides strong evidence that it is the preference to gamble itself, rather than over-confidence, that drives the investment into lottery-like securities. The findings presented in this chapter indicate that, regardless of an investor's intrinsic degree of risk aversion, their tendency to gamble increases after they make a profit from a past investment, and this effect is more distinct with investors who are non-gamblers by nature. This contradicts the assumptions of rational investor behaviour that form the neoclassical finance framework, but are consistent with the predictions of behavioural finance theories.

The above findings are robust when using different methods to define over-confident accounts and previous investment 'wins'. Further, these results are robust when we introduce additional factors. The greater the previous win, the more likely an investor will make a gambling investment decision. Investors who hold very few stocks tend to be more interested in lottery stocks. Investors who trade greater values are not likely to gamble through lottery stocks. As expected, female investors are less likely to gamble, and gambling preference decreases with age.

Chapter 5 Disposition Effect and Stock Market Gambling over Two Decades – Evidence from the Finland Stock Market

5.1 Introduction

In the previous two chapters, investor behavioural heuristics, namely the disposition effect, stock market gambling with lottery stocks and the house money effect are examined using retail investor data in Australia. The evidence from this analysis is robust and strong. However, the findings are from comparatively short sample periods post GFC. To rule out the possibility that the results are driven by the specific sample period and country used for studies in Chapters 3 and 4, examination of the biases is repeated using retail investor data from Finland over the previous two decades. Hypotheses that the disposition effect is evident (Hypothesis$_{5,1}$), lottery stocks and lottery preferred accounts underperform (Hypothesis$_{5,2}$), and that the house money effect exists (Hypothesis$_{5,3}$) over much longer time periods across different markets are tested in this chapter.

Recent literature finds that (early) life experience affects investors' risk preference (e.g., Malmendier and Nagel, 2011; Malmendier, Tate and Yan, 2011). In this chapter, we test the hypothesises that investors who are born at the time of the Great Depression are less loss averse (i.e., exhibit reduced disposition effect) (Hypothesis$_{5,4}$), and are less likely to invest in lottery stocks (Hypothesis$_{5,5}$). We also hypothesise that macro-economic conditions affect investors decision making and the behavioural biases such as the disposition effect and stock market gambling (Hypothesis$_{5,6}$). Analysis in this chapter contributes to investor behavioural literature by examining the joint effect of investor endogenous factors and exogenous factors, such as macroeconomic conditions, on stock market gambling tendency.

This chapter also examines the following matters that are not addressed in existing literature. One examination is on whether investors with one bias are more prone to have another bias. Specifically, this chapter aims at answering the question of whether investors who prefer lottery stocks are more affected by the disposition effect. This question has important implications because if investors are prone to invest in more risky and yet on-average losing lottery stocks, and at the same time are not willing to realise losses, then the aggregated effect can be low liquidity of certain depreciated lottery stocks. For the investors themselves, they are not only suffering from inferior returns as a result of 'freezing' their capital with existing bad investments that they should sell, but also risking greater loss by replacing winning stocks with low-return lottery stocks. Another question addressed in this chapter is whether lottery stocks are consistently defined as lottery stocks. This is important because if certain stocks repeatedly fall into the category of lottery stocks, which are shown to perform poorly, then they can be flagged accordingly.

The remainder of the chapter is structured as follows. Section 5.2 discusses the sample data available and presents descriptive statistics of the stocks and investors examined in this study. Section 5.3 discusses the methodology by which we measure the disposition effect, identify lottery stocks and risk-seeking investors; how we investigate life experience's impact on investors' behaviours; the design of OLS and logit regressions in the examination of factors that affect investor's proneness to behavioural biases; the measurement of over-confident investors and ex-post investor behaviour following portfolio gains. Section 5.4 reports the results, and Section 5.5 summarises these findings and concludes.

5.2 Sample and Data

The lottery stock analysis here employs stock information between 1991 and 2011, which includes day-end prices, daily high and daily low prices for all stocks listed on the Helsinki Stock Exchange. Investor analysis uses data from 1995 to 2011, which includes all registered individual investors on the Helsinki Stock Exchange, their date of birth, gender, trading transaction records with date, transaction price, buy or sale, and the daily holding on each investor's portfolio. Only investor accounts that are active for 6-months or longer are kept for the analysis. Stock and investor data are from Euroclear. Market index (HEX25), unemployment rate and corporate bankruptcy data are obtained from Bloomberg. Table 5-1 Reports the statistics of the stocks and investors in this study

Table 5-1
Stock and Investor Statistics

The table below reports the statistics of the stocks and investors used in this sample. Stocks include all stocks traded on the Helsinki Stock Exchange between 1991 and 2011. Investors include all investors actively traded for 6-months or longer during the period between 1995 and 2011 on the Helsinki Stock Exchange.

Panel A: Stock Statistics	
Total Number	234
Mean Price ($)	24.15
Median Price ($)	11.42
Max Price ($)	343.21
Min Price ($)	0.02
Panel B: Investor Statistics	
Total Number	385,429
Male	68.02%
Female	31.98%
Finnish Speaking	91.95%
Swedish and Other Languages	8.05%
Mean Age	51
Median Age	52

5.3 Research Design

5.3.1 Disposition Effect

In examining the disposition effect, the approach of Odean (1998) is followed. The detailed methodology is outlined in Chapter 3, Section 3.3. In examining the impact of micro- and macro-economic conditions on the disposition effect in the market, an OLS regression which requires Newey-West standard errors is designed, as below:

$$AVG\_DE_t = \alpha + \beta_1 CIR_t + \beta_2 PIR_t + \beta_3 NoUE_t + \beta_4 NoBR_{\ t} + \varepsilon_i \qquad (5\text{-}1)$$

In the model, the dependent variable, AVG_DE_t, is the mean difference between PLR and PGR across all investors in the market for a given month *t*, measuring the level of disposition effect in the market for the month. Two stock market performance variables are used: CIR_t and PIR_t. CIR_t is the market index return for month *t*; the HEX index is used in the return calculation. PIR_t is the market index (HEX) return of the month before *t*, and captures the market condition that is still fresh in the investors memory.

$NoUE_t$ is the unemployment level in month t. $NoBR_{\ t}$ is the number of bankruptcies during month t. Given shareholders only have a secondary claim in the case of bankruptcy, during times when bankruptcies are more likely, share investors are expected to want to exit positions in a failing company (losing stock) sooner. Therefore, as stated in Hypothesis$_{5,6}$, investors will be less likely to exhibit the disposition effect when they hear about / experience a greater number of bankruptcies.

5.3.2 Risk-seeking / Lottery Stocks

In the analysis of risk preference, we use the holding weight of lottery stocks to represent the level of risk-seeking. A high-level lottery stock holding weight signals a high-level of risk seeking. Lottery stocks are identified using 3 methods as outlined in detail in Chapter 4, Section 4.3, which also explains thoroughly how an account's lottery holding weight is calculated. To investigate which factors contribute to investors' tendency to gamble in the stock market, an OLS regression which requires Newey-West standard errors is designed, as follows:

$$LW_i = \alpha + \beta_1 PMAR_{it} + \beta_2 CMAR_{it} + \beta_3 PMMR_t + \beta_4 CMMR_t + \beta_5 UER_t + \beta_6 NoBR_t + \vartheta_1 M_i + \vartheta_2 OCA_i + \vartheta_3 LPA_i + \gamma_1 Gen1900_i + \gamma_2 Gen1910_i + \gamma_3 Gen1930_i + \gamma_4 Gen1940_i + \gamma_5 Gen1950_i + \gamma_6 Gen1960_i + \gamma_7 Gen1970_i + \gamma_8 Gen1980_i + \gamma_9 Gen1990_i + \varepsilon_i \quad (5\text{-}2)$$

where LW_i is the lottery holding weight of account *i* as defined in Equation 4-1. $PMAR_{it}$ is account *i*'s return in the month before *t*, and $CMAR_{it}$ is account *i*'s return in month *t*. Account returns are calculated as the value weighted returns of all the stocks in the portfolio. $PMMR_t$ is monthly market return in the month before *t*, and $CMMR_t$ is market return in month *t*. In calculating market returns, the HEX index is used. UER_t is the unemployment rate during period *t*. The unemployment rate is used in Mikesell (1994), and he finds that 'an increase in unemployment from 4 to 5 percent would be associated with around a 4.25 percent increase in quarterly lottery sales, other influences unchanged'(1994:165). $NoBR_t$ is the number of bankruptcies in the market during period *t*.

Several dummy variables are included. M_i takes the value of one if holder of account i is male, and 0 otherwise. OCA_i takes the value of 1 if account i is defined as an over-confident account, and 0 otherwise. As in Kumar (2009), an over-confident account is one with an average monthly turnover ranked in the top 10%, and average risk adjusted monthly return (four-factor alpha) is ranked in the lowest 10%. LPA_i takes the value of one if account i is a lottery preferred account, and 0 otherwise. An account is classified as a lottery preferred account if the average lottery holding weight of the account during the sample period ranks as the top 10% among all accounts. The rest of the dummy variables takes the value of 1 if the account holder i is born around the time indicated in the variable, and 0 otherwise. Generations born in the 1920's (depression babies) are used as the base to test the depression baby hypothesis; therefore, any differences seen in the generation dummy variables are the comparative differences between that group and the depression baby generation.

It is also possible that rather than the generation an investor belongs to, it is the actual age that is affecting the tendency to invest in lottery stocks. Therefore, another OLS regression is designed replacing the generation dummy variables with an actual age variable, Age. The regression is as following, where all variables are as defined previously, and Age is the age, in years, of the investor. Again, in obtaining the regression estimates, Newey-West standard errors is used to correct possible heteroscedasticity and autocorrelation.

$$LW_i = \alpha + \beta_1 PMAR_{it} + \beta_2 CMAR_{it} + \beta_3 PMMR_t + \beta_4 CMMR_t + \beta_5 UER_t + \beta_6 NoBR_t + \vartheta_1 M_i + \vartheta_2 OCA_i + \vartheta_3 LPA_i + \vartheta_4 Age_i + \varepsilon_i \quad (5\text{-}3)$$

5.3.3 Life Experience's Impact

To understand whether an individuals' life-time experiences affect their investment decision making, each investor is given a 'generation tag' based on the time they were born. These are compared to the level of biases of investors by their generation. A generation variable is also used in the OLS regressions described above.

5.4 Empirical Findings

The analysis finds strong evidence of the dominance of the disposition effect. As in Odean (1998), Brown, Chappel, da Silva Rosa and Water (2006) and Frino, Lepone and Wright (2015), the disposition effect is observed throughout the year, except for the last month of the financial year (December in the case of Finland). Table 5-2 shows that in all the months from January to November, fewer losses are realised compared to gains, when the same opportunities are available. May is the standout month, where 2.28% fewer losses are realised than gains. In December, however, due to tax-loss selling, 2.45% more losses are realised compared to gains. These findings are consistent with Hypothesis$_{5,1}$.

To further examine who is more likely to suffer from the disposition effect, and the impact of life-experience, additional partitions are formed based on the investors trading characteristics, their demographic features and the decade they were born in. Consistent with Frino, Lepone and Wright (2015), female investors suffer more from the disposition effect then males.

The high level of the disposition effect among the lottery-preferred investors compared to their counterparts suggests that investors who are prone to gambling are more likely to be subject to the disposition effect. Over-confident investors are not likely to suffer from the disposition effect. As in Kumar (2009), an over-confident account is one whose average monthly turnover is ranked in the top 10% and average risk-adjusted monthly return (based on the four-factor alpha) is ranked in the lowest 10%. One possible explanation is that over-confident investors are more decisive and trust their ability to recover losses, therefore are less likely to hesitate to close a losing investment position.

In the investigation of the life experience's impact on the disposition effect, we find that investors born during and around the Great Depression do not display the disposition effect. There might be 2 reasons for the phenomenon. First, people who lived through the depression are found to be more pessimistic about future stock returns (e.g., Malmendier and Nagel, 2011); therefore, they do not have high expectations that losing stocks will rebound to previous levels. This mindset could actually assist in forming the decision to sell losing stocks to prevent further loss. Second, even if there is a reasonable expectation for the depreciating stocks to become winners in the future, these investors are much older, so they are not in a position to wait for this to possibly occur. Therefore, $\text{Hypothesis}_{5,4}$ is not rejected.

Another interesting finding is that investors born in the 2000's exhibit high levels of the disposition effect. These investors are under the age of 10, so the decisions of investing and disposing of stocks would likely have been made by their parents / guardians. Given that the decision makers have opened a trading account and made investments in the name of their children, they are likely to be wealthy. Selling losing stocks in the name of a minor may not have the same tax benefit as there will be for the wealthy investors themselves. Further, not having to pay high capital gains tax could be a major reason for people to trade in their children's names; therefore, an even higher proportion of winning stocks are sold compared to losing stocks.

Table 5-2
Disposition Effect

This table reports the Disposition Effect as indicated by the difference between realised loss and realised gain (PLR – PGR) over time (1 January 1995 to 31 December 2011) by different partitions. It also reports the ratio of PGR/PLR, the higher value of which indicates a higher level of the disposition effect. PGR is Proportion of Gains Realised, calculated as the number of realised gains divided by the number of realised gains plus the number of paper (unrealised) gains. PLR is Proportion of Losses Realised, calculated as the number of realised losses divided by the number of realised losses plus the number of paper (unrealised) losses.

	PLR-PGR (%)	*t-statistic*	PGR/PLR
Panel A: Disposition Effect - Tax Selling			
January	-0.79	*-31.75*	1.08
February	-0.76	*-31.74*	1.08
March	-0.83	*-34.52*	1.09
April	-1.53	*-63.59*	1.16
May	-2.28	*-87.26*	1.22
June	-1.44	*-50.54*	1.14
July	-0.84	*-29.62*	1.08
August	-0.90	*-35.17*	1.09
September	-0.34	*-13.41*	1.03
October	-0.06	*-2.77*	1.01
November	-0.20	*-8.53*	1.02
December	2.45	*96.17*	0.80
Panel B: Disposition Effect – Trading Characteristics			
Lottery Preferred Accounts	-2.53	*-89.28*	1.22
Non Lottery Preferred Accounts	-0.50	*-66.5*	1.05
Over-confident Accounts	1.22	*26.94*	0.91
Non Over-confident Accounts	-0.69	*-94.38*	1.07
Panel C: Disposition Effect – Demographic Features			
Female	-0.87	*-41*	1.07
Male	-0.54	*-70.78*	1.05
Panel D: Disposition Effect – Life Time Experience			
Born in the 1900's	16.98	*14.07*	0.50
1910's	4.47	*23.25*	0.73
1920's - Depression Babies	1.73	*33.21*	0.85
1930's	0.19	*8.21*	0.98
1940's	-0.34	*-25.71*	1.04
1950's	-0.58	*-42.33*	1.06
1960's	-0.77	*-48.49*	1.07
1970's	-1.56	*-68.55*	1.13
1980's	-2.35	*-42.26*	1.15
1990's	-3.69	*-23.68*	1.21
2000's	-8.25	*-20.48*	1.43
All the Rest	-0.65	*-89.53*	1.06
Depression Babies	1.73	*33.21*	0.85

Another reason for the high levels of disposition effect among people born in the 2000's might be that given the account holders young age, they can afford many years of waiting till losing stocks' prices eventually go up again – if people believe that over longer horizons, most stock investments offer a positive return.

In the preliminary test, where we examine the disposition effect by years, it shows that in some years, especially the earlier years in the sample period, investors are not as affected by the disposition effect as they are in later years. We conjecture that macroeconomic conditions play an important role in the disposition effect. To test this hypothesis, we estimate a regression of the disposition effect (PLR-PGR) on variables that represent both micro- and macro-economic conditions. The results are presented in Table 5-3.

The negative intercept value indicates that overall, investors are prone to the disposition effect. Unexpectedly, stock market performance, whether it is during the same month or in the previous month, does not affect investors' loss-aversion level. The number of bankruptcies in the market does not have a significant impact on the level of disposition effect in the market, although the sign of the parameter does indicate that if there is any impact at all, a greater number of bankruptcies will reduce the disposition effect, as hypothesised.

Table 5-3
Macroeconomic Conditions' Role in Disposition Effect

OLS regression is estimated as following, using a stepwise method at a 0.05 entry and remaining level:

$$AVG_{DE_t} = \alpha + \beta_1 CIR_t + \beta_2 PIR_t + \beta_3 NoUE_t + \beta_4 NoBR_t + \varepsilon_i$$

In the model, the dependent variable, $\mathrm{AVG\_DE_t}$, is the mean difference between PLR and PGR across all investors in the market for a given month t, measuring the level of disposition effect in the market for the month. Two stock market performance variables are used: $\mathrm{CIR_t}$ and $\mathrm{PIR_t}$. $\mathrm{CIR_t}$ is the market index return for month t; the HEX index is used in the return calculation. $\mathrm{PIR_t}$ is the market index (HEX) return of the month before t, and captures the market condition that is still fresh in the investors memory.$\mathrm{NoUE_t}$ is the unemployment level in month t. NoBR_t is the number of bankruptcies during month t. Given shareholders only have a secondary claim in the case of bankruptcy, during times when bankruptcies are more likely, share investors are expected to want to exit positions in a failing company (losing stock) sooner. Therefore, as stated in Hypothesis5,6, investors will be less likely to exhibit the disposition effect when they hear about / experience a greater number of bankruptcies.

Variable	Estimate	SE	Pr > |t|
Intercept	-0.8084	0.0643	< 0.0001
CIR	0.0249	0.2037	0.9027
PIR	-0.1379	0.2039	0.4997
NoBR	0.0002	0.0003	0.4827
UER	9.5912	1.1978	< 0.0001
R-Square	*0.6325*		
Adj R-Square	*0.6251*		

A higher unemployment rate reduces the level of loss-aversion. This parameter estimate has a high value and the highest statistical significance. This could be explained by the simple fact that when investors are unemployed and thus have reduced or no income, they do not have options other than to sell losing stocks, instead of holding onto them for longer. This could also explain why during the earlier parts of the sample period, the disposition effect is generally not seen – equity markets at that time were less developed, and people did not have the same investing affluence as they do today. Selling losing stocks might not be a choice, rather, it was a necessity. The reality of financial hardship has made the behavioural bias, which is a preference when there are options, no longer an option. The high R-square values indicate the strong link between the unemployment rate and investment behavioural bias.

In the test of investor risk preference, we first test the hypothesis that lottery stocks underperform (Hypothesis$_{5,2}$) over this 20-year sample period, which is much longer than the sample used in Chapter 4. If lottery stocks are not an inferior investment over the long-term, then the heavy holdings of lottery stocks cannot be deemed as a bias. The following two tables present the stocks' performance by lottery stock categories. In Table 5-4, lottery stocks are defined using methods used in the existing literature, namely in Kumar (2009) and Bali, Cakici and Whitelaw (2011). In Table 5-5, lottery stocks are defined using a method that improves the approach in Bali, Cakici and Whitelaw (2011) – instead of assuming that investors make decision based on the stock performances in the previous calendar month, the generalised BCW approach uses a rolling window of 20-trading days before the day when lottery stocks are defined.

From Table 5-4, it is evident that lottery stocks significantly underperform other stocks. According to the Kumar method, when actual monthly returns are used, stocks that are at the two extremes, namely the lottery stocks and the non-lottery stocks, underperform the rest of the market. However, when average monthly alpha is used, lottery stocks are the only types of stocks that have significantly negative returns.

Table 5-4
Stock Performance by K Method and BCW Method

The following table presents the stock performance over the entire sample period (1 January 1991 to 31 December 2011) by lottery stock categories, using two different definitions. Under the K Method, each month all stocks are ranked independently by idiosyncratic volatility, idiosyncratic skewness and average end of day stock price for the preceding 6 (-6, -1) months. Lottery stocks for each month are defined as the stocks which *jointly* exhibit idiosyncratic volatility in the top 50%, idiosyncratic skewness in the top 50%, and price in the bottom 50%. Stocks which meet none of these criteria – i.e., are jointly below the median of idiosyncratic volatility and skewness, and above the median average price – are defined as 'Non-lottery', while stocks which meet some lottery criteria, but not all, are classified as 'Other'. Under the BCW definition, stocks are ranked by their maximum daily return (close-to-close) in the previous calendar month, and those stocks ranked in the top decile are defined as lottery stocks under the BCW definition.

	Avg Monthly Return (%)	*t-stats*	Avg Monthly Alpha (%)	*t-stats*
Panel A: Kumar Definition				
Panel A1				
Lottery	0.27	*1.28*	-0.08	*-2.13*
Non-lottery	0.26	*1.99*	0.04	*2.2*
Other Stocks	0.43	*4.21*	0.03	*2.21*
Panel A2				
Lottery Stocks	0.27	*1.28*	-0.08	*-2.13*
All The Rest	0.37	*4.62*	0.03	*3.09*
Panel B: BCW Definition				
Panel B1				
Least Lottery Like	1.19	*5.68*	0.24	*3.74*
1	0.79	*4.00*	0.06	*3.77*
2	0.78	*3.89*	0.05	*3.31*
3	0.45	*2.18*	0.03	*1.71*
4	0.45	*1.99*	0.00	*0.12*
5	0.72	*3.01*	0.06	*2.83*
6	0.39	*1.43*	0.02	*1.27*
7	0.13	*0.51*	-0.01	*-0.56*
8	0.09	*0.35*	-0.03	*-0.91*
Most Lottery Like	-0.41	*-1.24*	0.06	*0.98*
Panel B2				
All the Rest	0.55	*7.12*	0.05	*4.63*
Lottery Stock	-0.41	*-1.24*	0.06	*0.98*

When the BCW definition is used to define lottery stocks, a general pattern that the more lottery-like the stocks are, the worse the return, is evident. When the least lottery like stocks have a significantly positive return, lottery stocks have a negative return, using the actual monthly return, or a return that is not significantly different from zero when average monthly alpha is calculated.

Table 5-5
Stock Performance by Generalised BCW Method

The following table shows the stock performance over the entire sample period (1 January 1991 to 31 December 2011) by lottery stock categories, using the generalised BCW approach. For each trading day *t*, we obtain the maximum daily return for each stock over the previous 20-trading days, and then rank stocks by their maximum return. Stocks ranked in the top decile are defined as lottery stocks for day *t*.

	Average Monthly Return (%)	*t stats*
Panel A		
Least Lottery Like	0.62	*13.37*
1	0.47	*10.19*
2	0.48	*10.1*
3	0.47	*9.44*
4	0.69	*12.42*
5	0.56	*10.35*
6	0.24	*4.24*
7	0.25	*4.08*
8	0.27	*4.13*
Most Lottery Like	0.38	*4.39*
Panel B		
All the Rest	0.45	*24.82*
Lottery Stocks	0.38	*4.39*

The finding using the generalised BCW approach is consistent with the other 2 methods. There is a general pattern that the more lottery like a stock is, the lower the return. Given the findings in Table 5-4 and Table 5-5 are based on data over a 20-year period, they are not likely to be driven by specific market conditions. Therefore, we can conclude that lottery stocks, which are a riskier investment, underperform when compared to other stocks. This finding provides support for $\text{Hypothesis}_{5,2}$.

Having examined the performance of lottery stocks, the next step is to investigate the performance of investors that place a significant amount of their wealth in lottery stocks compared to their peers. Table 5-6 reports the account performance by their lottery holding weight ranking. Results indicate that accounts with the highest lottery stock holding perform the worst. Further, the highest lottery stock holding accounts are the only investors with an average annual return that is negative. Investors that have the lowest lottery stock holding weights rank second last in terms of investment returns – the returns for this group are not statistically different from zero. A possible explanation is that these investors have gone to the other extreme, becoming too risk averse. The remaining 8 out of the 10 groups of investors all have significantly positive annual returns, with the highest return groups concentrated on the side of low lottery stock holding rankings. Table 5-6 provides evidence that an overly strong preference in gambling results in inferior portfolio performance. Based on the results about lottery stock performance and gambling-preferred accounts' performance over a long time horizon, $\text{Hypothesis}_{5,2}$ is not rejected.

Table 5-6
Account Performance by Lottery Stock Holding Weight

This table presents the average annual returns of all registered individual investor accounts on the Helsinki Stock Exchange during the sample period (1 January 1995 to 31 December 2011). Accounts are ranked by their average lottery stock holding weight during their active account period. The actual lottery stock weight score LW_{it} for an account *i*, on day *t*, is computed as:

$$LW_{it} = \frac{\sum_{j \in L_t} n_{ijt} P_{jt}}{\sum_{j=1}^{N_{it}} n_{ijt} P_{jt}} \times 100\%$$

where L_t is the set of lottery-type stocks defined by the K Method on day *t*, N_{it} is the number of stocks in the portfolio of investor *i* on day *t*, n_{ijt} is the number of shares of stock *j* in the portfolio of investor *i* on day *t*, and P_{jt} is the close price of stock *j* on day *t*. The average account lottery holding weight is the average of the accounts LW_{it} during the sample period.

	Avg Account Annual Return (%)	*t stats*
Lottery Stocks Holding Weight Lowest	-0.02	*-0.29*
2	1.63	*9.67*
3	5.03	*63.81*
4	5.39	*71.48*
5	5.32	*72.07*
6	4.32	*57.07*
7	0.82	*10.43*
8	0.85	*9.87*
Lottery Stocks Holding Weight Highest	-0.54	*-4.47*

Doran, Jiang and Peterson (2011) find that there is a new-year effect for lottery stocks – people hold more lottery stocks in January than other months of the year. To test whether this is the case in the Finland market, we examine the aggregated holding weights of lottery stocks of individual investors across months. Interestingly, January is not significantly different from other months of the year. The month that stands out is June, when investors hold a lot fewer lottery stocks in their portfolio. Further investigations, beyond this chapter’s scope, are needed to examine whether this is something unique in Finland, and any possible explanations. The average aggregated lottery holding weight by month is reported in Table 5-7.

Table 5-7
Lottery Holding Weight by Month

This table reports the aggregated lottery stock holding weight, by month, during the sample period 1 January 1995 to 31 December 2011. Investors include all individual investors registered on the Helsinki Stock Exchange. Lottery stocks for each month are defined as the stocks which *jointly* exhibit idiosyncratic volatility in the top 50%, idiosyncratic skewness in the top 50%, and price in the bottom 50%.

	Lottery Weight – Mean (%)	Lottery Weight – Median (%)
January	12.22	9.65
February	13.28	9.20
March	13.04	8.82
April	12.69	9.18
May	11.02	10.59
June	9.65	8.86
July	10.42	8.47
August	13.26	10.62
September	13.23	9.50
October	13.32	10.17
November	13.98	10.50
December	12.63	10.14

Malmendier and Nagel (2011) find that people who have experienced low stock market returns throughout their lives (in particular, depression babies, i.e., people born between 1920 and 1929) are less likely to take financial risks. It is interesting to see whether depression babies hold less in lottery stocks compared to other investors. Table 5-8 reports average lottery stock holding weight partitioned by the time investors are born.

Table 5-8
Lottery Stock Holding Weight by Investor Birth Time

This table reports the aggregated average lottery stock holding weight by the time investors are born during the sample period 1 January 1995 to 31 December 2011. Investors used include all individual investors registered in Helsinki Stock Exchange. Lottery stocks for each month are defined as the stocks which *jointly* exhibit idiosyncratic volatility in the top 50%, idiosyncratic skewness in the top 50%, and price in the bottom 50%.

Decade Born	Avg Account LW (%)
1900's	7.45
1910's	6.44
1920's - Depression Baby	6.82
1930's	8.01
1940's	8.94
1950's	10.46
1960's	12.77
1970's	13.60
1980's	9.47
1990's	6.65

Lottery stock holding weights presented in Table 5-8 show that depression babies' holding in lottery stocks is in the lower range, although they are not the lowest among all investors. To further investigate whether the lottery stock holding weight is related to the year of birth, or the actual age of an investor, we group the lottery stock holding weights by investors born at different times and their ages. For example, we compare the lottery stock holdings of investors in their 30's by the time they were born, to see whether investors lottery holding weights are similar. Table 5-9 presents the cross comparison of lottery stock holding weights.

Table 5-9
Lottery Stock Holding Weight by Birth Time and Age

This table reports the aggregated average lottery stock holding weight by the time investors are born during the sample period 1 January 1995 to 31 December 2011. Investors include all individual investors registered on the Helsinki Stock Exchange. Lottery stocks for each month are defined as the stocks which *jointly* exhibit idiosyncratic volatility in the top 50%, idiosyncratic skewness in the top 50%, and price in the bottom 50%.

Age \ Born in	1900's	1910's	1920's	1930's	1940's	1950's	1960's	1970's	1980's	1990's
teenager								24.95%	9.42%	6.86%
18-19							22.18%	15.66%	9.61%	***6.28%***
20's						23.28%	15.08%	12.59%	***7.79%***	
30's					22.03%	12.76%	11.14%	***9.24%***		
40's				22.27%	10.82%	8.80%	***8.34%***			
50's			20.66%	9.45%	6.96%	***6.78%***				
60's		20.73%	7.73%	5.81%	***5.52%***					
70's	16.01%	6.16%	4.55%	***4.81%***						
80's	***6.47%***	4.80%	***3.70%***							
90's	6.88%	***3.68%***								

Market Time	1990's	1990's-2000's	2000's-2010's	2010's

Market Time	**1990's**	**2000's**	**2010's**
Avg LW (%)	17.33	10.25	7.51

Table 5-9 shows that age, the time investors are born, and the time in the market all play a significant role in determining the aggregated lottery stock holding weight. For example, across all the groups by different birth time, the lowest lottery holding weight occurs around the 2010's in the market. For example, investors born in the 1940's would be in their 60's when the aggregated lottery stock holding is 5.52%, which is the lowest through their investment life-time; similarly, investors born in the 1970's hold the lowest level of lottery stocks (9.24%) in their 30's when the market time is around 2010. At the same time, 9.24% is greater than 5.52%, reflecting the fact that younger investors (in their 30's) are more risk seeking than older investors (in their 60's), even when market conditions are the same. Also the time investors are born appears to have some impact. While no results stand-out for the depression babies per se, investors born in the 1970's have the highest lottery stock holdings in the same market time – as shown along the diagonal lines in Table 5-9.

To investigate the joint effect of investor and exogenous factors on investors' gambling preference, multivariate OLS regressions are estimated with an investor's average lottery holding weight the dependent variable. Table 5-10 reports the regression findings. As shown in the table, the regression has a comparatively high R-Square and Adjusted R-Square. This suggests that a multivariate regression that employs account demographic features, trading characteristics, performance and market conditions can explain investors risk preferences reasonably well.

Results indicate that when investors have made a gain, either in the period before the decision making, or in the same period as the decision making, they tend to invest more in lottery stocks, i.e., become more risk seeking. This provides evidence of the House Money effect. Previous and concurrent market performance appears to affect lottery stock investment in the opposite way; when the market is performing better, lottery stock holdings become lower. When the market is strong, investors do not need to rely on lottery stocks to make significant gains, therefore, the holdings in lottery stocks are negatively related to market performance.

Table 5-10
OLS Regression Results – Lottery Stock Weight Determinants (1)

This table reports the results of the OLS regression designed to test the determinants for investor's lottery stock holding weight. The regression is designed as following:

$$LW_i = \alpha + \beta_1 PMAR_{it} + \beta_2 CMAR_{it} + \beta_3 PMMR_t + \beta_4 CMMR_t + \beta_5 UER_t + \beta_6 NoBR_t + \vartheta_1 M_i + \vartheta_2 OCA_i + \vartheta_3 LPA_i + \gamma_1 Gen1900_i + \gamma_2 Gen1910_i + \gamma_3 Gen1930_i + \gamma_4 Gen1940_i + \gamma_5 Gen1950_i + \gamma_6 Gen1960_i + \gamma_7 Gen1970_i + \gamma_8 Gen1980_i + \gamma_9 Gen1990_i + \varepsilon_i$$

where the dependant variable is the average lottery stocks holding weight of an investor during the sample period. Lottery stocks for each month are defined as the stocks which *jointly* exhibit idiosyncratic volatility in the top 50%, idiosyncratic skewness in the top 50%, and price in the bottom 50%. The investors include all registered individual investor accounts on the Helsinki Stock Exchange during the sample period (1 January 1995 to 31 December 2011).

	Parameter Estimate	Standard Error	Pr > |t|
Intercept	-0.0772	0.0004	< 0.0001
PMAR	0.2030	0.0006	< 0.0001
CMAR	0.0634	0.0006	< 0.0001
PMMR	-0.2555	0.0010	< 0.0001
CMMR	-0.0054	0.0009	< 0.0001
UER	1.4921	0.0037	< 0.0001
NoBR	-0.0001	0.0000	< 0.0001
M	0.0166	0.0001	< 0.0001
OCA	0.0133	0.0006	< 0.0001
LPA	0.3278	0.0003	< 0.0001
Gen1900	-0.0125	0.0018	< 0.0001
Gen1910	-0.0040	0.0006	< 0.0001
Gen1930	0.0101	0.0003	< 0.0001
Gen1940	0.0181	0.0002	< 0.0001
Gen1950	0.0252	0.0002	< 0.0001
Gen1960	0.0338	0.0002	< 0.0001
Gen1970	0.0357	0.0003	< 0.0001
Gen1980	0.0182	0.0003	< 0.0001
Gen1990	0.0133	0.0005	< 0.0001
R-Square	*0.1791*		
Adj R-Square	*0.1791*		

Consistent with Mikesell's (1994) finding on lottery ticket sales, the lottery stock holding is seen to increase when the unemployment rate increases. One possible reason is that when people are out of their main income, they turn to lottery like investments for a chance to become suddenly rich and get out of their financial difficulty. Another reason might be that lottery stocks are much cheaper than non-lottery stocks. When people's income is reduced or cut-off, they may not be able to keep on holding more expensive investments, therefore they opt for cheaper lottery stocks as their investments.

The number of corporate bankruptcies negatively affects the lottery stock holding weight. Although the finding is not strong, it suggests that bankruptcies reduce investor confidence in riskier investments. As expected, male investors hold more lottery stocks than their female counterparts. This is consistent with the existing findings in literature that male investors are more risk-seeking than females. Over-confident investors hold more lottery stocks. Lottery preferred accounts hold more lottery stocks than other investors.

In the test of whether other generations are more risk seeking than depression babies, it is found that people born before the Great Depression are less risk seeking than the depression babies, while people born after are more likely to invest in lottery stocks. Based on these findings and the results from the cross reference table, Hypothesis$_{5,5}$ is rejected. This finding from the generation dummy variables might be driven by the greater number of younger investors in the group of the later generations when the lottery stock weights are examined. Therefore, it could indicate that generally, the younger people are, the more risk-seeking they are. With this possibility, another OLS regression using pooled data (Equation 5-3) is estimated, and the results are reported in Table 5-11.

Table 5-11
OLS Regression Results – Lottery Stock Weight Determinants (2)

This table reports the results of the OLS regression designed to test the determinants for investors lottery stock holding weight. The regression is designed as following:

$$LW_i = \alpha + \beta_1 PMAR_{it} + \beta_2 CMAR_{it} + \beta_3 PMMR_t + \beta_4 CMMR_t + \beta_5 UER_t + \beta_6 NoBR_t + \vartheta_1 M_i + \vartheta_2 OCA_i + \vartheta_3 LPA_i + \vartheta_4 Age_i + \varepsilon_i$$

where the dependant variable is an investor's average lottery stock holding weight during the sample period. The investors include all registered individual investor accounts on the Helsinki Stock Exchange during the sample period (1 January 1995 to 31 December 2011).

	Parameter	SE	Pr > |t|
Intercept	-0.0182	0.0004	< 0.0001
PMAR	0.2027	0.0006	< 0.0001
CMAR	0.0632	0.0006	< 0.0001
PMMR	-0.2524	0.0009	< 0.0001
CMMR	-0.0055	0.0008	< 0.0001
UER	1.4099	0.0037	< 0.0001
NoBR	-0.0001	0.0000	< 0.0001
Age	-0.0006	0.0000	< 0.0001
M	0.0171	0.0001	< 0.0001
OCA	0.0124	0.0006	< 0.0001
LPA	0.3279	0.0003	< 0.0001
R-Square	*0.1792*		
Adj. R-Square	*0.1792*		

The regression results indicate that, in general, investors are risk averse, as seen in the negative intercept estimate. However, each 1% increase in the previous month's portfolio return leads to an increase of about 0.20% lottery stock holding, and each 1% increase in the current month's portfolio return leads to an increase of about 0.06% of lottery stock holding. This is consistent with the 'House Money' effect[41] and the findings of the previous lottery stock study in Chapter 4. The overall market performance, both the month before and the same month, predicts lottery stock holding in the opposite direction. Unemployment rate leads to higher lottery holding rate, with each percentage of unemployment rate increase resulting in a 1.41% increase in investors' lottery stock holding. A greater number of

[41] People are more likely to take more risks after a previous win (house money); See Thaler and Johnson (1990).

corporate bankruptcies lead to a lower lottery holding weight, suggesting that investors are more cautious when there are more bankruptcies. Some features of the account holders, such as being male and over-confident increase the likelihood of an account holding more lottery stocks. However, investors generally hold less lottery stocks when they grow older. Given the results from the two regressions on gambling preference, and the regression on the disposition effect tendency, we conclude that macro-economic conditions affect the level of the disposition effect and the prevalence of stock market gambling. Based on these findings, Hypothesis$_{5,6}$ is not rejected.

5.5 Summary

Investor behavioural biases, in particular the disposition effect and risk seeking preference, are examined in this chapter. A large data set of all retail investors on the Helsinki Exchange over a sample period of two-decades is used to test whether the biases, which have been found in previous studies, still prevail when a longer sample period is examined, or if the observed biases are actually driven by market conditions of the particular shorter sample periods used in previous research.

Analysis in this chapter shows that the previous findings in literature, and the earlier chapters in this dissertation, are robust over a longer time horizon. The findings rule out the possibility that the previous chapters' results are driven by particular sample periods. In short, this chapter provides additional evidence to the following; (i) investors are prone to the disposition effect, (ii) lottery stocks underperform, (iii) lottery preferred accounts underperform, and (iv) the house money effect is robust. Previous findings regarding demographic features are robust in the analysis using this more comprehensive and longer sample. Female investors are more likely to be loss averse, but less risk seeking. The increase of age reduces the likelihood of gambling in the stock market.

One new issue examined in this chapter is the life time experience's impact on one's behavioural bias formation. It is found that a person's experience, as reflected by the time he/she is born, does influence the person's behaviour. People who have lived through the Great Depression are less likely to be loss averse. People who are born in the 1970's have experienced more prosperous economic conditions and are found to be more risk seeking than other generations.

Besides a person's background, trading characteristics and demographic features, the overall economic and stock market conditions at the time when an investor forms decisions, also affect the likelihood of behavioural biases. An increase of the unemployment rate, for example, reduces the disposition effect, but increases the likelihood of stock market gambling. The number of corporate bankruptcies reduces both the disposition effect and the house money effect. While stock market performance does not have a significant impact on the prevalence of the disposition effect, it does reduce the investment in lottery stocks.

In addition to providing evidence to the previously examined topics, this chapter sheds new light into investor behaviour. There appears to be an interaction between behavioural biases. Investors who are more likely to gamble in the market with lottery stocks, for example, are at the same time more likely to be loss averse, as seen in the increased level of the disposition effect. This is yet another example of the 'puzzle' that people engage in both gambling and buying insurance.

Chapter 6 The Price Impact of Director Trading and Announcements: Evidence from the Australian Securities Exchange

6.1 Introduction

In his 1972 seminal paper, Scholes documents that ‘by the time official reporting (for corporate insider transactions) is necessary, the market has fully adjusted for the value of the information.’ There are many studies based on U.S. and U.K. data with findings that support this argument. These findings naturally give reasons for market participants, regulators and academics to question whether reporting legal insider trading has any practical necessity beyond a formality and enhancing corporate public image, and whether the reporting is an efficiently beneficial signal to market participants.

The study of insider trading reporting commences with determining whether legally trading insiders trade randomly, and on average, do not outperform the market; or whether they time their trades well, utilising their superior knowledge of the company while trading (at least marginally) legally, and thus making abnormal profit. The majority of literature finds that legal insiders’ trading is based on information which enables abnormal profit over a long time horizon. In this chapter, we test Hypothesis$_{6,1}$ that company directors time their trades to obtain superior investment returns using Australian data.

Market efficiency theory states that in a semi-efficient market, stock prices reflect all publically available information. Given the market anecdotal belief, and vast academic evidence, that insider trading is based on superior knowledge of the firm, and therefore profitable, in a semi-efficient market like the Australian market[42], any information associated with an insider's trade will be incorporated into stock prices once it becomes public. The question then shifts to when this information becomes 'public'; either at the time of the release of the report by the ASX, or at some earlier time (rendering the ASX release redundant).

In this chapter, price behaviour surrounding both director trades, and associated market announcements, are examined. In Australia, the Australian Securities Exchange (ASX) requires listed companies to report trading of their directors within 5 trading days.[43] We hypothesise that price impact occurs at the time when the trading is announced to the market (Hypothesis$_{6,2}$), but not at the time of trading (Hypothesis$_{6,3}$). Analysis in this chapter employs a sample of corporate director trades, and associated disclosures, between January 2005 and December 2010, on the ASX. Specifically, we examine price movements around the day of the actual trade when the director's identity is not known to the market, as well as intraday price movements surrounding the exact disclosure time. The high frequency data also allows us to test Hypothesis$_{6,4}$ that the price impact of director trading announcements occurs rapidly. Further, having the precise announcement time enables measuring any 'surprise' factor contained in the announcement (by comparing price at announcement to directors' trade price), and provides evidence of the role of director trading in price discovery.

The remainder of this chapter is presented as follows. Section 6.2 compares the legal frameworks regulating insider trading in three different countries where a lot of studies focus on: U.S., U.K. and Australia. Section 6.2 describes the data set available and reports key

[42] There is rich literature about Australian market efficiency, for example, Aitken and Frino (1996).
[43] See ASX listing rules.

descriptive statistics. Section 6.3 outlines the methodology used in this chapter. Section 6.4 presents and discusses the results, and Section 6.5 concludes.

6.2 Trading Rules for Insiders in U.S., U.K. and Australia

To better understand the findings of existing studies, which are concentrated in U.K. and U.S. markets, it is essential to know the differences in the legal framework regulating company directors' trading. In most developed countries, trading based on inside information is illegal. That being said, insiders are not banned to trade stocks of their own company. Instead, terms regarding to when they can trade are imposed. In Australia and the U.K., insider trading rules apply to company non-executive directors and executives, both referred to as 'directors'. In the U.S., insider trading regulations apply to a larger group which includes non-executive directors, referred to as 'directors', executives referred to as 'officers', and large shareholders who own at least 10% of outstanding shares.

In terms of 'free' trading time, the U.K. is the only market that consistently includes in its regulation a 'close period' during which insiders are not allowed to trade for all companies.[44] Until recently, the U.S. and Australia provided companies with discretion of whether a 'close period' was required, and how it should be defined. In the U.S., there is still no 'close period' requirement; however, a director is prohibited from trading during 'Pension Fund Blackout Periods'.[45] Effective from 1 January 2011, a company listed on the Australian Securities

[44] During a close period, directors/insiders are precluded from trading the company's shares. However, trading during these periods is possible through company board approval on a case-by-case basis. Many companies, rather than defining a 'close period' when trading is not allowed, set a 'trading window' when trading is permitted.
[45] See SOX Act 2001.

Exchange is required to disclose its trading policy, which must include ‘closed periods’ for director trading.[46]

Not only are there rules on how and when directors can trade, but also directors are required to report or announce their trading according to certain rules. Historically, the timeframes for director trading disclosure vary significantly across the U.K., U.S. and Australia, with U.S. timeframes extending to 40 days from the date of the transaction. With the introduction of the SOX Act 2001 in the U.S., the current reporting requirements are similar; all within 5 trading days. In the U.K., directors are required to report to the company within 4 trading days of the transaction, and the company is required to report to a RIS[47] no later than the end of the following trading day.[48] U.S. SEC Rule 16a-3(g)(1)49 requires filing before the end of the second business day following the day of the directors transaction. In Australia, ASX Listing Rule 3.19A.2 requires the entity to report a director’s trading to the ASX, via Appendix 3Y, no later than 5 trading days after the transaction. While the ASX Listing Rule holds the entity responsible for lodging Appendix 3Y, CLERP 9 has extended the liability of continuous disclosure to individuals. Corporations Act 2001 205G requires the director to notify the relevant market operator within 14 days after any change in their holding interest (where the market operator can be, but is not limited to, the ASX).[50]

Requirements relating to the reporting timeframe are critical in insider trading/announcement studies, as the delay in reporting can lead to information leakage and reduced reaction in the

[46] ASX Listing Rules, Chapter 12 – ‘On-going requirements’.
[47] Regulated Information Services maintained by the Financial Services Authority (FSA), which is referred to as UK Listing Authority (UKLA) when acting as the authority under Financial Services and Markets Act 2000.
[48] UKLA Disclosure Rules and Transparency Rules DTR 3.1.2 and DTR 3.1.4
[49] Effective 29 August 2002.
[50] In the US, under Section 16(b) of the Securities and Exchange Act of 1933 – 1934, insiders must return all profits from a purchase and subsequent sale (or a sale and subsequent purchase) occurring within 6 months. There are no equivalent rules in either the U.K. or Australia.

market upon announcement. In addition, the announcement time is required to accurately measure price effects associated with the event. In the U.S., prior to improvements in processing electronic filings led to greater accuracy in 2002, there was no precise timestamp on filings. Currently, only EDGAR subscribers are able to obtain trade information concurrent with filings submitted to the SEC; there are often processing delays associated with publishing on the SEC website.[51] Therefore, studies using U.S. data prior to 2002 generally suffer from incorrect announcement times, using filing time as a proxy.

In Australia, according to an ASX officer enquired via a phone call, due to the human work involved, the time between electronic submission of Appendix 3Y and the actual release of the report vary with factors including time of the year, staff on post over the period etc. We therefore acquire a dataset, with timestamps accurate to the nearest second of the actual announcement, to obviate any potential bias that exists in prior research.

6.3 Sample and Data

Data used in this study cover the period 1 January 2005 to 31 December 2010. Director trading data, including trade date, trade direction, trade volume and trade price, are collected from all Appendix 3Y's submitted to ASX during this period. Several procedures are undertaken to clean the data from data entry errors, for example, entries with a trade volume greater than the total volume of the stock on the day are excluded, which reduce the original sample size by approximately 1,000 observations. Daily abnormal returns with an absolute value of greater than 100% as a result of reverse splits are also excluded in the abnormal return analysis. Director announcement time is collected from the Australian Company Reference Data provided by SIRCA. Company GICS codes are from DataStream for

[51] EDGAR is the electronic filing system used by the SEC.

currently listed companies, and www.delisted.com.au for delisted companies. All Ordinaries Index data set is sourced from Bloomberg. Intraday trading data, which include details of all transactions executed (price and volume), and associated quote level information (both prices and volumes of bid and ask quotes) is sourced from TRTH, provided by SIRCA.

Following Garfinkel and Nimalendran (2003) and Fidrmuc, Goergen, Renneboog (2006), for the announcement effect study, all trades in the same announcement are aggregated into one observation with the announcement volume being the netted trade amount, and the director trade price being the weighted average price of the announcement. For the trading effect study, all trades in the same stock by the same director on the same day are aggregated into a single observation, and the netted trade amount is used. We exclude the exercise of options, warrants and preference shares, as in Hillier and Marshall (2002) and Fidrmuc, Goergen, Renneboog (2006). Off-market trades are excluded to enable the comparison of on-market ‘trading effects’ and ‘announcement effects’.

Table 6-1 presents summary statistics of director trades and announcements included in the sample. Consistent with the majority of previous research, there are considerably more director purchases than sales. However, sales are larger trades, with the average volume of sales (275,527 shares) considerably larger than the average volume of purchases (126,834 shares), and the average trade value of sales ($111,854) considerably greater than the average trade value of purchases ($36,574). Directors’ purchases are more likely in firms with lower share prices compared to director sales. Director sales tend to be concentrated in stocks with larger trades, shown by a greater average daily trade volume (2,026,541 shares versus 1,551,192 shares), combined with smaller average daily number of trades (256 trades versus 295 trades). Table 6-1 also reports the number of working days between the first trade in a report and the announcement of the trade to the market. The average reporting delay is 3.47 days for purchases, and 4.54 days for sales. Over 90% of the reports in the sample meet the ASX reporting requirements. However, violations exist, with the worst case experiencing a delay of more than half a year.[52]

Table 6-1
Summary Statistics of Director Trades and Announcements

This table reports summary statistics for director trades and announcements. The sample of director trades and announcements is sourced from the ASX from 1 January 2005 to 31 December 2010, and is collected from Appendix 3Y's submitted to the ASX. Statistics include the number of trades, director trade volume (shares), director trade value (AUD), daily stock volume (shares), share price (AUD), daily stock trades and announcement delay (time between director trade and subsequent announcement to the market, in days). Both means and medians are reported separately for purchases and sales.

	Purchases (N = 6,431)		Sales (N = 615)	
	Mean	Median	Mean	Median
Director Trade Volume (shares)	126,834	27,025	275,527	60,471
Director Trade Value ($)	36,573	13,735	111,854	57,000
Daily Stock Volume (shares)	1,551,193	305,685	2,026,541	500,500
Share Price ($)	2.78	0.50	4.23	0.73
Daily Stock Trades	295	19	256	40
Announcement Delay (Days)	3.47	2	4.54	2

6.3 Research Design

This study examines price effects associated with both director trades and related announcements. The trading analysis is based on calculating Cumulative Abnormal Returns

[52] There are a very small number of announcements made before the director traded; these are excluded from the sample. It is worth noting that prior to the ASX announcement, and even prior to the actual trade, it is possible that the information is released via other channels (e.g., company websites) if the relevant companies have such corporate governance requirements. These cases are rare and excluded when identified, and we therefore consider the ASX website release as the first official release of the information.

(CARs) surrounding the director trade. To determine whether directors exhibit market timing ability, and purchase after periods of negative abnormal returns, or sell after periods of positive abnormal returns, CARs from 60 trading days to 1 trading day before the director trade are calculated. To determine if director trades are associated with favourable price movements post-trade, CAR's from 1 day to 60 days after the director trade are calculated.[53] We also calculate day-to-day abnormal returns from 5 trading days before the director trade to 5 trading days after the director trade, to examine possible shorter-term price reactions associated with the trades.

In preliminary analysis, the raw (unadjusted) results indicate that directors purchase after an 'extended period' of negative returns (for up to 60 trading days before the trade). If a 'pre-event' estimation period is employed to estimate Beta, there is a negative intercept for the market model, which will result in a positive abnormal return, even if there is no price movement in the post-event period, as found in Lecce, Lepone, McKenzie and Segara (2012). Seyhun (1986) also documents evidence of an upward bias in CAPM based abnormal returns. Brown and Warner (1985) conclude that 'the market-adjusted model does not suffer from this bias, performing well under a number of circumstances, and better than more complex methods'(1985: 88), and that the market-adjusted model has similar power to the OLS market model with daily data. Recent insider trading studies, including Lakonishok and Lee (2001), calculate abnormal returns by subtracting the index return. In this study, we use the market-adjusted model where R_{it} is stock i's return in interval t, and R_{M_t} is the return on the All Ordinaries index in interval t.

$$CARs(t_1, t_2) = \sum_{t=t_1}^{t_2} \left(R_{it} - R_{M_t}\right) \qquad (6\text{-}1)$$

[53] As shown by Easley, Kiefer and O'Hara (1997), a 60-day trading window has the benefit of both being long enough for precise estimation and being short enough for presumed stationarity to hold.

$$CAAR(t_1, t_2) = \frac{1}{t_2 - t_1} \sum_{t=t_1}^{t_2} \left(R_{it} - R_{M_t}\right) \tag{6-2}$$

Further analysis of trade price effects are based on partitioning by (i) trade value size quartiles, and (ii) whether it is a stock with thin-trading, which is defined as having a number of non-trading days above the median during the sample period.[54]

In the announcement analysis, we follow the estimation method used in Barclay and Litzenberger (1988). As there is significant variation in the trading/quoting frequency of stocks in the sample, the primary results are calculated using quotes, rather than trade prices, after certain time intervals. We use the prevailing bid-ask midpoint at the time of the announcement, and the 5 midpoints after the announcement, to calculate quote-to-quote returns.

$$R_n = \frac{Bid_n + Ask_n}{Bid_0 + Ask_0} - 1 \tag{6-3}$$

To determine possible factors affecting price effects, we partition return statistics using the same methods as mentioned above for the trade effect analysis. Further analysis is undertaken for the announcement effects to examine the significant price effects which are not seen in the overall trade effects. We divide the announcements into announcements with ‘surprise’ and without ‘surprise’. If at the announcement time, the prevailing bid-ask midpoint has moved in the ‘right’ direction since a director trade, i.e., it is higher than the director trade price[55] after a director purchase, or lower than the director trade price after a director sale, then the announcement is defined as one without ‘surprise’. If the announcement prevailing

[54] This is the definition used in Fidrmuc, Goergen, Renneboog (2006).

[55] The director price is the volume weighted average price of the aggregated trade.

bid-ask midpoint has moved in the 'wrong' direction since a director trade, then the announcement is defined as one with 'surprise'.

Several previous studies, including Brochet (2010), find that the longer the delay of the reporting/announcement, the smaller the abnormal return associated with the announcement. There are also studies finding more significant/greater returns when there are multiple directors trading together. We regress announcement abnormal returns (*R*) on the above mentioned explanatory variables, as well as a variable 'Materials' using OLS described below.

$$R = \alpha + \beta LogDTN + \gamma Materials + \delta Surprise + \rho Multiple + \varphi LogDelay + \nu LogVolume \quad (6\text{-}4)$$

LogDTN is the natural logarithm of the daily number of trades, calculated as the total number of trades in the stock over the sample period, divided by the number of trading days during that period. This variable addresses the thin-trading concern. *Materials* takes the value of 1 if the company's industry sector is Materials according to its GICS classification, 0 otherwise. This variable is introduced as companies in this sector comprise approximately 32% of all observations in the sample, and we are interested in whether this high proportion of the sample drives the overall results.

Surprise takes the value of 1 if the announcement is defined as one with surprise, 0 otherwise. This variable enables an improvement over the one-basket analysis which does not differentiate whether the market has naturally moved towards the director's expected direction without knowing about the director trade. *Multiple* takes the value of 1 if there is more than one director trading in the same direction for the same announcement, 0 otherwise.

LogDelay is the natural logarithm of the number of days between the trading date and the date the information is announced on the ASX website. *LogVolume* is the natural logarithm of the netted announcement volume.

To further examine the findings of the previously mentioned analyses, which show that the information is released to the market at the time of the announcement rather than the time of trade on the ASX, we regress the daily abnormal returns on the occurrence of trades and occurrence of announcements, respectively, using OLS. We then compare the two regressions for consistency with other results in this study.

$$AR = \alpha + \beta\ BuyTrade + \gamma\ SaleTrade \qquad (6\text{-}5)$$

$$AR = \alpha + \beta\ BuyA + \gamma\ SaleA \qquad (6\text{-}6)$$

For the first regression, *BuyTrade* takes the value of 1 when there is a director purchase on the day, 0 otherwise; *SaleTrade* takes value of 1 when there is a director sale on the day, 0 otherwise. For the second regression, *BuyA* takes value of 1 when there is an announcement whose net amount is a purchase on the day, 0 otherwise; *SaleA* takes value of 1 when there is an announcement whose net amount is a sale on the day, 0 otherwise.

6.4 Empirical Results

Table 6-2 presents results of the trade analysis. Long-term results indicate that directors exhibit market timing ability and outperform the market, with both purchases and sales associated with significantly negative (positive) CARs from 60 trading days before the trade, measuring -2.56% for purchases and 7.44% for sales. Post-execution, purchases experience significantly positive CARs all the way through 60 trading days after the trade. Although the price does not fall significantly after director sales, the profit realised by selling after the continuous price increase over the prior 60-day period (7.44%) is both statistically and economically significant. There are several possible explanations of the asymmetry in price reactions after director trades. One possibility is that the market does not interpret director sales as a negative signal; the sales could be motivated by liquidity or profit-taking purposes. Another explanation relates to potential litigation; a director is more likely to face legal action for trading if the price falls after a sale, and others suffer 'actual' losses, rather than for directors purchasing before price increases, and others failing to profit. Therefore, directors avoid selling before significant price falls. Given these findings, we do not reject $\text{Hypothesis}_{6,1}$.

Short-term returns exhibit no pattern around director trades. Most notably, there is no significant price effect on the day of the director trading, which, according to the semi-efficient market expectation, would be observable if the information of director trading is available to the market on the trade day. The lack of evidence of information effect persists until the fifth day, which is the time it takes on average for the announcements to be released. Combining these results, the evidence suggests that on the Australian market, the information of director trading is not available to the market at the time of the trade, or between the trade and the announcement. These results provide evidence to support $\text{Hypothesis}_{6,3}$.

Table 6-2
Price Effects Surrounding Director Trades

This table reports results for price effects surrounding director trades. The sample of director trades is sourced from the ASX from 1 January 2005 to 31 December 2010, and is collected from Appendix 3Y's submitted to the ASX. Panel A presents long-term abnormal returns (using the All Ordinaries Index as the benchmark) from 60 days before the director's trade to 60 days after the trade. Panel B presents short-term abnormal returns, from 5 days before the director's trade to 5 days after the trade. Mean abnormal returns and associated *t*-statistics are reported separately for purchases and sales.

	Purchases		Sales	
	Mean Return (%)	*t*-statistic	Mean Return (%)	*t*-statistic
CAR (-60, -1)	-2.56	*-7.01*	7.44	*4.44*
CAR (-50, -1)	-2.49	*-7.40*	5.95	*4.03*
CAR (-40, -1)	-2.58	*-8.56*	5.10	*3.81*
CAR (-30, -1)	-2.59	*-9.73*	4.02	*3.60*
CAR (-20, -1)	-2.28	*-10.71*	3.11	*3.37*
CAR (-10, -1)	-1.21	*-7.68*	1.32	*2.01*
AR (-1, 0)	-0.04	*-0.62*	-0.21	*-1.05*
AR (0, 1)	0.10	*1.80*	-0.07	*-0.37*
AR (-1, 1)	0.05	*0.60*	-0.29	*-1.10*
CAR (1, 10)	0.81	*5.43*	0.55	*0.99*
CAR (1, 20)	0.93	*4.63*	1.87	*2.07*
CAR (1, 30)	0.80	*3.29*	2.41	*2.41*
CAR (1, 40)	1.07	*3.76*	3.04	*2.62*
CAR (1, 50)	0.75	*2.37*	3.08	*2.19*
CAR (1, 60)	0.67	*1.92*	1.72	*1.12*

Earlier studies suggest that thin-trading may bias the results. To address this concern, we segregate long-term and short-term trading effects of thin-trading stocks from the non-thin-trading stocks. Table 6-3 presents results based on defining thin-trading the same way as Fidrmuc, Goergen, Renneboog (2006), where a thin-trading stock is one where the number of non-trading days during the sample period is above the median. Results based on active stock definition in Ding and Lau (2001)[56] are consistent with the findings presented in Table 6-3. The findings indicate that non-thin trading (more actively traded) stocks drive the results

[56] A stock is classified as 'active' if, on average, there are more than 10 trades per day during the 3 months before the first director trade, and 3 months after the last director trade.

reported in Table 6-2 for both long-term purchases and long-term sales. For short-term returns, while the non-thin trading stocks display the same price effect 4-days after director purchases (which coincides with the average announcement day), thin-trading stocks have significant price effects of 42 basis points the day following the purchase. A possible explanation is that thin-trading stocks are mainly held and traded by directors, thus by the end of the day, the market is able to notice the unusual increase in trading volume and speculate that directors are involved in the trade. This market speculation is reflected in the price the day after.

Table 6-3
Price Effects Surrounding Director Trades for Non-Thin-Trading and Thin Trading Stocks

This table reports results for price effects surrounding director trades. The sample of director trades is sourced from the ASX from 1 January 2005 to 31 December 2010, and is collected from Appendix 3Y's submitted to the ASX. Panel A presents long-term abnormal returns (using the All Ordinaries Index as the benchmark) from 60 days before the director's trade to 60 days after the trade. Panel B presents short-term abnormal returns, from 5 days before the director's trade to 5 days after the trade. Results are presented separately for non-thin-trading and thin-trading stocks. Mean abnormal returns and associated *t*-statistics are reported separately for purchases and sales.

	Non Thin-Trading Stocks				Thin-Trading Stocks			
	Purchases		Sales		Purchases		Sales	
	Mean Return (%)	*t*-statistic	Mean Return (%)	*t*-statistic	Mean Return (%)	*t*-statistic	Mean Return (%)	*t*-statistic
Panel A: Long-term returns								
CAR (-60, -1)	-2.59	*-5.66*	9.44	*4.09*	-2.50	*-4.14*	3.50	*1.79*
CAR (-50, -1)	-2.31	*-5.48*	8.35	*4.15*	-2.82	*-5.07*	1.34	*0.74*
CAR (-40, -1)	-2.70	*-7.23*	7.46	*4.16*	-2.35	*-4.62*	0.57	*0.32*
CAR (-30, -1)	-2.72	*-8.22*	5.39	*3.53*	-2.36	*-5.24*	1.40	*1.00*
CAR (-20, -1)	-2.57	*-9.84*	4.20	*3.32*	-1.75	*-4.78*	1.02	*0.90*
CAR (-10, -1)	-1.59	*-8.41*	2.07	*2.35*	-0.51	*-1.82*	-0.10	*-0.12*
AR (-1, 0)	-0.05	*-0.81*	-0.07	*-0.29*	0.00	*-0.04*	-0.48	*-1.40*

Table 6-3 (Continued)

	Non Thin-Trading Stocks				Thin-Trading Stocks			
	Purchases		Sales		Purchases		Sales	
	Mean Return (%)	*t*-statistic	Mean Return (%)	*t*-statistic	Mean Return (%)	*t*-statistic	Mean Return (%)	*t*-statistic
Panel B: Short-term returns								
AR (0, 1)	-0.08	*-1.18*	-0.06	*-0.24*	0.42	*3.93*	-0.09	*-0.33*
AR (-1, 1)	-0.14	*-1.55*	-0.13	*-0.36*	0.37	*2.63*	-0.60	*-1.79*
CAR (1, 10)	0.86	*4.84*	1.27	*1.73*	0.71	*2.68*	-0.81	*-1.01*
CAR (1, 20)	1.25	*5.04*	3.26	*2.79*	0.37	*1.08*	-0.79	*-0.59*
CAR (1, 30)	1.42	*4.69*	3.88	*2.89*	-0.29	*-0.72*	-0.39	*-0.30*
CAR (1, 40)	1.68	*4.73*	3.83	*2.53*	-0.02	*-0.04*	1.52	*0.87*
CAR (1, 50)	1.53	*3.92*	3.58	*1.94*	-0.62	*-1.16*	2.13	*1.03*
CAR (1, 60)	1.86	*4.27*	1.97	*1.00*	-1.44	*-2.53*	1.24	*0.52*

Table 6-4 reports results partitioned by director trade value quartiles. The results indicate that in the long term, while purchases and sales are well timed in terms of buying at low prices across all size groups, only the top 50% of sales sell at high prices, and it is the top 50% of purchases that predict the post-trade returns. In the short term, only the largest purchases display the price effect approximately 4-days after the trade that is seen in the overall result. We also partition the results by director trade volume quartiles; the findings are consistent with Table 6-4. These findings imply that director's trade in large size when they have confidence in their superior knowledge. Smaller trades are more likely to be for reasons other than utilising the information to make a profit.

Table 6-5 reports price effect results, separated by purchases and sales, for the announcement analysis. Results in Panel A indicate that the market reacts to purchase announcements on the same day, and the effects are permanent information effects as evidenced by the significant abnormal returns to 5-days after the announcement. Sales fail to trigger any significant market reaction. When examining the day of the announcement, the intraday results reported in Panel B suggest that the market reacts to purchase announcements very rapidly, with the return to the quote immediately after the announcement significantly positive. We therefore do not reject $Hypothesis_{6,4}$. These significantly positive quote-to-quote returns continue to 5 quotes after the announcement, and to the close of trade. For sale announcements, there is no immediate price reaction. This asymmetry could be driven by potential buyers reacting more rapidly to the announcement compared to existing holders who are the only potential sellers.

Table 6-4
Price Effects Surrounding Director Trades Across Director Trade Value Quartiles

This table reports results for price effects surrounding director trades. The sample of director trades is sourced from the ASX from 1 January 2005 to 31 December 2010, and is collected from Appendix 3Y's submitted to the ASX. Panel results are presented separately for trade value quartiles. Mean abnormal returns and associated *t*-statistics are reported separately for purchases and sales.

	Purchases				Sales			
	Large (%)	Medium-Large (%)	Medium-Small (%)	Small (%)	Large (%)	Medium-Large (%)	Medium-Small (%)	Small (%)
CAR(-60, -1)	-2.63	-2.47	-2.42	-2.72	6.54	15.16	2.33	5.70
t-stats	*-3.38*	*-3.31*	*-3.40*	*-4.05*	*2.16*	*3.54*	*0.99*	*1.71*
CAR(-50, -1)	-2.59	-2.28	-2.33	-2.78	5.55	12.10	1.67	4.43
t-stats	*-3.60*	*-3.33*	*-3.51*	*-4.55*	*1.96*	*3.43*	*0.69*	*1.60*
CAR(-40, -1)	-2.96	-2.37	-2.37	-2.62	6.15	9.62	1.46	3.02
t-stats	*-4.48*	*-3.91*	*-4.05*	*-4.81*	*2.25*	*3.34*	*0.61*	*1.15*
CAR(-30, -1)	-2.99	-2.17	-2.68	-2.53	4.13	7.71	1.35	2.82
t-stats	*-5.16*	*-4.01*	*-5.14*	*-5.27*	*1.94*	*2.96*	*0.67*	*1.35*
CAR(-20, -1)	-2.85	-2.00	-2.37	-1.87	2.58	5.37	1.74	2.76
t-stats	*-6.40*	*-4.65*	*-5.67*	*-4.62*	*1.38*	*2.64*	*1.00*	*1.62*
CAR(-10, -1)	-1.53	-1.01	-1.03	-1.28	0.65	3.17	1.49	-0.11
t-stats	*-4.50*	*-3.11*	*-3.36*	*-4.52*	*0.58*	*2.41*	*1.05*	*-0.08*
AR (-1, 0)	0.07	0.11	-0.20	-0.13	0.37	-0.36	-0.52	-0.35
t-stats	*0.59*	*0.98*	*-1.77*	*-1.06*	*0.98*	*-0.84*	*-1.39*	*-0.78*

Table 6-4 (Continued)

	Purchases				Sales			
	Large (%)	Medium-Large (%)	Medium-Small (%)	Small (%)	Large (%)	Medium-Large (%)	Medium-Small (%)	Small (%)
AR (0, 1)	0.13	-0.08	0.15	0.22	-0.32	0.10	-0.13	0.10
t-stats	*1.12*	*-0.71*	*1.41*	*1.81*	*-0.86*	*0.23*	*-0.50*	*0.22*
AR (-1, 1)	0.18	0.02	-0.07	0.06	0.06	-0.29	-0.66	-0.27
t-stats	*1.16*	*0.10*	*-0.46*	*0.40*	*0.11*	*-0.56*	*-1.55*	*-0.46*
CAR(1, 10)	1.52	0.62	0.56	0.52	1.16	0.92	-0.20	0.34
t-stats	*5.07*	*2.02*	*1.93*	*1.80*	*1.06*	*0.85*	*-0.21*	*0.24*
CAR(1, 20)	1.87	0.97	0.32	0.56	1.48	1.79	1.00	3.40
t-stats	*4.53*	*2.32*	*0.82*	*1.47*	*0.98*	*1.17*	*0.55*	*1.44*
CAR(1, 30)	1.09	1.14	0.45	0.53	1.62	1.06	3.70	3.31
t-stats	*2.19*	*2.23*	*0.94*	*1.15*	*0.98*	*0.51*	*1.88*	*1.40*
CAR(1, 40)	1.37	1.39	0.51	1.01	0.99	1.19	5.27	4.80
t-stats	*2.31*	*2.38*	*0.93*	*1.86*	*0.57*	*0.51*	*1.97*	*1.97*
CAR(1, 50)	1.33	1.70	-0.46	0.46	0.40	2.26	4.37	5.54
t-stats	*2.01*	*2.68*	*-0.72*	*0.78*	*0.18*	*0.73*	*1.52*	*1.83*
CAR(1, 60)	1.87	1.43	-0.53	-0.11	-1.59	0.11	3.54	5.14
t-stats	*2.59*	*2.06*	*-0.77*	*-0.17*	*-0.68*	*0.03*	*1.11*	*1.52*

Table 6-5
Price Effects Surrounding Director Trade Announcements

This table reports results for price effects around the day of director trade announcements, as well as the intraday effects on the announcement day. The sample of director trades and announcements is sourced from the ASX from 1 January 2005 to 31 December 2010, and is collected from Appendix 3Y's submitted to the ASX. Daily abnormal returns are calculated using daily close price with the All Ordinaries Index as the benchmark. Intraday returns are quote-to-quote returns calculated from the prevailing bid-ask midpoint at the time the announcement is released, to the 5 quotes after the announcement release, as well as to the close of trading. Mean returns and associated *t*-statistics are reported separately for purchases and sales.

	Purchases		Sales	
	Mean Return (%)	*t*-statistic	Mean Return (%)	*t*-statistic
Panel A: Average CARs surrounding Announcement Day				
(-5, -1)	0.02	*1.01*	0.15	*2.16*
(-4, -1)	0.07	*1.95*	0.18	*2.41*
(-3, -1)	0.11	*1.80*	0.25	*2.07*
(-2, -1)	0.12	*1.25*	0.34	*1.62*
(-1, 0)	0.64	*6.84*	-0.20	*-1.16*
(0, 1)	0.28	*3.45*	-0.01	*-0.07*
(0, 2)	0.23	*3.76*	0.01	*0.04*
(0, 3)	0.12	*3.90*	0.02	*0.23*
(0, 4)	0.08	*4.12*	0.03	*0.80*
(0, 5)	0.21	*1.11*	-0.04	*-0.91*
Panel B: Intra-day analysis				
(0, 1)	0.13	*2.80*	0.05	*1.59*
(0, 2)	0.20	*3.39*	0.07	*1.58*
(0, 3)	0.19	*3.23*	-0.04	*-0.78*
(0, 4)	0.24	*3.57*	-0.07	*-1.26*
(0, 5)	0.26	*4.06*	-0.07	*-1.35*
(0, close)	0.58	*7.94*	-0.23	*-2.42*

Table 6-6 further partitions the announcement effects by whether the announcement contains a 'surprise' factor. An announcement with 'surprise' is one where the prevailing bid-ask midpoint is lower than the director purchase price, or where the prevailing bid-ask midpoint is higher than the director sale price, i.e., where the market has moved in the ‘wrong’ direction since the director trade. Results indicate that if the price at announcement is lower than the directors purchase price, the market reacts rapidly, with significant returns from the subsequent quote to the close of trading. If the price at announcement is higher than the directors purchase price, the market will not ‘jump’ into action at the information, and there is no immediate price reaction. However, returns to the close of trading are still weakly significantly positive, implying that the market acknowledges that purchase announcements contain information.

For sales, if the price at announcement is higher than the director’s sale price, there are significant negative returns to the close of trade, while there are no significant price reactions when the price at announcement is lower than the director’s sale price. The results in Table 6-6 suggest that results in Table 6-5 are predominantly driven by announcements that contain a ‘surprise’ factor. As a robustness test, we also classify the announcements with ‘surprise’ as purchase announcements where the prevailing bid-ask midpoints are 3% (5%) higher than the director’s trade price, or sale announcements where the prevailing bid-ask midpoints are 3% (5%) lower than the director’s trade price. In both cases the results in Table 6-6 hold. These findings suggest that Hypothesis$_{6,2}$ is not rejected.

Table 6-6
Director Trade Announcements Intraday Price Effects Separated by 'Surprise' Factor

This table reports results for price effects surrounding director trade announcements. The sample of director trades and announcements is sourced from the ASX from 1 January 2005 to 31 December 2010, and is collected from Appendix 3Y's submitted to the ASX. Quote-to-quote returns are calculated from the prevailing bid-ask midpoint at the time the announcement is released, to the 5 quotes after the announcement release, as well as to the close of trading. Panel A presents results for price effects at announcement with 'surprise'; Panel B presents results for prices effects at announcement without 'surprise'. An announcement with 'surprise' is one where the prevailing bid-ask midpoint is lower than the director purchase price, or where the prevailing bid-ask midpoint is higher than the director sale price. Mean returns and associated *t*-statistics are reported separately for purchases and sales.

	Purchase		Sales	
	Mean Return (%)	*t*-statistic	Mean Return (%)	*t*-statistic
Panel A: Announcements with 'Surprise'				
(0, 1)	0.33	*3.99*	0.04	*1.07*
(0, 2)	0.46	*4.52*	0.02	*0.35*
(0, 3)	0.47	*4.68*	-0.07	*-1.14*
(0, 4)	0.52	*4.70*	-0.09	*-1.12*
(0, 5)	0.52	*4.55*	-0.09	*-1.33*
(0, close)	1.01	*9.06*	-0.37	*3.70*
Panel B: Announcements without 'Surprise'				
(0, 1)	-0.06	*-1.16*	0.07	*1.18*
(0, 2)	-0.05	*-0.78*	0.14	*1.76*
(0, 3)	-0.07	*-1.02*	-0.01	*-0.08*
(0, 4)	-0.02	*-0.29*	-0.05	*-0.67*
(0, 5)	0.01	*0.20*	-0.04	*-0.57*
(0, close)	0.18	*1.90*	-0.06	*-0.37*

Table 6-7 reports announcement effects partitioned by thin-trading following the classification method in Fidrmuc, Goregen and Renneboog (2006). While director purchases from both categories exhibit significant price reactions, the thin-trading stocks experience larger positive returns. For sales, only non-thin trading stocks exhibit significant price effects by the close of trade, implying that the market is not as sensitive to sale announcements as to purchase announcements, and only the non-thin trading stocks are active enough to have intraday price effects. Different methods[57] are used to group the stocks into active and non-active stocks as a robustness test. The results are consistent with the findings in Table 6-7.

Table 6-7
Price Effects Surrounding Director Trade Announcements for Stocks with and without Thin-trading

This table reports results for price effects surrounding director trade announcements. The sample of director trades and announcements is sourced from the ASX from 1 January 2005 to 31 December 2010, and is collected from Appendix 3Y's submitted to the ASX. Quote-to-quote returns are calculated from the prevailing bid-ask midpoint at the time the announcement is released, to the 5 quotes after the announcement release, as well as to the close of trading. Panel A presents results for stocks without thin trading; Panel B presents results for thin-trading stocks. Mean returns and associated *t*-statistics are reported separately for purchases and sales.

	Purchases		Sales	
	Mean Return (%)	*t*-statistic	Mean Return (%)	*t*-statistic
Panel A: Stocks without thin-trading				
(0, 1)	0.09	*2.02*	0.04	*2.08*
(0, 2)	0.11	*2.55*	0.04	*1.22*
(0, 3)	0.12	*2.44*	0.00	*0.05*
(0, 4)	0.12	*2.51*	-0.04	*-1.11*
(0, 5)	0.14	*2.80*	-0.04	*-1.23*
(0, close)	0.42	*6.21*	-0.23	*-2.45*
Panel B: Stocks with thin-trading				
(0, 1)	0.20	*2.05*	0.10	*0.86*
(0, 2)	0.35	*2.49*	0.17	*1.04*
(0, 3)	0.34	*2.30*	-0.22	*-0.98*
(0, 4)	0.50	*2.70*	-0.20	*-0.86*
(0, 5)	0.53	*3.04*	-0.20	*-0.92*
(0, close)	0.81	*5.37*	-0.28	*-1.16*

Table 6-8 presents announcement results partitioned by trade direction and trade value quartiles. Purchases experience consistency in terms of return magnitude and statistical significance across different trade size groups, except for the smallest group. Sales do not experience significant price effects when they are divided into different size groups, except

[57] Ding and Lau (2001).

that the medium-small group has the largest and most statistically significant negative return by close of trading. It appears that the announcement effects for sales are driven by this quartile. The results suggest that small trades are ignored by the market when the information is released. As with the trade analysis, we re-estimate the analysis by using trade volume quartiles, with the results consistent with results in Table 6-8, both in terms of return magnitude and statistical significance.

Determinant regression results are presented in Table 6-9. For purchases, if the announcement contains a surprise factor, i.e., if the prevailing market price at the time of announcement is lower than the director's purchase, the positive return is increased by 0.39% and 0.74% to the next quote and the close of trading, respectively. When returns are calculated to the close of trading, more actively traded stocks have significantly smaller returns as evidenced by the negative parameter for *LogDTN*; this is consistent with the findings in Table 6-7. Firms in the Materials industry sector experience returns 0.33% greater than other firms; this can be explained by the unique feature of mining companies, whose share prices are largely dependent on exploration outcomes and whose directors are perceived to know more than what is released to the market. The parameter for *LogDelay* is not significant, which implies that longer delays do not necessarily lead to information becoming less valuable; this is consistent which other findings that the announcement is the first source for the information of director trading. Trade size and the number of directors in the report do not appear to have any impact on the price movements. Results for sales are generally not significant. Again, the market appears to ignore sale announcements.

Table 6-8
Price Effects Surrounding Director Trade Announcements Across Trade-Value Quartiles

This table reports results for price effects surrounding director trade announcements. The sample of director trades and announcements is sourced from the ASX from 1 January 2005 to 31 December 2010, and is collected from Appendix 3Y's submitted to the ASX. Quote-to-quote returns are calculated from the prevailing bid-ask midpoint at the time the announcement is released, to the 5 quotes after the announcement release, as well as to the close of trading. Panel A presents results for large trades; Panel B for medium-large trades; Panel C for medium-small trades; Panel D for small trades. Mean returns and associated *t*-statistics are reported separately for purchases and sales.

	Purchases		Sales	
	Mean Return (%)	*t*-statistic	Mean Return (%)	*t*-statistic
Panel A: Large trades				
(0, 1)	0.10	*3.15*	0.06	*1.37*
(0, 2)	0.27	*2.93*	0.08	*1.04*
(0, 3)	0.27	*2.78*	0.05	*0.57*
(0, 4)	0.29	*2.82*	0.03	*0.36*
(0, 5)	0.32	*2.96*	-0.02	*-0.36*
(0, close)	0.51	*5.27*	-0.20	*-1.10*
Panel B: Medium-large trades				
(0, 1)	0.16	*1.80*	0.03	*0.84*
(0, 2)	0.18	*1.83*	0.14	*1.81*
(0, 3)	0.16	*1.49*	0.09	*1.02*
(0, 4)	0.31	*2.29*	0.04	*0.47*
(0, 5)	0.29	*2.34*	0.05	*0.64*
(0, close)	0.64	*4.78*	-0.15	*-0.89*
Panel C: Medium-small trades				
(0, 1)	0.26	*1.98*	0.05	*1.09*
(0, 2)	0.36	*2.57*	-0.03	*-0.39*
(0, 3)	0.30	*2.50*	-0.08	*-0.85*
(0, 4)	0.29	*2.20*	-0.20	*-1.55*
(0, 5)	0.28	*1.99*	-0.12	*-1.05*
(0, close)	0.89	*5.44*	-0.50	*-3.38*
Panel D: Small trades				
(0, 1)	0.02	*0.23*	0.06	*0.54*
(0, 2)	-0.03	*-0.22*	0.07	*0.59*
(0, 3)	0.03	*0.16*	-0.30	*-1.71*
(0, 4)	0.07	*0.36*	-0.20	*-1.41*
(0, 5)	0.14	*0.90*	-0.25	*-1.70*
(0, close)	0.28	*1.60*	-0.09	*-0.38*

Table 6-9
Regression Results Surrounding Director Trade Announcements

This table reports regression results for price effects surrounding director trade announcements. The sample of director trades and announcements is sourced from the ASX from 1 January 2005 to 31 December 2010, and is collected from Appendix 3Y's submitted to the ASX. The following regression is estimated

$$R = \alpha + \beta LogDTN + \gamma Materials + \delta Surprise + \rho Multiple + \varphi LogDelay + \nu LogValue$$

where R is return from the prevailing bid-ask midpoint at the time of the announcement to either (i) the following quote midpoint, or (ii) closing quote midpoint; *LogDTN* is the natural logarithm of the daily number of trades, calculated as the total number of trades in the stock over the sample period divided by the number of trading days during that period; *Materials* takes the value of 1 if the company's industry sector is Materials according to its GICS classification, zero otherwise (companies in this sector comprise approximately 32% of all observations in the sample); *Surprise* takes the value of 1 if the announcement is defined as one with surprise, zero otherwise; *Multiple* takes the value of 1 if there is more than one director trading in the same direction for the same announcement, zero otherwise; *LogDelay* is the natural logarithm of the number of days between the trading date and the date the information is announced on the ASX website; *LogValue* is the natural logarithm of the director trade value. Parameter estimates and associated *t*-statistics are reported separately for purchases (Panel A) and sales (Panel B).

	Return (0, 1)		Return (0, close)	
	Parameter Estimate	*t*-statistic	Parameter Estimate	*t*-statistic
Panel A: Purchases				
Intercept	-0.07	*-0.21*	0.09	*0.19*
LogDTN	-0.04	*-1.30*	-0.13	*-3.34*
Materials	0.01	*0.08*	0.33	*1.97*
Surprise	0.39	*3.69*	0.74	*4.63*
Multiple	-0.05	*-0.31*	-0.03	*-0.13*
LogDelay	-0.08	*-1.34*	-0.15	*-1.74*
LogValue	0.02	*0.72*	0.06	*1.38*
Panel B: Sales				
Intercept	-0.15	*-0.77*	-0.03	*-0.05*
LogDTN	-0.02	*-1.38*	0.04	*0.76*
Materials	0.00	*0.03*	0.12	*0.57*
Surprise	-0.05	*-0.83*	-0.29	*-1.48*
Multiple	0.07	*0.48*	0.22	*0.54*
LogDelay	0.06	*1.61*	0.06	*0.59*
LogValue	0.02	*1.22*	-0.03	*-0.64*

Regression results on occurrence of trade/announcement are reported in Table 6-10. Results in Panel A suggest that the occurrence of a director trade does not explain daily abnormal returns, which indicates that the information effect does not occur at the time of the trade. Results in Panel B, however, show that director trade announcements, particularly purchase announcements, explain daily abnormal returns, as evidenced by the high *F*-statistics and *t*-statistics. Results in Table 6-10 suggest that using data of a lower frequency, imprecise event time and/or from mixed market structures may lead to biased results for the trade effects and announcement effects analysis.

Table 6-10
Regression on Occurrence of Director Trade/Director Trade Announcement

This table reports regression results of occurrence of director trade/director trade announcement. The sample of director trades and announcements is sourced from the ASX from 1 January 2005 to 31 December 2010, and is collected from Appendix 3Y's submitted to the ASX. The following regressions are estimated:

$$AR = \alpha + \beta\ BuyTrade + \gamma\ SaleTrade$$
$$AR = \alpha + \beta\ BuyA + \gamma\ SaleA$$

where *AR* is calculated using daily close price with the All Ordinaries Index as the benchmark. *BuyTrade* takes value of 1 when there is a director purchase on the day, 0 otherwise; *SaleTrade* takes value of 1 when there is a director sale on the day, 0 otherwise. For the second regression, *BuyA* takes value of 1 when there is an announcement where the net amount is a purchase on the day, 0 otherwise, *SaleA* takes value of 1 when there is an announcement where the net amount is a sale on the day, and 0 otherwise. Parameter estimates and associated *t*-statistics are reported separately for trade (Panel A) and announcement (Panel B).

	Parameter Estimate	*t*-statistics
Panel A: Regression on Occurrence of Trade		
Intercept	0.02	*6.17*
BuyTrade	-0.06	*-0.96*
SaleTrade	-0.20	*-0.80*
F-Value	*0.78*	
Panel B: Regression on Occurrence of Announcement		
Intercept	0.02	*5.52*
BuyA	0.61	*11.58*
SaleA	-0.24	*-1.72*
F-Value	*68.51*	

6.5 Summary

This study examines the price behaviour surrounding both director trades, and associated market announcements, for the Australian market. Using a sample of director trades executed between 2005 and 2010, we find that over longer time periods of 120 trading days, director purchases are associated with significantly negative returns before the trade, and significantly positive returns after the trade. Sales are not associated with significant price movements after the trade. However, directors are able to sell at prices sufficiently close to the highest level over the 120 day trading period, and thus realise maximum profit by selling at the 'optimal' time. Larger trade size reflects director's greater confidence in their superior information. This is strong evidence that directors exhibit significant market timing, executing both their purchases and sales and adjusting their trade size to make significant abnormal profits. Directors in companies stocks that are actively traded do especially well. These findings provide indirect evidence that insiders are not victims of behavioural biases when they have superior information – they trade at the right time, not buying or selling too early or too late, as in the disposition effect.

The results also support that the market believes that directors' purchases contain information and the market reacts to the knowledge of director purchases. Announcements of director purchases have immediate and significant price impact, especially when the announcements relate to trades with possible information not already incorporated in the price (i.e., the price at the time of announcement is lower than the directors trade price). The market does not react significantly to the announcement of directors disposing of shares; however, if the announcement contains some 'surprise' component (i.e., the price at the time of announcement is higher than the directors trade price), there is some evidence of a negative price reaction to the close of trading. Announcements of director purchasing of thin trading stocks attract greater market attention and reaction.

Regression analysis suggests that price movements between the director's trade and subsequent announcement are the most important factor in determining the announcement effects. Speed of announcement has no significant impact on announcement returns, implying information leakage between trade and announcement, if any, is at a minimum. More actively traded stocks are likely to experience smaller price movements. Prices increase even more if the purchase in the announcement is in a mining stock.

The overall results also suggest that price discovery occurs at the ASX announcement time rather than the trading time. Further analysis reveals that price discovery happens very soon after the announcement is released; within a matter of seconds for director purchase announcements. Therefore, in reality it is extremely difficult for retail investors to act fast enough to take advantage of the price movement after director trading investment. Retail investors who blindly follow all director trades are effectively engaging in nothing but herding behaviour.

Current ASX requirements for reporting director trading are well justified and the purposes well served. We find that overall companies are in line with the 5-day time frame, which is efficient in current Australian market conditions. We conclude that in the Australian market, director trading helps price discovery, which happens at the time of the ASX announcement.

Chapter 7 Conclusions

This dissertation analyses stock market trading behaviour of retail investors. The importance of this subject is highlighted by the increasing participation of individual traders in equity markets. The behaviour of these investors not only affect their own wealth, but also on an aggregated level, have impact on market stability, price discovery and liquidity. Therefore, a better understanding of retail investor's behaviour and causes of certain behavioural patterns is relevant to both practitioners and academics. Behavioural finance studies, which acknowledge and investigate biases rather than taking the approach of traditional finance's unconditioned rationality assumptions, have revealed many interesting aspects of investor behaviour. A literature review in Chapter 2 summarises the studies in this area and identifies a number of gaps in the existing literature.

Traditional finance theories assume that investors are rational, risk averse and make decision with the sole aim of maximising their final wealth position. These theories are found to not adequately represent phenomena in financial markets. Behavioural finance research observes that investors make decisions that are financially negative to avoid loss, chase small chances of success and seek risk. A few behavioural biases have been documented; these include the disposition effect, gambling in the stock market and the house money effect. In this dissertation, rich proprietary data sets are employed in the examination of the concerned biases. In addition, improvements on the methodologies used are made in the analysis of these biases.

Chapter 3 focuses on the behavioural bias known as the disposition effect. This loss aversion behaviour is considered one of the most robust facts about the trading of individual investors.

However, existing studies use either certain investment types, or small investor samples, in the analysis of this bias, which largely restricts the conclusion of the findings. Further, an important factor in behavioural analysis, cultural background, has not been considered in the studies of the disposition effect. In Chapter 3, a large sample of investors on the Australian Securities Exchanges is examined for their investment in all common shares. In addition, a novel approach is employed to investigate the influence of cultural heritage. Using a surname list that has been tested in medical studies to accurately identify people with a Chinese ancestry, we are able to flag Chinese investors in a multi-cultural stock market. Findings in Chapter 3 provide strong evidence of the prevalence of the disposition effect across all investor groups. At the same time, we recognise this bias is more distinct among investors with certain characteristics. Being female, Chinese, less sophisticated or older all increase the likelihood of the disposition effect.

Although higher risk can lead to more loss, and investors are loss averse as we find in Chapter 3, risk seeking can exist at the same time as loss aversion. In Chapter 4 we focus on gambling behaviour in the stock market. As part of the analysis, the stocks investors gamble with, lottery stocks, are examined. Two different definitions of lottery stocks in the literature are improved, using both actual rather than inferred data, and a more precise methodology. The different definitions do not lead to varied findings; lottery stocks underperform regardless of the definition used. Further, investors who allocate a heavy weight to lottery stock investment suffer from lower returns compared to other investors. Two possibilities are considered for why investors choose lottery stocks; they may do so because they have a preference to gamble, or, they may have over-estimated their ability to choose the right stock at the right time, i.e. they may be over-confident. Further investigation into this reveals that it is the preference to gamble that drives the decision to invest in lottery stocks.

Analysis in Chapter 4 also provides evidence that not only does gambling preference differ between people, but also for the same person, it can vary with and without specific triggers. Specifically, prior outcomes appear to affect financial decision making. When investors achieve a portfolio gain, they are more likely to gamble with lottery stocks, and this is most pronounced among those who normally avoid gambling. The findings in Chapter 4 support the theory of the house money effect. Although literature on the house money effect is rich, existing studies using stock market data have only considered the case where realised gains are the ‘house money’. The use of realised gains poses several issues including reduced sample size, biased results and effects that cannot be separated from another driver – regret for not having made a larger gain. The results in Chapter 4 avoid these issues, and thus contribute to the literature by providing evidence of the house money effect with portfolio gains.

Having examined the biases using Australian data in Chapters 3 and 4, in Chapter 5 we use 20 years of stock and investor data from Finland to find evidence that the observed biases are (i) prevalent over a long time horizon through different market conditions, and (ii) universal and not restricted to a particular market. In addition, with the aid of a long sample period, we are able to investigate several new areas.

First, recent literature suggests that investors’ early life experience affects their investment behaviour and risk preferences. A comparison of the disposition effect in people born in different decades show that the generation investors belong to does make a difference in the level of loss aversion. Cross examination of age and birth time show that they both have an impact on investors’ tendency to gamble. While overall, younger people are more likely to gamble compared to older investors, investors born in the 1970s are found to have a higher holding weight of lottery stocks.

Second, 20 years of data enable the investigation of the impact of changes in macroeconomic conditions on investor behaviour, and the joint effect of these exogenous factors and investor endogenous factors. For example, while an increase in the unemployment rate reduces aggregated loss aversion among investors, possibly because of the reduced ‘affordability’ of such a bias, it increases the tendency for stock market gambling. While the disposition effect is not influenced by current market returns (this is another example of this bias being robust among investors), gambling with lottery stocks is reduced when the overall market is increasing.

Having examined the trading behaviour of retail investors across two different markets, in Chapter 6 we investigate a special group of individual investors, company directors trading their own companies’ shares. This group is of interest because as individuals, they are just as prone to behavioural bias as other investors are; however, because they are facilitated with superior information that reduces, or possibly eliminates the uncertainty of their investment outcomes, they are different from the rest of the market. Therefore, if in trading their own companies’ shares, this special group of individuals exhibit judgements and decisions that are not flawed by biases that are prevalent among retail investors, it will possibly be the result of information privilege.

Further, the study of director trading is interesting because by observing the price movements around trading and announcement releases, we can have a better understanding of how other investors react to insiders’ trading, and whether they can be rewarded by following these trades. The examination of price movements around both director trading and information announcement reveals that directors trade with good timing that enables them to earn superior returns. On the other hand, other retail investors are generally unable to profit in practice by piggybacking on directors' trades because price discovery occurs in a matter of seconds (or less) for frequently traded stocks.

In addition to addressing the matters as summarised above, this dissertation also suggests several potential future research avenues. The study of the disposition effect shows that investors engage in loss selling for tax purposes. In this case, stocks that have been depreciating should have an increased sales supply in the market which shall drive the price further down, possibly to below their 'true' values. It would be interesting to see who are buying these losers at the end of financial year, and how their investments perform in subsequent periods. In terms of the house money effect in Chapter 4, portfolio paper gains are used in the examination of the house money effect, because the use of realised gains cannot differentiate the effect of house money and the effect of regret for not having held the winners longer. An investigation of which of these two effects drives the increased risk seeking following realised gains will provide further insight into investors risk preference. These research topics are left for future work.

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