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Title Sheet

**LOCAL FUTURES TRADERS AND BEHAVIOURAL BIASES:
EVIDENCE FROM AUSTRALIA**

A thesis submitted in partial fulfilment of the
requirements for the award of the degree

DOCTOR OF PHILOSOPHY

from

UNIVERSITY OF WOLLONGONG

by

JOEL GRANT

**SCHOOL OF ACCOUNTING AND FINANCE
2007**

Thesis Certification

CERTIFICATION

I, Joel Grant, declare that this thesis, submitted in partial fulfilment of the requirements for the award of Doctor of Philosophy, in the School of Accounting and Finance, University of Wollongong, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications at any other academic institution.

Joel Grant

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Preface

Chapter 3 of this thesis entitled, “The House Money Effect and Local Traders at the Sydney Futures Exchange” has been accepted for publication in the Pacific-Basin Finance Journal, special edition on behavioural finance. It will be published in 2008.

Abstract

There is a large growing body of literature in finance highlighting anomalies in the behaviour of individual investors, which violate the axioms of rationality. However, much of the research draws upon the experimental findings of cognitive psychologists for explanations of these anomalies. One of the key motivating issues behind this thesis is to determine whether professional (“local”) traders exhibit psychological biases in their trading behaviour in the context of a real financial market setting. This research uses real-world trading data and includes every trade in share price index (SPI) futures contract placed by a local trader at the Sydney Futures Exchange (SFE) over the sample period 24 July, 1997 – 4 October, 1999. This approach is applied in three separate papers.

“The House Money Effect and Local Traders at the Sydney Futures Exchange”, analyses whether professional traders behave in a manner that is consistent with the house money effect or other behavioural phenomenon, in particular loss aversion. Existing work suggests that professional traders exhibit psychological inconsistencies in their trading behaviour (Coval and Shumway, 2005; Locke and Mann, 2004, 2005; Frino et al., 2004). This paper models afternoon risk on morning profit and morning losses, respectively. The results provide strong evidence of the house money effect. In particular, morning profits encourage local traders to increase their risk-taking attitudes in afternoon trading sessions.

“Trading Horizons and Behavioural Biases: Does Time Matter?”, analyses whether locals exhibit behaviour biases, such as the house money effect or loss aversion, over various trading horizons. Results reported in previous studies are mixed. Coval and Shumway (2005) find no evidence of abnormal trading behaviour across days, amongst proprietary traders at the Chicago Board of Trade (CBOT), while Locke and Mann (2004) provide substantial evidence of loss aversion across days, amongst floor traders at the Chicago Mercantile Exchange (CME). Results from this research report strong evidence of the house money effect. However, this bias is only evident

when locals evaluate their performance at high-frequency time intervals within intraday-trading cycles.

“Professional Futures Traders, Profits and Prices” analyses whether the behavioural biases of local traders affect prices. Work in this particular area is limited. Coval and Shumway (2005) report that proprietary traders at the Chicago Board of Trade (CBOT) behave in a manner that is consistent with loss aversion. Moreover, their results show that this behaviour impacts on short-term prices but has no longer-term impact. This research documents a similar finding, however, morning profits encourage local traders to buy contracts at higher prices and sell contracts at lower prices in the afternoon. This behaviour can be used to explain short-term afternoon price movements of one, two and three units, respectively. Results show that prices revert to earlier levels in the five-minute period following a price-setting trade, negating any permanent price impact.

Acknowledgements

Although personally, I have invested many years of dedication and commitment into this thesis so too have many others. First and foremost, to my supervisors, Professor David Johnstone and Professor Andrew Worthington for your invaluable support and words of wisdom throughout this process, I thank you sincerely. Also, to Joshua Coval, who patiently responded to my many e-mails concerning clarification on methodologies, thank you so much and to the Securities Industry Research Centre of Asia-Pacific for providing the data.

To my colleagues and fellow students at the University of Wollongong, thank you for the advice and support you provided during the five years of my candidature – Sandra Chapple, Robert Wixted, Robert Williams and Michael McCrae, in particular. Among my fellow students, I would particularly like to thank Zaffar Subedar and Andrew Lepone, with whom I have had the pleasure of sharing the PhD experience. I have become great friends with you during this time and think that we have all benefited from the friendship and roundtable discussions over many lunches together. Also a special thank you to Lyndon Ang for programming assistance in SAS.

Last but not least, to my family who have been my real backbone throughout this journey I honestly could not have accomplished this without you all. The love, support and encouragement you have provided is second to none and just one of the reasons why I love you all so much. This award is as much yours as it is mine.

Chapter 1 : Introduction

“Only two things are infinite, the universe and human stupidity, and I’m not sure about the former”, Albert Einstein.

This thesis focuses on the trading behaviour of professional (“local”) traders trading share price index (SPI) futures contracts at the Sydney Futures Exchange (SFE). Using real-world trading data and methods from the existing market-microstructure literature this thesis contributes to the area of behavioural finance and its application to individual investor behaviour.

One of the key motivating issues behind this work is that investor behaviour cannot be easily explained in the traditional framework. French and Poterba (1991) and Tesar and Werner (1995) document that individual investors prefer to invest in their domestic stock market, exhibiting a home bias, despite the benefits of diversifying internationally as proposed by traditional finance theory. Moreover, investors trade too much as a result of overconfidence (Odean, 1998b; Barber and Odean, 2000; 2001, 2002), hold losing positions too long and sell winning positions prematurely, demonstrating a disposition effect (Shefrin and Statman, 1985; Locke and Mann, 2005) and prefer to purchase stocks that somewhat “grab” their attention (Seasholes and Wu, 2004; Barber and Odean, 2005).

The field of behavioural finance has flourished over recent years, largely in response to the “flaws” that have emerged in traditional finance. Researchers often turn to experimental evidence compiled by cognitive psychologists to assist in providing explanations of investor behaviour (Haigh and List, 2005; List and Haigh, 2005; see Barberis and Thaler, 2003 for a review). However, studies should include individuals in their daily occupations and use real-world trading data as opposed to laboratory-based experiments to understand behaviour more thoroughly (Hirshleifer, 2001). This point was further emphasised by Rubinstein (2001, p.5) in a debate with Richard Thaler on the topic of market rationality. He writes,

“if we discover asset prices exhibit reversals, surprise of surprises, the behaviouralists tell us this is due to the documented tendency of individuals to overreact to recent events. Of course that could be true, but to believe it requires that we extrapolate from studies of individual decision making done in narrow and restricted conditions to the more complex and subtle environment of the securities markets”.

The approach used in this thesis, to test for behavioural biases amongst local futures traders, is aimed at filling the gap between experimental psychology and behavioural modelling. Using real-world trading data provides the opportunity to examine actual trading behaviour in the context of a practical financial market setting and move beyond the experimental psychology literature.

The trading data contains information on every trade in the share price index (SPI) futures contract at the Sydney Futures Exchange during the sample period extending 24th July, 1997 – 4th October, 1999. There were two distinguishing characteristics of the Sydney Futures Exchange during this time. First, the share price index futures contract was floor traded. This meant that locals could also observe the trading behaviour of other market participants and be mindful of the profits or losses they endured. Second, in contrast to US futures market settings examined in previous research there was a lunch break between 12:30p.m. and 2:00p.m. The significance of a lunch break presented local traders with time to reflect, absorb and digest their morning’s performance before entering the afternoon, possibly mitigating any behavioural phenomena between the two trading sessions.

The advantage of using real-world trading data is that proxies for risk, as well as profit, can be calculated and tests can be performed to determine whether locals behave rationally, or alternatively, whether they exhibit psychological inconsistencies in their trading behaviour. This approach is applied in three papers.

“The House Money Effect and Local Traders at the Sydney Futures Exchange”, analyses whether local traders exhibit the house money effect or other psychological inconsistencies, particularly loss aversion, in their trading behaviour. Specifically, it models afternoon risk on morning gains and morning losses, respectively. The results document a strong behavioural bias amongst local traders that is consistent with the house money effect. That is, morning profits entice locals to reduce their tolerance

towards risk in afternoon trading sessions. Whether this bias is costly to traders is less clear. The results suggest that overconfidence produced by morning profits does assist traders in making more profits in the afternoon. However, there is a turning point, which suggests that those traders driven most strongly by the house money effect incur significant losses.

“Trading Horizons and Behavioural Biases: Does Time Matter?”, analyses whether local traders are susceptible to behavioural biases, particularly the house money effect or loss aversion, over varying trading horizons. This chapter asks three key questions. Firstly, can locals’ afternoon profit explain their risk taking behaviour in the subsequent morning trading session? Secondly, does the profit of locals in one intra-day trading cycle influence their risk taking behaviour in the subsequent trading cycle? Thirdly, can the profit earned by locals today be used to explain their tolerance towards risk on the subsequent trading day? The results provide strong evidence of the house money effect. However, this bias is evident only when traders evaluate their performance at high frequencies. Specifically, if local traders record a profit in a cycle, they are more likely to become risk seeking in the following trading cycle. Other performance proxies, such as profit per trade and inventory per trade, are also significant in explaining risk across cycles. Further results suggest that profits earned today, either over the entire day or just in the afternoon, have no impact on a traders risk attitude on the subsequent trading day, either over the entire day or solely in the morning.

“Professional Futures Traders, Profits and Prices”, analyses whether trading irrationalities of locals affect prices. Each trading day is initially split into a morning trading session and an afternoon trading session before tests are performed to determine if morning profits directly affect afternoon price volatility. Both short-term and longer-term afternoon price volatility is examined to establish whether profitable trading opportunities arise for other market participants as a result of the psychological inconsistencies of local futures traders. The results report strong evidence of irrational behaviour, consistent with the house money effect, which does impact upon prices. Specifically, locals are more willing to purchase contracts at higher prices and sell contracts at lower prices, following profitable mornings as opposed to losing mornings – locals are more likely to move prices as their morning

profits increase. However, there is insufficient evidence to suggest that this behaviour affects prices over the longer term. The results suggest that more informed traders are aware of the trading irrationality of locals, following morning profits and therefore have no hesitation in trading aggressively against them. This explains why prices revert over the longer-term following price-setting traders placed by locals and disseminates any possible arbitrage profits.

This thesis is structured as follows. Chapter 2 reviews the literature on the application of behavioural finance to individual investor behaviour. It discusses the fundamental building blocks of behavioural finance, namely limits to arbitrage and psychology and compares it to traditional finance. Chapter 3 covers the first paper aimed at analysing the trading behaviour of locals at the Sydney Futures Exchange, by treating gains and losses as separate psychological drivers. Chapter 4 describes the second paper aimed at determining whether local's trading horizons affect their behaviour. Chapter 5 presents the third paper, which tests whether the behaviour of local futures traders affects prices. Chapter 6 summarises the findings and concludes.

Chapter 2 : The Application of Behavioural finance to Individual Investor Behaviour

2.1 Introduction

The foundations of traditional financial theory evolve from neoclassical economics, whereby models assume all individuals are rational expected utility maximisers (Von-Neumann and Morgenstern, 1944). Rationality in this sense implies two things. First, agents update their beliefs with the arrival of new information according to Bayes' Law and second, make normative acceptable choices, given their beliefs, in conjunction with Savages' (1954) notion of subjective expected utility (SEU).

It would be satisfying to know that the predictions of the traditional paradigm be confirmed in the data, though this is not the case. Instead, the traditional framework has suffered enormous setbacks, especially over the last two decades with strong evidence suggesting that individuals are not completely rational (see Barberis and Thaler (2003) for a recent summary of this literature). The implications are that basic assumptions and prescriptions concerning financial markets and financial market practitioners cannot be sufficiently explained in line with the traditional finance approach.

In response to the conjectures faced by traditional finance theory, or at least in part, a relatively new approach to finance has emerged. Behavioural finance in broad terms asserts that it is easier to understand financial markets and financial market participants by adopting models in which individuals are not completely rational. Some agents fail to update their beliefs given new information, while others might adjust their beliefs sufficiently but make choices that are not normatively acceptable.

Relaxing one or both of the tenets that underlies rationality, behavioural finance forms new models aimed at providing a clearer understanding of the complex nature of financial markets and the behaviour of individual investors.

This chapter reviews recent work in the rapidly expanding field of behavioural finance. Section 2.2 reviews the literature on what is considered the most classic objection to behavioural finance, namely that even if behavioural models contain agents that are not all completely rational, the behaviour of rational agents will disallow any sustainment of price deviation from fundamental values through a process referred to as arbitrage. Conversely, one of the main successes of behavioural finance is the strong evidence that suggests even if rational and less than fully rational agents interact in financial markets, irrationality can affect prices to the extent that substantial mispricings exist for prolonged periods of time. This body of evidence is referred to as “limits to arbitrage” and forms one of the two building blocks of behavioural finance.

Section 2.3 reviews the literature on psychology, which forms the second building block of behavioural finance. The two parts of experimental research compiled by cognitive psychologist that are of interest to behavioural finance researchers are: 1. The biases that arise when people form their beliefs and 2. The biases on people’s preferences or how people make choices given their beliefs. Academics often turn to this evidence to assist in explaining the behaviour of individuals and to identify why it is people are irrational (that is, how they violate Bayes’ Law or deviate from SEU)¹.

The remainder of this chapter is organised as follows. Section 2.4 reviews the literature that is applicable to investor behaviour. Since this is the major focus of the thesis most space is devoted to this specific application of behavioural finance. Section 2.5 discusses the effect of prior outcomes on risky choice for individual investors in sequential decision making problems. This is highly important for the

¹ Shleifer and Summers (1990) originally proposed the idea of the two building blocks of behavioural finance, namely limits to arbitrage and psychology. This idea is now widely accepted amongst researchers in the field.

future development of asset pricing models. Section 2.6 provides a summary and concludes².

2.2 Limits to Arbitrage

Under the traditional finance paradigm markets are completely efficient, and the hypothesis that prices reflect their fundamental values is termed the Efficient Market Hypothesis (EMH). Traditional theory argues that if less than fully rational investors cause the dislocation of prices from their fundamental value, rational investors will view this as an opportunity to make a riskless profit and will amend the dislocation through a process known as arbitrage. Though long-standing and compelling, this argument has come under severe scrutiny in recent times.

The new and rapidly expanding field of behavioural finance argues that although the irrationality of investors can cause price dislocations from fundamental values the process of arbitrage is both limited and risky. One of the major successes of behavioural finance is a compilation of theoretical and real-world evidence on the risks and limitations involved with arbitrage positions.

This section provides a brief overview of the traditional approach to finance, namely the EMH and then discusses the theoretical risks involved with arbitrage positions. Extensive real-world evidence of the limitations to arbitrage, which acts as strong support for behavioural finance research is also provided.

² Recent surveys of behavioural finance literature that are most relevant to this thesis include Shleifer (2000), who provides an introduction to behavioural finance with primary attention given to the theoretical and empirical evidence of limits to arbitrage. This is covered in section 2.2. Hirshleifer (2001) focuses mainly on the application of behavioural finance to asset pricing. This is briefly summarised in section 2.5. Barberis and Thaler (2003) provide a comprehensive review of the most current research in the field and consider several applications of behavioural finance as well as areas of future research. The chapter adopts a structure similar to that of Barberis and Thaler (2003). However, here the entire focus is on the application of behavioural finance to individual investors. For further summaries of behavioural finance the reader should refer to Shefrin (2000), Ritter (2003), Daniel, Hirshleifer and Teoh (2002) and Vissing-Jorgensen (2004).

2.2.1 Traditional Finance Theory - Market Efficiency

According to Fama (1970, p.83) a market is considered to be efficient if, “prices always ‘fully reflect’ available information”. Put simply, prices are representative of their true fundamental values, which is the discounted summation of all future dividend payments. In an efficient market, prices are set by ‘fully’ rational agents making it impossible for any investment strategy to earn an excess return on a risk-adjusted basis. The traditional approach can be interpreted simply as:

“Prices are right” = “No free lunch”

If prices are right then investors are restricted to earn only what the market has to offer, that is, there is no free lunch for the taking. Equivalently, if investors can only earn what the market has to offer, that is, there is no free lunch up for grabs then prices must be right (Barberis and Thaler, 2003).

The traditional paradigm suggests that if less than fully rational investors (noise traders) cause prices to deviate from their true fundamental values then fully rational investors (arbitrageurs) will view this as an opportunity to make a riskless profit through a process known as arbitrage. The ‘quick-thinking’ action by arbitrageurs will then force prices back to their fundamental values (Fama, 1965; Ross, 2005).

This idea was first proposed by Friedman (1953). To illustrate his line of thinking consider the following example. Suppose that shares in the National Australia Bank (NAB) are currently trading at a price of \$30, which also represents the fundamental value. However, with no release of information noise traders begin to unload their shares in NAB and as a result the price falls to \$28. To profit from this scenario an arbitrageur would buy the NAB share at the current price of \$28 and hedge their exposure by short selling a close substitute share (a share that is highly correlated with the NAB), such as the Commonwealth Bank of Australia (CBA). The high demand for NAB shares by arbitrageurs then pushes the price back to \$30 resulting in a riskless profit of \$2.

Freidman's (1953) argument is compelling and has provided strong support for the traditional framework for many years. It can be summarised on the basis of two assertions. Firstly, when prices deviate from their fundamental values this lures investors into the market by providing them with an attractive investment opportunity and secondly, arbitrageurs will act swiftly to profit from the mispricing, their actions forcing prices back to fundamental levels.

Empirical evidence of market efficiency dates back to the event studies of Fama, Fisher, Jensen and Roll (1969) although the first to be published was by Ball and Brown (1968). In each of the event studies, the speed at which stock prices adjusted to the release of new information regarding stock splits and earnings announcements was analysed. The results of both provided strong evidence of market efficiency. Specifically, the market appeared to anticipate the release of new information with stock prices absorbing most of the information by the time of the announcement date and making rapid and accurate adjustments afterwards to incorporate any information that hadn't already been considered.

Recent empirical evidence supporting market efficiency is the noted inability of professional fund managers to outperform the market (Rubinstein, 2001)³.

2.2.2 Behavioural Finance Theory

The previous section provides a brief overview of market efficiency, describes how a rational agent (arbitrageur) could make a riskless profit when stock prices deviate from their fundamental values and also provides some empirical evidence in support of market efficiency. This section, describes the theoretical idea of arbitrage from a behavioural finance standpoint. In particular, the severe risks and limitations involved in the process are discussed.

³ Jensen (1968) was the first to analyse the performance of professional money managers. His study included 115 mutual funds that were analysed over the period 1955-64. The results indicate that professional money managers did not outperform the market, which provided strengthening support for market efficiency. The reader is referred to Fama (1991) for a summary of subsequent papers on the performance of professional money managers and institutional portfolio managers.

Behavioural finance disputes that when rational agents attempt to arbitrage from mispricings in the market the process is NOT entirely riskless. In actual fact, behavioural finance theory argues that there are severe risks and limitations involved with this process. To highlight the point, consider the palindrome statement previously used to describe an efficient market.

$$\boxed{\text{"Prices are right"} = \text{"No free lunch"}}$$

Behavioural finance agrees that if prices are right, there is no free lunch and no investors can earn in excess of what the market offers on a risk-adjusted basis. However, the theory of behavioural finance objects to the converse of this statement, which implies that if there is no free lunch, prices must be right. Instead,

$$\boxed{\text{"No free lunch"} \neq \text{"Prices are right"}}$$

If less than fully rational agents cause price dislocations from fundamental values, behavioural finance argues that strategies used to profit from the mispricings can be both risky and costly. Because of the risks and costs involved, investment opportunities arising from the mispricings might sometimes appear unattractive for investors. Depending on the level of unattractiveness, prices could remain dislocated from their fundamental values for prolonged periods of time. In light of Friedman's (1953) argument, behavioural finance only objects to his first assertion, namely that an attractive investment strategy for a rational agent will evolve from a mispricing in the market.

If the relationship between no free lunch and prices are right is broken, as suggested by behavioural finance theory, then a large body of empirical evidence supporting market efficiency becomes questionable. For example, if professional money managers and portfolio managers of mutual funds are unable to outperform (or 'beat') the market on a risk-adjusted basis, this evidence inevitably tells us nothing about market efficiency because prices simply, might not be right.

2.2.3 Theoretical Risks

The previous section mentions the severe risks involved with arbitrage positions and how this could lead to rendering investment strategies as both risky and costly, which could potentially cause prices to remain dislocated from fundamental values for long periods of time. This section introduces and discusses those aforementioned theoretical risks in more detail.

Fundamental Risk

Fundamental risk (Shleifer, 2000) is sometimes also referred to as substitutability risk (Wurgler and Zhuravskaya, 2002). It is the uncertainty that arises given the imperfect nature of the cash flows of two stocks. To illustrate the concept of fundamental risk, the reader should refer to the earlier example of arbitrage in section 2.2.1 above.

It was mentioned in that example, that rational agents would purchase NAB shares for \$28 and hedge their exposure by shorting a close substitute stock such as CBA⁴. This seems intuitively plausible since both stocks belong to the broader financial sector. Thus, if adverse news relating to the banking sector is released to the market both stocks should theoretically fall by approximately the same amount leaving the arbitrageur unscathed. However, if firm-specific information relating to the immediate future of NAB is released to the market then its share price could fall below \$28, while that of CBA remains unchanged creating a painful loss for the arbitrageur.

The idea of finding close or even perfect substitutes in the market presents a challenge in itself making it near impossible to completely remove fundamental risk (Roll, 1988; Wurgler and Zhuravskaya, 2002). Furthermore, even if a perfect substitute does exist there is the possibility that it too could be miss-priced.

Noise Trader Risk

When less than fully rational agents dislocate prices from their fundamental values, arbitrageurs also face noise trader risk. This is the risk that prices, once dislocated, will deviate even further from fundamental values simply because of the pessimistic

⁴ A perfect substitute would be a stock that has identical cash flows in all states of the world to the one that is being traded.

or optimistic outlook of noise traders. It seems plausible, that if less than fully rational investors can initially dislocate prices from their fundamental values then an arbitrageur should also consider the possibility of prices diverging further. This idea of noise trader risk was first proposed by De Long, Shleifer, Summers and Waldmann (1990a).

To illustrate their idea, suppose that in the earlier example of arbitrage, after the initial dislocation of the NAB share price, noise traders remain pessimistic about the future performance of NAB and therefore continue to unload their holdings. As a result, the intense selling pressure created by noise traders continues to push the price of NAB shares down from \$28 to \$25.

This poses as a severe problem for the arbitrageur because they would have purchased NAB shares for \$28 and shorted CBA shares for \$30 with the belief that the prices of the two stocks would converge. However, because the two stocks are close but not entirely perfect substitutes, the unwillingness of noise traders to hold NAB shares has led to a further decline in share price, while the price of CBA shares have remained unchanged. If the mispricing continues to worsen from the arbitrageur's perspective (that is, the prices diverge further) then they might be forced to liquidate their position leading to potentially large losses⁵.

Noise trader risk has also been studied by Shleifer and Vishny (1997) and more recently by Jackson (2003). Jackson's (2003) study not only provided evidence of noise trader risk but also found that it was being generated more by institutional investors than by individual investors. This result could also be evidence of institutional investors trading in the same direction as noise traders. To explain this logic further, consider a positive feedback economy as suggested by De Long, Shleifer, Summers and Waldmann (1990b), in which traders purchase more of a stock this period if it performed well last period. If this is the case then arbitrageurs, such as institutional investors, will sometimes trade in the same direction as noise traders rather than attempt to correct the mispricing by trading in the opposite direction.

⁵ An arbitrageur also faces the risk that the investor, who owns the stocks he has shorted, wants it back. If this situation arises and prices have diverged the arbitrageur will be forced to liquidate their position before the trade is complete, leading to potentially steep losses.

Arbitrageurs know that the previous price increase will attract more positive feedback traders next period pushing the price up (down) even further at which time they will exit and profit from the price increase (decrease). Since institutional investors generally invest more money than individual investors their behaviour can also have a greater impact on share prices, causing them to deviate from fundamental values.

Flynn's (2003) study of over 400 closed-end funds also provides strong evidence of noise trader risk. Surprisingly though, he found noise trader risk and Fama-French risk factors to be uncorrelated, which indicates noise trader risk is independent and therefore cannot be hedged. This finding provides valuable support for behavioural finance, in particular the risk that is involved with arbitrage positions.

If rational agents consider the possibility of prices deviating further from their fundamental values because of noise trader risk, they will initially perceive the process of arbitrage as being risky. In addition, if as Flynn's study indicates, noise trader risk cannot be eliminated through hedging, rational agents will view the process of arbitrage with more risk and possibly deter them from correcting mispricings.

Implementation Costs and Regulation

Implementation costs are the costs associated with performing transactions in the arbitrage process that make the position appear less attractive. Since arbitrage involves buying one asset and shorting another, transactions costs such as brokerage, bid-ask spread and price impact as well as the cost of shorting an asset and short sale constraints are all classified as implementation costs.

D'Avolio (2002) studied the magnitude of the borrowing fees associated with short sales and reported that they are generally low, ranging between 10 and 15 basis points, making it attractive for investors looking to arbitrage. However, there were instances in which the fees were very large, rendering short sales unattractive for investors and therefore limiting arbitrage possibilities.

Short sales can also be constrained. Firstly, if the investor who owns the stock is unwilling to lend it to another investor, then the short sale cannot take place. Secondly, some professional money managers and institutional investors are restricted

by regulatory bodies to use short sales as part of their investment strategies. Both of these constraints can create problems by limiting arbitrage opportunities and as a result mispricings in financial markets can persist (Jones and Lamont, 2002).

The time it takes to find and learn about a mispricing as well as the resources required to correct it are considered to be implementation costs also (Merton, 1987). Finding a miss-priced stock isn't a straightforward procedure. An investor must calculate a fundamental value, which involves discounting future cash flows back to the present. This poses as a problem in itself given that fluctuations in inflation and interest rates will impact the discount rate. If the discount rate implemented is higher than it should be then a stock could appear to have a lower fundamental value than it actually does, leading investors to believe that the stock is overvalued. Similarly, if investors apply a discount rate that is lower than it should be then a stock could appear to have a higher fundamental value than it actually does, leading investors to think that the stock is undervalued. Miss-interpretations of undervalued and overvalued stocks stemming from miss-calculations of their fundamental values make the process of finding a mispricing risky as well as time consuming.

Synchronisation Risk

Synchronisation risk, an idea proposed by Abreu and Brunnermeier (2002), is the idea that uncertainty arises because arbitrageurs attempt to pick the time when their peers will exploit a common exposed mispricing in the market. In contrast to noise trader risk, which stems from the trading activities of less than fully rational investors, synchronisation risks stems from the uncertainty of arbitrageur's regarding the timing decisions of other rational arbitrageurs. Therefore, if rational arbitrageurs attempt to time the correction of the mispricing then arbitrage can be limited and prices can remain dislocated from their fundamental values for long periods of time.

In contrast, to the traditional approach, real-world arbitrage entails both risks and costs, which under certain conditions can limit arbitrage and cause prices to remain dislocated from their fundamental values.

First, suppose that an arbitrageur is faced only with fundamental risk (that is, the risk that arises from not finding a perfect substitute to the stock that has deviated from its

fundamental value). There are two certain conditions that must hold to ensure arbitrage is limited: 1. All arbitrageurs must be risk averse. If this is true then the mispricing cannot be corrected by a single arbitrageur taking a large position in the under or over valued stock. 2. The fundamental risk is systematic, which implies that it cannot be diversified away by taking many such positions. If this is true then the mispricing cannot be corrected by many arbitrageurs each taking small positions in the under or over valued stock. The presence of noise trader risk, implementation costs and synchronisation risk will only limit arbitrage opportunities further and hence, allow mispricings to persist for longer.

Second, suppose that an arbitrageur has found a perfect substitute, which implies that there is no fundamental risk and that the only type of risk they face is that from noise traders. De Long et al. (1990a) report that even if a perfect substitute is found and there are no implementation costs and no other sources of risk, the effect of noise trader risk alone, can limit arbitrage opportunities altogether. Similar to above, there are two conditions that must hold for this to occur: 1. All arbitrageurs must be risk averse and have short horizons. As was previously discussed, this condition ensures that the mispricing cannot be corrected by a single arbitrageur. However, the extension of the first condition, that arbitrageurs must also have short horizons, is the central contribution of Shleifer and Vishny (1997). They report that given the real world relevance of arbitrage and the possibility that rational agents might be forced to liquidate their positions early, adhering to potentially steep losses, they must also have short horizons. 2. The noise trader risk is systematic. This condition ensures that the mispricing cannot be corrected by many such arbitrageurs each taking small positions.

If certain implementation costs, such as the time it takes to not only find but learn about a mispricing as well as the cost of the resources required to correct it, are taken into account then arbitrage can be limited even in the absence of the second condition. This is because arbitrageurs will view the mispricing simply as being too expensive to exploit.

Third, suppose that an arbitrageur has found a perfect substitute and that there is no noise trader risk and no implementation costs. Abreu and Brunnermeier (2002) report that in the absence of fundamental risk, noise trader risk and implementation costs

arbitrage can be delayed because of synchronisation risk. However, there are certain conditions that must hold for this to occur: 1. All arbitrageurs must be risk averse and competitive. As stated above, this ensures that the mispricing cannot be corrected by a single arbitrageur. Behavioural traders will simply absorb trade imbalances from arbitrageurs because it will be interpreted as a random fluctuation in order flow and the mispricing will persist. In their model the mispricing will only disappear if a critical proportion of rational arbitrageurs trade on their information, which when aggregated, has an order flow exceeding that of the behavioural traders. Arbitrageurs must also be competitive because if they wait too long before attempting to exploit a common mispricing then they could potentially forego profit opportunities. 2. Arbitrageurs become sequentially aware of the mispricing. This condition ensures that arbitrageurs have differing opinions regarding the timing of the correction in the market. This appears intuitively acceptable because in reality one arbitrageur might receive information and learn of a mispricing immediately while another might not receive the information immediately and therefore not learn of the same mispricing until later. Furthermore, arbitrageurs will be unaware of when they became aware of the mispricing relative to other rational arbitrageurs. This uncertainty amongst arbitrageurs regarding the timing of when their peers will act to exploit a common mispricing can limit arbitrage opportunities.

2.2.4 Empirical Evidence

The previous section presents the theoretical risks and costs involved with arbitrage. It is argued that because of these risks and costs rational arbitrageurs might view the process as unattractive, limiting profit opportunities and hence causing mispricings to persist.

As described by Barberis and Thaler (2003, p.8) “in principle, any example of persistent mispricing is immediate evidence of limited arbitrage” because if arbitrage were not limited the mispricing would be corrected as soon as the price departed from its fundamental value. If it were this simple, there would be an abundance of real-world evidence in support of limited arbitrage.

The problem, however, arises from Fama (1970) and what he terms the “joint hypothesis problem”. Simply put, any test to confirm a mispricing is really a joint test of both the mispricing itself and of a model of discount rates used in the calculation of the fundamental value. It is therefore difficult to conclude beyond any reasonable doubt that arbitrage is indeed limited. Despite these tremendous difficulties, researchers have managed to isolate some phenomena in financial markets that provide very strong evidence of persistent mispricings. This section presents real-world evidence that supports and illustrates the theoretical risks and costs described earlier.

Dual Listed Companies (DLC)

A dual listed company is formed when two separate companies contractually agree to operate their businesses as though it were a unified company, while both retain their legal identity and existing stock exchange listings. From a company’s perspective, there are three main motivations to adopt a dual listed company structure as opposed to merging with another company:

1. Tax benefits. If two companies were to merge outright then a large capital gains tax could result. However, with a dual listed company no such capital gain is realised and therefore no tax is to be paid.
2. National preservation of existing companies. If two companies adopt a dual listed structure then they both retain their separate legal and existing stock exchange listings. However, if the two companies had agreed to merge then one would lose their identity and trade under the name of the company that bought it outright. This can sometimes become a political issue.
3. Reduces investor flow-back. Suppose two companies are considering merging and the company that is showing interest is an international company listed on the New York Stock Exchange (NYSE). If the merge goes ahead then the domestic stock will be delisted from all indices in the home country. An institutional investor with a passive investment strategy, fearing the confirmation of the merger will sell their holdings in the domestic stock causing the price to decline. However, by adopting a dual listing structure, companies can reduce investor flow-back because institutional

investors following a passive investment strategy can hold stock without fear that it will be delisted from the index they are tracking.

Dual listed companies can be structured in three ways: 1. Combined entities structure. Under this structure, one or more jointly owned holding companies hold the assets of the two separate companies. 2. Separate entities structure. Here the key characteristic is that each company holds and manages their own assets and 3. Stapled stock structure, which as the name implies, stocks of the two companies are somewhat stapled together so they cannot be traded separately. The purpose of this structure is to minimise shares of the dual listed company trading at a premium or discount relative to each other.

Given that dual listed companies are effectively perfect substitutes, thereby eliminating fundamental risk altogether, they provide researchers with an attractive means of testing the limits of arbitrage using real-world trading data.

In their study of dual listed companies, Royal Dutch and Shell Transport, Froot and Dabora (1999) present the most widely documented phenomenon of real-world limited arbitrage⁶. In 1907, the two companies agreed to merge their interests and remain trading as completely separate enterprises. As a result, they became the first ever dual listed companies. Shares of Royal Dutch were primarily traded in the U.S. and the Netherlands and accounted for 60% of the total cash flows of the two companies whereas Shell Transport was primarily traded in the U.K. and accounted for 40% of the total cash flows of the two companies. Given the 60:40 split between cash flows and zero substitution risk the dual listed companies should always maintain a price ratio of 3:2. That is, Royal Dutch should always be worth 1.5 times the value of Shell Transport.

⁶ Rosenthal and Young (1990) were among the first to test for mispricings in dual listed companies. In their study, they analysed Royal Dutch and Shell Transport as well as the Unilever twins and found no logical explanation for the price disparity between each pair of twin shares. Although their work was completed later, Froot and Dabora (1999) contributed to the literature in terms of the evidence they found regarding the price disparity between twin shares. In their study they also analysed Royal Dutch and Shell Transport, the Unilever twins as well as the Anglo-American corporation of Smithkline Beecham. However, they report that the price disparity was in part attributable to the correlation of each stock with the index in the country of its main listing.

Results of the study document strong evidence of a persistent inefficiency. In fact, for almost a century, the ratio of the share prices deviated from the efficient market benchmark of 1.5. Moreover, the deviations from the benchmark were not always small. The results show one instance of Royal Dutch trading at a discount of 35% and it wasn't until 2001, three years later, when the twin shares finally sold at par.

This finding alone provides strong evidence of the limits to arbitrage. If an arbitrageur wanted to exploit the mispricing as few tried but disastrously failed (see, in particular, the example of Long-term Capital Management in Shefrin, 2000) then according to the text book version of arbitrage, they would purchase the undervalued stock and short the other. This would appear intuitively plausible for rational arbitrageurs since Royal Dutch and Shell Transport are perfect substitutes. Therefore, adverse news relating to either of the twin shares would result in a co-movement in share price of equal proportions, eliminating all fundamental risk. There were no implementation costs because shorting either of the shares would have been a straightforward process. Hence, the only form of risk faced by rational arbitrageurs was that of noise trader risk – the uncertainty that arises as to whether the mispricing will worsen in the future from the pessimistic outlook of noise traders.

As the results show, noise trader risk is powerful enough to keep the twin shares from trading at par and brought about in some cases huge losses for arbitrageurs. This coincides with what was discussed earlier concerning how noise trader risk alone can limit arbitrage if certain conditions hold. First, arbitrageurs must be risk averse and have short horizons to ensure that the mispricing cannot be corrected by a single arbitrageur. Second, noise trader risk must be systematic to ensure that the mispricing cannot be corrected by many such arbitrageurs each taking small positions. Given that the mispricing persisted for so long, there is a strong argument that both conditions are true.

Recently, another study has emerged, which provides further support for the real-world limits of arbitrage. Extending from Rosenthal and Young (1990) and Froot and Dabora (1999), De Jong, Rosenthal and Van Dijk (2003) examine all existing dual listed companies to their knowledge. In total they identify thirteen dual listed companies, all of which have one of three types of structures as previously discussed.

The motivation for their study stems from three sources. First, since previous work, there has been an emergence of dual listed companies and their price behaviour has not been analysed. Second, not all dual listed companies have been examined together (their similarities, differences and pricing patterns) to distinguish whether more recent dual listed companies have learned from some older twins to possibly reduce the mispricings. Third, in the eighty-two years extending from 1907-1989 there were five dual listed companies and in the eleven year period from 1990-2001 there were eight. Dual listed companies are becoming more popular and if companies are considering adopting a this type of structure as opposed to merging it is important that researchers understand the pricing behaviour, not only from the perspective of arbitrage but also from a corporate finance viewpoint.

The results of their study are remarkable. In all thirteen cases there is strong evidence of large price deviations from par values with maximum absolute deviations ranging between 15% and 50%. Furthermore, they report that the mispricings are time-varying and that the variations can in large part be explained by the correlation of stocks with indices in their domestic markets, which also confirms the findings of Froot and Dabora (1999)⁷. These results provide further evidence for persistent market inefficiencies and in particular enormous support for the limited arbitrage argument of behavioural finance.

Index Inclusions

Stock market indices are value weighted (market value of shares times the number of shares outstanding) and serve to represent the performance of a basket of stocks. For example, the ASX 200 is a value weighted index of Australia's top 200 stocks and is used to monitor the performance of these stocks. In the U.S. the S&P 500 is an index that includes America's top 500 stocks. This particular index was developed with the intent to represent the entire U.S. economy.

⁷ For further support of the impediments of arbitrage in the view of dual listed companies see Norman (1971) and Oswald (2001) who present evidence of persistent mispricings between the twins ARCO and Exxon.

Sometimes, stocks are added to indices but only if stocks that are currently listed decide to merge with another company, lose market capitalisation or go bankrupt. At any time though, the index should always include a certain amount of stocks that it is designed to represent. When stocks are added to the index, their fundamental values don't change. For example, consider a stock that was ranked 501st on a value weighted basis. Suppose that it then became the 500th ranked company as a result of a merge between two companies currently included in the S&P 500. If the stock is then transferred and included in the S&P 500, theoretically, its share price should remain the same since the fundamental value has not changed.

Research, however, suggests otherwise and provides strong evidence that mispricings exist when stocks are added to indices. For example, Harris and Gurel (1986) and Shleifer (1986) study the inclusions of stocks on the S&P 500. They report an average increase in share price of 3.5% for stocks that were newly included in the index. Furthermore, they find that the much of the price jump persisted indefinitely.

When stocks are added to an index, both fundamental risk and noise trader risk limit arbitrage opportunities for rational traders. The difficulties associated with finding a close substitute and the near impossibility of finding a perfect substitute for individual stocks has previously been discussed. Even if a perfect substitute were available, there is always the possibility that noise trader risk could strengthen providing further support for the share price. This seems completely reasonable given that passive investment managers, who strategise to track the S&P 500 index, must include the newly added stock into their portfolio.

When evidence of persistent mispricings began to emerge for stocks following their inclusion into an index, some researchers argued that the price increase could be rationally explained by either information or liquidity effects. This argument seems plausible given the higher publicity and higher turnover for stocks in the S&P 500 and cannot be completely discarded. However, support for the persistent mispricings argument was considerably strengthened by Kaul, Mehrotra and Morock (2000). Their study focused on the TS300 Canadian index, which includes on a value weighted basis the largest 300 Canadian stocks. In 1996, due to regulatory requirements, the TS300 changed the weights of some of its component stocks, which

resulted in significant price changes. However, given that the stocks were already included in the index at the time of the reweighing, information and liquidity effects can be excluded as possible explanations of price movements.

Extending previous work, Wurgler and Zhuravskaya (2002) analyse the relationship between the price increase and substitutability risk (fundamental risk) of individual stocks added to the S&P 500 index⁸. They report that stocks with higher substitutability risk increase in price more following their addition to the index than stocks with low substitutability risk. Intuitively, this makes sense because if close or perfect substitutes exist then arbitrageurs will be motivated to act on the mispricing immediately given their low perception of the risks involved.

Equity Carve-Outs

Sometimes, a large company might own one or more smaller subsidiary companies. If the subsidiary company is sold through an initial public offering (IPO) this process is referred to as an equity carve-out. When these situations arise, it presents researchers with an attractive opportunity to analyse the price behaviour of both the parent and subsidiary companies. If for example, the subsidiary company is worth half the value of the parent company then shareholders indirectly hold 1.5 shares in the subsidiary company. Therefore, when the subsidiary company is sold, the share price of the parent company should theoretically be 1.5 times that of the subsidiary. If the price is different from its fundamental value then an attractive investment opportunity exists for rational arbitrageurs. They will attempt to exploit the mispricing by purchasing the undervalued stock and shorting the other, thereby forcing prices back to fundamental levels.

The process, in theory, seems straightforward entailing no risks for rational arbitrageurs. However, research focussed at analysing the price behaviour of equity carve-outs provides additional support for the impediments of arbitrage. In particular,

⁸ Gurun and Booth (2006) present a similar study. However, they focus mainly on the relationship between substitutability risk and abnormal trading activities of individual stocks. Their results document that individual stocks with low substitutability risk are more likely to have abnormal trading activity than those with high substitutability risk. Furthermore, this result can be used to explain the high volume return premium documented by Gervais, Kaniel and Mingelgrin (2001).

when parent companies sell off their subsidiaries, there is strong evidence of persistent mispricings.

Mitchell, Pulvino and Stafford (2002) analysed eighty-two situations over the period 1985-2000 in which the market value of a parent company was below that of its ownership stake in a publicly-traded subsidiary⁹. They track each of the parent-subsidiary pairs until an event occurs that eliminates the link between the two firms or the mispricing was simply corrected. Remarkably, they report that 30% of the time, the link between parent and subsidiary companies is terminated before prices converge. They also find that the average time from the initial mispricing to a terminating event (which also incorporates convergence) is 236 days.

As a result of the uncertainty surrounding the timing of the mispricing (synchronisation risk as described earlier) Mitchell et al. (2002) also report that the investment opportunity often presents a return that is lower than the risk-free rate¹⁰. Furthermore, their results document that arbitrageurs could earn 50%-100% higher returns if the capital requirements are relaxed. These findings along with the uncertainty regarding the distributions of returns discourage rational arbitrageurs from attempting to exploit the mispricing and thereby contribute to the persistence of negative-stub-values.

Lamont and Thaler (2003) provide additional support for the limited arbitrage view of equity carve-outs. They focus on the parent-subsidiary pair of 3Com and Palm and report that when 3Com spun-off Palm, shares in the subsidiary traded for \$95. Since shareholders of 3Com indirectly owned 1.5 shares of Palm, 3Com shares should have been trading at their fundamental value of \$142. Instead they traded for only \$81, a massive \$14 below that of Palm. Furthermore, this severe mispricing persisted for weeks. Lamont and Thaler (2003) report that certain implementation costs, such as the

⁹ These situations are referred to as “negative-stub-values”. Negative-stub-values can also result from one company acquiring a large stake in another publicly-traded company.

¹⁰ Horizon risk is the risk that an arbitrageur’s returns will be reduced by increasing the time it takes for prices to converge.

constraints imposed on short-sellers play most part in the persistence of the negative-stub-value¹¹.

Put-Call Parity Violations

According to the put-call parity,

$$c + Xe^{-rt} = p + S_0 \quad (2.1)$$

where, c = the current price of a call option, X = the exercise (strike) price, r = the risk-free rate, t = time, p = current price of a put option and S_0 = the current price of the stock underlying the options.

To illustrate the idea of the put-call parity, suppose the left-hand side of (2.1) is named portfolio A, and the right-hand side of (2.1) portfolio B, then at time (T) portfolio A = portfolio B. Therefore, the values of the two portfolios today must also be equal. If the options are priced according to their fundamental values then this ‘no-arbitrage’ parity should always hold.

Lamont and Thaler (2003) provide strong evidence for a violation of the put-call parity. Moreover, there results also violate another, slightly different no-arbitrage condition, which states that at-the-money call options should always cost more than at-the-money put options (Hull, 2000). In their study they find that on one particular day, at-the-money put options were trading at twice the value of at-the-money call options. This result strongly indicates that options traders believed the value of the underlying stock (Palm) was too highly priced (i.e. a put option gives the holder the right but not the obligation to sell stock at a future date for an agreed upon price today) whilst their counterparts in the equity market trading Palm shares didn’t share this view.

¹¹ For further evidence of the limitations of arbitrage in the view of equity carve-outs, the reader is referred to Cornell and Liu (2001), Schill and Zhou (2001), and Tezel and Schnusenberg (2000). The results of these studies report that short-sale constraints and high demand for the subsidiary company create severe impediments for rational arbitrageurs therefore allowing negative-stub-values to persist.

This segmentation result documented by Lamont and Thaler (2003) can be exploited further by understanding how traders can ‘synthesize’ stocks. To do this they employ a simple strategy of simultaneously purchasing a call option, selling a put option and holding the value of the exercise price to maturity. This portfolio will have a value equal to the stock price at time (T) providing that the call and put options both share the same expiry date. Consequently, the cost of a synthetic long today should equate to the current price of the stock. To see this mathematically, rearrange (2.1) as

$$c - p + Xe^{-rt} = S_0 \quad (2.2)$$

where, all variables are as described earlier.

Lamont and Thaler (2003) report that Palm options, as well as other negative-stub-values consistently violate this condition. The prices of the synthetic long position and the underlying stock deviate so far from parity that at one stage Lamont and Thaler (2003) report the synthetic long position to be trading at a 23% discount to the price of the underlying stock.

Ofek, Richardson and Whitelaw (2002) provide additional support for the violation of equation (2.2). They describe the violation as a wide-spread phenomenon that is in part attributable to the difficulties and costs associated with short selling the underlying stock. They analyse over 80,000 pairs of options (at-the-money call and put options with the same expiry dates) and find that the violation to (2.2) is asymmetric. That is, there are more cases in which,

$$c - p + Xe^{-rt} \leq S_0 \quad (2.3)$$

as opposed to,

$$c - p + Xe^{-rt} \geq S_0 \quad (2.4)$$

This indicates that if (2.2) is violated then generally, the synthetic long is less than the underlying stock. In the case of arbitrage opportunities this presents a severe problem for rational arbitrageurs, especially if there are constraints on short sales and implementation costs involved. Lamont and Thaler (2003) and Ofek et al. (2002) both provide evidence that a persistent violation of (2.2) is attributable to both the costs involved in shorting the underlying stock and short sale constraints from the demand of arbitrageurs attempting to exploit the violation.

Other Empirical Evidence

Researchers have unravelled what has become an influx of evidence supporting the limits of arbitrage argument. Gabaix, Krishnamurthy and Vigneron (2005) and Boudoukh, Richardson, Stanton, and Whitelaw (1997) provide support for the impediments of real-world arbitrage in the mortgage-backed securities market. Collin-Dufresne, Goldstein, and Martin (2001) on the other hand analyse the corporate bond market and document that a simple Merton (1974) model fails to accurately explain the price behaviour of the corporate bonds. Additionally, Berndt, Douglas, Duffie, Ferguson, and Schranz (2005) focus on data from credit default swaps and report a similar finding. They find large swings in the risk-premia incorporated in default swaps.

2.3 Psychology

In view of arbitrage, this thesis argues that in real-world situations the process can present rational investors with several forms of risk that can impede risk-free profits. The previous section describes the theoretical risks and summarises the body of real-world phenomena, which presents strong evidence of persistent mispricings amongst various financial instruments.

In order to assist in the understanding and explanation of why prices remain dislocated from their fundamental values for long periods of time, behavioural finance theory assumes that some investors are less than fully rational (that is, they violate Bayes' Law and/or make decisions that aren't normatively acceptable). To increase their knowledge of the irrationalities of investors, researchers often turn to the

experimental evidence compiled by cognitive psychologists. They pay particular attention to the biases investors make when forming beliefs and also the biases of preferences, that is, the decisions they make, given their beliefs.

This section reviews some of the psychological evidence that appears useful to behavioural finance researchers and in particular relevant to this thesis. For a more thorough understanding, however, the reader is directed to the summaries of Camerer (1995), Rabin (1998, 2001), Tversky and Kahneman (1981, 1986), Shiller (1998), Kahneman and Riepe (1998) and also to the edited volumes of Kahneman, Slovic and Tversky (1982), Kahneman and Tversky (2000) and Gilovich, Griffin and Kahneman (2002).

2.3.1 Biases in the Formation of Beliefs

In most cases, financial decisions are made under extreme circumstances of high uncertainty and high complexities. For this reason, investors mainly rely on heuristics (or rules of thumb) to somewhat assist in the decision making process¹². However, reliance on intuition can be highly disadvantageous. An investors who is less than fully rational will be prone to biases and cognitive illusions in there intuitive judgement. As a result the investor could make decisions without acknowledging the risks involved, experience outcomes they didn't anticipate, might not be able to justify their trading behaviour and could possibly blame themselves or others in the presence of an unattractive outcome. This section reviews some of the biases that investors are prone to when forming their expectations concerning future events.

Overconfidence

To illustrate the concept of how individuals are overconfident in their judgment consider the following. Suppose you are initially asked, what will be the value of the All Ordinaries Index (AOI) in a week from now according to your most accurate judgement? Then, using your one-week prediction of the All Ordinaries index, create a lower bound so that you are 99% sure the actual value in one week will be greater

¹² A heuristic is defined as the process by which people find things out for themselves, usually by trial and error. It is the use of trial and error that leads people to develop rules of thumb.

than this and also provide an upper bound such that you are 99% certain that the actual value of the All Ordinaries index in one week will be less than this.

If you carefully followed the instructions you should have predicted a value plus a lower and upper bound with which you are 98% certain the actual value of the All Ordinaries index will lie between in one week. There are three possible outcomes from the question that was presented;

1. The value of the All Ordinaries index is lower than your lower bound (also referred to as a low surprise).
2. The value of the All Ordinaries index is between you lower and upper bounds.
3. The value of the All Ordinaries index is higher than your upper bound (also referred to as a high surprise).

If your judgement is unbiased and you are aware of the limits of your knowledge then you should expect 1% of low surprises, 1% of high surprises and no surprises 98% of the time when the actual value of the All Ordinaries index in one week falls inside your confidence interval. Individuals, whose judgements are not biased, as in this case, are said to be well-calibrated in their prediction of probabilities.

Research reports that individuals are very rarely well-calibrated, with a highly biased judgement in subjective confidence intervals. In most cases there are far too many surprises (15%-20%) indicating that confident intervals are set too narrowly reflecting the overconfident abilities of individuals. Alpert and Raiffa (1982) provide support for the overconfidence bias in view of confidence intervals. In their study, they report that approximately 40% of the time, surprises occurred, therefore yielding 60% of cases in which individuals were well-calibrated (that is, the outcome fell inside the barriers of their confidence interval)¹³.

Additionally, research documents that individuals are rarely well-calibrated when estimating probabilities. Fischhoff, Slovic and Lichtenstein (1977) report that when

¹³ Overly narrow confidence intervals can also be, at least in part, attributable to another form of bias resulting from anchoring and adjustment heuristics. This is discussed further in the section below.

individuals believe an event is certain to occur it actually only occurs around 80% of the time and conversely, when they believe that an event is near impossible to occur it actually occurs around 20% of the time. For example, one might say that they are 95% certain premierships favourites Canterbury will overcome, bottom of the table South Sydney in this weeks National Rugby League Match, reflecting their overconfident behaviour. As it turns out, South Sydney won the match and premierships favourites Canterbury failed to make the playoffs. In fact the two Grand Finalists from 2004 failed to make the playoffs in 2005.

Surprisingly, the most accurate, unbiased judgements of confidence intervals and probability estimates come from two groups of professionals: meteorologists and horse racing handicappers. This is generally the case since both types of professionals face repetitive tasks each day, deal with forecasting explicit probabilities daily and obtain accurate and efficient feedback from outcomes as they occur. If these conditions are not met then overconfident behaviour is to be predicted amongst both professionals and non-professionals.

Overconfidence can also, at least in part, be promoted by two other forms of irrationalities exhibited by individuals: 1. Hindsight bias and 2. Self-attribution bias. Psychological evidence reports that individuals rarely have the ability to honestly and accurately reconstruct, subsequent to an event, what they thought of the event before it actually occurred. This behaviour is referred to as hindsight bias. The general finding is that most individuals tend to exaggerate their estimates of the probability of an event, after its occurrence. If investors believe they accurately predicted the probability of an event by exaggerating their previous estimate after it occurred then this could promote overconfident behaviour by fostering the illusion that they have the ability to accurately predict future events. This bias in expectations could potentially lead to steep losses.

Self-attribution bias, as the name implies, arises when investors attribute successful outcomes to their talent of prediction and blame failure on bad luck (Wolosin, Sherman and Till, 1973; Langer and Roth, 1975; Miller and Ross, 1975). According to Hastorf, Schneider and Polifka (1970) we are prone to attribute success to our own dispositions and failure to external forces. The talent with which an investor attributes

to themselves, however, could quite possibly be the result of good luck, leading to a severe bias in judgement. To illustrate the idea of self-attribution bias, consider an investor, who has recorded several quarters of investment success. This can promote overconfident behaviour since the investor can be eluded to believe they have the ability to accurately predict future events (Gervais and Odean, 2001).

Representativeness

In many situations individuals are concerned about whether subject A belongs to group B or the likelihood that outcome A was generated by model B. When making their decision, individuals rely on the representativeness heuristic. Simply put, if subject A is highly representative of a group B then the probability of A belonging to B will be high. That is, as the degree to which A resembles B increases the likelihood of A belonging to B increases¹⁴. To illustrate the idea of judgement by representativeness consider the following:

“Steve is very shy and withdrawn, invariably helpful, but with little interest in people, or in the world of reality. A meek and tidy soul, he has a need for order and structure, and a passion for detail”, (Tversky and Kahneman, 1974 p.1124).

When individuals apply the representative heuristic to assess the probability that Steve is, for example a farmer, pilot, librarian, sales assistant or doctor, their decision is highly dependent upon how representative (or similar) he is of a particular stereotype. Kahneman and Tversky (1973) report that individuals will use representative heuristics (similarity) and probability, in exactly the same way, when ranking the occupations from the list. However, this approach can generate severe biases because judgement under representativeness (or similarity) is not influenced by the factors that should affect judgement based on probabilities.

¹⁴ The idea of representativeness is captured by Bayes' Law. It states that if b is an attribute (ripped and torn clothes) and A is a class of people (homeless), $p(b|A)$ is the probability that an individual will have attribute b, given that they belong to class A and $p(A|b)$ is the probability that an individual belongs to class A, given that they have attribute b, then Bayes's Law implies $\partial p(A|b)/\partial p(b|A) > 0$.

1. Base rate frequency neglect

The first factor that should be used when making decisions based on probabilities but not when applying the representative heuristic to assess the likelihood of outcomes, is prior probabilities (or the base rate frequency) of previous outcomes. In Steve's case above, for example, the fact that there are many more doctors than pilots throughout the world should at least be considered when assessing the probability that Steve is a pilot rather than a doctor. However, consideration of base rate frequencies does not change how representative Steve is of the stereotypes of both doctors and pilots. Therefore, for an individual assessing the probability that Steve is a pilot rather than a doctor, using the representative heuristic, prior probabilities of outcomes will be neglected.

Kahneman and Tversky (1973) test this hypothesis directly. In their experiment, subjects are split into two groups. Both groups are shown the same 100 personality descriptions of professionals that are gathered from either engineers or lawyers. However, base rate frequencies are manipulated such that the first group is told that the proportion of engineers to lawyers is (70/30) while the second group is told that the proportion of engineers to lawyers is (30/70). Therefore, any assessment of probability in the first group should be more heavily weighted towards the professional being an engineer since there are 70 engineers and only 30 lawyers. In contrast, any assessment of probability in the second group should be more heavily weighted towards the professional being a lawyer since there are 70 lawyers and only 30 engineers.

Results of their experiment, however, document that subjects essentially provide identical probability judgements. This indicates that when evaluating the likelihood that the professionals are engineers or lawyers, subjects base their probabilities on how representative the description was of each of the stereotypes, while paying no attention the base rate frequencies of prior outcomes¹⁵. Furthermore, in the absence of

¹⁵ This belief can also lead to a form of overconfidence. If a description of person A closely resembles a particular stereotype B then individuals will be more confident that person A belongs to group B, therefore assigning a higher probability to their prediction. The predictive ability of the individual and the reliability of the data (for example, how old it is) are essentially not considered by the individual. To them the description that resembles a particular stereotype holds more weight than any other information. This unwarranted overconfidence is referred to as the illusion of validity.

information (when the descriptions of the professionals are not included in the experiment) subjects correctly use the base rate frequencies in their probability assessments of the professionals. That is, subjects judge the probability that the unknown professional is an engineer with 70% likelihood in the first group and with 30% likelihood in the second group¹⁶.

2. Sample size neglect

The second factor that should be included when making decisions based on probabilities and not when assessing the likelihood of an outcome under the representativeness heuristic is the sample size. Generally, when individuals use the representative heuristic to evaluate the probability of obtaining an outcome from a sample their guesstimate will be representative of that from the wider population. For example, Kahneman and Tversky (1973) report that subjects in an experiment record an equal probability of obtaining an average height of above 6 feet for samples of 10, 100 and 1000 men. However research indicates that ignorance towards sample size can create a severe bias. Tversky and Kahneman (1974, p.1125) examine this further by conducting an experiment in which subjects (undergraduate students) are given the following scenario and question:

“A certain town is served by two hospitals. In the larger hospital about 45 babies are born each day and, in the smaller hospital about 15 babies are born each day. As you know, about 50% of all babies are boys. However, the exact percentage varies from day to day. Sometimes it might be higher than 50%, sometimes lower”.

Given that each hospital recorded, over an entire year, the amount of days on which more than 60% of all babies born were boys, subjects were then given three choices and asked, which hospital they thought recorded more of these days. The choices were:

¹⁶ Individuals also use the representative heuristic to predict outcomes. However, if they disregard prior probabilities and evaluate their prediction based on the favourableness of the description then essentially, their predictions will be insensitive to the reliability of the evidence contained in the description and also the accuracy of their predictions.

- a). the smaller hospital
- b). the larger hospital
- c). about the same (that is, within 5% of each other)

The results of experiment report that 21 subjects answered a, similarly 21 answered b and the large majority 53 answered c. The correct answer to the scenario is actually a (the smaller hospital) because as the sample size increases, the distribution of babies should become more similar to that of the entire population (i.e. 50% boys and 50% girls). This suggests that b (the larger hospital) should have recorded an answer closer to 50%. The reason that most (53) subjects chose c (about the same) is because the events were described by the same statistic. Therefore, subjects assessing probabilities using the representative heuristic will view the events as equally representative of the entire population. The belief that even small samples will reflect the overall population is also known as the law of small numbers (Rabin, 2002).

When making intuitive judgements based on posterior probabilities (that is, decisions concerning the likelihood that sample A was drawn from population B rather than population C), neglecting the sample size can also generate another type of bias. Tversky and Kahneman (1974, p.1125) present the following example to illustrate:

“Imagine an urn filled with balls, of which $\frac{2}{3}$ are of one colour and $\frac{1}{3}$ of another. One individual has drawn 5 balls from the urn, and found that 4 were red and one was white. Another individual has drawn 20 balls and found that 12 were red and 8 were white. Which of the two individuals should feel more confident that the urn contains $\frac{2}{3}$ red balls and $\frac{1}{3}$ white balls, rather than the opposite?”

In most cases, individuals would believe that the first case provides stronger evidence of the urn containing predominantly red balls because of the higher proportion of red balls drawn from the sample. Once again, because of the representative heuristic, individuals base their judgement on the proportion of red balls drawn and neglect the sample size even though it should be used to calculate the actual posterior odds. Additionally, estimates of posterior odds are far less than the actual values obtained. Edwards (1968) and Slovic and Lichtenstein (1971) provide supporting evidence of

the underestimation of posterior odds in experiments similar to the one described above. This behavioural bias is commonly referred to as conservatism¹⁷.

3. Misconceptions of chance

The third factor that should be included when evaluating a decision under laws of probability but not included when assessing the same decision using the representative heuristic is that of chance. To illustrate, individuals often believe that the sequence H-T-H-T-T-H from a fair coin is much more likely than the sequence H-H-H-H-H-T from the same fair coin. That is, they expect that the eventual characteristics of the sequence be represented not only at the end of the overall sequence but also within the intermediate smaller (local) steps along the way. For example, if a run of tails eventuate from the tossing of a coin then an individual erroneously believes that a head is due because the occurrence of a head will be more representative of the sequence than the occurrence of an additional tail.

Individuals often apply this intuitive judgement at casinos, on the roulette wheel in particular, following runs of red or black. This is termed the gambler's fallacy (Tversky and Kahneman, 1971). Generally, people perceive chance as a self-correcting process. They believe that if a chance event causes a deviation from equilibrium then it will induce a deviation in the opposite direction to somewhat restore the equilibrium. However, as a chance event occurs, deviations are not corrected, rather they are diluted.

Availability

Sometimes individuals are concerned with the probability of an event occurring or the frequency of a class. To assist in the decision making process people often rely on another judgemental heuristic, known as availability. As the name suggests, availability refers to the ease with which instances or occurrences can be brought to mind. To illustrate this idea, suppose that an individual is asked to evaluate the risk of cancer among middle-aged people. In order to assist, the individual filters through

¹⁷ Neglecting sample sizes can also lead to the hot-hand phenomenon. For example, consider a sports fan watching a rugby league match. If successive points have been scored as a result of a particular player touching the ball then spectators become convinced that whenever that player touches the ball additional points will be scored because they are having a 'hot' streak.

their mind searching for the availability of information concerning cancer among their family, friends and cases they have heard.

The application of the availability heuristic can be useful for individuals assessing frequencies of classes or evaluating probabilities, especially when there are instances of large classes because information can be extracted more easily and applied than in instances of smaller classes. However, research documents that sole reliance on the availability heuristic can lead to severe biases since availability is affected by factors other than the frequencies of outcomes and probabilities.

1. Retrieving instances

If an individual is asked to predict the frequency of a particular class then the number they assign depends on the amount of instances they can retrieve, relating to the specific class (that is, the instances that appear more familiar to them). Instances that are more easily retrieved will have greater impact on their decision regarding the frequency of the class. This type of bias is referred to as familiarity. It implies that even if two classes, for example men and women, have the same amount of instances, for example famous people, individuals will predict that the class they are more familiar with will have more famous people than the other (Tversky and Kahneman, 1974).

Additionally, salience is another factor that can affect the retrieving of instances amongst individuals. If evaluating the subjective probability of being attacked by a shark, for example, those having witnessed the event in real-life will often perceive the risk as being higher than those that heard about the attack on the radio.

2. Effectiveness of the search set

When individuals rely on the availability heuristic to assist them in decision making, the effectiveness of the search set is critical because it can lead to a bias in judgement. Search sets vary depending on the question at hand. Generally though, when a question is posed individuals somewhat 'search' (or recall) contexts in which the words in the question are used. For example, do you think that abstract words, such as love, are used more often than concrete words, such as water?

In answering this question individuals search their memory for contexts in which both types of words are used. For example, one common statement that springs to mind is, I love you, which highlights the context of how abstract words are used. Individuals then search for contexts in which concrete words are used such as, I'll have a water thanks. The decision they make depends on the availability of contexts. If, for example, the contexts in which abstract words appear more readily available this will lead the individual to conclude that abstract words are more common than concrete words even though this might be the wrong answer (Tversky and Kahneman, 1974).

3. Ability to imagine

Individuals that rely on the availability heuristic, when evaluating subjective probabilities in real-life situations are prone to yet another bias because of the ability to imagine (or foresee) things. The extent of this bias is therefore related to an individual's imaginability. In most cases, likely occurrences are easier to imagine than unlikely ones. However, those that have more of an imaginable mind might be more risk averse, for example, when considering a financial investment. They might even foresee too many contingencies (or dangers) and attribute more risk than is warranted to a particular activity, for example, abseiling. Conversely, someone with less imaginability might take excessive amounts of risk because they don't have the ability to think of potential disasters that could eventuate from a particular type of activity, such as sky diving.

4. Illusory correlation

In some situations, individuals might be asked to assess the frequency of the co-occurrence of particular events and for this they rely on the availability heuristic to assist with their judgement. However, research documents that reliance on the availability heuristic generates another form of bias.

In these situations, it is the assessment of the frequency with which two events occur at the same time that is biased. It is generated by the individual's perception of the strength of the relationship between the two events in question. Evidence indicates that individuals will inaccurately conclude that two events will more frequently occur if the strength of their bond is strong. In contrast, if individuals perceive the strength

of the bond between two events to be weak then they will conclude that the events have infrequently occurred together in the past (Tversky and Kahneman, 1974).

Anchoring and Adjustment

In many situations, when individuals are concerned with making decisions they rely on anchoring and adjustment heuristics. To assist in the decision making process, individuals often start at an initial value. This value is sometimes arbitrary but can also be the result of a partially formularised computation or generated by the formulation of a problem. Nevertheless, individuals generally use this as a starting point and adjust away from it to generate a final estimate. However, research documents that the adjustments are insufficient (Slovic and Lichtenstein, 1971). There is a bias towards the initial values since the final estimates vary according to the starting points. Tversky and Kahneman (1974) refer to this phenomenon as anchoring.

1. Insufficient adjustment

To illustrate the concept of insufficient adjustment consider the experiment Tversky and Kahneman (1974) perform in their study. Subjects are asked to estimate (in percentage terms) the amount of African Nations in the United Nations. In the presence of the subjects, a wheel of fortune is spun to determine arbitrary initial values. Different starting points are given to different groups of students. Once the groups are given their initial values, they are instructed to firstly, indicate whether they think the amount of African Nations is lower or higher than their starting value and then secondly, estimate the actual percentage of African Nations in the United Nations. The results of their experiment provide supporting evidence for insufficient adjustment. In particular, they report that when given an initial value of 10, the subject's median estimate is 25% and when assigned a starting point of 65, the subject's median estimate for the amount of African Nations in the United Nations is 45%¹⁸.

Anchoring not only occurs when individuals are provided with a starting point but can also result from an incomplete computation of a problem. In the same study, Tversky

¹⁸ Tversky and Kahneman (1974) also report that the introduction of monetary rewards for accuracy did not reduce the anchoring phenomenon.

and Kahneman (1974) perform another experiment to test this hypothesis. Subjects in this case are split into two groups. The first group is asked, within five seconds, to estimate $1 \times 2 \times 3 \times 4 \times 5 \times 6 \times 7 \times 8$, while the second group was asked, within five seconds, to estimate $8 \times 7 \times 6 \times 5 \times 4 \times 3 \times 2 \times 1$.

Often when individuals are faced with decisions such as this, they tend to complete too few computations of the entire problem and extrapolate or adjust away from it. In doing so, however, individuals insufficiently adjust their estimate and their overall result is usually lower than the true value. If this intuition is correct then subjects in the first group should provide a lower estimate of the entire calculation than the opposing students in the second group¹⁹. These predictions are confirmed by the results of the experiment. In particular, the median response of 512 obtained from subjects in the first group is substantially lower in comparison to the median response of 2,250 from subjects in the second group. Overall, both of these estimates are much lower than the true solution to the problem of 40,320.

2. Evaluation of conjunctive and disjunctive events

In some situations, individuals have to decide between different types of events. To assist in the decision making process, they often rely on the anchoring and adjustment heuristics. However, research documents that by relying on these heuristics, individuals are prone to another form of bias arising from the evaluation of conjunctive and disjunctive events.

In an earlier study, Bar-Hillel (1973) conducts an experiment to test this phenomenon. Overall there are three different types of events used for the experiment: 1. A simple event, such as drawing a marble from a bag containing 50% red marbles and 50% blue marbles, 2. A conjunctive event, such as drawing a red marble seven times in succession, with replacement from a bag containing 90% red marbles and 10% blue marbles and 3. A disjunctive event, such as drawing a red marble, at least once in seven successive attempts, with replacement from a bag containing 90% red marbles and 10% blue marbles.

¹⁹ This is because subjects in the first group have an ascending sequence. Therefore, the result of a few computations reading left to right will yield a smaller estimate of the entire computation than the estimates obtained by subjects in the second group with a descending sequence.

Subjects are then presented with two of the three events and asked to decide which gamble they would prefer to take. When given the choice between the simple event (1) and the conjunctive event (2) subjects choose the conjunctive event even though the probability of choosing a red marble is only 0.48 in comparison to 0.5 from the simple event. Furthermore, when given the choice between the simple event (1) and the disjunctive event (3) subjects choose the simple event even though the probability of obtaining a red marble is only 0.5 compared to 0.52 from the disjunctive event.

Hence, in both situations subjects prefer to choose the event that offers the lower probability of obtaining a red marble. These findings can be readily explained by the anchoring phenomenon. Since the simple event (1) offers subjects a 50% chance of obtaining a red ball in any independent draw, this provides a natural starting point. Therefore, when presented with a choice between the simple event (1) and either the conjunctive event (2) or disjunctive event (3), subjects adjust their probability estimates from the initial value of 0.5. However, adjustments are insufficient and often remain too close to the initial value. Since the conjunctive event (2) offers a probability that is lower than the simple event (1) and the disjunctive event (3) offers a probability that is higher than the simple event (1), subjects overestimate the probability of obtaining a red ball from the conjunctive event and underestimate the probability of obtaining a red ball from the disjunctive event.

3. Assessment of subjective probability distributions

Sometimes individuals are concerned with forming probability distributions (or confidence intervals) for stock prices or market indices, such as the ASX 200. In situations such as this, individuals often rely on the anchoring and adjustment heuristics. Research documents, however, that a severe bias can arise. If, for example, individuals are asked to estimate a lower bound, X_1 and an upper bound X_{99} of the ASX 200 in one month from now, essentially they are providing a probability distribution in which there is an equal 1% chance that the actual value falls below X_1 or rests above X_{99} and a 98% chance that it lies between X_1 and X_{99} one month from today. When choosing their estimates for X_1 and X_{99} , individuals often adjust from an initial value (or starting point). This initial value is generally their best estimate of ASX 200 in one month from today. Since evidence documents that adjustments from

starting points are usually insufficient, the resulting 98% confidence intervals are set too narrow in most situations. Consequently, individuals become surprised when the actual value falls outside their confidence interval.

2.3.2 Biases in Preferences

The previous section discusses some of the psychological biases arising from the formation of beliefs. How these biases affect probability estimates of various prospects (events) for individuals are also outlined. This section focuses on how people use their probability estimates to evaluate risky prospects (events) and assign values to future outcomes²⁰. That is, the biases attributable to individual preferences - how people make choices given their beliefs.

Prospect Theory

Traditionally, in economics, individuals are perceived as being completely rational. Economists believe that rational individuals behave in accordance with a set of axioms – substitution (or cancellation), transitivity, dominance and invariance as well as the technical assumptions of comparability and continuity²¹ – and that if the preferences of individuals satisfy these axioms then their choices can be explained by expected utility theory. The idea of expected utility theory was proposed by Von Neumann and Morgenstern (1944). However, in the years following, experimental research highlights consistent violations of the set of axioms associated with their theory.

In particular, Allais (1953) reports evidence that individuals overweigh outcomes that appear certain and underweight those that appear merely probable, an idea that Kahneman and Tversky (1979) labelled the certainty effect. Ellsberg (1961) also provides supporting evidence of this phenomenon, which led many researchers to abandon the substitution axiom from the traditional model altogether (Allais, 1979;

²⁰ According to Kahneman and Tversky (1979, p.263) a prospect $(x_1, p_1; \dots; x_n, p_n)$ is a contract that yields outcome x_i with probability p_i , where $p_1 + p_2 + \dots + p_n = 1$.

²¹ For further discussion on the set of axioms underlying EUT, the reader is referred to Tversky and Kahneman (1986).

Hagen, 1979; Fishburn, 1983; Luce and Narens, 1985). Furthermore, other models omit the transitivity axiom but keep dominance and invariance (Fishburn, 1982; 1984).

Generally speaking, researchers have attempted to account for violations of the principles underlying expected utility theory in alternative theories by simply weakening either the substitution axiom or the transitivity axiom. However, this intuition cannot be extended to account for violations of the dominance and invariance axioms since each of those particular axioms are essential for a normative model but are descriptively invalid²².

The result of such work has created an influx of new, opposing non-expected utility theories, each more dedicated at explaining or matching the experimental evidence. According to Barberis and Thaler (2003), some of the more established theories include; weighted utility theory (Chew and MacCrimmon, 1979; Chew, 1983), implicit expected utility theory (Chew 1989; Dekel, 1986), disappointment aversion (Gul, 1991), regret theory (Bell, 1982; Loomes and Sugden, 1982), rank-dependent utility theories (Quiggin, 1982; Segal, 1987, 1989; Yaari, 1987) and arguably the most infamous, prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992).

Like Barberis and Thaler (2003), however, this thesis focuses on prospect theory since it captures the results of experimental research most effectively amongst all of the alternative-competing theories. In fact, Barberis and Thaler (2003) go as far as describing other non-expected utility theories as quasi-normative theories, in that they simply relax one or more of the tenets underlying traditional expected utility theory. One problem with this is that researchers are essentially attempting to do two jobs at once (i.e. descriptive and normative). As a result many of the competing expected utility theories that have been proposed lack either descriptive or normative appeal.

²² For a summary of the evidence supporting violations of both the dominance axiom and invariance axiom see Tversky and Kahneman (1986).

Prospect theory assumes that there are two distinct phases (earlier and later) in the decision making process: 1. The editing stage and 2. The evaluation stage. The purpose of the initial editing stage is for individuals to analyse, organise and reformulate the prospects offered into a simpler representation from which they can more easily evaluate and choose. To do this, individuals often rely on various forms of operations to transform the outcomes and probabilities associated with each of the prospects.

Evidence indicates that individuals code the outcomes of prospects as either gains or losses, rather than as final states of wealth (Kahneman and Tversky, 1979). The gains and losses are defined relative to some reference point (or status quo) that is normally equal to the current value of some asset (usually zero) such that gains or losses correspond to the amounts received or paid. However, the reference point can vary substantially amongst individuals. It is highly dependent upon the expectations of each individual²³ and also by the formulation of the prospects offered²⁴.

Alternatively, individuals sometimes reduce the complexities of certain prospects by combining the probabilities associated with identical outcomes. For example, the prospect {1000, 0.1; 1000, 0.1} could be reduced to {1000, 0.2} to make it simpler for the decision maker to choose between the alternatives. In other cases, when there is an element of certainty and an element of risk, individuals segregate the certain part from the part that attributes risk. For example, the prospect {300, 0.8; 200, 0.2} would in most cases be reduced to a sure gain of \$200 and a gamble {100, 0.8}.

The preceding forms of editing operations are applied to each prospect separately, whereas the subsequent editing procedures are applied to a set of two or more prospects at the same time.

Cancellation is an operation individuals use to disregard components of prospects that are shared. This simplifies the choice between alternatives for individuals because it allows them to focus on the components that distinguish each of the alternatives

²³ See Andreassen (1993) for evidence of this.

²⁴ See Schoemaker (1980) for evidence of this.

offered. However, this approach might create inconsistencies amongst the preferences of individuals since the decomposition of a pair of prospects can be broken into common and distinguishable components in more than one way. This phenomenon is labelled the isolation effect (Kahneman and Tversky, 1979).

Individuals also apply the cancellation operation when prospects have common constituents. For example, the choice between $\{100, 0.5; -200, 0.3; 500, 0.2\}$ and $\{100, 0.5; -400, 0.3; 750, 0.2\}$ would in most cases be transformed to $\{-200, 0.3; 500, 0.2\}$ and $\{-400, 0.3; 750, 0.2\}$. Additionally, individuals sometimes round probabilities and their associated outcomes for simplicity. For example, the prospect $\{101, 0.49\}$ would in most cases be reformulated and presented as $\{100, 0.5\}$. Simplification of prospects can create inconsistencies since highly unlikely outcomes could be disregarded.

In the second stage, once prospects have been edited to assist individuals in deciding between alternatives, they are evaluated and the one that offers the highest value is chosen. The overall values (V) of the edited prospects are expressed in terms of two scales, namely (π) and (v).

1. Decision Weights

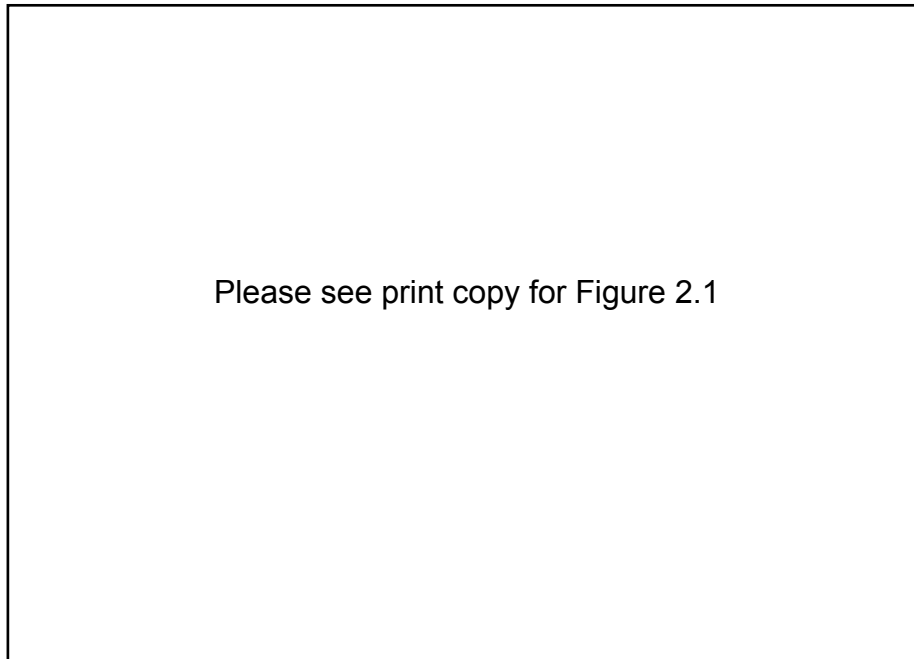
In contrast to expected utility theory, where the utility of an uncertain outcome is weighted by its probability, prospect theory assumes that the first scale (π), offers a decision weight $\pi(p)$ for each probability p . The idea is to reflect the impact of p on the overall value (V) of the prospect. Hence, the value of an uncertain outcome is multiplied by a decision weight²⁵.

The weighting function has properties that capture many of the inconsistencies (or violations) of the underlying axioms of expected utility theory documented in experimental evidence. First, impossible events are discarded (i.e. $\pi(0) = 0$) and the function is normalised such that $\pi(1) = 1$. Second, for outcomes with low probabilities, $\pi(p) > p$ but $\pi(p) + \pi(1-p) \leq 1$. That is, lower probabilities are

²⁵ The decision weights themselves are a monotonic function of p but not a probability. See Kahneman and Tversky for proof that $\pi(p) + \pi(1-p) < 1$.

overweighted, medium and high probabilities are underweighted and the latter is more pronounced than the former²⁶. Third, $\pi(pq)/\pi(p) < \pi(pqr)/\pi(pr)$ for all $0 < p, q, r \leq 1$. That is, for any fixed probability ratio q , the ratio of decision weights when the probability of the outcome is small will be closer to unity than when the probability of the outcome is high. For example, $\pi(0.1)/\pi(0.2) > \pi(0.4)/\pi(0.8)$.

Figure 2.1: A Hypothetical Weighting Function



Source: Kahneman and Tversky (1979, p.283)

2. The Value Function

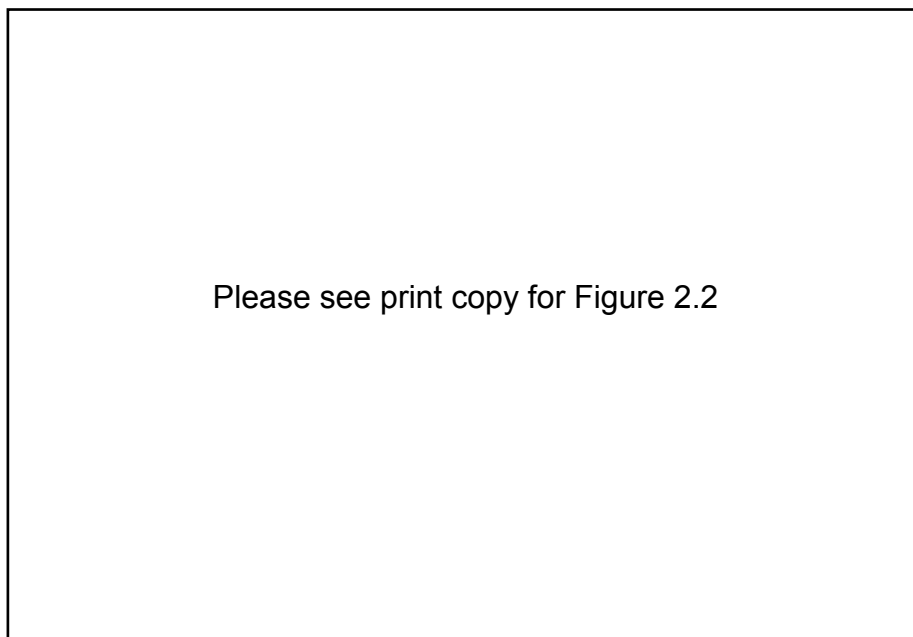
In much the same way as expected utility theory, the second scale (v), assigns a value $v(x)$ to each outcome x , which represents the subjective value of a particular outcome offered by the prospect. However, recall that prospect theory assumes outcomes are measured as gains and losses relative to some reference point (status quo) and not in terms of final wealth as predicted by expected utility theory. The reference point actually serves as the zero point on the scale, which indicates that (v) measures the

²⁶ This simultaneously justifies why individuals have preferences for insurance contracts as well as lottery tickets. When there is a very small chance of winning a very large sum of money individuals will become risk-seeking even though they are generally risk averse over the domain of gains. Similarly, if there is a very small chance of incurring a very large loss individuals become extremely risk averse even though they are generally risk-seeking over the domain of losses.

value of the deviations from the status quo. That is, v measures the value of gains and losses.

Prospect theory assumes that this value function is commonly S-shaped – concave over the domain of gains (risk averse) and convex over the domain of losses (risk-seeking) with a kink at the origin as illustrated in Figure 2.2.

Figure 2.2: A Hypothetical Value Function



Source: Kahneman and Tversky (1979, p.279)

Marginal utility of both gains and losses decreases with their respective magnitudes²⁷. For example, the difference in subjective value between a \$10 and \$20 gain is more than the difference in subjective value between a \$110 and \$120 gain. The same relationship holds for the corresponding losses. Another distinguishing characteristic of prospect theory's value function is that it is steeper over the domain of losses. That is, the disutility (displeasure) associated with losing a sum of money is more than the corresponding utility (pleasure) of winning the same amount – a phenomenon called loss aversion. This finding is reflective in individual's reluctance to accept fair bets, such as a toss of a coin where the probability associated with winning or losing a certain sum of money is the same.

²⁷ Galanter and Pliner (1974) were among the first to propose this idea.

Therefore, according to prospect theory, when presented with a regular prospect $\{x, p; y, q\}$ ²⁸, individuals will determine the overall value according to:

$$V(x, p; y, q) = \pi(p)v(x) + \pi(q)v(y) \quad (2.5)$$

where $v(0) = 0$, $\pi(0) = 0$, $\pi(1) = 1$ and $x \leq 0 \leq y$ or $y \leq 0 \leq x$.

If, however, the prospect offered to individuals is either strictly positive or strictly negative then in the editing phase they will apply the segregation operation to reformulate the prospect. In this situation, individuals generally separate sure (risk-less) gains or losses from the alternative probable (risky) outcomes as described earlier. Therefore, when determining the overall value of prospects of this kind, individuals apply:

$$V(x, p; y, q) = v(y) + \pi(p)[v(x) - v(y)] \quad (2.6)$$

where $p + q = 1$ and $x > y > 0$ or $x < y < 0$.

That is, the value of a strictly positive or strictly negative prospect is equal to the value of the certain outcome plus the value-difference between the outcomes multiplied by the decision weight attributable to the most extreme outcome. To illustrate this idea consider the following example used by Kahneman and Tversky (1979). The value (V) of the prospect $\{400, 0.25; 100, 0.75\}$ would be equal to $v(100) + \pi(0.25)[v(400) - v(100)]$. The distinguishing feature of equation (2.6) is that a decision weight is assigned to the value-difference of the outcomes, which is the risky component but not to the value of the certain (risk-less) outcome since $\pi(1) = 1$.

²⁸ A prospect is strictly positive if all outcomes are positive and strictly negative if all outcomes are negative. In both situations $p + q = 1$. In contrast, a prospect is regular (simple) if there is at most two non-zero outcomes. Prospects of this kind offer outcome x with probability p , outcome y with probability q and nothing with probability $1 - p - q$, where $p + q \leq 1$.

Not surprisingly, many of the elements in the evaluation model described by prospect theory have appeared in various expected utility theories proposed by other researchers. Markowitz (1952) was the first to propose that it would be more likely individual's code outcomes as gains and losses relative to some reference point rather than as final states of wealth. This assumption has been widely incorporated into experimental measurements of utility (Davidson et al. 1957; Mosteller and Nogee (1951). However, in contrast to prospect theory, Markowitz (1952) reports evidence of risk-seeking behaviour in preferences among both positive and negative prospects. This led Markowitz (1952) to propose a utility function that was concave and convex in both the domain of gains and the domain of losses. That is, it retains the expectation principle of expected utility theory. A problem with this is that many researchers have provided evidence of consistent violations of the expectations principle.

Edwards (1962) was among the first to replace probabilities with decision weights. This intuition was examined further in subsequent experimental studies (Anderson and Shanteau, 1970; Tversky, 1967) and similar models were developed. Fellner (1965) applied the concept of decision weights to assist in the explanation of ambiguity aversion, while van Dam (1975) attempted to scale decision weights.

Following on from their original version of prospect theory and based on other experimental evidence Tversky and Kahneman (1992) propose an extended version to incorporate prospects offering more than two outcomes. When determining the overall value (V) of a prospect offering outcome x_i with probability p_i this time individuals apply:

$$V(x_i, p_i) = \sum_{i=1}^n \pi_i v(x_i) \quad (2.7)$$

where, $v = x^\alpha$ if $x \geq 0$, $v = -\lambda(-x)^\alpha$ if $x < 0$ and $\pi_i = w(P_i) - w(P_i^*)$, where

$$w(P) = \frac{P^\gamma}{(P^\gamma + (1-P)^\gamma)^\gamma} \cdot P_i \quad (P_i^*) \text{ is the probability that the prospect yields an outcome}$$

that is at least as good as (strictly better than) x_i .

The use of experimental evidence allows Tversky and Kahneman (1992) to estimate $\alpha = 0.88$, $\lambda = 2.25$ and $\gamma = 0.65$. Note that (λ) is a measure of loss aversion and has typically been estimated as approximately 2. This indicates that the disutility (pain) of a loss is approximately equal to double the utility (satisfaction) of a gain of equal magnitude. Alternatively, the pain of a \$100 loss is roughly offset from the joy of a \$200 gain.

2.4 Application: Individual Investor Behaviour

In light of traditional finance theory, the previous sections provide strong support for behavioural finance and its intuitive appeal. First, the theoretical risks and real-world evidence confirming behavioural finance's predictions of the limitations to arbitrage are discussed. Second, the body of experimental work compiled by cognitive psychologists, which behavioural finance advocates rely on to more accurately understand specific forms of investor behaviour is reviewed.

This section focuses on one of the many applications of behavioural finance, namely the application to investor behaviour. Specifically, it introduces the real-world evidence, which has been used to describe the behaviour of individual investors.

2.4.1 Insufficient Diversification

Traditional finance theory suggests that individuals should hold a proportion of domestic assets that is equivalent to their country's share of world capitalisation (Sharpe, 1964; Lintner, 1965)²⁹. Yet many studies have revealed that investors tend to exhibit a 'home bias' when making decisions concerning their portfolio holdings. For some reason(s) investors tend to prefer to invest domestically as opposed to investing internationally resulting in under-diversified portfolios. Statman (1987) was among

²⁹ Shapiro (1999) reports that the most optimal portfolio (from a risk-return viewpoint) consists of an investment in at least 40% international (non-American) assets and 60% domestic (American) assets, which also confirms the predictions made by traditional finance theory.

the first to notice this puzzling phenomenon and prompted researchers to investigate the issue further.

In their study, French and Poterba (1991) report domestic ownership of the U.S market to be 92.2%, the Japanese market to be 95.7%, the U.K market to be 92%, the German market to be 79% and the French market to be 89.4%. Tesar and Werner (1995) conduct a similar study but analyse the proportion of international investments over a period of 20 years extending from 1970-1990. Although their results indicate that for some of the countries the proportion of international investments increases with time, the portfolio allocations in aggregate are well below the levels predicted by traditional finance. They report that by 1990, the U.K. had 32% of its holdings invested internationally, Japan 11% and Germany 10%. As for Canada and the U.S. the level of international ownership remains constant throughout the period ranging between 2 and 4%³⁰.

There is also strong evidence of a home bias at home. Huberman (2001) analyses the geographical distribution of shareholders of U.S. telephone companies and reports that investors prefer to invest in their local telephone companies than in telephone companies outside of the state they live. Additionally, Grinblatt and Keloharju (2001b) report evidence of a home bias amongst Finnish investors. The results of their paper document how Finnish investors prefer to purchase domestic stocks, especially companies that present annual reports in their native language and are controlled by Finnish executives. Massa and Simonov (2003) report a similar finding for Swedish investors and Feng and Seasholes (2004) for Chinese investors.

Taking a different approach, Benartzi (2001) studies the portfolio allocation decisions of investors in 401(k) plans and reports evidence of a strong bias towards holding company stock. In particular, over 30% of the assets in defined contribution schemes are invested in company stock and surprisingly, much of this is attributable to voluntary employee contributions. In view of this form of home bias, supporting evidence is provided by Huberman and Sengmuller (2004) and Driscoll et al. (1995).

³⁰ Bohn and Tesar (1996) provide additional support in view of a home bias reporting that U.S. investors share only 8% of international equities.

They argue that the bias arises because individuals perceive their own company stock to be less risky than a diversified index.

Several researchers have attempted to explain the home bias on normative grounds but have encountered severe difficulties (see Lewis (1999) and Karolyi and Stulz (2003) for a review). The puzzle becomes even more jumbled, however, when normative portfolio choice models account for human capital. The models suggest that investors should short their own national stock market given the high correlation between human capital and one's own national market (Baxter and Jermann, 1997).

Other researchers have attempted to account for the bias by reporting that the phenomenon arises as a result of information asymmetries (Gehrig, 1993; Brennan and Cao, 1997). The idea is that information relating to domestic stocks is more precise and readily available than international securities, which allows investors to review their preferences regarding the future prospects of domestic securities more easily.

Further explanations of the home bias include the benefits of hedging domestic risk, such as inflation, human capital or interest rates, with domestic securities (Adler and Dumas, 1983; Cooper and Kaplanis, 1994), the high transaction costs associated with international investments (Black, 1974; Stulz, 1981; Kang and Stulz, 1997), institutional barriers for international investments and a difference between the world float portfolio and the world market portfolio, given investors' preferences for domestic equities. Demarzo et al. (2004) also adds that frictions in goods markets cause investors to hold similar, under-diversified portfolios.

While there is strong evidence pertaining to the home bias the cause of the phenomenon remains unresolved. In fact, most empirical work indicates that these explanations are either insignificant to account for the high level of home bias reported in the data or add to the degree of home bias itself (Baxter and Jermann, 1997; French and Poterba (1991); Tesar and Werner (1995) and Dahlquist et al. (2003)).

The most accurate explanation concerning the home bias stems from evidence compiled by psychologists. Research documents that individuals dislike ambiguous situations, where the probability distribution for outcomes from a gamble are not transparent. Ellsberg (1961) was the first to notice this behaviour and termed it ambiguity aversion. To understand how individuals are affected by ambiguity, he conducts an experiment in which participants are offered a choice between two gambles. The first gamble presents an urn containing 100 balls, 50 of which are red and 50 of which are blue. The second gamble presents an urn also, however this time participants are told that there are 100 balls but are not told how many of each colour the urn contains. Participants are informed of the positive payoff they receive if they guess the colour of the ball correctly. Ellsberg (1961) reports that a large majority of participants elect to take the first gamble because of its known probability distribution while avoiding the second gamble because of its ambiguity.

While Ellsberg's (1961) results provide a valuable understanding of how individuals behave, there is no subjective probability estimates assigned to the gambles in his experiment. In financial markets, however, there is subjectivity involved with decisions individuals make. For example, an investor might have to calculate the probability of a share price increasing/decreasing by \$0.50 as a result of the Reserve Banks decision to increase/decrease interest rates.

Heath and Tversky (1991) conduct an experiment to test whether ambiguity aversion holds under subjective probabilities. Their results document that individuals will prefer their own judgement (an ambiguous gamble) over an equi-probable event (a known probability gamble) when they perceive themselves to be skilful and knowledgeable. Heath and Tversky (1991) label this phenomenon the competence effect.

To illustrate the competence effect, consider an experiment similar to that of Ellsberg (1961). However, this time suppose that participants initially state their subjective knowledge level regarding a football game. They are then required to predict who they think will win and provide a corresponding subjective probability estimate for

their selection³¹. They are then given a choice between two gambles. The first is their judgement and the second is a lottery in which there is an equal chance of winning. The competence effect indicates that individuals will bet on their own judgement when they feel highly competent of predicting the outcome of the football game. Surprisingly, Heath and Tversky (1991) report that participants elect to choose their own judgment even in situations where the lottery provides a greater chance of winning. When participants don't feel competent with their selection, they choose the matching lottery³².

Graham, Harvey and Huang (2005) argue that an individual's competence level can be used to partly explain the home bias phenomenon. Their results indicate that investors who are competent (i.e. perceives his or herself to be skilful and knowledgeable) will be more aware of the risks and benefits resulting from international investments and will therefore hold well diversified portfolios³³. On the other hand, those that perceive themselves to be incompetent will refrain from investing internationally resulting in under diversified portfolios. This argument can also be extended to explain the home bias at home puzzle.

Graham et al. (2005) also document that investors who are more optimistic about the U.S. market invest significantly less in foreign securities, leading to a home bias. Their results confirm the predictions of Strong and Xu (2003) and Kilka and Weber (2000) who both provide strong evidence that investors are more optimistic about the familiar, their national stock market. They also report that optimism for the familiar led to an increase investment in familiar stocks.

The competent effect seems like a plausible explanation for the home bias phenomenon, however, Graham et al. (2005, p.8) also acknowledge that familiarity is

³¹ This allows researchers to measure subjective competence in two dimensions – by how knowledgeable participants perceive themselves to be and by the probability estimates being correct.

³² It is worth noting here that according to traditional economics, in particular expected utility theory, individuals should only be concerned with the final payoff from a gamble – not their confidence over the probability distribution of outcomes. That is, preferences and probabilities should be independent of each other, which is contrary to this finding.

³³ Graham et al. (2005) empirically model investor competence in terms of investor demographics such as age, gender, education and salary. Their results show that male investors with higher levels of education and higher salaries are more likely to believe that they are competent investors as opposed to women and those with lower levels of education and salaries.

an element of competence, but argue that it is “not the whole story”. Accordingly, the competence effect is when individuals perceive themselves to be skilful and knowledgeable. Thus, an individual who is unfamiliar with foreign securities but feels competent in their ability to invest internationally might still invest in foreign markets.

This is contrary to Huberman (2001) who argues that a home bias arises simply as a result of investors preferring the more familiar. Huberman (2001, p.676) indicates “that by nature agents feel favourable about and charitable toward that with which they are comfortable or familiar, including investment opportunities that are close to home”. Although some might disagree, Huberman’s (2001) explanation has strong support from the marketing literature, which suggests that an individuals’ liking toward particular stimuli can be influenced through repeated exposure to those stimuli (see Bornstein (1989) for a review). Additionally, researchers report that repeated exposure to stimuli can facilitate an agent’s ability to think about it more and lead to a preference for it also³⁴.

Ackert, Church, Tompkins and Zhang (2005) conduct a laboratory-based study to investigate whether investors’ home bias in the U.S. and Canada is undermined by their familiarity with firms. They achieve this by controlling for the information (the firm’s home base/geographical location and the firm’s name) provided to participants in the study, which allows them to focus on whether investment (portfolio allocation) decisions change with changes in the information set.

The results of their study suggest that by providing information regarding a firm’s home base, but not its identity, is not sufficient to change investment behaviour. Put simply, participants refuse to invest in firms that are located close to home, given this information alone. Further evidence arising from the study indicates that participants are more likely to invest in firms they were familiar with, when receiving company specific information, such as its name and business focus. Importantly, this is a laboratory-based experiment in which real-world information asymmetries were absent.

³⁴ See for example, Bornstein and D’Agostino (1992), Janiszewski (1993) and Shapiro (1999).

Unlike previous work documenting a bias for domestic equity investments in portfolio choice on an aggregate basis, Karlsson and Norden (2007) analyse the differences in home bias on an individual level for portfolios that are formed as part of the Swedish pension plan. Their study allows them to venture further than earlier work on the topical home bias puzzle and investigate the impact of investor demographics (such as gender, age, education, employment, etc) on the likelihood of exhibiting a home bias.

The results of their paper document that individuals are more prone to a home bias if they work in the public sector as opposed to the private sector. Karlsson and Norden (2007) argue that those in the private sector have lower job security than those in the public sector and as a result, they are more likely to invest internationally. Since a domestic slowdown increases the chances of workers in the private sector losing their jobs (reducing consumption levels) international investments will not be affected (consumption levels might increase or remain constant), hence smoothing their overall consumption. They also report that individuals that have previously been exposed to working with risky assets, have higher levels of education and have more money invested in the Swedish pension plan are less likely to have a home bias.

This result is consistent with the idea that the most sophisticated investors are less likely to show a home bias. It also provides additional support for the findings of Grinblatt and Keloharju (2001b), who report that less sophisticated investors (non-professionals) have a higher tendency than more sophisticated investors (professionals) to invest locally. Karlsson and Norden (2007) also documented that men are more likely to invest domestically than women. They believe that this finding is attributable to the overconfidence phenomenon via a preference for the most familiar.

In contrast, Lutje and Menkhoff (2004) analyse the responses of over 230 professional fund managers in Germany to determine whether professional investors exhibit a home bias. Given that money managers are professional investors (meaning that they should exhibit the most rational behaviour) and have no investment restrictions, their portfolios should be well diversified. Surprisingly, the results of their study indicate that fund managers invest approximately three times more in the domestic market

than they should. They report that the home bias is related to factors such as proximity, perceived informational advantage as well as expectations of higher returns in the domestic market. Moreover, they document that the relations of these factors occur simultaneously making it difficult to isolate a single hypothesis of why there is a home bias.

Coval and Moskowitz (1999) also report evidence of a home bias amongst U.S. mutual fund managers. Their findings document that fund managers prefer to invest in companies whose headquarters are located close to their home base. In a subsequent paper, however, Coval and Moskowitz (2001) report that these funds actually perform well, indicating that an informational advantage might be apparent as opposed to a preference for the familiar.

In summary, there is strong evidence which pertains to the fact that individuals dislike ambiguous situations. However, in situations where an individual feels competent in their ability to predict an outcome, they will almost always back themselves in light of a gamble offering an equi-probable chance of winning. That is, they will choose an ambiguous event (their self-evaluated expert level) over a known probable event. Research also documents that individuals give preference to the things that appear most familiar to them. Therefore, from a behavioural finance perspective, aversion to ambiguous situations, competence and preference for the familiar can play a central role in providing a simplistic explanation for the home bias phenomenon³⁵.

2.4.2 Excessive Trading

If as traditional financial theory predicts, markets are efficient and individuals are all rational expected utility maximisers then investors should only trade when the marginal benefits of doing so are at least equal to, if not exceed the marginal costs associated with the trade (Grossman and Stiglitz, 1980). However, contrary to this assumption is evidence of the high level of turnover in financial markets that cannot

³⁵ Other behavioural explanations for the home bias phenomenon come from French and Poterba (1991) and Uppal and Wang (2003) who argue that systematic differences in the expectations of domestic and foreign securities amongst investors cause most to invest domestically as opposed to internationally resulting in under diversified portfolios.

be explained by the trading needs of rational investors. Rational investor's should only trade to rebalance their portfolios, minimise the taxes they pay and make periodic contributions and withdrawals to their portfolios. Furthermore, if a rational investor possessed valuable information and decided to trade speculatively, they will generally choose not to trade with each other (Barber and Odean, 2001).

Behavioural finance offers a straightforward explanation of why there is excessive trading activity among investors in financial markets – overconfidence. Section 2.3.1 discusses how individuals exhibit overconfidence in their subjective judgements. As such, evidence compiled from psychologists suggests that most individuals are overconfident regarding their abilities (Frank, 1935) and tend to overestimate the precision of their knowledge (Alpert and Raiffa, 1982; Fischhoff, Slovic, and Lichtenstein, 1977). They are even unrealistically optimistic about the outcomes of futures events (Weinstein, 1980; Kunda, 1987), pure chance events (Marks, 1951; Irwin, 1953; Langer and Roth, 1975) and self-evaluations (Greenwald, 1980).

In addition, research documents that individuals are more overconfident when they are presented with difficult tasks, are required to make forecasting decisions with low predictability and for undertakings that lack efficient and precise feedback (Fischhoff, Slovic, and Lichtenstein, 1977; Lichtenstein, Fischhoff, and Phillips 1982; Yates, 1990; Griffin and Tversky, 1992). Stock selection in financial markets can be considered a difficult task given the randomness of stock prices and noisy feedback. Hence, when investors select stocks based on their subjective judgements they exhibit high levels of overconfidence, even to the extent that experts become more overconfident than novices (Griffin and Tversky, 1992)³⁶.

Strong evidence pertains that overconfidence can be used to explain the excessive trading behaviour of individual investors across world financial markets³⁷. Benos

³⁶ Overconfidence has been observed among various types of professional. Some of which include, Clinical psychologists (Oskamp, 1965), physicians and nurses (Christensen-Szalanski and Bushyhead, 1981; Baumann, Deber, and Thompson, 1991), investment bankers (Stael von Holstein 1972), engineers (Kidd, 1970), entrepreneurs (Cooper, Woo, and Dunkelberg, 1988), lawyers (Wagenaar and Keren, 1986), negotiators (Neale and Bazerman, 1990), and managers (Russo and Schoemaker, 1992).

³⁷ See Glaser, Noth and Weber (2004) for a comprehensive review of overconfidence models, their predictions and empirical tests.

(1998), Caballe and Sakovics (2003), Kyle and Wang (1997), Odean (1998b), and Wang (1998) all model static overconfidence by incorporating the assumption that individuals tend to overestimate the precision of their own information signals, as discussed above³⁸. They achieve this by modifying the models of Diamond and Verrecchia (1981), Hellwig (1980), Grossman and Stiglitz (1980), Kyle (1985), and Kyle (1989).

All of the models predict that overconfidence will generate excessive trading behaviour, provided that past returns are used as a proxy for overconfidence. This occurs because when overall market returns are high, some investors overestimate the precision of their information signals leading to overconfidence. Investors that are overconfident mistakenly attribute increases in wealth to their own expertise of selecting stocks that outperform the market – also known as self-attribution bias. When investors exhibit this behaviour, they often underestimate the variance of stock returns and also trade more frequently in subsequent periods because of the miss-calibrated error bounds they impose around their return forecasts.

Odean (1999) provides a direct test of the proposition that overconfidence leads to excessive trading by investigating whether investor's profits are great enough to cover their trading costs. Odean (1999) randomly selects 10,000 active individual investor's accounts from a discount brokerage house and analyses approximately 163,000 transactions over the period 1987-1993 to investigate this link. Surprisingly, the results of the study indicate that not only do the securities investor's purchase, insufficiently outperform those they sell to account for the trading costs involved, the securities they purchase, extraordinarily, under perform those they sell. The assumption that individuals overestimate the precision of their information might contribute to the results, however, Odean (1999) reports that it is not sufficient to explain them. Odean (1999) documents that individuals must systematically misinterpret information they possess or that is available to them.

Barber and Odean (2000) conduct a similar study, however, they analyse the performance of common stocks held directly by households at a discount brokerage

³⁸ Static overconfidence implies that individuals' overconfidence levels remain constant over time.

house. This enables them to report on the aggregate performance of individuals. They monitor the performance of 78,000 household accounts over the six year period 1991-1997. The results of their study provide supporting evidence that overconfidence generates excessive trading, but more importantly, it is hazardous to individuals' wealth levels. Barber and Odean (2000) report that although the gross performance of households that trade frequently is approximately equal to the gross performance of households that trade infrequently, their annualised net performance is much different. Specifically, their results show that households with high turnover (in excess of 8.8% per month), earn a net annualised geometric mean of 11.4% compared to a mean of 18.5% for households with lower turnover levels. Barber and Odean (2000) also document that households significantly under-perform relevant benchmarks over the same time period (after accounting for transaction costs).

Barber and Odean (2001) provide supporting evidence that overconfidence generates excessive trading, but show that this behaviour is more profound in males than in females. Using a similar dataset to Barber and Odean (2000), Barber and Odean (2001) analyse the trading accounts of 35,000 households over the period 1991-1997. They report firstly, that men trade 45% more than women and secondly, that it reduces their net performance by 2.65 percentage points per year as opposed to 1.72 percentage points for women.

Barber and Odean (2002), working with the same dataset, analyse the trading behaviour of over 1,600 individuals that switch from phone-based trading to online trading during the 1990's. This presents a setting in which individuals have greater access to information and lower transaction costs. They report that those who switch to online trading perform well before making the switch, beating the market the market by more than 2%. However, after making the switch, the results show that individuals trade much more frequently, are more speculative with their trades and most importantly do not make as much money. These findings cannot be explained by market frictions, such as transaction costs, execution speed and access to relevant information, since they are all enhanced when making the switch to online trading. Overconfidence can, however, explain the excessive trading behaviour and the decrease in profits of those who switch.

Gervais and Odean (2001) provide a more formal study in which they develop a multi-period model that describes both the process by which individuals learn about their own ability and how a bias in this learning process can generate overconfidence. In their model, investors are initially unaware of their trading ability, however, learn of this through experience. When investors accurately forecast dividends for the next period they improperly update their beliefs (forecasts for the subsequent period) and mistakenly attribute their success to their superior forecasting ability, becoming overconfident³⁹.

Their results indicate that investor overconfidence changes dynamically with both successes and failures to predict future dividends. Surprisingly, they report that investors exhibit their highest levels of overconfidence early in their career but find that this declines as they age and evaluate their abilities more realistically. They also show that for any level of learning bias and trading experience successful traders are the most overconfident. According to Gervais and Odean (2001, p.2) “overconfidence does not make traders wealthy, but the process of becoming wealthy can make traders overconfident”. Furthermore, the results confirm the predictions that aggregate overconfidence is higher following market gains and lower following market losses. Gervais and Odean (2001) also highlight that higher overconfidence leads to higher turnover, which indicates that turnover is higher following market gains as opposed to market losses.

These results also confirm the findings of Statman, Thorley and Vorkink (2006) who report four key findings. First, higher market turnover is attributable to overall market returns, which is consistent with the prediction of the overconfidence hypothesis. Second, on an individual security level turnover is positively related to both individual stock returns and market returns. Statman et al. (2006) document that the positive relation between turnover and individual stock returns is consistent with the disposition effect, while the positive relation between turnover and market returns is further evidence of overconfidence. Third, the positive relation between turnover and individual stock returns is more evident in small capitalisation stocks. Fourth, there is

³⁹ In contrast to the static overconfidence models described earlier, the advantage of a dynamic overconfidence model allows the researchers to monitor changes in overconfidence over time.

some predictability based on turnover (trading volume) for individual stocks. Specifically, higher volume stocks tend to provide positive returns in the one month that follows but then negative returns in subsequent months⁴⁰.

2.4.3 The Selling Decision

Shefrin and Statman (1995) initially observed the tendency of investors to hold losing stocks too long and sell winning stocks too early. They labelled this behaviour the disposition effect. Since then, several studies have provided strong evidence of this puzzling phenomenon. In particular, Odean (1998a) analyses the trading behaviour for 10,000 investors accounts he randomly selects from a database of clients at a discount brokerage house in the U.S. The dataset contains approximately 160,000 transactions extending over the period 1987-1993. Overall the results indicate that investors realise their gains more readily than their losses. Odean (1998a) reports that investors prefer to sell stocks from which they will obtain a profit as opposed to selling those from which they will incur a loss. Furthermore, Odean (1999) documents that this result holds for all months except December, where there is evidence of tax motivated selling.

Shapira and Venezia (2001) also provide an empirical study of the disposition effect. Analysing financial market data from an Israeli stockbroker, they too report strong evidence of a disposition effect among both professional and independent investors, although the effect is more pronounced amongst independent investors. In a Finnish setting, Grinblatt and Keloharju (2001a) find a similar disposition effect among both household investors and institutional investors, even after controlling for a number of variables that might affect trading. In a futures market setting, Heisler (1994) reports strong evidence of the disposition effect among a group of futures traders. Locke and Mann (2005) and Frino, Johnstone and Zheng (2004) document the same finding among professional futures traders in the U.S. and Australia, respectively. Furthermore, Jordan and Diltz (2004) report that approximately 65% of the day

⁴⁰ This result is similar to the findings reported by Daniel, Hirshleifer and Subrahmanyam (1998) who argue that self-attribution bias can intensify overreactions, which can possibly lead to short-term momentum and long-term reversals in stock prices.

trader's in their study hold losing trades longer than profitable ones, exhibiting strong evidence of the disposition effect⁴¹.

Weber and Camerer (1998) argue that a conclusive test of the disposition effect using real financial market data is difficult. Given the various expectations of investors as well as their subjective decisions, it is hard to control for these in large market settings such as the New York Stock Exchange (NYSE). They therefore propose an experimental design, which enables them to observe the trading decisions of individual investors for six stocks only, and hence provide a direct test of the disposition effect. The results of their experiment provide supporting evidence for the disposition effect. In particular, the results show that investors are more willing to sell stocks that increase in value relative to the purchase price and hold onto those that decrease in value. When the results are aggregated across all six stocks, 60% of those sold are winners and less than 40% of those sold are losers. Weber and Camerer (1998) also document that these results hold when the reference point is taken to be the price of the stock in the period prior to when it is purchased⁴².

In addition to the strong evidence supporting the disposition effect, research shows links between the disposition effect and several stock market phenomena. Rangelova (2001) reports that the disposition effect is more evident in large capitalisation stocks, while Dhar and Zhu (2002) provide evidence in support of the notion that the more sophisticated investors, particularly those able to analytically process information, exhibit less of a dispositional behaviour⁴³. Furthermore, Grinblatt and Han (2001) present a model and hypothesise that momentum effects are connected to the

⁴¹ Genesove and Mayer (2001) also report evidence of the disposition effect among home owners, Czarnitzk and Stadtmann (2005) among those who purchase investor magazines and Kaustia (2004) and Brown, Chappel, da Silva Rosa and Walter (2006) provide dispositional evidence among traders in initial public offerings (IPO's).

⁴² Oehler, Heilmann, Lager and Oberlander (2002) also find evidence of a disposition effect in experimental markets. Furthermore, in a similar study, Chui (2001) modifies the experiment of Weber and Camerer (1998) and reports that a psychological tendency known as the locus of control can be used as a proxy to explain the disposition effect observed in the study. Kirchler, Maciejovsky and Weber (2005) also provide experimental evidence of the disposition effect in Austria. They document that participants in their experiment who experience a gain sell their assets more vigorously than those who experience a loss.

⁴³ This finding is in contrast to the results of Chen, Kim, Nofsinger and Rui (2004) who report that investor sophistication does not necessarily mitigate overconfidence or the disposition effect or improve the trading performance of Chinese investors.

disposition effect. Their predictions are borne out in the data even to the extent that their results indicate that a variable, which measures the difference between aggregate paper gains and losses in a stock, drives, in large part, the momentum effect. This stylised fact is confirmed by the findings of Strobl (2003) who also reports evidence that the disposition effect is consistent with price momentum.

It is difficult to explain the dispositional behaviour among individuals using a rational expectations framework. Nonetheless, researchers have tried. In particular, Lakonishok and Smidt (1986) argue that portfolio rebalancing can, at least in part, explain why investors ride their losses but realise their gains too early. According to traditional portfolio theory, investors that do not hold the market portfolio are required to rebalance their portfolio by selling a proportion of the shares that have increased in value to restore a sufficiently diversified portfolio.

Lakonishok and Smidt (1986) also report that information differences among investors could be linked to the disposition effect. They suggest that if investors purchase stocks on positive information, and as a result the price increases, their willingness to sell could reflect their rational belief that the information has been properly absorbed into the stock price. Conversely, if the price falls the investor will hold, rationally believing that the positive information is yet to be reflected into the stock price. Furthermore, Harris (1988) suggests that higher transaction costs associated with lower priced stocks can also contribute to the disposition effect. Since losing investments are more likely to be lower in value, than opposing winning investments, investors might simply refrain from selling their losing investments to avoid the high transaction costs.

Despite rational justifications, the literature clearly favours behavioural explanations of the disposition effect⁴⁴. The first, originally proposed by Shefrin and Statman (1985), combines the ideas of prospect theory (Kahneman and Tversky, 1979) and mental accounting (Thaler, 1985). In contrast to traditional expected utility theory, prospect theory presents an S-shaped utility function defined over gains and losses,

⁴⁴ Odean's (1998a) results are detrimental to the rational explanations of the disposition effect. He reports that even after controlling for the alternative rational motivations, investors still prefer to sell winners and hold losers (p.1779).

rather than final wealth levels. Over the domain of gains the function is concave and investors are assumed to be risk averse, while over the domain of losses the function is convex and investors are assumed to be risk seeking. Furthermore, the convexity for losses is steeper than the concavity for gains.

The point corresponding to a zero gain or zero loss is referred to as the status quo or reference point. The idea of mental accounting suggests that investors hold separate mental account for each individual stock. Thus, combining the idea of prospect theory and mental accounting assumes that investor's value individual stocks using an S-shaped utility function over gains and losses relative to some reference point (which is usually taken to be the purchase price)⁴⁵. To see how this argument provides an explanation of the disposition effect, consider the following illustration from Barberis and Thaler (2003, p.51).

“Suppose that a stock that was originally bought at \$50 now sells for \$55. Should the investor sell at this point? Suppose that the gains and losses of prospect theory refer to the sale price minus the purchase price. In this case, the utility from selling the stock is $v(5)$. Alternatively, the investor can wait another period, whereupon we suppose that the stock could revert to \$50 or rise to \$60 with equal probability; in other words, we abstract from belief-based trading motives by saying that the investor expects the stock price to stay flat. The expected value of waiting and selling next period is then $0.5v(0) + 0.5v(10)$. Since the value function (v) is concave in the region of gains, the investor sells now. In a different scenario, the stock may currently be trading at \$45. This time, the comparison is between $v(-5)$ and $0.5v(-10) + 0.5v(0)$, assuming a second period distribution of \$40 and \$50 with equal probability. Convexity of (v) pushes the investor to wait. Intuitively, by not selling, he is gambling that the stock will eventually break even, saving him from having to experience a painful loss”.

The second possibility presupposes that investors have an irrational belief in mean reverting stock prices. That is, investors believe that today's losers will soon outperform today's winners. If the expected returns of today's losers are greater than

⁴⁵ Odean (1998a) acknowledges that although the purchase price is considered the fundamental and most logical value to use as the reference point, for long term investments it might only be a determinant.

today's winners then this belief can be justified on rational grounds. However, if investors persistently believe that today's losers will soon outperform today's winners and today's losers provide consistently lower expected returns than today's winners, then the disposition effect can be explained by an irrational belief in mean reversion among investors. This prediction seems intuitively plausible and has strong support from Andreassan (1988) who reports that in an experimental setting participants trade stocks as though they expect short-term mean reversion in their prices. Odean (1998a) also provides evidence of an irrational belief in mean reversion among traders from a discount broker. Specifically, he reports that the stocks investors sell outperform those they continue to hold, which does not show any indication of stock prices mean reverting to their original levels.

2.4.4 The Buying Decision

While most research focuses on the selling decisions of investors as the previous section outlines, only a small amount of literature focuses on the buying decisions of investors. This is because theoretical models of financial markets treat buying and selling as two sides of the one coin. That is, informed traders are equally likely to purchase a stock with positive information as they are to sell a stock with negative information. In fact in most formal models, buying and selling are treated as the same action but with opposite signs⁴⁶.

However, in reality the decision of 'what to buy' poses as a complex problem for investors, given the extraordinary amount of stocks trading on world financial markets. In contrast, when making a decision to sell, investors generally turn to the stocks in their own portfolios and this is in main part attributable to the short selling constraints imposed upon individuals. Hence, it is just as important to understand how individual investors decide which stocks to buy as it is to understand how they decide which stocks to sell.

According to rational economic models agents should make decisions that maximise their expected utility and even though when faced with numerous alternatives agents

⁴⁶ See for example the rational models of Grossman and Stiglitz (1980) and Kyle (1985).

incur search costs, their search set should be unbiasedly selected. However, in practice attention-based characteristics interfere (somewhat mitigate) with the preferences of individuals to the extent that individuals tend to limit their search set by choosing stocks that attract their attention and later buy the ones they prefer from the set already selected. Research provides strong evidence of this phenomenon

Lee (1992) monitors the trading activity of over 230 stocks around the time of their earnings announcements for customers who place market orders of less than \$10,000. He reports a net buying effect among traders following both positive and negative earnings surprises and argues that news might attract investor's attention, or alternatively, retail stockbrokers that make more buy recommendations than sell recommendations might contact their clients around the time of earnings announcements. Hirshleifer, Myers, Myers and Teoh (2004) also report evidence of a net buying effect among individual investors subsequent to both positive and negative earnings announcements.

Odean (1999) provides an understanding of how individuals decide to buy stocks. He shows that unlike stocks individual investors decide to sell, which are mainly prior winners, the stocks they choose to purchase are evenly split between prior winners and prior losers. Odean (1999) documents, however, that this decision is conditional on whether the stocks were a big prior winner or a big prior loser. In other words, individuals base their purchasing decisions on stocks exhibiting the most extreme movements, simply because they attract the most attention. Odean (1999) suggests that contrarian investors purchase recent losers and trend followers purchase recent winners.

Seasholes and Wu (2004) also provide evidence of investors purchasing stocks that attract their attention. They analyse the trading activity of stocks that have recently reported new highs on the Shanghai stock exchange. The results of their study highlight an increase in net buying among those stocks hitting the new high levels. Furthermore, Seasholes and Wu (2004) document that prices of these stocks revert to pre-event levels within ten trading days and that a small group of professional traders profit from the short-lived price surge, anticipating the increase in demand at the expense of the more uninformed individual trader.

Barber and Odean (2005) provide a direct test of the hypothesis that individual investors are more likely to purchase rather than sell attention-grabbing stocks. In their study they focus on individual investors as opposed to institutional investors since it is more likely that individuals purchase attention-grabbing stocks than institutional investors. They use three proxies to determine whether individuals are paying attention to a particular stock: 1. A stock's abnormal trading volume, 2. A stock's (previous) one-day return and 3. Whether the stock appears in the news. Their predictions are borne out in the data. In particular, the results show that individual investors make about twice as many purchases than sales in stocks reporting an abnormally high turnover (the highest 5%) and make almost twice as many purchases than sales for stocks with an extremely low return on the previous day (the lowest 5%). The results are not as strong for professional investors as predicted. Barber and Odean (2005) argue that institutional investors, as part of their job, have more time to search through all of the alternative investment options and not limit their search set by way of attention.

2.5 The Effect of Prior Outcomes on Risky Choice

The previous section discusses the application of behavioural finance to investor behaviour. It is important that researchers are aware, however, of the problems and criticisms that might arise by simply adopting pre-existing psychological evidence to explain investor behaviour. One of the purposes of psychological work is to analyse individual behaviour in general, not specifically the behaviour of investors in financial markets. According to Hirshleifer (2001, p.1577), “it is often not obvious how to translate pre-existing evidence from psychological experiments into assumptions about investors in real financial settings”. As a possible solution Hirshleifer (2001, p.1577) adds, “routine experimental testing of the assumptions [...] of asset pricing theories is needed to guide modelling”.

While some might argue, a majority would probably agree that prospect theory most accurately captures experimental evidence of the inconsistencies and violations of the axioms (principles) underlying expected utility theory. Moreover, it provides a foundation for a descriptive model of decision making under uncertainty. One of the limitations associated with the model however, is that it is only applicable to one-shot prospects (gambles).

As discussed in section 2.3.2 above, prospect theory was originally designed for prospects in which there were at most two outcomes, with known stated probabilities (Kahneman and Tversky, 1979). Since then, however, the theory has been generalised to incorporate prospects that offer more than two outcomes also with known stated probabilities (Tversky and Kahneman, 1992). In reality though, individuals are repeatedly (often) faced with making decisions in uncertain situations, indicating that most individuals have likely experienced the pleasure associated with a gain and/or the pain associated with a loss previously. Not surprisingly, research documents that prior outcomes (from previous decisions) do influence the subsequent choices individuals make (Arkes and Blumer, 1985; Staw, 1981; Thaler, 1980; Laughhunn and Payne, 1984).

More research is required, which extends prospect theory and related literature and analyses investor behaviour in real financial market settings. This is to provide a thorough understanding of investment behaviour which will eventually allow researchers to develop asset pricing models that are much more sophisticated at predicting prices. This section provides a review of the literature concerning the effects of prior outcomes on risky choice.

2.5.1 House money Effect

Thaler and Johnson (1990) extend the idea of prospect theory and investigate how prior gains and losses affect risky choice (decision-making under uncertainty for sequential decisions). In their paper, Thaler and Johnson (1990) initially investigate how individuals encode gains and losses. They propose, for two-shot prospects (in extension to prospect theory's one-shot approach), that individuals apply alternative editing rules to simplify and reformulate prospects in the initial editing phase. In

particular, they propose four alternatives to the ones previously described by prospect theory: 1. Prospect theory with no memory, 2. Prospect theory with memory, 3. Concreteness and 4. Hedonic editing.

The first, prospect theory with no memory, which is consistent with prospect theory itself, assumes that individuals simply reformulate and evaluate prospects independently. That is, previous outcomes do not influence subsequent choices. The second, prospect theory with memory, which is inconsistent with prospect theory, assumes that previous outcomes do attribute to the subsequent decisions individuals make. The third, concreteness simply assumes that individuals will not make any editing adjustments to the prospect offered to them and will simply evaluate it as it appears⁴⁷. Individuals applying this editing rule will evaluate prospects in the same manner as those that apply prospect theory with no memory. The fourth, hedonic editing assumes that individuals edit prospects in a certain manner that makes them appear most pleasant (or least unpleasant). The hedonic editing hypothesis, originally proposed by Thaler (1985), assumes that individuals will follow editing rules from four principles whenever possible:

1. Segregate gains
2. Integrate losses
3. Segregate small gains from larger losses (the ‘silver-lining’ principle)
4. Integrate (cancel) smaller losses with larger gains

Thaler (1985) provides a test of the hedonic editing hypothesis by conducting an experiment to determine whether individuals prefer to segregate their gains and integrate their losses. In this particular experiment, subjects are presented with four pairs of scenarios relating to two fictitious people Mr A and Mr B. In each case, two events occur to Mr A and a single event to Mr B and participants are asked to judge who they believe is the happiest (or least happy in the case of losses).

The results of the experiment support the hedonic editing principals in that a majority of subjects select the frame predicted by the theory. That is, in the presence of gains, 64-75% select Mr A as being the happiest, which implies that people prefer to

⁴⁷ The concreteness hypothesis was proposed by Slovic (1972).

segregate gains and in the case of losses, 70-72% selects Mr B as the unhappiest, suggesting that people prefer to integrate losses.

Although the results of Thaler's (1985) paper appear to support the editing rules 1-4 above, it does not provide a direct test of the hedonic editing hypothesis. Put simply, it reports how individuals prefer to have gains and losses framed for them, while the hypothesis conjectures that individuals will reframe prospects in a manner that makes them appear most pleasant (or least unpleasant). To directly test the hypothesis individuals need to make choices reflecting their preferences for certain prospects.

Thaler and Johnson (1990) propose that one way to do this is to ask subjects to make choices about the timing of events. Thaler and Johnson (1990) assume that temporal separation facilitates segregation and conversely that the integration of events is easier and more convenient if they occur on the same day. To examine this, Thaler and Johnson (1990) conduct an experiment that is almost identical to that of Thaler (1985), however in this study subjects are given a choice relating to the timing of events. Specifically, when participants are presented with scenarios of pairs of events relating to gains and losses, they are asked whether they would prefer the events occur on the same day or a week or two apart. In the case of gains 63% of participants choose to have the events occur apart supporting the hedonic editing hypothesis. However, in the case of losses 57-75% of participants choose also to have the events spread out over a week or two.

Thaler and Johnson (1990) obtain these results repeatedly in the case of small or large losses, for non-monetary as well as monetary losses and for related and unrelated pairs of events. They describe the results of their experiment as "a severe blow to the hedonic editing hypothesis" (p. 649). When subjects are asked why they prefer to have losses segregated over time most respond with the same two reasons: 1. Given the choice, they would not integrate the second loss of the day with the first loss of the day and 2. The pain associated with the second loss would hurt more after the first loss than if it was experienced alone.

Thaler and Johnson (1990) explore further the failure of subjects to integrate losses. In their subsequent experiment the first set of results show that students feel less pain

losing \$9 following a gain of \$30 than by itself, which supports the hedonic editing hypothesis. Subsequent results show that a large majority of students are more affected by a \$9 loss after an initial loss of \$30, than by itself, refuting the hedonic editing hypothesis. Extending this, participants are less affected by a loss of \$9 following much larger losses of \$250 or \$1000.

The results of Thaler and Johnson's (1990) first two experiments led them to dismiss the hedonic editing hypothesis for two reasons: 1. When subjects are presented with prospects in the one-stage format (eg a sure gain of \$20 and a 50-50 gamble to win \$11 or \$29) they will not segregate the sure gain and 2. Subjects can't come to terms with integrating losses. They therefore, propose the quasi-hedonic editing hypothesis – the term quasi implies that it follows the hedonic editing rules but only part of the time. According to the quasi-hedonic editing hypothesis, in a two-stage prospect involving losses individuals will not integrate the second loss with the first. In the case of a two-stage prospect involving a gain and a loss they will integrate the loss with the gain, providing the gain occurs first.

In their final experiment, Thaler and Johnson (1990) test the editing rules of the quasi-hedonic editing hypothesis in the domain of risky choice, which is the main focus of their study. They apply two different methods to account for the assumptions made by various editing rules: 1. Between-subject comparisons of responses to alternative representations of the same problem since some rules suggest that presentation format has no effect on choices and 2. Within subject comparisons since various editing rules imply differences concerning the role of prior outcomes on risky choice. Subjects participating in the experiment are allowed to make up to a maximum of eight choices regarding the gambles presented. One half of the participants receive the problems in a two-stage format while the other half receives the problems in a one-stage format.

There are only two types of prospects used for this experiment. In the first subjects are offered a fair chance of winning or losing \$ x versus the status quo, while in the second, subjects are offered the choice between a sure gain of \$ x and a gamble offering a one-third chance to win \$3 x and a two-third chance of winning nothing. In addition, each of the prospects in the second are combined with four various levels of initial outcomes (\$15, \$0, -\$2.25, and -\$7.50).

Thaler and Johnson (1990) report that all four editing rules (prospect theory with memory, prospect theory with no memory, concreteness and hedonic editing) could be refuted as a result of their final experiment. Prospect theory with memory and hedonic editing are rejected as a result of the presentation format having an effect on choice. Additionally, the effect of prior outcomes on risky choice accounts for more than a 30% shift in preferences between the one and two-stage versions of the problems. This is in contrast to the predictions made by the editing rules of prospect theory with memory and concreteness, which suggest that prior outcomes will not affect risky choice. If this were true the problems selected by participants in the experiment should have been representative of loss aversion. Overall, the quasi-hedonic editing hypothesis is much more accurate at capturing the results, although there is concern regarding the ambiguity of its predictions, which makes it difficult to test empirically.

From their final experiment, Thaler and Johnson (1990) document three additional findings. First, individuals become more risk averse following losses especially when there is no chance to break even. Furthermore, the emotional effect of a loss can sensitise individuals to a subsequent loss of a similar magnitude. This suggests that the prediction prospect theory makes for one-stage prospects, regarding individual's risk-seeking attitudes over the domain of losses, cannot be extended as a more general finding to incorporate more complex prospects.

Second, the quasi-hedonic editing hypothesis predicts that individuals will become risk-seeking after an initial gain. It follows that any subsequent loss, smaller than the original gain, will be cancelled by integrating it with the initial gain. This is often referred to as gambling with the house money, a phrase that is commonly used by gamblers at casinos. The intuition is that losing the 'house's money' isn't as painful as losing one's own cash. Hence, after an initial gain, losses are perceived as reductions in wealth, which continually facilitates risk-seeking behaviour until all winnings have been depleted. As expected, one-stage prospects are unable to create the feeling of being ahead therefore the prediction of prospect theory is more likely.

Third, individuals change their risk-taking behaviour when faced with prospects that might allow them to break even. For two-stage prospects, when an initial loss is incurred most individuals become risk averse. However, when presented with the possibility of breaking even this can mitigate the influence of risk aversion and facilitate risk-seeking behaviour⁴⁸.

2.5.2 Loss Aversion

In contrast to the house money effect, loss aversion implies that individuals become risk seeking following losses rather than gains. There is strong evidence highlighting this behavioural phenomenon among professional traders in the context of a real financial market.

Coval and Shumway (2005) study the behaviour of proprietary traders at the Chicago Board of Trade (CBOT). The results of their study document that morning losses encourage professional traders to take more afternoon risk than normal, which is consistent with loss aversion. In fact, traders recording morning losses purchase contracts at higher prices and sell contracts at lower prices in the afternoon, in an attempt to win back morning losses. The abnormal behaviour disrupts short-term prices in the afternoon, creating more volatility than normal, however this disseminates within the five-minute period following the initial price-setting trade.

Locke and Mann (2004) analyse the risk attitudes of floor traders at the Chicago Mercantile Exchange (CME). They report that in aggregate traders significantly increase their risk-taking behaviour following periods of losses, confirming the findings of Coval and Shumway (2005) and providing additional support for loss aversion. On a cross-sectional basis of individual traders Locke and Mann (2004) report that the most successful traders exhibit a behavioural bias that is consistent with overconfidence. Although the most successful traders from the morning take the largest risks in the afternoon, the bias is limited by trading experience.

⁴⁸ Other experimental research providing evidence of the house money effect includes; Battalio, Kagel and Komain (1988), Keasey and Moon (1996) and Weber and Zuchel (2003).

Weber and Zuchel (2003) also offer support for loss aversion, albeit not in the context of a real financial market setting. In their experimental design, participants are given one of two problems that have an identical set of attainable probability outcomes but differ in presentation format. The first problem represents that of a dynamic portfolio choice that would normally be observed in a financial market setting. Participants are given an initial sum of money and are required to invest it over two successive periods. They can choose between a risky asset for which the price fluctuates randomly and a risk free asset, such as cash. The second problem represents that of a two stage lottery or gamble similar to the one shot gamble offered by prospect theory. Participants are given money at the beginning of each period in order to purchase the lottery tickets that will generate random payoffs.

Weber and Zuchel (2003) test whether the responsibility of choosing an initial outcome changes the behaviours of the participants from when they are assigned an initial outcome. Their result highlight that prior outcomes affect the choices individuals make regarding future prospect. Specifically, participants increase their risk-taking attitudes following losses. In contrast, results of the second problem provide support for the house money effect, with participants taking more risk following gains⁴⁹.

Benartzi and Thaler (1995, p.75) argue that, “two factors contribute to an investor being unwilling to bear the risks associated with holding equities, loss aversion and a short evaluation period”. They refer to this combination as myopic loss aversion. Benartzi and Thaler (1995) define the evaluation period as the length of time over which an investor aggregates returns and the planning horizon as the length of time an investor is looking to invest. An investor with an evaluation period of one year behaves much the same as if he had a planning horizon of one year. Therefore, when

⁴⁹ Selten, Abbink and Cox (2001) propose learning direction theory as an alternative to describe how prior outcomes affect risky choice for sequential decision making. In this theory, the decision maker believes there is an optimal decision point and following the outcome feedback from past actions, they adjust their future decisions in an attempt to converge to the optimal point. This theory can be best illustrated through an example. Consider an auction market setting in which the bidder wins. They should adjust their future bids downward, realising that they previously bid too high. On the other hand, if the bidder loses then next time around they will adjust their bid upward, realising that their previous bid was too low.

they approximate the evaluation period of investors in their study, they are also implicitly estimating their time (planning) horizons.

In a model consisting of loss aversion, the more frequent an investor evaluates their portfolio the less attractive will appear a high return, high risk investment, such as stocks. From this, Benartzi and Thaler (1995) pose the question that if investor's utility functions are defined by prospect theory preferences, how often would they be required to evaluate their portfolio in order to explain the equity premium puzzle? They formulate the question in two ways. First, what evaluation period would make an investor indifferent between holding an all stock portfolio as opposed to an all bond portfolio and second, with this evaluation period, what combination of stocks and bonds in a portfolio would maximise their prospective utility function?

They use simulations but first draw random samples of n-monthly returns (with replacement) from historic monthly returns over the period (1926-1999) for stocks, bonds and T-bills to generate distributions. Returns in each of the distributions are ranked from best to worst and the return is computed at twenty intervals along the cumulative distribution. Following this, they compute the prospective utility of holding stocks, bonds and T-bills over various evaluation periods, beginning at one month and increasing on a monthly scale. The simulations are conducted in four ways. The stock index returns are compared to the T-bill returns and 5-year bond returns in both real and nominal terms. Benartzi and Thaler (1995) emphasise that attention should be mostly given to the comparison between stocks and bonds in nominal terms. Their results document that the equilibrium evaluation period is approximately thirteen months in nominal terms and between ten and eleven months in real terms.

MaCurdy and Shoven (1992) also provide strong evidence of how loss aversion can cause individuals to avoid investing in stocks as opposed to bonds. They too document the advantage of investing in stocks over bonds over the period 1876 to 1990 but in a rather different way. That is, they look at the evidence from the point of view of a faculty member saving for their retirement. They ask each faculty member how they would have done, had they invested in portfolios of either all stocks or all bonds over their working lifetime, assuming that 10% of their salary each year was

invested. They find that faculty members investing in portfolios of all stocks would have outperformed their colleagues in virtually all time periods, and usually by a large margin. They conclude from their study that people must be, “confused about the relative safety of different investment over long horizons,” (p. 12).

Overall, evidence indicates that prior outcomes affect the subsequent choices individuals make. There is strong evidence of the house money effect, which indicates that individuals take on more risk following a prior gain and loss aversion, which assumes the opposite that individuals become risk seeking following a previous loss. There is inconclusive evidence, however, as to which one of these findings is the most accurate or most correct and questions such as can an investor exhibit both the house money effect and loss aversion together, remain unanswered.

More research is needed to properly understand the effect of prior outcomes on risky choice for individual investors in uncertain situations, such as in financial markets. Understanding this behaviour is critical for the future development of behavioural finance.

2.6 Summary

In traditional economics, agents are considered to be rational expected utility maximisers. This led to what is known today in the field of finance, as the efficient market hypothesis (EMH), a hypothesis which states that prices fully reflect all available information. Advocates of the efficient market hypothesis believe that on a risk adjusted basis investors can never earn in excess of what the market returns. Furthermore, that if prices dislocate from their fundamental values then rational agents will correct the short-term mispricing through a process referred to as arbitrage.

Strong evidence to the contrary, however, has paved the way for a new competing theory, namely behavioural finance. Still in the development phase, behavioural finance combines the two pillars of limits to arbitrage and experimental psychology to more accurately explain the mechanics of financial markets and in particular the

behaviour of financial market practitioners. Unlike traditional finance, behavioural finance offers a theoretical framework in which individuals are not completely rational. That is, they insufficiently update their beliefs with the arrival of new information, hence violating Bayes' Law and make choices that cannot be explained on normative grounds in accordance with the notion of Savages' (1954) subjective expected utility (SEU).

In contrast to the traditional approach, which describes the process of arbitrage as being riskless, behavioural finance assumes that there are many theoretical risks and costs involved. Some of these include; fundamental risk, noise trader risk, implementation costs and regulation as well as synchronisation risk, which can all significantly limit the potential profits of rational agents. Furthermore, widespread empirical evidence of persistent mispricings provides strong support in view of behavioural finance and the limitations involved with arbitrage.

In order to explain and properly understand the irrationalities individuals exhibit in their behaviour, researchers often resort to experimental evidence compiled by cognitive psychologists. Since behavioural finance assumes individuals are not completely rational, it seems intuitively plausible to understand how individuals insufficiently adjust their beliefs with the arrival of new information or make choices that are not normatively acceptable. For this reason, researchers focus on two elements of psychologists work: 1. Biases in the formation of beliefs and 2. Biases in preferences or how individuals make decisions given their beliefs.

Research has uncovered many abnormalities in investor's behaviour that simply cannot be explained on rational grounds. In particular, investors tend hold under diversified portfolios, exhibiting a 'home bias' towards domestic stocks despite the benefits from international investments. Evidence also shows that investor's trade too excessively, have a tendency to ride their losses too long and sell their winners too early, which is commonly referred to as the disposition effect and prefer to purchase stocks that somewhat 'grab' their attention. Furthermore, research shows the prior outcomes affect the way individuals make choices. Both types of investors, namely institutional and individual, exhibit these biases.

In summary, the literature strongly favours behavioural explanations of market phenomena and investor behaviour. It is important to note, however, that behavioural finance does not undermine all that has been accomplished on rational grounds, but merely extends traditional work to more accurately explain the workings of financial markets and provide a clearer understanding of the way individual investors behave. Although research has provided several insights in relation to investor behaviour, behavioural finance is still in the developing phase and requires much more research to provide an even greater understanding of the way individuals behave before sufficient and accurate models of asset prices can be developed.

Chapter 3 : The House Money Effect and Local Traders on the Sydney Futures Exchange

The previous chapter reviews the literature on the application of behavioural finance to individual investor behaviour – the focus of this thesis. The evidence compiled points to several inconsistencies in the behaviour of investors, which violate the underlying assumptions of traditional finance theory. Much of the research, however, is experimental and more research using real-world trading data is needed. This chapter deals with this issue directly by performing a series of tests to determine whether professional (“local”) traders at the Sydney Futures Exchange behave rationally.

3.1 Introduction

There is little published evidence of inconsistency or irrationality in professional futures traders’ behaviour. The only existing studies based on actual in-market trading decisions are Coval and Shumway (2005), Locke and Mann (2004; 2005) and Frino et al. (2004). Other published studies concerning futures traders are experimental. Most recently, a laboratory study by Haigh and List (2005) found that professional CBOT futures traders show apparently greater irrationality than less experienced decision makers (students). The in-markets rather than in-laboratory trading behaviour of professional futures traders is yet to be extensively documented.

Thaler and Johnson (1990) note that unlike studies of other behavioural biases, there has been very little real-world empirical study demonstrating the house money effect. Laboratory studies by Thaler and Johnson (1990), Battalio et al. (1990) and Keasey and Moon (1996) document that prior gains lead to increased risk-taking in

subsequent periods – the house money effect.⁵⁰ This chapter contributes to the literature by employing actual trading data to test for the house money effect and related behavioural inconsistencies, particularly loss aversion, amongst “locals”⁵¹ on the Sydney Futures exchange⁵².

Brown et al. (2006) find evidence of the house money effect among a broad population of stock market traders. This chapter extends the study by examining the behaviour of professional futures traders. Futures markets offer idealised conditions for the study of biases in one period’s trading based on the trader’s results in the preceding period. Whereas most market settings provide ambiguous trading horizons, futures trades by locals are most often conducted in short cycles and almost always closed out by the end of trading each day (Duffy et al., 1998; Kuserk and Locke, 1993, 1994; Manaster and Mann, 1996). Other characteristics that make professional futures traders ideal for study are that they trade predominately on their own account, and are therefore not subject to agency biases in their behaviour, and can trade in either direction (long or short) at any moment (Locke and Mann 2004, p.3).

It is plausible in this context of closed daily trading cycles that a trader’s risk-taking may be influenced by results recorded earlier in a given day, and less likely to be influenced by profits or losses incurred on previous days (Coval and Shumway 2005, p.8). In contrast to the Chicago Board of Trade (CBOT) and the Chicago Mercantile Exchange (CME), the Sydney Futures Exchange closed for lunch during the data period examined. The lunch break in trading provides a natural dividing point in the middle of each trading day (see Frino and Winn, 2001). Its effect is important to this research, not merely because it creates an unambiguous divide within the daily trading cycle, but because it provides traders with time to reflect upon their morning trades and respective profits or losses. In principle, this “time out” should provide a “cooling off” period and hence relieve any tendency to irrational behaviour in the afternoon.

⁵⁰ Related market-based studies by Odean (1998b; 1999) and Barber and Odean (2000; 2001; 2002) find that amateur traders are overconfident and hence trade excessively. Moreover, Griffin and Tversky (1992) report that professionals are more likely to be overconfident than others.

⁵¹ Locals are professional futures traders and members of futures exchanges that trade exclusively on their own account and are usually granted trading privileges such as direct access to the trading floor.

⁵² Turnover on the Sydney Futures Exchange ranks it among the top 15 futures exchanges in the world. Four main contracts are currently traded by open outcry including the Share Price Index (SPI) Futures contract – the focus of this study (Frino and Winn, 2001).

Drawing on the risk-measurement methods developed by Coval and Shumway (2001; 2005), this chapter compares the levels of risk-taking by locals trading in afternoons following morning gains, and morning losses, respectively. The results suggest that locals on the Sydney Futures Exchange exhibit a strong behavioural bias consistent with the house money effect. That is, morning profits seem to encourage locals to become risk-seeking in afternoon trading sessions. Whether this bias causes traders to make afternoon losses or reduced profits is less obvious. The results suggest that up to a point the bravado or feeling of confidence produced by morning profits assists traders to make additional afternoon profits, but that those trades driven most strongly by the house money effect tend to result in significant losses.

The remainder of this chapter is organised as follows. Section 3.2 describes the data and section 3.3 outlines the method used for the analysis. Section 3.4 compares the house money effect and loss aversion, while section 3.5 presents the results and section 3.6 summarises the findings and concludes.

3.2 Data

Data for this research was provided by the Sydney Futures Exchange,⁵³ sourced from a host log file of the electronic clearing and settlement system known as STACS (Sydney Futures Exchange Trade Allocation and Confirmation System). This file describes transactions in the nearest-to-maturity contract for the SPI Futures contract over the period 24th July, 1997 to 4th October, 1999. This time period was chosen for the following reasons. First, the Sydney Futures Exchange was only able to provide data from 24th July, 1997 and second, the Sydney Futures Exchange shifted to an automated rather than floor trading system for the SPI futures contract from 4th October, 1999 onwards. The sample period excludes holidays on which the Sydney Futures Exchange closed at lunchtime⁵⁴.

⁵³ For further detail on the data and institutional detail the reader should refer to Frino et al. (2004).

⁵⁴ Good Friday, Christmas Eve and New Years Eve and were excluded from the sample because it wasn't possible to examine trader profitability in the afternoon trading session.

Each record in the data represents a single trade and contains the security code, date, time, volume, buyer identity and seller identity. A local trader's account is represented by an identification number between 1 and 224. The data allows reconstruction of the inventory positions of individual trader's accounts on a trade-by-trade basis. A total of 40 trader-accounts were active throughout the sample period.⁵⁵

3.3 Research Methodology

To enable testing of the house money hypothesis, each trading day in the sample is split into morning and afternoon trading sessions. Over the sample period studied, the SPI futures contract traded from 9:50a.m. to 4:25p.m. with lunchtime closure between 12:30p.m. and 2:00p.m. (Frino and Winn, 2001). The morning trading session is therefore defined as the interval from 9:50a.m. to 12:30p.m. while the afternoon trading session is defined as the period from 2:00p.m. to 4:25p.m. The effect of morning profits on afternoon risk-taking is examined for all local traders to assess the rationality of their trading behaviour.

For each trader, a realised profit is calculated on each trade that reduces (or changes the sign of) the trader's inventory exposure (long or short) and is calculated against the weighted average cost (WAC) of inventory at the time of the trade. For example, if a trader places the following five consecutive trades in the SPI futures contract: buy 2 at 3000 index points, buy 4 at 3003, buy 6 at 3007, sell 6 at 3008 and sell 6 at 3012, then the corresponding WAC's at each trade would be 3000, 3002, 3004.5, 3004.5 and 3004.5, respectively.

The WAC is updated whenever a trader accumulates inventory, either long or short and remains constant while the trader is exhausting inventory (long or short). In the illustration used above, the trader does not realise a profit until the fourth trade in the sequence, since up to this point inventory is being accumulated. The realised profit for the fourth and fifth trades is $21 = 3.5 \times 6$ index points and $45 = 7.5 \times 6$ index points,

⁵⁵ Local accounts were required to be active on at least two mornings throughout the sample period to enable a standard deviation to be calculated on a trader specific basis for the standardised profit measure and normalised risk measures.

respectively. A new WAC is calculated from the next trade onwards since after the fifth trade in the sequence all inventories are exhausted. This process is applied repeatedly to allow aggregate morning and afternoon profits to be calculated for each trader-day in the sample.

Measuring trader risk is more complicated. For this, the method advanced by Coval and Shumway (2001; 2005) to find the “total dollar risk” assumed by a given trader over a given period is adopted. The level of risk (volatility) in the SPI futures contract varies throughout the trading day. To assess the risk implicit in a given trading position at a given time of day, a multinomial logistic regression model is used to estimate the probabilities of the possible price changes over the following minute. Following Coval and Shumway (2001; 2005), the model has the form:

$$\text{Log}_e \left[\frac{p_t(k)}{1 - p_t(k)} \right] = \alpha_i + X'\beta \quad 1 \leq k \leq 9$$

where, $p_t(k) = \Pr(Y \leq k | X)$ represents the conditional probability that the price change Y in the SPI futures contract over the following minute t is less than or equal to k price ticks,⁵⁶ and $X'\beta = \beta_1 x_1 + \dots \beta_5 x_5 + \beta_{113} d_{113} \dots \beta_{199} d_{199}$, where x_n is the absolute price change (in ticks) occurring in the n^{th} preceding minute ($1 \leq n \leq 5$) and d_j is a dummy variable (0 or 1) indicating the time of day in five-minute intervals ($118 \leq j \leq 197$).⁵⁷

Prices changes Y in the SPI futures contract take values $k=1,2,\dots,9$, where k represents the unit change in the SPI within a given one-minute interval (Appendix 1 shows the distribution of k). The fitted values from the regression are used, firstly, to construct cumulative probabilities for each ordered value k of the dependent variable Y , conditional on the vector of explanatory variables, X . The discrete probabilities

⁵⁶ A price tick is a one unit change in the price of SPI futures contract.

⁵⁷ There are 80 time-of-day dummy variables in total, ranging from 118-197 inclusive. Dummy d_{118} corresponds to the 118th five-minute period of the day (9:50a.m.) while d_{197} corresponds to the 197th five-minute period of the day (4:25p.m.).

$q_t(k)$ for each of the possible one-minute price changes $k=1,2,\dots,9$ are found by subtracting consecutive cumulative probabilities $p_t(k)$.

Finally, the summation of each absolute price change k multiplied by its respective discrete probability is used to calculate an expected absolute price change at each time (minute) t of the day as follows:

$$\text{Expected Absolute Price Change}_t = \sum_{k=1}^9 k \times q_t(k)$$

The risk associated with any position taken by local i at time t (measured in minutes) is then calculated as:

$$\text{Risk}_{i,t} = |\text{Inventory}_{i,t}| \times \text{Expected Absolute Price Change}_t$$

where $\text{Inventory}_{i,t}$ is trader i 's inventory exposure (long or short) as at time t , measured as a number of contracts. The total risk assumed by local i over any given period is given by the sum of minute-by-minute risks, $\sum \text{Risk}_{i,t}$, calculated over that period. Coval and Shumway (2005) call this “total dollar risk”. Furthermore, to ensure the robustness of this risk measure, two alternative measures of cumulative risk incurred over a given interval are calculated for each individual trader. These are the number of contracts traded by that individual and number of trades placed.

Trader heterogeneity in relation to margin constraints and risk tolerance means that a large dollar exposure for one trader is not necessarily large for another (Locke and Mann, 2004; Coval and Shumway, 2005). To allow for individual differences, all risk measures are normalised on a trader-specific basis. This requires calculating a mean and standard deviation for each of three afternoon risk measures for each local trader in the sample. To normalise the risk measures for an individual trader, the trader-specific mean is subtracted from afternoon risk and the result divided by the trader-specific standard deviation. As a result, all three normalised afternoon risk measures have standard deviations equal to one by construction. Morning risk measures are calculated the same way.

As with risks, different traders have different perceptions about what constitutes a large profit. However, profit is standardised on a trader-specific basis as opposed to being normalised. That is, traders' morning profits are divided by their trader-specific standard deviations only. This is based on the assumption that a profit constitutes a gain in wealth relative to the psychological reference point of zero (any profit greater than zero has a positive psychological impetus). A positive standardised value represents a psychological profit.

If, on the other hand, profits were normalised, a profit greater than zero but less than the trader's average profit would show as a negative, potentially misrepresenting its positive psychological value. By standardising rather than normalising profits, this psychological relationship is preserved. Afternoon profit measures are standardised the same way.

An alternative perspective, advocated by Coval and Shumway (2005, p.11) and Locke and Mann (2005, p.434), and tracing to Kahnemann and Tversky (1979, p.286), suggests that a profit not much more than zero is hardly a profit in any strong psychological sense. Moreover, because locals have overheads and opportunity costs to consider, including the costs of their seats on the exchange, it is plausible that their psychological break-even point for a day's trading is greater than zero. This is all the more reasonable if they require some minimum return as compensation for the risk of loss borne every day they trade. To make this experiment more robust against this possibility, the analysis is repeated using normalised rather than standardised trader profits, following Coval and Shumway (2005, p.11). Profits are normalised on a trader-by-trader basis. This is achieved by subtracting from each trader's daily profit his mean profit calculated over the entire data period. The mean is measured this way to capture an estimate of the trader's "inherent" personal average profit, which is presumably more than enough to compensate him for his involvement in the game (otherwise he would not be there).

To test the relationship between morning profit and afternoon risk among all local traders, each of three afternoon risk measures is regressed on standardised morning profit, outstanding morning inventory, an interaction variable (profit \times inventory) and

one of three morning risk measures.⁵⁸ The outstanding morning inventory is normalised on a trader-specific basis in the same way as the three risk measures. This variable is included in the regression because locals experiencing profitable mornings may enter the afternoon with much larger outstanding inventory, adding therefore to afternoon risk (Coval and Shumway, 2005). The first model estimated is thus:

$$\text{Risk}_{i,t}^A = \alpha + \beta_{\pi} \pi_{i,t}^M + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi I} \pi_{i,t}^M |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M \quad (3.1)$$

where, for trader i on day t , $\text{Risk}_{i,t}^A$ is a normalised afternoon risk measure, $\pi_{i,t}^M$ is the standardised morning profit, $|\text{INV}_{i,t}^M|$ is the normalised absolute value of outstanding morning inventory, and $\text{Risk}_{i,t}^M$ is a normalised morning risk measure.

As a robustness check of the regression results above, a logistic regression is performed to determine whether local traders have higher probability of assuming greater than average afternoon risk following profitable mornings. The logistic model is defined as follows:

$$\text{Prob}(I[\text{Risk}_{i,t}^A] > 0) = \frac{\exp X'\beta}{1 + \exp X'\beta} \quad (3.2)$$

where, for trader i on date t , $I[\text{Risk}_{i,t}^A]$ is an indicator variable that equals 1 if normalised afternoon risk is positive and 0 otherwise, and

$$X'\beta = \alpha + \beta_{\pi} I(\pi_{i,t}^M > 0) + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi I} I(\pi_{i,t}^M > 0) |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

where, for local trader i on day t , $I(\pi_{i,t}^M > 0)$ is an indicator variable that is equal to one if standardised morning profit is positive and zero otherwise. All other terms in (3.2) are as defined for model (3.1).

⁵⁸ An interaction variable is included to account for the possibility that local traders unwind winning and losing positions in different ways. This possibility was suggested by Shefrin and Statman (1985), Odean (1998a), and Locke and Mann (2005) and implemented by Coval and Shumway (2005).

In addition to the Coval and Shumway (2005) model replicated in (3.1) and similar to the method explained by Locke and Mann (2005), this chapter also tests for a relationship between unrealised morning profit (“book profit”) and afternoon risk-taking. It is feasible that traders mentally mark-to-market after the morning session, in which case their mental construct of morning profit might include both realised and unrealised morning profits, either in aggregate or as separate mental accounts. Two further models estimated are thus:

$$\text{Risk}_{i,t}^A = \alpha + \beta_{\pi} (\pi_{i,t}^{M,R} + \pi_{i,t}^{M,U}) + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi R} \pi_{i,t}^{M,R} |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M \quad (3.3)$$

and

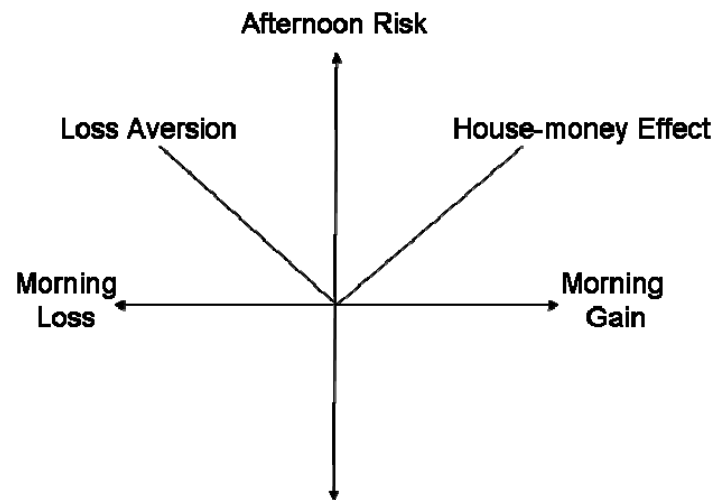
$$\text{Risk}_{i,t}^A = \alpha + \beta_{\pi R} \pi_{i,t}^{M,R} + \beta_{\pi U} \pi_{i,t}^{M,U} + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi R} \pi_{i,t}^{M,R} |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M \quad (3.4)$$

where, for trader i on day t , $\pi_{i,t}^{M,R}$ equals the standardised morning realised profit and $\pi_{i,t}^{M,U}$ equals the standardised morning unrealised profit. All other terms in models (3.3) and (3.4) are as defined previously.

3.4 House Money Effect Versus Loss Aversion

In testing for the house money effect, it is crucial to disentangle this psychological bias from that of loss aversion (Odean, 1998a), otherwise known as the disposition effect. Loss aversion and the house money effect are symmetrical opposites. One suggests that higher morning profits prompts higher afternoon risk, and the other suggests that higher morning losses prompts higher afternoon risk. The house money effect and loss aversion are, therefore, two separate and psychologically independent drivers of increased risk-taking in afternoon trading. Their respective effects are depicted in the V-shape function shown in Figure 3.1.

Figure 3.1: Morning Gains and Morning Losses and Afternoon Risk-taking



To separate the house money effect from loss aversion experimentally, it is necessary to redefine a trader's morning profit as either a gain or a loss. A gain occurs only when profit is greater than zero, according to the definition $\text{Gain} = \text{Max}(\text{Profit}, 0)$. Gains are thus either positive or zero, and a morning profit of \$1000 is represented by a "gain" of +\$1000 and a "loss" of zero. Similarly a "loss" occurs only when profit is less than zero, according to the definition $\text{Loss} = \text{Min}(\text{Profit}, 0)$. Losses are thus either negative or zero, and a morning profit of -\$1000 implies a "gain" of zero and a "loss" of -\$1000.

There is a large body of theory and evidence in behavioural finance indicating the distinction between gains and losses as separate mental entities. The S-shaped value function of Kahneman and Tversky (1979) is built on the understanding that human decision makers react disparately to gains and losses (both measured against a common psychological reference point). Coval and Shumway (2005, pp.3,7,8) do not make this distinction. They treat profit as a continuous variable over both negative and positive domains. Gains and losses are thus treated equally, in the sense that a change in morning profit from say -\$3000 to -\$1000 is taken as having the same effect exactly on afternoon risk-taking as a change from \$1000 to \$3000. The proposed model, shown in Figure 1, would suggest that although these two effects on risk-taking may be of similar magnitude, they will be in opposite directions.

Specifically, under the loss aversion hypothesis a change in morning profit from $-\$3000$ to $-\$1000$ would reduce afternoon risk-taking, whereas, under the house money hypothesis, a change in morning profit from $\$1000$ to $\$3000$ would increase afternoon risk-taking.

The problem essentially is that by treating gains as positive profits and losses as negative profits, and including only profit in a regression model, rather than gains and losses as separate explanatory variables, it is not possible to observe both the house money effect (a positive regression coefficient) and loss aversion (a negative regression coefficient) at the same time. Instead, if the two biases coexist but tend to be about equal in effect, then the regression coefficient on the profit variable will tend to be near to zero, and neither bias will be revealed.

To test for the house money effect within a model that controls for loss aversion and the separate, albeit possibly symmetric, effects of gains and losses on trader behaviour, one further regression model is estimated:

$$\text{Risk}_{i,t}^A = \alpha + \beta_{\pi G} \pi_{i,t}^{M,G} + \beta_{\pi L} \pi_{i,t}^{M,L} + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi G I} \pi_{i,t}^{M,G} |\text{INV}_{i,t}^M| + \beta_{\pi L I} \pi_{i,t}^{M,L} |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M \quad (3.5)$$

where $\pi_{i,t}^{M,G} = \text{Max}[0, \pi_{i,t}^M]$, $\pi_{i,t}^{M,L} = \text{Min}[0, \pi_{i,t}^M]$, and $\pi_{i,t}^M$ is the standardised morning profit of trader i on day t . All other terms in model (3.5) are as defined above.

3.5 Results

Table 3.1 below provides summary statistics of morning and afternoon profit measures, total dollar risk, average trade size, number of trades and the absolute value of outstanding morning inventory for all trader days (Panel A), locals with profitable mornings (Panel B) and locals with losing mornings (Panel C).

The total number of observations (trader-days) is 3646. There are 2263 observations (62%) that relate to days on which locals trade profitably over the morning. The locals' overall average standardised morning profit from Panel A is 0.151. Since profit figures have been standardised on a trader-specific basis, this implies that locals

earn an average of 15.1% of one standard deviation of their morning profits per morning. Locals' overall average afternoon profits are also positive, at 0.101 standard deviations.

Note that the overall average for each of the risk measures and absolute outstanding inventory for the morning and afternoon are equal to zero by construction since each of our trader-specific risk measures is mean-adjusted (i.e. the mean has been subtracted from the actual value before dividing by the trader-specific standard deviation). However, when all observations are partitioned into those with either profitable mornings (Panel B) or losing mornings (Panel C) and take averages, the afternoon risk-taking behaviour amongst locals who experience profitable mornings is higher than those experiencing a morning loss. Specifically, in Panel B locals with profitable mornings assume 3.3% more total dollar risk in the afternoon than average, place trades that are 2.8% larger than average and trade 4.1% more than average. In contrast, Panel C reports that locals experiencing a morning loss take 5.3% less total dollar risk in the afternoon than average, place trades that are 4.6% smaller than average and trade 6.7% less frequently than average in the afternoon.

Panel D of Table 3.1 reports the *t*-statistics for the differences in means between locals with profitable mornings and locals with losing mornings, for each of the three risk measures and absolute inventory. The results document that the additional afternoon risk taken by locals with profitable mornings is significantly larger than the afternoon risk taken by locals with losing mornings (for each risk measure employed). There is no statistical difference between the means for absolute inventory. Afternoon standardised profits are larger following profitable mornings (14.9% of one standard deviation) than losing mornings (2.2% of one standard deviation), suggesting that additional afternoon risk assumed by locals after a morning profit is highly beneficial.⁵⁹

⁵⁹ Although locals take on more risk in the afternoon following morning profits than they do following morning losses, this above-average risk can also be associated with larger afternoon profits.

Table 3.1: Descriptive Statistics by Trader-Day

Table 3.1 reports summary statistics by trader-day for the trading activity of locals in SPI futures contracts at the SFE over the period 24 July, 1997 to 4 October, 1999. The table includes the mean and standard deviation of trader-specific standardised profits and normalised total dollar risk, average trade size, number of trades and absolute outstanding morning inventory for: (i) all trader-days in the sample, (ii) locals with profitable mornings and (iii) locals with losing mornings reported in Panel A, Panel B and Panel C respectively.

Variable	Morning			Afternoon	
	Mean	Median	Std Dev.	Mean	Std Dev.
Panel A: All Trader-Days (N = 3646)					
Profits	0.151	0.133	1.007	0.101	1.004
Total Dollar Risk	0	-0.270	0.995	0	0.995
Average Trade Size	0	-0.252	0.995	0	0.995
Number of Trades	0	-0.193	0.995	0	0.995
Absolute Inventory	0	-0.364	0.995	0	0.995
Panel B: Locals with Profitable Mornings (N = 2263)					
Profits	0.630	0.402	0.743	0.149	1.048
Total Dollar Risk	0.007	-0.246	0.992	0.033	1.035
Average Trade Size	-0.003	-0.247	0.976	0.028	1.020
Number of Trades	0.036	-0.139	0.991	0.041	1.016
Absolute Inventory	-0.044	-0.364	0.932	-0.010	0.945
Panel C: Locals with Losing Mornings (N = 1383)					
Profits	-0.632	-0.347	0.884	0.022	0.922
Total Dollar Risk	-0.011	-0.309	1.000	-0.053	0.922
Average Trade Size	0.005	-0.269	1.025	-0.046	0.950
Number of Trades	-0.058	-0.244	0.998	-0.067	0.956
Absolute Inventory	0.072	-0.337	1.086	0.016	1.071
Panel D: t-statistics of Differences of Means Between Locals With Profitable Mornings (Panel B) and Losing Mornings (Panel C)					
Total Dollar Risk	2.61 ***				
Average Trade Size	2.22 **				
Number of Trades	3.23 ***				
Absolute Inventory	0.74				

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Table 3.2 reports the regression results of model 3.1. Consistent with Table 3.1, these results suggest that local traders exhibit a behavioural bias consistent with the house money effect. Specifically, a one standard-deviation increase in standardised morning profits is associated with 5.47% more total dollar risk in the afternoon than average (Panel A), placing trades that are 4.98% larger than average (Panel B) and trading 5.31% more than average (Panel C) in the afternoon also. The slope coefficient of the morning profit variable in Table 3.2 is significant at the 1% level for each of the three risk measures.

Both outstanding morning inventory and each of the morning risk measure terms are significant at the 1% level. This implies that local traders entering the afternoon with larger outstanding inventory positions will assume greater than average risk as they extend and/or unwind these positions. Morning risk variables are highly significant, indicating that if the average local trader assumed above average risk in the morning then he will continue to do so in the afternoon.

To protect against results driven by outliers, model 3.1 was re-estimated with the sample winsorised with respect to both morning profit and inventory (observations were excluded when the winsorised variable was greater than two standard deviations away from its mean over all traders). In both cases, the morning profit and inventory variables remain significant at 1%. The signs and significance of the interaction and morning risk variables were also unaltered.

As a further robustness test allowing for trader-specific psychological benchmarks in what constitutes a “profit” from morning trading, model 3.1 is re-estimated using normalised rather than standardised morning profits. This allows for the possibility that individual traders require some “standard” level of profit before they recognise any psychological gain from morning trading, as if they see overhead recovery or a given daily “wage” as a psychological minimum. Results are not included here, but are identical in all relevant respects to those shown in Table 3.2. The signs and statistical significance levels of the model coefficients are unaltered.

Table 3.2: Morning Profits and Afternoon Risk-taking

Table 3.2 reports the results of a regression relating the morning profits of locals at the SFE to their afternoon risk behaviour. The regression has the basic form,

$$\text{Risk}_{i,t}^A = \alpha + \beta_{\pi} \pi_{i,t}^M + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi I} \pi_{i,t}^M |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

There are three different measures of risk used for this regression: (i) total dollar risk, (ii) average trade size and (iii) number of trades. The sample contains 3646 trader-days.

Risk Variable	α	β_{π}	β_I	$\beta_{\pi I}$	β_R
Panel A: Total Dollar Risk					
	-0.0083	0.0547	0.0768	0.0073	0.3436
<i>t</i> -statistics	(-0.55)	(2.79)***	(3.64)***	(0.81)	(13.87)***
<i>p</i> -values	0.5839	0.0053	0.0003	0.4147	<.0001
$R^2 = 0.1475$	$F = 158.64^{***}$				
Panel B: Trade Size					
	-0.0075	0.0498	0.0812	0.0006	0.3397
<i>t</i> -statistics	(-0.49)	(2.78)***	(4.19)***	(0.09)	(16.20)***
<i>p</i> -values	0.6221	0.0054	<.0001	0.9272	<.0001
$R^2 = 0.1449$	$F = 155.43^{***}$				
Panel C: Number of Trades					
	-0.0080	0.0531	0.0568	0.0002	0.3533
<i>t</i> -statistics	(-0.52)	(3.06)***	(3.23)***	(0.03)	(18.47)***
<i>p</i> -values	0.6011	0.0023	0.0013	0.9765	<.0001
$R^2 = 0.1431$	$F = 153.16^{***}$				

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Table 3.3 reports the regression results of model 3.2. The results, consistent with Tables 3.1 and 3.2, indicate that local traders who make money in the morning have a higher probability of taking more than average afternoon risk, for each of the three risk measures.

Table 3.3: Binary Results Relating Morning Profits to Afternoon Risk-taking

Table 3.3 reports the results of a logistic regression relating morning profits to afternoon risk-taking by local traders at the SFE. Both morning profits and afternoon risk are measured in binary form. The regression has the basic form,

$$\text{Prob}(\text{Risk}_{i,t}^A > 0) = \frac{\exp X'\beta}{1 + \exp X'\beta}$$

where:

$$X'\beta = \alpha + \beta_{\pi} I(\pi_{i,t}^M > 0) + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi I} \pi_{i,t}^M |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

There are three different measures of risk used for this regression: (i) total dollar risk, (ii) average trade size and (iii) number of trades. The sample contains 3646 trader-days.

Risk Variable	α	β_{π}	β_I	$\beta_{\pi I}$	β_R
Panel A:	Pr(Afternoon Total Dollar Risk > Mean Afternoon Total Dollar Risk)				
Total Dollar Risk	-0.8659	0.1845	0.1138	0.0897	0.6630
<i>p</i> -values	<.0001	0.0175	0.0491	0.2410	<.0001
$R^2 = 0.1374$					
Panel B:	Pr(Afternoon Trade Size > Mean Afternoon Trade Size)				
Trade Size	-0.6990	0.1382	0.0759	0.1007	0.6405
<i>p</i> -values	<.0001	0.0672	0.1798	0.1822	<.0001
$R^2 = 0.1295$					
Panel C:	Pr(Afternoon Number of Trades > Mean Afternoon Number of Trades)				
Number of Trades	-0.7211	0.2926	0.0758	0.1563	0.6259
<i>p</i> -values	<.0001	0.0001	0.1615	0.0332	<.0001
$R^2 = 0.1341$					

For total dollar risk (Panel A) their probability increases from 0.296 to 0.335 (an increase of slightly more than 13%). Similarly, for trade size (Panel B) their probability increases from 0.3340 to 0.3611 (an increase of slightly more than 8%). For number of trades (Panel C) their probability increases from 0.3204 to 0.3974 (an increase of slightly more than 24%).

See Appendix 2 for details of the derivation of these results using the estimated coefficients from model 3.2. The slope coefficient of the morning profit variable is highly significant for total dollar risk and number of trades, and weakly significant for trade size.

Table 3.4 reports the regression results for model 3.3. The results provide further evidence of a house money effect amongst local traders. Specifically, when traders' mental construct of morning profits includes both realised and unrealised morning profit in aggregate, a one standard-deviation increase in morning profit is associated with 2.67% more total dollar risk in the afternoon than average (Panel A), placing trades in the afternoon that are 2.36% larger than average (Panel B) and trading 2.97% more than average (Panel C) in the afternoon also.

Both outstanding morning inventory and each of the morning risk measures are significant at the 1% level. This implies that local traders entering the afternoon with larger outstanding inventory positions assume greater than average risk as they extend and/or unwind these positions. Morning risk variables are highly significant, which suggests that if the average local trader assumed above average risk in the morning, then he or she will continue to do so in the afternoon.

Table 3.4: Morning Realised and Unrealised Profits and Afternoon Risk-taking

Table 3.4 reports the results of a regression relating the morning realised and unrealised profits of locals at the SFE to their afternoon risk behaviour. The regression has the basic form,

$$\text{Risk}_{i,t}^A = \alpha + \beta_{\pi} (\pi_{i,t}^{M,R} + \pi_{i,t}^{M,U}) + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi R} \pi_{i,t}^{M,R} |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

There are three different measures of risk used for this regression: (i) total dollar risk, (ii) average trade size and (iii) number of trades. The sample contains 3603 trader-days.

Risk Variable	α	β_{π}	β_I	$\beta_{\pi I}$	β_R
Panel A: Total Dollar Risk					
	-0.0052	0.0267	0.0724	0.0000	0.3482
<i>t</i> -statistics	(-0.34)	(1.98)**	(3.25)***	(0.01)	(13.95)***
<i>p</i> -values	0.7343	0.0479	0.0011	0.9934	<.0001
$R^2 = 0.1459$	$F = 154.86^{***}$				
Panel B: Trade Size					
	-0.0043	0.0236	0.0772	-0.0016	0.3452
<i>t</i> -statistics	(-0.28)	(1.87)*	(3.73)***	(-0.47)	(16.39)***
<i>p</i> -values	0.7789	0.0620	0.0002	0.6384	<.0001
$R^2 = 0.1449$	$F = 153.65^{***}$				
Panel C: Number of Trades					
	-0.0053	0.0297	0.0532	-0.0028	0.3602
<i>t</i> -statistics	(-0.34)	(2.48)**	(2.78)***	(-0.74)	(18.82)***
<i>p</i> -values	0.7304	0.013	0.0054	0.4576	<.0001
$R^2 = 0.1442$	$F = 152.74^{***}$				

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Table 3.5 presents the regression results of model 3.4. The results show clearly the impact of realised and unrealised morning profit on afternoon risk as separate

psychological drivers. There is strong evidence that realised morning profits encourage local traders to increase their risk-taking in afternoon trading sessions, consistent with the findings presented earlier. In particular, a one standard-deviation increase in morning realised profits is associated with 6.11% more total dollar risk in the afternoon than average (Panel A), placing trades in the afternoon that are 5.40% larger than average (Panel B) and trading 5.49% more than average (Panel C) in the afternoon also. The slope coefficient of the morning realised profit variable in Table 3.5 is significant at the 1% level for each of the three risk measures.

There is insufficient evidence, however, contrary to Locke and Mann (2005), to suggest that unrealised morning profits affect the risk-taking behaviour of locals in afternoon trading sessions. The slope coefficient of the unrealised morning profit term in Table 3.5 is insignificant at the 10% level for each of the three risk measures.

Both outstanding morning inventory and each of the morning risk measures are significant (at the 1% level). This implies that local traders entering the afternoon with larger outstanding inventory positions will assume greater than average risk as they extend and/or unwind these positions. Morning risk variables are highly significant, again indicating that if the average local trader assumed above average risk in the morning then they will continue to do so in the afternoon.

Table 3.5: Morning Realised and Unrealised Profits and Afternoon Risk-taking

Table 3.5 reports the results of a regression relating the morning realised and unrealised profits of locals at the SFE to their afternoon risk behaviour. The regression has the basic form,

$$\text{Risk}_{i,t}^A = \alpha + \beta_{\pi R} \pi_{i,t}^{M,R} + \beta_{\pi U} \pi_{i,t}^{M,U} + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi R} \pi_{i,t}^{M,R} |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

There are three different measures of risk used for this regression: (i) total dollar risk, (ii) average trade size and (iii) number of trades. The sample contains 3603 trader-days.

Risk Variable	α	$\beta_{\pi R}$	$\beta_{\pi U}$	β_I	$\beta_{\pi I}$	β_R
Panel A: Total Dollar Risk						
	-0.0083	0.0611	-0.0225	0.0798	0.0098	0.3446
t -statistics	(-0.54)	(3.02)***	(-1.11)	(3.65)***	(1.10)	(13.80)***
p -values	0.5888	0.0026	0.2675	0.0003	0.2711	<.0001
$R^2 = 0.1487$	$F = 126.86^{***}$					
Panel B: Trade Size						
	-0.0074	0.5400	-0.0184	0.0827	0.0025	0.3421
t -statistics	(-0.48)	(2.93)***	(-0.93)	(4.10)***	(0.36)	(16.14)***
p -values	0.6318	0.0034	0.3518	<.0001	0.7182	<.0001
$R^2 = 0.1466$	$F = 124.71^{***}$					
Panel C: Number of Trades						
	-0.0079	0.0549	-0.0090	0.0568	0.0005	0.3569
t -statistics	(-0.51)	(3.04)***	(-0.42)	(3.06)***	(0.07)	(18.51)***
p -values	0.6068	0.0024	0.6730	0.0022	0.9420	<.0001
$R^2 = 0.1452$	$F = 123.43^{***}$					

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Table 3.6 reports the regression results of model 3.5. There is strong evidence of local traders taking on greater afternoon risk following morning gains, consistent with the house money effect. Specifically, a one standard deviation increase in morning profits leads local traders to take 7.51% more total dollar risk in the afternoon than average (Panel A), place trades in the afternoon that are 3.73% larger than average (Panel B) and place 7.39% more trades in the afternoon than average.⁶⁰

Contrary to Coval and Shumway (2005) and Locke and Mann (2005), the results indicate that local traders take on less than average risk in the afternoon following morning losses, and thus do not show the bias known as loss aversion (see Figure 3.1). A one standard deviation decrease in morning profits induces local traders to take 2.92% less total dollar risk in the afternoon than average (Panel A), place trades in the afternoon that are 5.79% smaller than average (Panel B) and place 2.78% less trades than average in the afternoon (Panel C).⁶¹

These results imply an asymmetric reaction to morning gains and losses (considered separately). Prior findings and theory (particularly prospect theory) in behavioural finance suggest that afternoon risk can be expected to increase with either morning gains (the house money effect) or morning losses (loss aversion). The results show that of these separate effects, the house money effect is stronger in our sample. This effect explains the positive sign of the morning profit variable in model 3.1, where (following Coval and Shumway, 2005) morning profit takes both positive and negative values and is not treated separately as either a gain or a loss.

⁶⁰ The slope coefficient for the morning profit variable is significant at the 1% level for total dollar risk (Panel A) and at the 5% level for number of trades (Panel C) but insignificant for trade size (Panel B).

⁶¹ The slope coefficient for the morning loss variable is significant at the 5% level for trade size (Panel B) but insignificant for both total dollar risk (Panel A) and number of trades (Panel C).

Table 3.6: Morning Profits and Losses and Afternoon Risk-taking

Table 3.6 reports the results of a regression relating the morning gains and morning losses of locals at the SFE to their afternoon risk behaviour. The regression has the basic form,

$$\text{Risk}_{i,t}^A = \alpha + \beta_{\pi G} \pi_{i,t}^{M,G} + \beta_{\pi L} \pi_{i,t}^{M,L} + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi GI} \pi_{i,t}^{M,G} |\text{INV}_{i,t}^M| + \beta_{\pi LI} \pi_{i,t}^{M,L} |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

There are three different measures of risk used for this regression: (i) total dollar risk, (ii) average trade size and (iii) number of trades. The sample contains 3646 trader-days.

Risk Variable	α	$\beta_{\pi G}$	$\beta_{\pi L}$	β_I	$\beta_{\pi GI}$	$\beta_{\pi LI}$	β_R
Panel A: Total Dollar Risk							
	-0.0193	0.0751	0.0292	0.0931	-0.0042	0.0257	0.3382
<i>t</i> -statistics	(-0.85)	(2.11)**	(0.94)	(3.75)***	(-0.34)	(2.37)**	(12.59)***
<i>p</i> -values	0.3975	0.0353	0.3449	0.0002	0.733	0.0178	<.0001
$R^2 = 0.1477$	$F = 106.28^{***}$						
Panel B: Trade Size							
	0.0022	0.0373	0.0579	0.1001	-0.0095	0.0181	0.3437
<i>t</i> -statistics	(0.10)	(1.16)	(1.97)**	(4.52)***	(-1.39)	(1.70)	(14.87)***
<i>p</i> -values	0.9221	0.2443	0.0487	<.0001	0.1638	0.0889	<.0001
$R^2 = 0.1453$	$F = 104.30^{***}$						
Panel C: Number of Trades							
	-0.0195	0.0739	0.0278	0.0696	-0.0096	0.0158	0.3488
<i>t</i> -statistics	(-0.92)	(2.45)**	(1.03)	(3.40)***	(-1.41)	(1.59)	(17.33)***
<i>p</i> -values	0.3580	0.0145	0.3052	0.0007	0.1574	0.1114	<.0001
$R^2 = 0.1432$	$F = 102.50^{***}$						

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

3.5.1 Do Traders Exhibiting the House Money Effect Lose?

When a trader with morning profits takes abnormal risk in the afternoon relative to personal norms, there are possible explanations in both rational and irrational decision models. One rational explanation is that the trader has made so much morning profit that the wealth effect or change in slope of his utility function is such that he is now qualitatively less risk averse (this requires that he is diminishingly risk averse; a common presumption in economic decision theory). This research excludes this explanation on the basis that morning profits are rarely if ever going to be so large that they change the trader's risk aversion so markedly.

A more plausible rational explanation, proposed by Coval and Shumway (2005, pp.5, 8), is that the quality of the signals on which locals base their trades varies from day to day in a way that is observable (observable to locals, but not to others necessarily). If some days offer relatively clear or frequent (short-lived) trading signals, locals will make both additional trades (take greater risk) and additional profits. This would give the appearance of the house money effect – since morning profits would be positively correlated with afternoon risk-taking – but would in fact be due to rational traders exploiting the availability of good trading signals.

Evidence of whether locals' afternoon risk-taking is driven more by rational or behavioural forces will eventually be reflected in their trading profits. Any rational explanation implies that, on average at least, the trader will gain rather than lose from all risk-taking. Moreover, his monetary profits must be sufficient to compensate for risk according to the curvature of his utility function. Conversely, any irrational or behavioural explanation means that he will gain only by luck, and hence lose on average in an efficient (fairly priced) market.

To test between these two possible explanations, this chapter examines the afternoon trading profits of all locals, particularly those who are most apparently driven by the house money effect. All 3646 trader-days in the sample are partitioned into categories based on morning normalised profits, identifying the biggest morning winners (profit results more than 3 standard deviations above the trader's mean) and the biggest

losers (profit results more than 3 standard deviations below the trader's mean). The first observation, documented in Table 3.7, is that there is a clear upward trend in afternoon risk-taking (however measured) when the trader's morning normalised profits increase (consistent with the house money effect). Bootstrap significance tests reveal that this relationship is statistically significant.⁶² There is a general, but weaker, increase in afternoon risk as morning profits decrease (loss aversion). This is consistent with earlier regression results.

Results summarised in Table 3.7 suggest clearly that as afternoon risk-taking increases, fuelled or strongly correlated with higher morning profits, afternoon standardised trader profits ultimately become negative. In particular, the average profit for the category of trader-days with both largest morning profits and largest afternoon risk-taking is negative. This is interesting in that it suggests that the appearance of the house money effect among locals is not necessarily a natural side effect of prolonged rational trading under favourable conditions (trader-days with high signal quality), at least not in the case of the most extreme category. Rather, on these trader-days, traders appear to take heightened risks following morning profits, resulting in losses which could have been averted by simply not trading or trading less.

Note, however, that the fifth to seventh most profitable-in-the-morning categories of trader-days show that afternoon increases unambiguously with morning profit but does not result in negative profits in the afternoon. These traders would seem, therefore, to be less driven by the house money effect, or to incur less cost as a result of not being so affected by the behavioural bias.

⁶² The methodology employed in these tests is as follows. To find the tail-area probability of a sample mean (e.g. mean afternoon number of trades) equal to or higher than the observed mean, conditional on the null hypothesis that this observation is independent of all other factors observed, bootstrap samples (permutations) of the appropriate size are drawn repeatedly from the pooled data set containing all trader-days. The sample size in each test is the number of observations in the category of trader-days under test (e.g. in the fourth category, it is 1128 observations per sample). The number of bootstrap samples drawn in each test is 10,000 (this is sufficient to produce p -values accurate to at least the third decimal place). A sample mean is calculated for each of the 10,000 samples, and the proportion of sample means lying in the designated tail-area is the bootstrap p -value of the mean actually observed.

Table 3.7: Costs to Traders of the House Money Effect

Table 3.7 reports summary statistics for all 3646 observed trader-days categorized by the size of the trader's normalised morning profit on that trader-day. Average afternoon risk measures: (i) total dollar risk, (ii) average trade size and (iii) number of trades, and afternoon normalised profits, are shown for each category of trader-days. Afternoon risk generally increases with morning normalised profit, consistent with the house money effect. The category of trader-days showing the highest morning profit has the highest afternoon risk but also the lowest afternoon normalised profits of all the trader-day categories.

Bootstrap p -values are shown in parentheses. These represent the probability of the result observed or a higher value of that variable under random permutations of the pooled data (i.e. under the assumption that each observation is determined by a random draw from the entire sample independent of all other factors observed). Each of the three afternoon risk measures is highly statistically significant for the categories of trader-days showing the highest average normalised morning profit. Afternoon profits increase significantly with both morning profit and afternoon risk, but become negative for category of trader-days that shows both the highest average morning profit and the highest afternoon risk.

Morning Normalised Profit	Afternoon (Normalised by Trader)				
	Trader- days	Total Dollar Risk	Trade size	Number of Trades	Afternoon Profit
−3 or less	33	0.128 (.2161)	0.136 (.2111)	−0.021 (.5314)	−0.117 (.8811)
−2 to −3	38	0.309 (.0347)	0.404 (.0111)	0.234 (.0789)	−0.013 (.7452)
−1 to −2	184	0.116 (.0595)	0.127 (.0453)	0.096 (.1020)	−0.019 (.9475)
0 to −1	1128	−0.099 (.9999)	−0.095 (.9998)	−0.105 (.9999)	0.034 (.9820)
0 to +1	1840	−0.056 (.9927)	−0.047 (.0778)	−0.030 (.9020)	0.134 (.0913)
+1 to +2	315	0.353 (.0001)	0.314 (.0000)	0.302 (.0001)	0.222 (.0179)
+2 to +3	72	0.429 (.0003)	0.366 (.0021)	0.441 (.0004)	0.339 (.0360)
+3 or more	36	0.972 (.0000)	0.696 (.0001)	0.604 (.0003)	−0.123 (.9421)

This raises an interesting possibility not previously emphasised in the literature on behavioural investment biases. Specifically, it is possible that such biases can actually increase profits by cancelling or reducing the influence of opposing biases. Imagine for example that the trader is not so omni-rational that he can judge instinctively

within any information environment how much risk (what number of contracts or what exposure) is exactly the right amount for someone of his wealth and utility function under those circumstances. Indeed, he may be conservative and thus tend to take too little risk relative to the rational ideal for someone of his particular wealth, utility function and (information dependent) ability to pick profitable trades. In this case, he may actually benefit from the house money effect, in that previous profits give him the impetus or “Dutch courage” required to trade nearer to his full ability. This may give the common impression that “fortune favours the brave” or “success breeds success”, since by overcoming his innate inhibition (a form of economic irrationality) he is able to exploit the full extent of his inferential ability and accrue maximum possible trading profits or utility. If the house money effect assists in this way, then one behavioural bias (under-confidence) is offset by another (the house money effect, or profit-induced over-confidence), resulting in an effectively rational or more nearly rational level of risk-taking.

3.6 Summary

This chapter uses trading data from the Sydney Futures exchange to test for behavioural biases in the trading decisions of professional traders (“locals”) in the pit. It extends the previous findings from related contexts of Coval and Shumway (2005), Locke and Mann (2004; 2005) and Frino et al. (2004). In contrast to the findings of Coval and Shumway (2005) and Locke and Mann (2004; 2005), who report strong evidence of loss aversion among professional traders at the CBOT and CME, respectively, this research finds no evidence of loss aversion among locals. There are several possible explanations of the differences in these results from those of previous studies. In particular, this analysis differs from other studies by treating gains and losses as separate and distinct psychological drivers, either of which may affect trader behaviour whatever the effect of the other.

If profit is not bisected this way, its influence on subsequent trading risk may be self-cancelling. That is, a profit of x or $-x$ may have much the same large positive effect on subsequent trading risk (as shown in Figure 3.1), giving the impression overall that previous trader profit (gain or loss) does not materially influence subsequent risk-

taking. Alternatively, suppose that profits of x and $-x$ both lead to an increase in trading risk, but the effect of $-x$ is stronger than the effect of x . In this case, an experimental design that treats negative and positive profits as merely different amounts of the same psychological influence will find evidence of loss aversion but not of the house money effect. Conversely, if the house money effect is the stronger of the two forces, it will be revealed, in less than its full effect, but loss aversion will not. To avoid this experimental design deficiency, this chapter redefines profit as either a “gain” or a “loss” and includes measures of gains and losses as separate explanatory variables in our model of afternoon risk-taking (negative profits are treated as zero gains, and positive profits as zero losses). This design offers a more powerful test of both the house money effect and the effect of loss aversion, which may coexist in a single market or within the possibly multiple and competing psychological biases of an individual trader.

Using this experimental design, the findings suggest that locals on the Sydney Futures Exchange trade in a way consistent with the “house money effect” – that is, with a tendency to take greater risk when trading with profits rather than with initial capital. Consistent with Odean (1998b; 1999), but contrary to Locke and Mann (2005), this evidence suggests that there are costs to such irrational trading. Specifically, the class of trades or trader-days most affected apparently by a trader’s tendency to gamble with the “house money”, namely those exhibiting the greatest morning profits and largest afternoon risks, result in the lowest afternoon trading profits. The house money effect would appear, therefore, at least in its most severe manifestation, to prompt a potentially costly departure from rational decision making, rather than a harmless eccentricity (cf. Coval and Shumway 2005).

Chapter 4 : Trading Horizons and Behavioural Biases: Does Time Matter?

Chapter 2 provides a comprehensive review of the application of behavioural finance to individual investor behaviour. Chapter 3 reports that local traders at the Sydney Futures Exchange exhibit a psychological bias in their trading behaviour, commonly known as the house money effect. This finding adds to existing research highlighting the irrational behaviour of professional traders in futures markets (Coval and Shumway, 2005; Locke and Mann, 2004, 2005; Frino et al. 2004). Despite these findings, the area of individual investor behaviour requires further attention. The purpose of this chapter is to contribute to the literature by testing whether local traders exhibit different forms of irrational behaviour over varying trading horizons.

4.1 Introduction

It is now widely accepted that local traders in futures markets trade in short cycles and almost always close out their inventory positions by the end of each trading day (Duffy et al., 1998; Kuserke and Locke, 1993; Manaster and Mann, 1996). In the context of this daily trading regime, it is reasonable to assume that a trader's risk-taking behaviour is more likely to be influenced by profits or losses earned earlier in the day as opposed to profits or losses earned over previous days. It is possible however, that not all local traders evaluate their profits at the daily horizon and that other trading horizons are important. For this particular reason, this chapter performs several tests to determine whether various trading horizons, influences the trading behaviour of local traders at the Sydney Futures Exchange⁶³.

Existing research directed at testing the effect of trading horizons on investor behaviour provides evidence that is mixed. Coval and Shumway (2005) ask the

⁶³ A weakness of this approach is that it doesn't allow traders to have different trading horizons.

question of whether profits earned by proprietary traders at the CBOT today, could be used to explain their risk-taking behaviour tomorrow. In their study, they use overlapping days such that today's profits are regressed against tomorrow's risk and tomorrow's profits are regressed against the following day's risk and so forth, for each trader in the sample.

The results provide inconclusive evidence of a behavioural bias across days. That is, there is no detectable relationship between a proprietary trader's profit today and their risk-taking behaviour tomorrow for all overlapping observations in the sample period.

Locke and Mann (2004) provide a study in which several tests are implemented to determine whether trading horizons influences the trading behaviour of floor traders at the CME. In their study, however, they analyse trading horizons ranging from a single day to a maximum of five days. That is, they pose the question of whether profits earned by the floor traders over the past k days where $k = 1, 2, 3, 4$, or 5 could explain their risk-taking behaviour today.

In contrast to the findings of Coval and Shumway (2005), Locke and Mann (2004) report strong evidence of loss aversion across days. Specifically, they find that if floor traders lose over any of the previous k days where $k = 1, 2, 3, 4$, or 5 then this encourages them to take additional risk today in an attempt to recover their previous losses. The results also show that as k increases, the psychological effect of a loss on the floor trader's risk-taking behaviour today, diminishes. That is, floor traders are more affected by a loss yesterday rather than five days ago although both significantly influence their risk-taking behaviour today.

Clearly, the aspect of trading horizons in relation to investor behaviour has not yet been fully explored. This chapter contributes to the literature by focusing on two new trading horizons – afternoon profit and morning risk-taking across trading days and profit and risk-taking across intra-day cycles. The first poses the question of whether afternoon profits earned by local traders at the Sydney Futures Exchange today can be used to explain their risk-taking behaviour tomorrow morning. The second asks the question of whether profit earned in one intra-day trading cycle can influence risk-taking behaviour in the next trading cycle. To allow comparison with the results of

Coval and Shumway (2005) and Locke and Mann (2004) this chapter also examines profit and risk-taking across daily trading horizons – does profit earned today affect the risk-taking behaviour of local traders tomorrow?

The remainder of this chapter is organised as follows. Section 4.2 describes the data and section 4.3 describes the methodology used for the analysis. Section 4.4 presents the results, while section 4.5 summarises the findings and concludes.

4.2 Data

Data for this research was provided by the Sydney Futures Exchange,⁶⁴ sourced from a host log file of the electronic clearing and settlement system known as STACS (Sydney Futures Exchange Trade Allocation and Confirmation System). This file describes transactions in the nearest-to-maturity contract for the SPI Futures contract over the period 24th July, 1997 to 4th October, 1999. This time period was chosen for the following reasons. First, the Sydney Futures Exchange was only able to provide data from 24th July, 1997 and second, the Sydney Futures Exchange shifted to an automated rather than floor trading system for the SPI futures contract from 4th October, 1999 onwards. The sample period excludes holidays on which the Sydney Futures Exchange closed at lunchtime.

Each record in the data represents a single trade and contains the security code, date, time, volume, buyer identity and seller identity. A local trader's account is represented by an identification number between 1 and 224. The data allows reconstruction of the inventory positions of individual trader's accounts on a trade-by-trade basis. A total of 40 trader-accounts were active throughout the sample period.⁶⁵

⁶⁴ For further detail on the data and institutional detail the reader should refer to Frino et al. (2004).

⁶⁵ Local accounts were required to be active on at least two mornings throughout the sample period to enable a standard deviation to be calculated on a trader specific basis for the standardised profit measure.

4.3 Research Methodology

To enable testing of the trading horizon hypothesis, each trading day in the sample is split into morning and afternoon trading sessions. Over the sample period studied, the SPI futures contract traded from 9:50a.m. to 4:25p.m. with lunchtime closure between 12:30p.m. and 2:00p.m. (Frino and Winn, 2001). The morning trading session is therefore defined as the interval from 9:50a.m. to 12:30p.m. while the afternoon trading session is defined as the period from 2:00p.m. to 4:25p.m. The effect of morning profits on afternoon risk-taking is examined for all local traders to assess the rationality of their trading behaviour.

For each trader, a realised profit is calculated on each trade that reduces (or changes the sign of) the trader's inventory exposure (long or short) and is calculated against the weighted average cost (WAC) of inventory at the time of the trade. For example, if a trader places the following five consecutive trades in the SPI futures contract: buy 2 at 3000 index points, buy 4 at 3003, buy 6 at 3007, sell 6 at 3008 and sell 6 at 3012, then the corresponding WAC's at each trade would be 3000, 3002, 3004.5, 3004.5 and 3004.5, respectively.

The WAC is updated whenever a trader accumulates inventory, either long or short and remains constant while the trader is exhausting inventory (long or short). In the illustration used above, the trader does not realise a profit until the fourth trade in the sequence, since up to this point inventory is being accumulated. The realised profit for the fourth and fifth trades is $21 = 3.5 \times 6$ index points and $45 = 7.5 \times 6$ index points, respectively. A new WAC is calculated from the next trade onwards since after the fifth trade in the sequence all inventories are exhausted. This process is applied repeatedly to allow aggregate morning and afternoon profits to be calculated for each trader-day in the sample.

Measuring trader risk is more complicated. For this, the method advanced by Coval and Shumway (2001; 2005) to find the "total dollar risk" assumed by a given trader over a given period is adopted. The level of risk (volatility) in the SPI futures contract varies throughout the trading day. To assess the risk implicit in a given trading position at a given time of day, a multinomial logistic regression model is used to

estimate the probabilities of the possible price changes over the following minute. Following Coval and Shumway (2001; 2005), the model has the form:

$$\text{Log} \left[\frac{p_t(k)}{1 - p_t(k)} \right] = \alpha_i + X'\beta \quad 1 \leq k \leq 9$$

where, $p_t(k) = \Pr(Y \leq k | X)$ represents the conditional probability that the price change Y in the SPI futures contract over the following minute t is less than or equal to k price ticks,⁶⁶ and $X'\beta = \beta_1 x_1 + \dots \beta_5 x_5 + \beta_{113} d_{113} \dots \beta_{199} d_{199}$, where x_n is the absolute price change (in ticks) occurring in the n^{th} preceding minute ($1 \leq n \leq 5$) and d_j is a dummy variable (0 or 1) indicating the time of day in five-minute intervals ($118 \leq j \leq 197$).⁶⁷

Prices changes Y in the SPI futures contract take values $k=1,2,\dots,9$, where k represents the unit change in the SPI within a given one-minute interval (Appendix 1 shows the distribution of k). The fitted values from the regression are used, firstly, to construct cumulative probabilities for each ordered value k of the dependent variable Y , conditional on the vector of explanatory variables, X . The discrete probabilities $q_t(k)$ for each of the possible one-minute price changes $k=1,2,\dots,9$ are found by subtracting consecutive cumulative probabilities $p_t(k)$.

Finally, the summation of each absolute price change k multiplied by its respective discrete probability is used to calculate an expected absolute price change at each time (minute) t of the day as follows:

$$\text{Expected Absolute Price Change}_t = \sum_{k=1}^9 k \times q_t(k)$$

⁶⁶ A price tick is a one unit change in the price of SPI futures contract.

⁶⁷ There are 80 time-of-day dummy variables in total, ranging from 118-197 inclusive. Dummy d_{118} corresponds to the 118th five-minute period of the day (9:50a.m.) while d_{197} corresponds to the 197th five-minute period of the day (4:25p.m.).

The risk associated with any position taken by local i at time t (measured in minutes) is then calculated as:

$$\text{Risk}_{i,t} = |\text{Inventory}_{i,t}| \times \text{Expected Absolute Price Change}_t$$

where $\text{Inventory}_{i,t}$ is trader i 's inventory exposure (long or short) as at time t , measured as a number of contracts. The total risk assumed by local i over any given period is given by the sum of minute-by-minute risks, $\sum \text{Risk}_{i,t}$, calculated over that period. Coval and Shumway (2005) call this “total dollar risk”. Furthermore, to ensure the robustness of this risk measure, two alternative measures of cumulative risk incurred over a given interval are calculated for each individual trader. These are the number of contracts traded by that individual and number of trades placed.

Trader heterogeneity in relation to margin constraints and risk tolerance means that a large dollar exposure for one trader is not necessarily large for another (Locke and Mann, 2004; Coval and Shumway, 2005). To allow for individual differences, all risk measures are normalised on a trader-specific basis. This requires calculating a mean and standard deviation for each of three afternoon risk measures for each local trader in the sample. To normalise the risk measures for an individual trader, the trader-specific mean is subtracted from afternoon risk and the result divided by the trader-specific standard deviation. As a result, all three normalised afternoon risk measures have standard deviations equal to one by construction. Morning risk measures are calculated the same way.

As with risks, different traders have different perceptions about what constitutes a large profit. However, profit is standardised on a trader-specific basis as opposed to being normalised. That is, traders' morning profits are divided by their trader-specific standard deviations only. This is based on the assumption that a profit constitutes a gain in wealth relative to the psychological reference point of zero (any profit greater than zero has a positive psychological impetus). A positive standardised value represents a psychological profit.

If, on the other hand, profits were normalised, a profit greater than zero but less than the trader's average profit would show as a negative, potentially misrepresenting its positive psychological value. By standardising rather than normalising profits, this psychological relationship is preserved. Afternoon profit measures are standardised the same way.

An alternative perspective, advocated by Coval and Shumway (2005, p.11) and Locke and Mann (2005, p.434), and tracing to Kahnemann and Tversky (1979, p.286), suggests that a profit not much more than zero is hardly a profit in any strong psychological sense. Moreover, because locals have overheads and opportunity costs to consider, including the costs of their seats on the exchange, it is plausible that their psychological break-even point for a day's trading is greater than zero. This is all the more reasonable if they require some minimum return as compensation for the risk of loss borne every day they trade. To make this experiment more robust against this possibility, the analysis is repeated using normalised rather than standardised trader profits, following Coval and Shumway (2005, p.11). Profits are normalised on a trader-by-trader basis. This is achieved by subtracting from each trader's daily profit his mean profit calculated over the entire data period. The mean is measured this way to capture an estimate of the trader's "inherent" personal average profit, which is presumably more than enough to compensate him for his involvement in the game (otherwise he would not be there).

4.3.1 Afternoon Profit and Morning Risk-taking across Days

To examine the relationship between afternoon profit and morning risk-taking across days, each of three morning risk measures is regressed on afternoon standardised profit and each of the three corresponding afternoon risk measures from the preceding trading day.

There is no need to include an outstanding inventory variable in the regression since the assumption that local traders go home 'flat' or end the day with zero inventories is adopted (Kuserke and Locke, 1993). It is therefore unlikely to result in a mis-specification error. This assumption has previously been incorporated by Manaster and Mann (1996), Coval and Shumway (2001; 2005) and Locke and Mann (2004)

also. Moreover, given that local traders begin each trading day with zero inventories, there is no need to include an interaction variable linking profits and outstanding inventory to account for traders unwinding winning or losing positions differently. The first model estimated is thus:

$$\text{Risk}_{i,t}^M = \alpha + \beta_{\pi} \pi_{i,t-n}^A + \beta_R \text{Risk}_{i,t-n}^A \quad (4.1)$$

where, for local trader i on date t , $\text{Risk}_{i,t}^M$ is a normalised morning risk measure and for local trader i on date $t-n$, $\pi_{i,t-n}^A$ is the standardised afternoon profit and $\text{Risk}_{i,t-n}^A$ is a normalised afternoon risk measure. Note that, n represents the number of days between today and the preceding trading day for each local. Thus, if $n \neq 1$ this morning's risk is regressed on afternoon profit and afternoon risk from the preceding n^{th} trading day. Alternatively, $n = 1$ implies that this morning's risk is regressed on the profits earned and risk taken yesterday afternoon. This chapter firstly examines all observations together (whereby n can equal any value) and secondly all consecutive trading days (whereby $n = 1$ only).

Importantly, the significance of the profit variable in model 4.1 could be influenced by the individual effects of local trader's gains or losses obtained in the preceding afternoon. Either effect alone (house money or loss aversion) could result in a significant estimate of β_{π} . For this reason model 4.1 is extended such that the risk-taking assumed by local traders in the morning is regressed on their gains and losses respectively, from the previous afternoon. To capture this effect the second model estimated is:

$$\text{Risk}_{i,t}^M = \alpha + \beta_{\pi} \pi_{i,t-n}^{A,G} + \beta_{\pi} \pi_{i,t-n}^{A,L} + \beta_R \text{Risk}_{i,t-n}^A \quad (4.2)$$

where, for trader i on day $t-n$, $\pi_{i,t-n}^{A,G} = \text{Max}[0, \pi_{i,t-n}^A]$, $\pi_{i,t-n}^{A,L} = \text{Min}[0, \pi_{i,t-n}^A]$. All other terms in model 4.2 are as described earlier.

4.3.2 Profit and Risk-taking across Intra-day Cycles

To analyse the relationship between profit and risk-taking across intra-day cycles, each traders profit, profit per trade, inventory per trade and risk are initially aggregated per cycle. Each of the three risk measures (for the current cycle) is then regressed on the profit, profit per number of trades, inventory per number of trades and one of three corresponding risk measures from the previous cycle. Since the cyclic trading horizons of locals are being examined there is no need to include either an outstanding inventory variable or an interaction variable linking profits and inventory⁶⁸. To account for the possibility that local traders are influenced by additional psychological drivers over the cyclic trading horizon, both of the variables profit per trade and inventory per trade included in the model. The third model estimated is thus:

$$\text{Risk}_{i,t,c} = \alpha + \beta_{\pi} \pi_{i,t,c-1} + \beta_{\varpi} \varpi_{i,t,c-1} + \beta_{\delta} \delta_{i,t,c-1} + \beta_R \text{Risk}_{i,t,c-1} \quad (4.3)$$

where, for trader i on date t in cycle c , $\text{Risk}_{i,t,c}$ is a normalised cyclic risk measure and for trader i on date t in cycle $c-1$, $\pi_{i,t,c-1}$ is the standardised profit, $\varpi_{i,t,c-1}$ is the standardised profit per number of trades, $\delta_{i,t,c-1}$ is the normalised inventory per number of trades and $\text{Risk}_{i,t,c-1}$ is a normalised cyclic risk measure.

4.3.3 Profit and Risk-taking across Days

To study the relationship between profit and risk-taking across days, both variables, profit and risk, are initially aggregated over a daily horizon for each local trader in the sample. Each of the three daily risk measures is then regressed on the profit and each of the three risk measures from the preceding trading day. There is no need to include neither an outstanding inventory variable nor an interaction variable linking profits and outstanding inventory to account for local traders unwinding winning and losing

⁶⁸A cycle refers to a ‘round trip’ in which locals begin with zero inventories and end with zero inventories, having realised a profit/loss in between.

positions differently since the assumption that all inventories are exhausted by the end of each trading day is adopted. Therefore, the fourth model estimate is:

$$\text{Risk}_{i,t} = \alpha + \beta_{\pi} \pi_{i,t-n} + \beta_R \text{Risk}_{i,t-n} \quad (4.4)$$

where, for local trader i on date t , $\text{Risk}_{i,t}$ is a normalised daily risk measure and for local trader i on date $t-n$, $\pi_{i,t-n}$ is the standardised daily profit and $\text{Risk}_{i,t-n}$ is a normalised daily risk measure. Note that, n is the date difference between today and the previous trading day for each local. Hence, if $n \neq 1$ today's risk is regressed on profit and risk from the preceding n^{th} trading day. Alternatively, if $n = 1$ today's risk is regressed on the profit earned and risk taken yesterday. This chapter firstly examines all observations together (whereby n can equal any value) and secondly all consecutive trading days (whereby $n = 1$ only).

In much the same way as described above, model 4.4 is adjusted to incorporate the daily gains and losses of local futures traders as separate psychological drivers to account for their individual effects. The fifth model estimated is thus:

$$\text{Risk}_{i,t} = \alpha + \beta_{\pi} \pi_{i,t-n}^G + \beta_{\pi} \pi_{i,t-n}^L + \beta_R \text{Risk}_{i,t-n} \quad (4.5)$$

where, for trader i on date $t-n$, $\pi_{i,t-n}^G$ equals the standardised daily gain when the trader made a profit and zero when the trader made a loss. Similarly, for trader i on date $t-n$, $\pi_{i,t-n}^L$ equals the standardised daily loss when the trader made a loss and zero when the trader made a gain. All other variables are as described earlier.

4.4 Results

4.4.1 Afternoon Profit and Morning Risk-taking across Days

Table 4.1 reports the summary statistics (mean and standard deviation) for afternoon and morning profit measures, total dollar risk, average trade size and number of trades

for all trader days (Panel A), locals with profitable afternoons (Panel B) and locals with losing afternoons (Panel C). The total number of observations is 2939. There are 1732 observations (59%) that relate to days on which locals trade profitably during the afternoon. The local's overall average standardised afternoon profit from Panel A is 0.121. Since profit figures have been standardised on a trader-specific basis, this implies that locals earn an average of 12.1% of one standard deviation of their afternoon returns per afternoon. Local's overall average profits on the subsequent morning are also positive at 0.143.

Table 4.1: Descriptive Statistics by Trader-Day: All Observations

Table 4.1 reports summary statistics by trader-day for the trading activity of locals in SPI futures contracts at the SFE over the period 24 July, 1997 to 4 October, 1999. The table includes the mean and standard deviation of trader-specific standardised profits and normalised total dollar risk, average trade size, number of trades and absolute inventory for (i) all trader-days in the sample, (ii) locals with profitable afternoons and (iii) locals with losing afternoons reported in Panel A, Panel B and Panel C, respectively.

Variable	Afternoon		Morning	
	Mean	Std Deviation	Mean	Std Deviation
Panel A: All Trader Days (N = 2939)				
Profits	0.121	1.002	0.143	1.002
Total Dollar Risk	0	0.993	0	0.993
Average Trade Size	0	0.993	0	0.993
Number of Trades	0	0.993	0	0.993
Panel B: Locals with Profitable Afternoons (N = 1732)				
Profits	0.600	0.845	0.146	0.9953
Total Dollar Risk	0.007	0.948	-0.008	0.996
Average Trade Size	0.019	0.959	-0.002	0.992
Number of Trades	0.060	0.999	-0.000	0.988
Panel C: Locals with Losing Afternoons (N = 1207)				
Profits	-0.566	0.797	0.139	1.070
Total Dollar Risk	-0.010	1.055	0.011	0.989
Average Trade Size	-0.027	1.040	0.003	0.994
Number of Trades	-0.086	0.978	0.001	1.001
Panel D: T-statistics of Differences of Means Between Locals With Profitable afternoons (Panel B) and Losing Afternoons (Panel C)				
Total Dollar Risk	0.45		0.51	
Average Trade Size	1.22		0.13	
Number of Trades	3.95***		0.03	

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Note that the overall average for each of the risk measures for the afternoon and subsequent morning are equal to zero by construction since each of the trader-specific risk measures are mean-adjusted. That is, the mean has been subtracted from the actual values before dividing throughout by the trader-specific standard deviation.

However, partitioning all observations into those with either profitable afternoons (Panel B) or losing afternoons (Panel C) and taking averages, the results document that the risk-taking behaviour amongst locals in the subsequent morning is much the same, irrespective of the gains or losses experienced in the preceding afternoon. While the average for each of the morning risk measures reported in Panel B is negative, they are very close to zero. Similarly, although the averages for each of the morning risk measures reported in Panel C are positive they too are very close to zero. The results presented in Panel D document that there is no significant difference in the average morning risk-taking behaviour of local traders. Specifically, local traders will on average take the same amount of risk in the morning and this is independent of the gains or losses incurred in the preceding afternoon.

Table 4.2 reports the regression results of model 4.1 for all trader days over the sample period. Consistent with Table 4.1, these results indicate that local traders don't exhibit any form of behavioural biases. The slope coefficient of the afternoon profit variable in Table 4.2 is statistically insignificant at the 1% level for each of the three risk measures. This implies that neither an increase nor decrease in a local trader's afternoon profit today will psychologically influence their risk-taking behaviour in the subsequent morning's trading session.

Afternoon risk variables are highly significant, suggesting that if the average local trader takes more than average risk in the afternoon then they will continue to do so in the subsequent morning also.

Table 4.2: Afternoon Profits and Morning Risk-Taking Across Days

Table 4.2 reports the results of a regression relating the afternoon profits of locals at the SFE to their risk behaviour in the subsequent morning. The regression has the basic form,

$$\text{Risk}_{i,t}^M = \alpha + \beta_{\pi} \pi_{i,t-n}^A + \beta_R \text{Risk}_{i,t-n}^A$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 2939 trader-days (all observations).

Risk Variable	α	β_{π}	β_R
Panel A:			
Total Dollar Risk	0.0006	-0.0048	0.25639
t-statistics	(0.03)	(-0.27)	(14.36) ^{***}
p-values	0.9739	0.7843	<.0001
$R^2 = 0.0650$	F-stat = 103.18 ^{***}		
Panel B:			
Trade Size	0.0008	-0.0067	0.2630
t-statistics	(0.05)	(-0.38)	(14.75) ^{***}
p-values	0.9635	0.7022	<.0001
$R^2 = 0.0684$	F-stat = 108.86 ^{***}		
Panel C:			
Number of Trades	0.0011	-0.0092	0.2421
t-statistics	(0.06)	(-0.52)	(13.45) ^{***}
p-values	0.9504	0.6052	<.0001
$R^2 = 0.0576$	F-stat = 90.78 ^{***}		

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level

Table 4.3 reports the regressions results of model 4.2 for all trader days over the sample period. There is insufficient evidence to suggest that either effect alone,

afternoon gains or afternoon losses today, psychologically influence the morning risk-taking behaviour of local traders on the subsequent trading day.

Table 4.3: Afternoon Profits, Losses and Morning Risk-Taking Across Days

Table 4.3 reports the results of the regression relating the afternoon gains and afternoon losses of local traders at the SFE to their risk behaviour in the subsequent morning. The regression has the basic form,

$$\text{Risk}_{i,t}^M = \alpha + \beta_{\pi} \pi_{i,t-n}^{A,G} + \beta_{\pi} \pi_{i,t-n}^{A,L} + \beta_R \text{Risk}_{i,t-n}^A$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 2939 trader-days (all observations, not necessarily consecutive trading days).

Risk Variable	α	$\beta_{\pi G}$	$\beta_{\pi L}$	β_R
Panel A:				
Total Dollar Risk	0.0093	-0.0177	0.0128	0.2623
t-statistics	(0.41)	(-0.64)	(0.38)	(12.90)***
p-values	0.6847	0.5191	0.7048	<.0001
$R^2 = 0.0648$	F-stat = 68.90***			
Panel B:				
Trade Size	0.0087	-0.0186	0.0093	0.2677
t-statistics	(0.39)	(-0.69)	(0.28)	(13.69)***
p-values	0.6969	0.4904	0.7758	<.0001
$R^2 = 0.0682$	F-stat = 72.67***			
Panel C:				
Number of Trades	-0.044	-0.0009	-0.0203	0.2399
t-statistics	(-0.20)	(-0.04)	(-0.64)	(12.82)***
p-values	0.8430	0.9719	0.5222	<.0001
$R^2 = 0.0573$	F-stat = 60.56***			

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

The slope coefficients for both the afternoon profit variable and the afternoon loss variable are statistically insignificant at the 10% level for each of the risk measures presented in Panel A, Panel B and Panel C, respectively. Afternoon risk variables are highly significant, suggesting that if the average local trader takes more than average risk in the afternoon then they will continue to do so in the subsequent morning.

Table 4.4 reports the summary statistics (mean and standard deviation) for afternoon and morning profit measures, total dollar risk, average trade size and number of trades for all consecutive trader days (Panel A), locals with profitable afternoons (Panel B) and locals with losing afternoons (Panel C).

The total number of observations is 1867. There are 1105 observations (59%) that relate to days on which locals trade profitably during the afternoon. The local's overall average standardised afternoon profit from Panel A is 0.148. Since profit figures have been standardised on a trader-specific basis, this implies that locals earn an average of 14.8% of one standard deviation of their afternoon returns per afternoon. Local's overall average profits on the following morning are also positive at 0.140.

Note that the overall average for each of the risk measures for the afternoon and following morning are equal to zero by construction since each of our trader-specific risk measures are mean-adjusted. That is, the mean has been subtracted from the actual values before dividing throughout by the trader-specific standard deviation. The results presented in Panel D document that there is no significant difference in the average morning risk-taking behaviour of local traders following either gains or losses from the previous afternoon.

Table 4.4: Descriptive Statistics by Trader-Day: Consecutive Trading Days

Table 4.4 reports summary statistics by trader-day for the trading activity of locals in SPI futures contracts at the SFE over the period 24 July, 1997 to 4 October, 1999. The table includes the mean and standard deviation for trader-specific standardised profits and normalised total dollar risk, average trade size and number of trades for (i) all consecutive trader-days in the sample only, (ii) locals with profitable afternoons and (iii) locals with losing afternoons reported in Panel A, Panel B and Panel C respectively.

Variable	Afternoon		Morning	
	Mean	Std Deviation	Mean	Std Deviation
Panel A:	All Trader Days (N = 1867)			
Profits	0.148	1.004	0.140	1.003
Total Dollar Risk	0	0.992	0	0.992
Average Trade Size	0	0.992	0	0.992
Number of Trades	0	0.992	0	0.992
Panel B:	Locals with Profitable Afternoons (N = 1105)			
Profits	0.627	0.890	0.143	0.958
Total Dollar Risk	0.004	0.945	-0.007	0.984
Average Trade Size	0.021	0.954	-0.001	0.990
Number of Trades	0.062	0.987	-0.001	0.985
Panel C:	Locals with Losing Afternoons (N = 762)			
Profits	-0.547	0.712	0.137	1.066
Total Dollar Risk	-0.006	1.057	0.010	1.003
Average Trade Size	-0.030	1.043	0.002	0.994
Number of Trades	-0.089	0.992	0.002	1.002
Panel D:	T-statistics of Differences of Means Between Locals with Profitable Afternoons (Panel B) and Losing Afternoons (Panel C)			
Total Dollar Risk	0.21		0.36	
Average Trade Size	1.07		0.06	
Number of Trades	3.24***		0.06	

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Table 4.5 reports the regression results of model 4.1 for all consecutive trader days over the sample period only. Supporting the results presented thus far, there is no significant evidence to suggest that local trader's morning risk today is influenced by the risk taken in yesterday's afternoon trading session.

Table 4.5: Afternoon Profits and Morning Risk-Taking Across Days

Table 4.5 reports the results of a regression relating the afternoon profits of locals at the SFE to their risk behaviour on the following morning. The regression has the basic form,

$$\text{Risk}_{i,t}^M = \alpha + \beta_{\pi} \pi_{i,t-1}^A + \beta_R \text{Risk}_{i,t-1}^A$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 1867 trader-days (all consecutive trading days only).

Risk Variable	α	β_{π}	β_R
Panel A:			
Total Dollar Risk	0.0045	-0.0303	0.3269
t-statistics	(0.20)	(-1.39)	(14.87) ^{***}
p-values	0.8387	0.1632	<.0001
$R^2 = 0.1051$	F-stat = 110.56 ^{***}		
Panel B:			
Trade Size	0.0056	-0.0381	0.3231
t-statistics	(0.26)	(-1.75) [*]	(14.67) ^{***}
p-values	0.7984	0.0805	<.0001
$R^2 = 0.1026$	F-stat = 107.64 ^{***}		
Panel C:			
Number of Trades	0.0039	-0.0266	0.2958
t-statistics	(0.18)	(-1.20)	(13.25) ^{***}
p-values	0.8599	0.2284	<.0001
$R^2 = 0.0852$	F-stat = 87.95 ^{***}		

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

While there is mild evidence of loss aversion – a one standard-deviation decrease in afternoon profits will result in local's traders placing trades that are 3.81% larger than average (Panel B) – the t-statistic is significant at only the 10% level. With the coefficients of the afternoon profit variables for total dollar risk (Panel A) and number of trades (Panel C) being insignificant at the 10% level of confidence, there is inconclusive evidence to suggest a true loss aversion bias in trading behaviour.

Afternoon risk variables are highly significant, suggesting that if the average local trader takes more than average risk in the afternoon then they will continue to do so in the following morning.

Table 4.6 reports the regressions results of model 4.2 for all consecutive trader days over the sample period only. There is no evidence to suggest that afternoon gains or afternoon losses today independently influence the morning risk-taking behaviour of local traders tomorrow.

The slope coefficients for both the profit variable and the loss variable are statistically insignificant at the 10% level for each of the risk measures presented in Panel A, Panel B and Panel C, respectively. Afternoon risk variables are highly significant, suggesting that if the average local trader takes more than average risk in the afternoon then they will continue to do so in the subsequent morning.

Table 4.6: Afternoon Profits, Losses and Morning Risk-Taking Across Days

Table 4.6 reports the results of the regression relating afternoon gains and afternoon losses of local traders at the SFE to their risk behaviour on the following day. The regression has the basic form,

$$\text{Risk}_{i,t}^M = \alpha + \beta_{\pi} \pi_{i,t-1}^{A,G} + \beta_{\pi} \pi_{i,t-1}^{A,L} + \beta_R \text{Risk}_{i,t-1}^A$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 1867 trader-days (all consecutive trading days only).

Risk Variable	α	β_{π_G}	β_{π_L}	β_R
Panel A:				
Total Dollar Risk	0.0064	-0.0329	-0.0259	0.3281
t-statistics	(0.23)	(-1.03)	(-0.58)	(13.37)***
p-values	0.8192	0.3041	0.5637	<.0001
$R^2 = 0.1046$	F-stat = 73.67***			
Panel B:				
Trade Size	0.0041	-0.0360	-0.0415	0.3223
t-statistics	(0.15)	(-1.15)	(-0.95)	(13.55)***
p-values	0.8830	0.2523	0.3446	<.0001
$R^2 = 0.1021$	F-stat = 71.72***			
Panel C:				
Number of Trades	-0.0122	-0.0050	-0.0631	0.2903
t-statistics	(-0.44)	(-0.16)	(-1.47)	(12.62)***
p-values	0.6566	0.8718	0.1419	<.0001
$R^2 = 0.0852$	F-stat = 58.96***			

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

4.4.2 Profit and Risk-Taking across Intra-day Cycles

Table 4.7 reports the regression results of model 4.3. There is strong evidence of a behavioural bias among local futures traders in the form of the house money effect. Surprisingly, the results show that local trader's risk-taking attitudes are more heavily influenced by inventory per trade and profit per trade, within a cycle, than profit alone. Specifically, a one-standard deviation increase in inventory per trade for a cycle will encourage local traders to take 13.98% more total dollar risk than average (Panel A), place trades which are 15.02% larger than average (Panel B) and place 11.64% more trades than average (Panel C), in the next trading cycle. The slope coefficient of inventory per number of trades is highly significant for each of the three risk measures.

In terms of profit per number of trades, a one standard-deviation will entice the average local trader to assume 6.36% more total dollar risk than average (Panel A), place trades that are 6.04% larger than average (Panel B) and trade 5.26% more than average (Panel C), in the subsequent cycle. The slope coefficient of the profit per trade variable is statistically significant at the 1% level for each of the three risk measures.

In comparison, a one standard-deviation increase in cyclic profit will encourage local traders to take 2.57% more total dollar risk than average (Panel A), place trades that are 2.31% larger than average (Panel B) and place 1.90% more trades than average (Panel C), in the subsequent cycle. The slope coefficient of the profit variable is statistically significant at the 10% level for total dollar risk (Panel A) and average trade size (Panel B) but not so for number of trades (Panel C).

All three corresponding risk measures are insignificant indicating that the risk a local assumes in a cycle is independent of the risk they assumed in the previous cycle.

Table 4.7: Profit and Risk-Taking Across Intra-day Cycles

Table 4.7 reports the results of a regression relating the cyclic profits of locals at the SFE to their risk behaviour in the subsequent cycle. The regression has the basic form,

$$\text{Risk}_{i,t,c} = \alpha + \beta_{\pi} \pi_{i,t,c-1} + \beta_{\varpi} \varpi_{i,t,c-1} + \beta_{\delta} \delta_{i,t,c-1} + \beta_R \text{Risk}_{i,t,c-1}$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C, respectively. The sample contains 9930 cycles.

Risk Variable	α	β_{π}	β_{ϖ}	β_{δ}	β_R
Panel A:					
Total Dollar Risk	-0.0010	0.0257	0.0636	0.1398	-0.0126
t-statistics	(-0.10)	(1.90) [*]	(6.13) ^{***}	(13.34) ^{***}	(-0.94)
p-values	0.9210	0.0569	<.0001	<.0001	0.3482
$R^2 = 0.0295$	F-stat = 76.56 ^{***}				
Panel B:					
Trade Size	-0.0000	0.0231	0.0604	0.1502	-0.0171
t-statistics	(-0.00)	(1.71) [*]	(5.79) ^{***}	(14.19) ^{***}	(-1.27)
p-values	0.9965	0.0872	<.0001	<.0001	0.2030
$R^2 = 0.0328$	F-stat = 85.13 ^{***}				
Panel C:					
Number of Trades	0.0002	0.0190	0.0526	0.1164	-0.0159
t-statistics	(0.02)	(1.39)	(5.26) ^{***}	(11.49) ^{***}	(-1.17)
p-values	0.9814	0.1638	0.0001	<.0001	0.2409
$R^2 = 0.0175$	F-stat = 45.31 ^{***}				

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

4.4.3 Profit and Risk-Taking across Days

Table 4.8 reports the regression results of model 4.4 for all trader days over the sample period. There is insufficient evidence to suggest that a local trader's risk attitude today is significantly influenced by the profit earned on the previous trading day.

Table 4.8: Profit and Risk-Taking Across All Trading Days

Table 4.8 reports the results of a regression relating the daily profits of locals at the SFE to their risk behaviour on the subsequent trading day. The regression has the basic form,

$$\text{Risk}_{i,t} = \alpha + \beta_{\pi} \pi_{i,t-n} + \beta_R \text{Risk}_{i,t-n}$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 4296 trader-days.

Risk Variable	α	β_{π}	β_R
Panel A:			
Total Dollar Risk	0.0595	0.0272	0.2710
t-statistics	(3.90) ^{***}	(1.84) [*]	(18.43) ^{***}
p-values	<.0001	0.0656	<.0001
$R^2 = 0.0748$	F-stat = 174.57 ^{***}		
Panel B:			
Trade Size	0.0649	0.0203	0.2828
t-statistics	(4.30) ^{***}	(1.39)	(19.30) ^{***}
p-values	<.0001	0.1648	<.0001
$R^2 = 0.0807$	F-stat = 189.43 ^{***}		
Panel C:			
Number of Trades	0.0815	0.0097	0.2561
t-statistics	(5.41) ^{***}	(0.67)	(17.27) ^{***}
p-values	<.0001	0.5059	<.0001
$R^2 = 0.0658$	F-stat = 152.21 ^{***}		

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

While there is mild evidence of the house money effect – a one standard-deviation increase in daily profits will encourage local traders to take 2.72% more total dollar risk than average (Panel A) – the profit coefficient is merely significant at the 10% level. Moreover, the slope coefficients of the profit variable for both trade size and number of trades are insignificant at the 10% level.

Daily risk variables are highly significant, suggesting that if the average local trader takes more than average risk in throughout the day then they will continue to do so on the subsequent trading day.

Table 4.9 reports the results of model 4.5 for all trader days over the sample period. The results provide some evidence of losses impacting on the risk-taking behaviour of local traders on the subsequent trading day.

In particular, a one standard-deviation decrease in daily profit will result in local traders taking 5.19% less total dollar risk than average (Panel A), placing trades that are 5.12% lower than average (Panel B), however, trading 0.52% more than average (Panel C), on the subsequent trading day. While the coefficient of the profit variable is statistically insignificant for each of the three risk measures, the coefficient of the loss variable is significant at the 5% level for both total dollar risk (Panel A) and trade size (Panel B), but it is insignificant for the number of trades (Panel C).

Daily risk variables are highly significant, suggesting that if the average local trader takes more than average risk in throughout the day then they will continue to do so on the subsequent trading day.

Table 4.9: Profits, Losses and Risk-Taking Across All Trading Days

Table 4.9 reports the results of a regression relating the daily gains and daily losses of locals at the SFE to their subsequent days' risk behaviour. The regression has the basic form,

$$\text{Risk}_{i,t} = \alpha + \beta_{\pi} \pi_{i,t-n}^G + \beta_{\pi} \pi_{i,t-n}^L + \beta_R \text{Risk}_{i,t-n}$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 4296 trader-days.

Risk Variable	α	$\beta_{\pi G}$	$\beta_{\pi L}$	β_R
Panel A:				
Total Dollar Risk	0.0733	0.0049	0.0519	0.2797
t-statistics	(3.75)***	(0.20)	(1.97)**	(16.88)***
p-values	0.0002	0.8439	0.0487	<.0001
$R^2 = 0.0748$	F-stat = 116.82***			
Panel B:				
Trade Size	0.0820	-0.0074	0.0512	0.2932
t-statistics	(4.27)***	(-0.31)	(1.97)**	(17.95)***
p-values	<.0001	0.7593	0.0486	<.0001
$R^2 = 0.0809$	F-stat = 127.01***			
Panel C:				
Number of Trades	0.0731	0.0234	-0.0052	0.2523
t-statistics	(3.88)***	(1.00)	(-0.21)	(16.13)***
p-values	0.0001	0.3183	0.8328	<.0001
$R^2 = 0.0657$	F-stat = 101.65***			

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Table 4.10 reports the regression results of model 4.4 for all consecutive trader days in the sample. There is insufficient evidence to suggest that yesterday's profits influences today's risk for local traders in the sample. Specifically, the slope coefficient for the profit variable is statistically insignificant for each of the three risk

measures. Daily risk variables are highly significant, suggesting that if the average local trader takes more than average risk throughout the day then they will continue to do so on the following day also.

Table 4.10: Profit and Risk-Taking Across Consecutive Trading Days

Table 4.10 reports the results of a regression relating the daily profits of locals at the SFE to their risk behaviour on the following trading day. The regression has the basic form,

$$\text{Risk}_{i,t} = \alpha + \beta_{\pi} \pi_{i,t-1} + \beta_R \text{Risk}_{i,t-1}$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 2339 trader-days (all consecutive trading days only).

Risk Variable	α	β_{π}	β_R
Panel A:			
Total Dollar Risk	0.0991	0.0313	0.3399
t-statistics	(4.82) ^{***}	(1.49)	(16.86) ^{***}
p-values	<.0001	0.1354	<.0001
$R^2 = 0.1126$	F-stat = 149.27 ^{***}		
Panel B:			
Trade Size	0.1189	0.0198	0.3559
t-statistics	(5.68) ^{***}	(0.93)	(17.57) ^{***}
p-values	<.0001	0.3511	<.0001
$R^2 = 0.1187$	F-stat = 158.43 ^{***}		
Panel C:			
Number of Trades	0.1216	0.0125	0.3206
t-statistics	(5.92) ^{***}	(0.60)	(15.84) ^{***}
p-values	<.0001	0.5495	<.0001
$R^2 = 0.0987$	F-stat = 129.01 ^{***}		

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Table 4.11 reports the regression results of model 4.5 for all consecutive trader days in the sample. There is insufficient evidence to conclude that the risk-taking behaviour of local traders today is influenced by either the profits or losses earned yesterday.

Table 4.11: Profits, Losses and Risk-Taking Across Consecutive Trading Days

Table 4.11 reports the results of a regression relating the daily gains and losses of locals at the SFE to their risk behaviour on the following trading day. The regression has the basic form,

$$\text{Risk}_{i,t} = \alpha + \beta_{\pi} \pi_{i,t-1}^G + \beta_{\pi} \pi_{i,t-1}^L + \beta_R \text{Risk}_{i,t-1}$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 2339 trader-days (all consecutive trading days only).

Risk Variable	α	$\beta_{\pi G}$	$\beta_{\pi L}$	β_R
Panel A:				
Total Dollar Risk	0.1024	0.0262	0.0382	0.3418
t-statistics	(3.90)	(0.80)	(0.97)	(15.38)***
p-values	<.0001	0.4255	0.3317	<.0001
$R^2 = 0.1122$	F-stat = 99.48***			
Panel B:				
Trade Size	0.1343	-0.0042	0.0520	0.3648
t-statistics	(5.07)	(-0.13)	(1.30)	(16.35)***
p-values	<.0001	0.8990	0.1948	<.0001
$R^2 = 0.1186$	F-stat = 105.91***			
Panel C:				
Number of Trades	0.1194	0.0159	0.0079	0.3197
t-statistics	(4.67)	(0.51)	(0.21)	(15.09)***
p-values	<.0001	0.6125	0.8361	<.0001
$R^2 = 0.0983$	F-stat = 85.98***			

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

The coefficients of both the daily profit and daily loss variables are statistically insignificant for all three risk measures. Afternoon risk variables are highly significant, suggesting that if the average local trader takes more than average risk in the afternoon then they will continue to do so in the subsequent morning.

4.5 Summary

This chapter uses real-world trading data from the Sydney Futures Exchange to test for behaviour biases among professional (“local”) traders over varying trading horizons. Most studies, using real-world futures data, draw on the conclusions of Duffy et al. (1998), Kuserk and Locke (1993, 1994) and Manaster and Mann (1996), which suggest that professional trader’s trade in short cycles and almost always close out their positions at the end of each trading day to go home ‘flat’. There is the possibility, however, not all traders evaluate their performance at the end of each trading day and for this reason, profits earned over varying time periods, could potentially influence their tolerance towards risk in subsequent trading periods.

This chapter contributes to existing literature (Coval and Shumway, 2005; Locke and Mann, 2004) by focusing on two trading horizons, which up to this point, have not yet been researched. The first poses the question of whether afternoon profits earned today can be used to explain the risk-taking behaviour of local trader’s tomorrow morning. Results from this analysis provide insufficient evidence of psychological inconsistencies in the trading behaviour of local traders. The second asks the question of whether profits earned in one trading cycle can influence the risk-taking behaviour of local trader’s in the next trading cycle. The findings provide strong evidence that local’s on the Sydney Futures Exchange trade in a way that is consistent with the “house money effect” – that is, with a tendency to take greater risk when trading with profits rather than with initial capital. Moreover, the house money effect is more pronounced in the profit per trade and inventory per trade than in bottom line profit per cycle.

This chapter also tests whether profits earned today affect the risk-taking behaviour of local trader’s tomorrow. In two recent studies dealing with this issue directly, Coval

and Shumway (2005) and Locke and Mann (2004) report mixed results. Coval and Shumway (2005) find insufficient evidence of psychological biases among proprietary traders at the Chicago Board of Trade (CBOT). In contrast, Locke and Mann (2004) provide strong evidence of loss aversion amongst floor traders at the Chicago Mercantile Exchange (CME) over various daily horizons. Specifically, they find that profits earned over the past k days, where $k = 1, 2, 3, 4$, or 5 weigh negatively on the risk-taking behaviour of floor traders today. Results from this analysis align with those from Coval and Shumway (2005). There are no apparent behavioural biases evident in the trading behaviour of locals at the Sydney Futures Exchange over a daily trading horizon.

Overall, results from this analysis suggest that profits earned by local traders at the Sydney Futures Exchange influence their risk-taking behaviour when they evaluate their performance at high-frequency intervals. Specifically, there is strong evidence of a house money effect within intra-day trading cycles, but no evidence of behavioural biases across trading days.

Chapter 5 : Professional Futures Traders, Profits and Prices

Chapter 2 reviews the literature on individual investor behaviour. Chapter 3, documents that professional (“local”) futures traders at the Sydney Futures Exchange decrease their tolerance towards afternoon risk following profitable morning trading sessions. Chapter 4 reports that local traders’ willingness to take risk within an intra-day trading cycle increases, if in the previous cycle they record a profit. Both of the preceding chapters use real-world trading data and contribute to the literature by providing strong evidence of the house money effect. The next logical question is whether this form of irrational behaviour is strong enough to influence prices and provide profitable trading opportunities for other market participants? This chapter addresses the question directly.

5.1 Introduction

Early-stage research in behavioural finance concentrated on adopting ideas from psychologists to assist in the explanation of market anomalies, such as the equity premium puzzle Benartzi and Thaler (1995), the status quo bias Samuelson and Zeckhauser (1988) and the volatility puzzle Mehra and Prescott (1985).

The focus then turned to applying behavioural finance to investor behaviour. Despite the challenges raised by Campbell (2000) such as investor’s ambiguous trading horizons and the confidentiality surrounding real-world trading data, researchers have managed to provide valuable insights into their trading behaviour (Coval and Shumway, 2005; Glaser et al., 2004; Locke and Mann, 2004; 2005; Frino et al., 2004).

In a recent summary of the applications of behavioural finance, Barberis and Thaler (2003) note that one of the many directions for future research in behavioural finance is to produce more empirical oriented studies. The usefulness of these types of studies

will enable researchers to test the reliability of predictive models and answer questions such as do investors behave in the same manner as the models suggest?

Attention in the discipline now lies with the question of whether behavioural biases affect prices. In a recent paper, Coval and Shumway (2005) test this hypothesis amongst proprietary traders at the Chicago Board of Trade. Their results show that prices set in the afternoon by traders with morning losses revert more strongly to normal levels than prices set by traders with morning gains. This suggests that traders with morning losses have only a temporary impact on afternoon prices. Generally, other participants in the pit regard them as noise traders, attempting to recover losses they have previously incurred, and for this reason have no problem in trading aggressively against them. Consistent with these findings, Coval and Shumway (2005) also report that traders with losing mornings create an increase in short-term afternoon price volatility, however this disseminates within ten minutes of their price-setting trade, having no affect on longer-term afternoon price volatility.

Barberis, Huang and Santos (2001) also test whether behavioural biases affect prices. They develop a model aimed at predicting future stock returns, as opposed to futures prices. The model departs slightly from the consumption-based model (which suggests that investors derive utility solely from the wealth generated from consumption) to incorporate also the utility from changes in financial wealth in previous transactions.

Their results document that traders become less tolerant towards risk following run-up periods in stock prices since the utility from previous gains has a cushioning effect on the disutility of potential future losses. In contrast, following periods of falling stock prices, traders are found to be more advert towards risk because of the possibility of losing more. They conclude that because of this psychological tendency among investors, it is possible to explain the high premium, excess volatility and predictability of observed stock returns.

There is clearly a shortage of work dealing with this issue directly. More research is required to assist in the construction of behavioural-based models aimed at predicting asset prices with greater accuracy than traditional models currently employed.

This chapter adds to the literature by addressing the question of whether the behavioural biases of professional (“local”) futures traders at the Sydney Futures Exchange influence prices. Each day is split into a morning and afternoon trading session and tests are performed to determine whether trader irrationality contributes to afternoon price volatility. The permanence of the afternoon volatility is also examined to determine whether profitable opportunities arise for other market participants as a result of the psychological inconsistencies of local futures traders.

The remainder of this chapter proceeds as follows. Section 5.2 describes the data and section 5.3 explains the methodology used for the analysis. Section 5.4 presents the results and section 5.5 summarises the findings and concludes.

5.2 Data

Data for this research was provided by the Sydney Futures Exchange,⁶⁹ sourced from a host log file of the electronic clearing and settlement system known as STACS (Sydney Futures Exchange Trade Allocation and Confirmation System). This file describes transactions in the nearest-to-maturity contract for the SPI Futures contract over the period 24th July, 1997 to 4th October, 1999. This time period was chosen for the following reasons. First, the Sydney Futures Exchange was only able to provide data from 24th July, 1997 and second, the Sydney Futures Exchange shifted to an automated rather than floor trading system for the SPI futures contract from 4th October, 1999 onwards. The sample period excludes holidays on which the Sydney Futures Exchange closed at lunchtime.

Each record in the data represents a single trade and contains the security code, date, time, volume, buyer identity and seller identity. A local trader’s account is represented by an identification number between 1 and 224. The data allows

⁶⁹ For further detail on the data and institutional detail the reader should refer to Frino et al. (2004).

reconstruction of the inventory positions of individual trader's accounts on a trade-by-trade basis. A total of 40 trader-accounts were active throughout the sample period.⁷⁰

5.3 Research Methodology

To enable testing of the price impact of irrational behaviour hypothesis, each trading day in the sample is split into morning and afternoon trading sessions. Over the sample period studied, the SPI futures contract traded from 9:50a.m. to 4:25p.m. with lunchtime closure between 12:30p.m. and 2:00p.m. (Frino and Winn, 2001). The morning trading session is therefore defined as the interval from 9:50a.m. to 12:30p.m. while the afternoon trading session is defined as the period from 2:00p.m. to 4:25p.m. The effect of morning profits on afternoon risk-taking is examined for all local traders to assess the rationality of their trading behaviour.

For each trader, a realised profit is calculated on each trade that reduces (or changes the sign of) the trader's inventory exposure (long or short) and is calculated against the weighted average cost (WAC) of inventory at the time of the trade. For example, if a trader places the following five consecutive trades in the SPI futures contract: buy 2 at 3000 index points, buy 4 at 3003, buy 6 at 3007, sell 6 at 3008 and sell 6 at 3012, then the corresponding WAC's at each trade would be 3000, 3002, 3004.5, 3004.5 and 3004.5, respectively.

The WAC is updated whenever a trader accumulates inventory, either long or short and remains constant while the trader is exhausting inventory (long or short). In the illustration used above, the trader does not realise a profit until the fourth trade in the sequence, since up to this point inventory is being accumulated. The realised profit for the fourth and fifth trades is $21=3.5 \times 6$ index points and $45=7.5 \times 6$ index points, respectively. A new WAC is calculated from the next trade onwards since after the fifth trade in the sequence all inventories are exhausted. This process is applied

⁷⁰ Local accounts were required to be active on at least two mornings throughout the sample period to enable a standard deviation to be calculated on a trader specific basis for the standardised profit measure.

repeatedly to allow aggregate morning and afternoon profits to be calculated for each trader-day in the sample.

Measuring trader risk is more complicated. For this, the method advanced by Coval and Shumway (2001; 2005) to find the “total dollar risk” assumed by a given trader over a given period is adopted. The level of risk (volatility) in the SPI futures contract varies throughout the trading day. To assess the risk implicit in a given trading position at a given time of day, a multinomial logistic regression model is used to estimate the probabilities of the possible price changes over the following minute. Following Coval and Shumway (2001; 2005), the model has the form:

$$\text{Log} \left[\frac{p_t(k)}{1 - p_t(k)} \right] = \alpha_i + X'\beta \quad 1 \leq k \leq 9$$

where, $p_t(k) = \Pr(Y \leq k | X)$ represents the conditional probability that the price change Y in the SPI futures contract over the following minute t is less than or equal to k price ticks,⁷¹ and $X'\beta = \beta_1 x_1 + \dots \beta_5 x_5 + \beta_{113} d_{113} \dots \beta_{199} d_{199}$, where x_n is the absolute price change (in ticks) occurring in the n^{th} preceding minute ($1 \leq n \leq 5$) and d_j is a dummy variable (0 or 1) indicating the time of day in five-minute intervals ($118 \leq j \leq 197$).⁷²

Prices changes Y in the SPI futures contract take values $k=1,2,\dots,9$, where k represents the unit change in the SPI within a given one-minute interval (Appendix 1 shows the distribution of k). The fitted values from the regression are used, firstly, to construct cumulative probabilities for each ordered value k of the dependent variable Y , conditional on the vector of explanatory variables, X . The discrete probabilities $q_t(k)$ for each of the possible one-minute price changes $k=1,2,\dots,9$ are found by subtracting consecutive cumulative probabilities $p_t(k)$.

⁷¹ A price tick is a one unit change in the price of SPI futures contract.

⁷² There are 80 time-of-day dummy variables in total, ranging from 118-197 inclusive. Dummy d_{118} corresponds to the 118th five-minute period of the day (9:50a.m.) while d_{197} corresponds to the 197th five-minute period of the day (4:25p.m.).

Finally, the summation of each absolute price change k multiplied by its respective discrete probability is used to calculate an expected absolute price change at each time (minute) t of the day as follows:

$$\text{Expected Absolute Price Change}_t = \sum_{k=1}^9 k \times q_t(k)$$

The risk associated with any position taken by local i at time t (measured in minutes) is then calculated as:

$$\text{Risk}_{i,t} = |\text{Inventory}_{i,t}| \times \text{Expected Absolute Price Change}_t$$

where $\text{Inventory}_{i,t}$ is trader i 's inventory exposure (long or short) as at time t , measured as a number of contracts. The total risk assumed by local i over any given period is given by the sum of minute-by-minute risks, $\sum \text{Risk}_{i,t}$, calculated over that period. Coval and Shumway (2005) call this “total dollar risk”. Furthermore, to ensure the robustness of this risk measure, two alternative measures of cumulative risk incurred over a given interval are calculated for each individual trader. These are the number of contracts traded by that individual and number of trades placed.

Trader heterogeneity in relation to margin constraints and risk tolerance means that a large dollar exposure for one trader is not necessarily large for another (Locke and Mann, 2004; Coval and Shumway, 2005). To allow for individual differences, all risk measures are normalised on a trader-specific basis. This requires calculating a mean and standard deviation for each of three afternoon risk measures for each local trader in the sample. To normalise the risk measures for an individual trader, the trader-specific mean is subtracted from afternoon risk and the result divided by the trader-specific standard deviation. As a result, all three normalised afternoon risk measures have standard deviations equal to one by construction. Morning risk measures are calculated the same way.

As with risks, different traders have different perceptions about what constitutes a large profit. However, profit is standardised on a trader-specific basis as opposed to

being normalised. That is, traders' morning profits are divided by their trader-specific standard deviations only. This is based on the assumption that a profit constitutes a gain in wealth relative to the psychological reference point of zero (any profit greater than zero has a positive psychological impetus). A positive standardised value represents a psychological profit.

If, on the other hand, profits were normalised, a profit greater than zero but less than the trader's average profit would show as a negative, potentially misrepresenting its positive psychological value. By standardising rather than normalising profits, this psychological relationship is preserved. Afternoon profit measures are standardised the same way.

An alternative perspective, advocated by Coval and Shumway (2005, p.11) and Locke and Mann (2005, p.434), and tracing to Kahnemann and Tversky (1979, p.286), suggests that a profit not much more than zero is hardly a profit in any strong psychological sense. Moreover, because locals have overheads and opportunity costs to consider, including the costs of their seats on the exchange, it is plausible that their psychological break-even point for a day's trading is greater than zero. This is all the more reasonable if they require some minimum return as compensation for the risk of loss borne every day they trade. To make this experiment more robust against this possibility, the analysis is repeated using normalised rather than standardised trader profits, following Coval and Shumway (2005, p.11). Profits are normalised on a trader-by-trader basis. This is achieved by subtracting from each trader's daily profit his mean profit calculated over the entire data period. The mean is measured this way to capture an estimate of the trader's "inherent" personal average profit, which is presumably more than enough to compensate him for his involvement in the game (otherwise he would not be there).

5.3.1 Short-term Afternoon Price Volatility

To examine the effect of morning profit on short-term afternoon price volatility price-setting trades are identified as trades placed by locals, which results in a shift in the SPI futures contract by at least one unit from the previous price. The number of afternoon price-setting trades placed by each local in the sample is calculated for each

trading day. The average number of afternoon price-setting trades is also calculated for each local. The difference between these two measures is then regressed on morning profit, outstanding morning inventory, an interaction variable (profit \times inventory) and one of three morning risk measures⁷³.

The outstanding morning inventory is normalised on a trader-specific basis in the same way as each of the three risk measures defined above. This variable is included in the regression because locals experiencing profitable mornings may enter the afternoon with much larger outstanding morning inventory and it is essential to control for the additional afternoon risk created by this carryover Coval and Shumway (2005). The first model estimated is thus:

$$\Delta_{i,t}^A - \bar{\Delta}_i^A = \alpha + \beta_{\pi} \pi_{i,t}^M + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi I} \pi_{i,t}^M |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M \quad (5.1)$$

where, for trader i on date t , $\Delta_{i,t}^A$ is the number of afternoon price-setting trades, $\bar{\Delta}_i^A$ is the average number of afternoon price-setting trades, $\pi_{i,t}^M$ is the standardised morning profit, $|\text{INV}_{i,t}^M|$ is the normalised absolute value of outstanding morning inventory, and $\text{Risk}_{i,t}^M$ is a normalised morning risk measure.

Extending from Coval and Shumway (2005) this process is repeated several times with distinct but subtle changes. First, the effect of morning profits on short-term afternoon price volatility is examined separately for long and short trades. This is to determine whether locals exhibit the same trading behaviour when they are purchasing or selling inventory. Second, price-setting trades are redefined as trades that are responsible for shifting the SPI futures contract by: i) at least two index points, ii) at least three index points and iii) at least one index point from the price recorded two trades earlier. The first two changes are implemented to determine whether morning profits can encourage local traders to purchase contracts (sell contracts) at higher (lower) prices than the one prevailing at the previous trade. The

⁷³ An interaction variable is included to account for the possibility that local traders unwind winning and losing positions in different ways. This possibility was suggested by Shefrin and Statman (1985), Odean (1998a), and Locke and Mann (2000) and implemented by Coval and Shumway (2005).

third change is implemented to mitigate the effect of bid-ask bounce since approximately 80% of all price changes account for either a zero or one unit shift in the SPI futures contract (see appendix 1).

Furthermore, a logistic regression is implemented as a robustness check of the regression results to determine whether local traders increase their likelihood of placing more than average price-setting trades in the afternoon following profitable mornings. The logistic model is defined as follows:

$$\text{Prob}(\Delta_{i,t}^A - \bar{\Delta}_{i,t}^A > 0) = \frac{\exp X'\beta}{1 + \exp X'\beta} \quad (5.2)$$

where, for local trader i on date t , $\text{Prob}(\Delta_{i,t}^A - \bar{\Delta}_{i,t}^A > 0)$ is the probability that the short-term afternoon price volatility measure is greater than zero. This is a dichotomous variable that equals 0 if afternoon normalised risk is positive and 1 otherwise. Also, $X'\beta = \alpha + \beta_\pi I(\pi_{i,t}^M > 0) + \beta_I |INV_{i,t}^M| + \beta_{\pi I} I(\pi_{i,t}^M > 0) |INV_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$ where, for local trader i on date t , $I(\pi_{i,t}^M > 0)$ is an indicator variable that is equal to one if standardised morning profit is positive and zero otherwise. All other variables are as described earlier.

5.3.2 Longer-term Afternoon Price Volatility

A series of tests are performed to examine the effect of morning profits on longer-term afternoon price volatility. Price-setting trades, as previously defined, are initially identified and then in a manner similar to that of Coval and Shumway (2005) price patterns are coded using references. The four price patterns are: Reversal, Reversal (RR), Reversal, Continuation (RC), Continuation, Continuation (CC) and Continuation, Reversal (CR).

Extending from Coval and Shumway (2005), however, two additional price patterns are identified. They are No Identifiable (NI) price pattern and a One Continuation (OC) price pattern. These are included because the data suggests that not all price patterns fall into the four categories defined by Coval and Shumway (2005). Simply

omitting observations of this kind could severely compromise the true nature of the results.

To highlight how price patterns are coded, consider the following illustration. Suppose (3000, 3001, 3000, 3001) are the prices of the SPI futures contract recorded from the four most recent trades. Assume that the price difference between the last two trades in the sequence represents the price-setting trade placed by a local trader. The first three prices represent a reversal since the price initially changed from 3000 to 3001 and then reverted back to 3000. Similarly, the last three prices also represent a reversal because the price initially fell from 3001 to 3000 but then rose back to its original level of 3001. This price pattern would thus, be identified as (RR).

Once all price-setting trades have been identified and price patterns coded, trades are partitioned into price reversals or price continuations. Reversals and continuations are determined by the price behaviour of the SPI futures contract in the five-minute period following a price-setting trade⁷⁴. Specifically, the price change caused by a price-setting trade might revert to earlier levels or continue in the same direction. Price reversals and price continuations are measured as the percentage of the price-setting trades' movement that is either reversed or continued over the next five minutes.

The data is then segregated into two datasets, one for price reversals and the other for price continuations. In each dataset, morning profitability as well as trade direction (long or short) is identified. This allows the effect of morning profits on longer-term afternoon price volatility to be analysed and also determine whether trade direction impacts upon the result. These relations are shown separately for price reversals and price continuations.

To ensure that the results from above are robust, an additional test is implemented to examine the effect of morning profitability on longer-term afternoon price volatility. In particular, the price difference between the price-setting trade now and the price five minutes later is regressed on the three previous price changes and three

⁷⁴ On average there are 10 trades performed per minute.

interaction variables linking morning profitability and each of the price changes (profit \times price change). The regression model estimated is thus:

$$P_{t+5} - P_t = \alpha + \beta_{p1}\Delta P_1 + \beta_{p2}\Delta P_2 + \beta_{p3}\Delta P_3 + \beta_{IP1}I(\pi_{i,t}^M > 0)\Delta)_1 + \beta_{IP2}I(\pi_{i,t}^M > 0)\Delta)_2 + \beta_{IP3}I(\pi_{i,t}^M > 0)\Delta)_3 \quad (5.3)$$

where, P_{t+5} = the price of the SPI futures contract at time $t+5$, which is five minutes after the price-setting trade, P_t = the price of the SPI futures contract at time t , which is the time of the price-setting trade, ΔP_1 = the price change immediately before the price-setting trade, ΔP_2 = the second price change before the price-setting trade, ΔP_3 = the third price change before the price-setting trade and $I(\pi_{i,t}^M > 0)$ is an indicator variable that is equal to one if local trader i on date t recorded a morning profit and zero otherwise.

5.4 Results

Table 5.1 reports the regression results of model 5.1. There is strong evidence which suggests that morning profits affect short-term afternoon price volatility. Specifically, the results indicate that between 50.93% (Panel C) and 67.93% (Panel B) of local traders place more than average price-setting trades in the afternoon following a one standard-deviation increase in morning profits. The slope coefficient of the morning profit variable in Table 5.1 is statistically significant at the 1% level for each of the three risk measures reported in Panel A, Panel B and Panel C, respectively.

Morning risk variables are also highly significant. This implies that if the average local trader assumed more than average morning risk they will place more than average price-setting trades in the afternoon.

Table 5.1: Morning Profits and Short-term Afternoon Price Volatility

Table 5.1 reports the results of a regression relating the morning profits of locals at the SFE to short-term afternoon price volatility. The regression has the basic form,

$$\Delta_{i,t}^A - \bar{\Delta}_{i,t}^A = \alpha + \beta_{\pi} \pi_{i,t}^M + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi I} \pi_{i,t}^M |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 3646 trader-days. Price-setting trades are identified as trades by locals that result in a shift in the SPI by at least one unit from the previous price.

Dependent Variable	α	β_{π}	β_I	$\beta_{\pi I}$	β_R
Panel A:		Total Dollar Risk			
Price Volatility	-0.0914	0.6043	0.1764	-0.0097	2.6897
<i>t</i> -statistics	(-0.68)	(4.14) ^{***}	(1.25)	(-0.16)	(19.01) ^{***}
<i>p</i> -values	0.4977	<.0001	0.2130	0.8745	<.0001
$R^2 = 0.1111$	F-stat = 114.86 ^{***}				
Panel B:		Trade Size			
Price Volatility	-0.1027	0.6793	0.0950	-0.0179	2.6753
<i>t</i> -statistics	(-0.76)	(4.65) ^{***}	(0.66)	(-0.29)	(18.70) ^{***}
<i>p</i> -values	0.4468	<.0001	0.5079	0.7713	<.0001
$R^2 = 0.1085$	F-stat = 111.87 ^{***}				
Panel C:		Number of Trades			
Price Volatility	-0.0772	0.5093	0.3658	0.0222	2.8593
<i>t</i> -statistics	(-0.58)	(3.51) ^{***}	(2.67) ^{***}	(0.36)	(20.85) ^{***}
<i>p</i> -values	0.5631	0.0005	0.0076	0.7161	<.0001
$R^2 = 0.1271$	F-stat = 133.65 ^{***}				

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Tables 5.2 and 5.3 also report the regression results of model 5.1, however, for long and short trades, respectively. While both tables provide additional support for the results presented above, a greater proportion of local traders selling inventory in the afternoon place more than average price-setting trades following morning profits than those that purchase inventory in the afternoon.

In particular, Table 5.2 shows that when local traders are buying inventory in the afternoon, between 20.06% (Panel C) and 28.79% (Panel B) of them place above average price-setting trades following a one standard-deviation increase in morning profits. Table 5.3, on the other hand, reveals that when local traders are selling inventory in the afternoon, between 30.87% (Panel C) and 39.14% (Panel B) of them place above average price-setting trades following a one standard-deviation increase in morning profits.

The slope coefficient of the morning profit variables in both Table 5.2 and Table 5.3 are significant at the 1% level for each of the three risk measures reported in Panel A, Panel B and Panel C of each table, respectively. Morning risk variables are highly significant also, implying that if the average local trader assumed more than average morning risk they will place more than average price-setting trades in the afternoon.

Table 5.2: Morning Profits and Short-term Afternoon Price Volatility

Table 5.2 reports the results of a regression relating the morning profits of locals at the SFE to short-term afternoon price volatility for trades that are long. The regression has the basic form,

$$\Delta_{i,t}^A - \bar{\Delta}_{i,t}^A = \alpha + \beta_{\pi} \pi_{i,t}^M + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi I} \pi_{i,t}^M |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 3646 trader-days.

Dependent Variable	α	β_{π}	β_I	$\beta_{\pi I}$	β_R
Panel A:		Total Dollar Risk			
Price Volatility	-0.0379	0.2499	0.0672	0.0167	1.4025
<i>t</i> -statistics	(-0.52)	(3.13)***	(0.87)	(0.50)	(18.14)***
<i>p</i> -values	0.6066	0.0018	0.3852	0.6188	<.0001
$R^2 = 0.0994$	F-stat = 101.60***				
Panel B:		Trade Size			
Price Volatility	-0.0437	0.2879	0.0202	0.0127	1.4083
<i>t</i> -statistics	(-0.59)	(3.61)***	(0.26)	(0.38)	(18.03)***
<i>p</i> -values	0.5535	0.0003	0.7969	0.7050	<.0001
$R^2 = 0.0985$	F-stat = 100.60***				
Panel C:		Number of Trades			
Price Volatility	-0.0306	0.2006	0.1664	0.0333	1.4891
<i>t</i> -statistics	(-0.42)	(2.53)**	(2.22)**	(1.00)	(19.85)***
<i>p</i> -values	0.6755	0.0116	0.0263	0.3186	<.0001
$R^2 = 0.1139$	F-stat = 118.18***				

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Table 5.3: Morning Profits and Short-term Afternoon Price Volatility

Table 5.3 reports the results of a regression relating the morning profits of locals at the SFE to short-term afternoon price volatility for trades that are short. The regression has the basic form,

$$\Delta_{i,t}^A - \bar{\Delta}_{i,t}^A = \alpha + \beta_{\pi} \pi_{i,t}^M + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi I} \pi_{i,t}^M |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 3646 trader-days.

Dependent Variable	α	β_{π}	β_I	$\beta_{\pi I}$	β_R
Panel A:		Total Dollar Risk			
Price Volatility	-0.0535	0.3544	0.1092	-0.0264	1.2872
<i>t</i> -statistics	(-0.78)	(4.79)***	(1.52)	(-0.85)	(17.97)***
<i>p</i> -values	0.4333	<.0001	0.1278	0.3959	<.0001
$R^2 = 0.1036$	F-stat = 106.31***				
Panel B:		Trade Size			
Price Volatility	-0.0590	0.3914	0.0749	-0.0306	1.2670
<i>t</i> -statistics	(-0.86)	(5.29)***	(1.03)	(-0.98)	(17.48)***
<i>p</i> -values	0.3880	<.0001	0.3032	0.3262	<.0001
$R^2 = 0.0997$	F-stat = 101.86***				
Panel C:		Number of Trades			
Price Volatility	-0.0467	0.3087	0.1994	-0.0111	1.3702
<i>t</i> -statistics	(-0.69)	(4.20)***	(2.88)***	(-0.36)	(19.72)***
<i>p</i> -values	0.4906	<.0001	0.0041	0.7195	<.0001
$R^2 = 0.1183$	F-stat = 123.23***				

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Table 5.4 reports regression results of model 5.1, however, for price-setting trades that were responsible for shifting the SPI by at least two units. Similarly, Table 5.5 presents results of the same regression model, but for price-setting trades that caused at least a three unit shift in the SPI. Both, Table 5.4 and Table 5.5 provide strong evidence which suggests that local trader's morning profitability significantly impacts upon short-term afternoon price volatility. These results support but extend those reported in Table 5.1 above.

In particular, Table 5.4 shows that between 26.38% (Panel C) and 35.59% (Panel B) of locals are willing to place more than average price-setting trades in the afternoon following a one standard-deviation increase in morning profits. This is despite the fact that a trade has to be responsible for causing at least a two unit shift in the SPI to be classified a price-setting trade.

Similarly, the results presented in Table 5.5 document that between 16.95% (Panel C) and 22.09% (Panel B) of locals are willing to place more than average price-setting trades in the afternoon following a one standard-deviation increase in morning profits. This finding is quite remarkable since a trade has to be responsible for shifting the SPI by at least three units before it can be deemed a price-setting trade.

The slope coefficient of the morning profit variable reported in Panel A, Panel B and Panel C, of each of the tables respectively, is statistically significant at the 1% level for each of the three risk measures. Morning risk variables, across both tables are also highly significant at the 1% level for each of the three measures. This implies that if the average local trader assumed more than average morning risk they will place more than average price-setting trades in the afternoon.

Table 5.4: Morning Profits and Short-term Afternoon Price Volatility

Table 5.4 reports the results of a regression relating the morning profits of locals at the SFE to short-term afternoon price volatility. The regression has the basic form,

$$\Delta_{i,t}^A - \bar{\Delta}_{i,t}^A = \alpha + \beta_{\pi} \pi_{i,t}^M + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi I} \pi_{i,t}^M |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 3646 trader-days. Price-setting trades are identified as trades by locals that result in a shift in the SPI by at least two units from the previous price.

Dependent Variable	α	β_{π}	β_I	$\beta_{\pi I}$	β_R
Panel A:		Total Dollar Risk			
Price Volatility	-0.0458	0.3010	0.0526	0.0306	1.6294
<i>t</i> -statistics	(-0.59)	(3.56)***	(0.64)	(0.86)	(19.91)***
<i>p</i> -values	0.5571	0.0004	0.5205	0.3903	<.0001
$R^2 = 0.1173$	F-stat = 122.10***				
Panel B:		Trade Size			
Price Volatility	-0.0540	0.3559	0.0435	0.0232	1.5051
<i>t</i> -statistics	(-0.69)	(4.18)***	(0.52)	(0.65)	(18.05)***
<i>p</i> -values	0.4921	<.0001	0.6028	0.5178	<.0001
$R^2 = 0.1016$	F-stat = 104.10***				
Panel C:		Number of Trades			
Price Volatility	-0.0402	0.2638	0.2018	0.0449	1.5827
<i>t</i> -statistics	(-0.52)	(3.11)***	(2.52)**	(1.26)	(19.76)***
<i>p</i> -values	0.6061	0.0019	0.0116	0.2080	<.0001
$R^2 = 0.1160$	F-stat = 120.55***				

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Table 5.5: Morning Profits and Short-term Afternoon Price Volatility

Table 5.5 reports the results of a regression relating the morning profits of locals at the SFE to short-term afternoon price volatility. The regression has the basic form,

$$\Delta_{i,t}^A - \bar{\Delta}_{i,t}^A = \alpha + \beta_{\pi} \pi_{i,t}^M + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi I} \pi_{i,t}^M |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 3646 trader-days. Price-setting trades are identified as trades by locals that result in a shift in the SPI by at least three units from the previous price.

Dependent Variable	α	β_{π}	β_I	$\beta_{\pi I}$	β_R
Panel A:	Total Dollar Risk				
Price Volatility	-0.0275	0.1799	0.0011	0.0415	1.0553
<i>t</i> -statistics	(-0.54)	(3.28 ^{***})	(0.02)	(1.80)	(19.85 ^{***})
<i>p</i> -values	0.5869	0.0011	0.9839	0.0727	<.0001
$R^2 = 0.1154$	F-stat = 119.93 ^{***}				
Panel B:	Trade Size				
Price Volatility	-0.0337	0.2209	0.0180	0.0353	0.9089
<i>t</i> -statistics	(-0.66)	(3.97 ^{***})	(0.33)	(1.51)	(16.69 ^{**})
<i>p</i> -values	0.5123	<.0001	0.7413	0.1315	<.0001
$R^2 = 0.0894$	F-stat = 90.44 ^{***}				
Panel C:	Number of Trades				
Price Volatility	-0.0260	0.1695	0.1208	0.0474	0.9247
<i>t</i> -statistics	(-0.51)	(3.05 ^{***})	(2.30 ^{**})	(2.03 ^{**})	(17.60 ^{***})
<i>p</i> -values	0.6118	0.0023	0.0213	0.0426	<.0001
$R^2 = 0.0966$	F-stat = 98.39 ^{***}				

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

Table 5.6 reports regression results of model 5.1, however for price-setting trades that were responsible for shifting the SPI by at least one unit from the price recorded two trades earlier.

Table 5.6: Morning Profits and Short-term Afternoon Price Volatility

Table 5.6 reports the results of a regression relating the morning profits of locals at the SFE to short-term afternoon price volatility. The regression has the basic form,

$$\Delta_{i,t}^A - \bar{\Delta}_{i,t}^A = \alpha + \beta_{\pi} \pi_{i,t}^M + \beta_I |\text{INV}_{i,t}^M| + \beta_{\pi I} \pi_{i,t}^M |\text{INV}_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 3646 trader-days. Price-setting trades are identified as trades by locals that result in a shift in the SPI by at least one unit from the price recorded two trades earlier.

Dependent Variable	α	β_{π}	β_I	$\beta_{\pi I}$	β_R
Panel A:		Total Dollar Risk			
Price Volatility	-0.1008	0.6672	0.1730	-0.0242	2.9171
<i>t</i> -statistics	(-0.72)	(4.37)***	(1.17)	(-0.38)	(19.73)***
<i>p</i> -values	0.4741	<.0001	0.2425	0.7062	<.0001
$R^2 = 0.1183$	F-stat = 123.22***				
Panel B:		Trade Size			
Price Volatility	-0.1130	0.7478	0.0813	-0.0329	2.9113
<i>t</i> -statistics	(-0.80)	(4.90)***	(0.54)	(-0.51)	(19.48)***
<i>p</i> -values	0.4231	<.0001	0.5875	0.6090	<.0001
$R^2 = 0.1161$	F-stat = 120.69***				
Panel C:		Number of Trades			
Price Volatility	-0.0853	0.5633	0.3769	0.0106	3.1077
<i>t</i> -statistics	(-0.61)	(3.72)***	(2.64)**	(0.17)	(21.71)***
<i>p</i> -values	0.5406	0.0002	0.0084	0.8679	<.0001
$R^2 = 0.1358$	F-stat = 144.24***				

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

The results provide strong evidence which suggests that morning profitability affects short-term afternoon price volatility even after controlling for bid-ask bounce. Specifically, the results show that between 56.33% (Panel C) and 74.78% (Panel B) of local traders place above average price-setting trades in the afternoon following a one standard-deviation increase in morning profits.

This finding confirms the results presented in the tables above. Moreover, they eliminate the possibility of earlier results being driven by bid-ask bounce, which also adds robustness. Specifically, local traders who record profitable mornings are more willing to purchase (sell) inventory in the afternoon at higher (lower) prices than traders recording morning losses. Since the added risk-taking in the afternoon is partly attributable to the profits earned during the morning trading session, this also acts as support for the house money effect.

The slope coefficient of the morning profit variable in Table 5.6 is significant at the 1% level for each of the three risk measures reported in Panel A, Panel B and Panel C, respectively. Each morning risk variable is highly significant at the 1% level also. This implies that if an average local trader takes more than average risk in the morning they tend to place more than average price-setting trades in the afternoon.

Table 5.7 reports the regression results of model 5.2. Consistent with the findings reported in the tables above, the results show that local traders increase their probability of placing above average price-setting trades in the afternoon following profitable morning trading sessions. Specifically, for total dollar risk (Panel A) their probability increases from 0.3257 to 0.4059. This represents an increase in likelihood of approximately 24.6%. Similarly, for trade size (Panel B) their probability increases from 0.3242 to 0.4036. This represents an increase in likelihood of 24.5%. Finally, for number of trades (Panel C) their increase in probability ranges from 0.3214 to 0.4042, representing an increase in likelihood of 25.8%.

Table 5.7: Binary Results Relating Morning Profits to Short-term Afternoon Price Volatility

Table 5.7 reports the results of a logistic regression relating morning profits to short-term afternoon price volatility by local traders at the SFE. Both morning profits and short-term afternoon price volatility are measured in binary form. The regression has the basic form,

$$\text{Prob}(\Delta_{i,t}^A - \bar{\Delta}_{i,t}^A > 0) = \frac{\exp X'\beta}{1 + \exp X'\beta}$$

where:

$$X'\beta = \alpha + \beta_{\pi} I(\pi_{i,t}^M > 0) + \beta_I |INV_{i,t}^M| + \beta_{\pi I} \pi_{i,t}^M |INV_{i,t}^M| + \beta_R \text{Risk}_{i,t}^M$$

There are three different measures of risk used for this regression (i) total dollar risk, (ii) number of trades and (iii) average trade size reported in Panel A, Panel B and Panel C respectively. The sample contains 3646 trader-days. Price-setting trades are identified as trades by locals that result in a shift in the SPI by at least one unit from the previous price.

Dependent Variable	α	β_{π}	β_I	$\beta_{\pi I}$	β_R
Panel A:	Total Dollar Risk				
Price Volatility	-0.7257	0.2381	0.0594	0.1051	0.5710
<i>p</i> -values	<.0001	0.0014	0.2880	0.1558	<.0001
$R^2 = 0.1057$					
Panel B:	Trade Size				
Price Volatility	-0.7409	0.2528	0.0473	0.1014	0.5584
<i>p</i> -values	<.0001	0.0007	0.3928	0.1683	<.0001
$R^2 = 0.1043$					
Panel C:	Number of Trades				
Price Volatility	-0.7182	0.1959	0.0896	0.1163	0.6105
<i>p</i> -values	<.0001	0.0094	0.0978	0.1097	<.0001
$R^2 = 0.1250$					

Table 5.8 reports summary statistics for the various price patterns leading up to and including the price-setting trade (Panel A). Also included are the frequencies of price reversals and price continuations in the five-minute period following price-setting trades (Panel B).

Table 5.8: Frequency of Price Patterns, Price Reversals and Price Continuations

Table 5.8 shows the frequency of price patterns reported in Panel A and the frequency of price reversals and price continuations reported in Panel B. Price-setting trades are identified as trades by locals that result in a shift in the SPI by at least one unit from the previous price. The sample contains 25598 price setting trades.

Panel A: Frequency of Price Patterns Preceding Price-Setting Trades

Code	Price Pattern	Frequency	Percent	Cumulative Percent
1	RR	6177	24.13	24.13
2	RC	2472	9.66	33.79
3	CC	352	1.38	35.16
4	CR	2436	9.52	44.68
5	NI	11915	46.55	91.23
6	OC	2246	8.77	100.00

Panel B: Frequency of Price Reversals and Price Continuations Following Price-Setting Trades

	Frequency	Percent	Cumulative Percent
Price Reversals	13295	51.94	54.41
Price Continuations	8157	31.87	88.51
No Reversal or Continuation	4146	16.20	100.00

The sample contains 25598 price-setting trades. Surprisingly, no identifiable price pattern (NI) is the most common of the six possibilities (46% of all price-setting trades), followed by RR (24%), RC and CR (10%), OC (9%) and CC (1%). Coval and Shumway (2005) did not include the (NI) price pattern in their analysis and since it is the most common, questions arise such as: Did they not experience this price behaviour leading up to a price-setting trade in their data sample? Would their results be the same if this price pattern did occur but wasn't accounted for? Either way it justifies the significance of recording the results herein. Additionally, Panel B shows that the most common price adjustment in the five-minute period following a price-setting trade, is a reversal (52%), followed by a continuation (32%) and no movement in price (16%).

Table 5.9 reports the overall results of the analysis of morning profit and longer-term afternoon price volatility for each of the six price patterns {NI, RR, RC, CR, OC and CC}. Price-setting trades are categorised according to whether the trade is long or short and divided further according to the morning profitability of local traders.

The results show that the overall averages are statistically different from zero. The negative coefficients indicate that prices on average revert back to earlier levels. The averages are economically feasible since the bid-ask spread at the Sydney Futures Exchange is generally one unit for the SPI futures contract. Therefore, asymmetrically when large purchases push the price up by one unit or large sales push the price down by one unit the price will revert by approximately 0.4 on average. The findings also show that for price-setting trades that have a continuation pattern {RC, CC, or OC} the reversals are approximately equal to one unit. This indicates that prices revert much stronger in the five-minute period following price-setting trades that result in a continuation.

Looking at the results for long trades (purchases), there is no evidence of a difference in afternoon price permanence between locals that traded with morning gains and those that traded with morning losses. That is, irrespective of a local trader's morning profitability, the price of the SPI reverts on average in the five-minute period following price-setting trades. Although the differences extend from -0.111 to 0.653 with an average of -0.019 none of the differences are statistically significant.

The results for short trades (sales) are similar to those reported above for long trades (purchases). Generally, there is no evidence of a difference in afternoon price permanence between locals that traded with morning gains and those that trade with morning losses. The price reversal differences range from -0.294 to 0.346 with an average difference of -0.015, however, none are highly significant.

These finding suggests that morning profits do not affect longer-term afternoon price permanence for price-setting trades that are either long or short.

Table 5.9: Morning Profits and Overall Afternoon Price Permanence

Table 5.9 reports the results of the analysis of morning profits and longer-term afternoon price volatility. Price-setting trades are identified as trades by locals that result in a shift in the SPI by at least one unit from the previous price. Price setting trades are coded according to the price pattern leading up to the trade. There are 6 price patterns in total. Reversal, Reversal (RR), Reversal, Continuation (RC), Continuation, Continuation (CC), Continuation, Reversal (CR), No identifiable price pattern (NI) and One Continuation (OC). Price setting trade are then divided further within each category depending on the whether the price-setting trade is long or short and also to account for morning profitability. The sample contains 3646 trader-days from which there are 25598 price-setting trades placed by locals.

Price Pattern	Overall Five-minute Price Movements					
		Long			Short	
	Gain	Loss	Diff.	Gain	Loss	Diff.
RR	-0.288	-0.253	-0.035	-0.303	-0.382	0.079
T-stat	(-4.78)	(-3.14)	(-0.35)	(-5.94)	(-5.62)	(0.93)
RC	-1.084	-0.973	-0.111	-1.011	-0.717	-0.294
T-stat	(-10.55)	(-7.18)	(-0.65)	(-10.56)	(-5.34)	(-1.78)
CC	-1.273	-1.926	0.653	-1.109	-1.455	0.346
T-stat	(-3.96)	(-4.24)	(1.17)	(-4.17)	(-4.55)	(0.83)
CR	-0.016	0.014	-0.03	0.079	0.037	0.042
T-stat	(-0.18)	(0.13)	(-0.21)	(0.93)	(0.34)	(0.31)
NI	-0.376	-0.395	0.019	-0.407	-0.381	-0.026
T-stat	(-8.54)	(-6.65)	(0.27)	(-10.15)	(-7.02)	(-0.37)
OC	-0.781	-0.675	-0.106	-0.891	-0.960	0.069
T-stat	(-7.38)	(-4.64)	(-0.59)	(-9.32)	(-6.07)	(0.37)
Average	-0.428	-0.409	-0.019	-0.458	-0.443	-0.015
T-stat	(-14.11)	(-10.16)	(-0.39)	(-16.71)	(-11.77)	(-0.32)

Table 5.10 reports the results of the analysis of morning profits and longer-term afternoon price volatility for each of the six price patterns {NI, RR, RC, CR, OC and CC} also, but for reversals only. The movement, in percent, triggered by a price-setting trade that is reversed over the following five-minutes is termed a price reversal.

Price reversals are categorised according to trade direction, long (purchases) or short (sales) and further partitioned on the basis of morning profitability.

Table 5.10: Morning Profits and Afternoon Price Permanence: Reversals

Table 5.10 reports the results of the analysis of morning profits and longer-term afternoon price volatility for reversals only. Price-setting trades are identified as trades by locals that result in a shift in the SPI by at least one unit from the previous price. Price reversals are measured as the average percentage of the price-setting trade's movement that is reversed in the 5-minutes following the price-setting trade. Price setting trades are coded according to the price pattern leading up to the trade. There are 6 price patterns in total. Reversal, Reversal (RR), Reversal, Continuation (RC), Continuation, Continuation (CC), Continuation, Reversal (CR), No identifiable price pattern (NI) and One Continuation (OC). Price setting trades are then divided into separate categories for long or short trades and also for morning profitability. The sample contains 3646 trader-days from which there are 25598 price-setting trades placed by locals.

Price Pattern	Price Reversals					
	Gain	Long Loss	Diff.	Gain	Short Loss	Diff.
RR	-2.087	-1.979	-0.107	-1.892	-1.918	0.026
T-stat	(-31.47)	(-26.37)	(-1.07)	(-36.59)	(-29.22)	(0.31)
RC	-2.648	-2.584	-0.064	-2.623	-2.429	-0.194
T-stat	(-24.35)	(-20.41)	(-0.39)	(-25.21)	(-18.88)	(-1.17)
CC	-2.889	-3.018	0.129	-2.355	-2.649	0.293
T-stat	(-9.59)	(-6.99)	(0.25)	(-10.98)	(-7.71)	(0.72)
CR	-1.474	-1.550	0.076	-1.396	-1.534	0.138
T-stat	(-21.20)	(-16.96)	(0.66)	(-19.67)	(-11.84)	(0.94)
NI	-2.246	-2.271	0.025	-2.123	-2.154	0.031
T-stat	(-48.05)	(-38.16)	(0.33)	(-53.80)	(-38.02)	(0.45)
OC	-2.450	-2.560	0.109	-2.482	-2.669	0.187
T-stat	(-25.34)	(-17.14)	(0.61)	(-23.22)	(-15.84)	(0.93)
Average	-2.209	-2.197	-0.012	-2.107	-2.140	0.033
T-stat	(-69.88)	(-55.65)	(-0.23)	(-74.96)	(-54.04)	(0.67)

Overall, price reversal averages are significantly different from zero. Surprisingly, however, the results show that the average price reversal is about two units. From an

economic viewpoint this is not feasible since the bid-ask spread on the Sydney Futures Exchange is generally one unit for the SPI. Therefore, sometimes, when large purchase orders hit the market and force the price up by at least one unit, or alternatively, large sell orders flood the market and force the price down by at least one unit, the price reverts by an average of two units in the following five-minute period. Furthermore, the results indicate that prices revert much stronger following a continuation price pattern {RC, CC, or OC}, ranging from -2.355 to as high as -3.018, which is also considerably higher than the overall average price reversion.

Examining the results for long trades (purchases), there is no evidence of a difference in afternoon price reversion between locals that traded with morning gains and those that traded with morning losses. Specifically, the differences in price reversion extend from -0.107 to 0.129 with an average of -0.012. However, none of the differences are statistically significant.

Observing the results for short trades (sales), they are similar to the findings reported above for long trades (purchases). There is no evidence of a difference in afternoon price reversion between locals that traded with morning gains and those that traded with morning losses. In particular, the range of price reversion differences extend from -0.194 to 0.293 with an average of 0.033.

Table 5.11 reports the results of the analysis of morning profits and longer-term afternoon price volatility for each of the six price patterns {NI, RR, RC, CR, OC and CC} also, but for continuations only. The movement, in percent, triggered by a price-setting trade that is continued over the following five-minutes is termed a price continuation. Price continuations are categorised by trade direction, long (purchases) or short (sales) and further partitioned on the basis of morning profitability.

Table 5.11: Morning Profits and Afternoon Price Permanence: Continuations

Table 5.11 reports the results of the analysis of morning profits and longer-term afternoon price continuations. Price-setting trades are identified as trades by locals that result in a shift in the SPI by at least one unit from the previous price. Price continuations are measured as the average percentage of the price-setting trade's movement that is continued in the 5-minutes following the price setting trade. Price setting trades are coded according to the price pattern leading up to the trade. There are 6 price patterns in total. Reversal, Reversal (RR), Reversal, Continuation (RC), Continuation, Continuation (CC), Continuation, Reversal (CR), No identifiable price pattern (NI) and One Continuation (OC). Price setting trade are then divided to account for a long or short trade and also morning profitability. The sample contains 3646 trader-days from which there are 25598 price-setting trades placed by locals.

Price Pattern	Price Continuations					
	Gain	Long Loss	Diff.	Gain	Short Loss	Diff.
RR	2.196	2.188	0.008	1.995	1.987	0.008
T-stat	(28.30)	(20.42)	(0.06)	(28.72)	(23.43)	(0.07)
RC	2.039	2.316	-0.278	2.008	2.476	-0.468
T-stat	(15.82)	(12.94)	(-1.26)	(17.01)	(11.67)	(-1.93)
CC	2.728	2.625	0.103	2.949	1.778	1.171
T-stat	(5.11)	(1.76)	(0.07)	(2.92)	(4.34)	(1.08)
CR	2.036	2.103	-0.067	2.120	1.881	0.239
T-stat	(10.47)	(12.46)	(-0.26)	(15.18)	(12.44)	(1.16)
NI	2.262	2.206	0.056	2.148	2.089	0.060
T-stat	(43.06)	(32.17)	(0.65)	(41.67)	(34.39)	(0.75)
OC	2.240	2.304	-0.064	1.978	2.283	-0.306
T-stat	(15.41)	(14.90)	(-0.30)	(18.96)	(11.13)	(-1.33)
Average	2.209	2.205	0.004	2.088	2.089	-0.001
T-stat	(53.98)	(43.86)	(0.06)	(57.00)	(45.06)	(-0.02)

Overall, price continuation averages are significantly different from zero. The results show that the average price continuation is about two units, which is of a similar magnitude to results presented for price reversals. Once again, from an economic viewpoint this is not feasible since the bid-ask spread on the Sydney Futures Exchange is generally one unit for the SPI.

Therefore, sometimes, when large purchase orders hit the market and force the price up by one unit, or alternatively, large sell orders flood the market and force the price down by one unit, the price continues by an average of two units in the five-minute period following. The results also indicate that prices continue the strongest following a continuation, continuation price pattern {CC}, ranging from 1.778 to as high as 2.949.

Looking at the results for long trades (purchases), there is no evidence of a difference in afternoon price continuation between locals that traded with morning gains and those that traded with morning losses. Specifically, the differences in average price continuations extend from -0.278 to 0.103 with an average of 0.004. However, none of the differences are statistically significant.

Similarly, the results reported for short trades (sales), show insufficient evidence of morning profitability influencing afternoon price permanence. That is, afternoon price continuations are the same irrespective of the gains or losses earned by local traders during the morning trading session.

Table 5.12 reports the regression results of model 5.3 with i) no interaction variables linking morning profits and two price changes leading up to the price-setting trade and ii) interaction variables linking both morning profit and the two price changes leading up to the price-setting trade. The results of (i) show that price-setting trades as well as the two price changes preceding the price-setting trade are statistically significant in estimating the price of the SPI five minutes into the future⁷⁵.

Since the bid-ask spread at the Sydney Futures Exchange is typically one unit for the SPI futures contract, a value of -0.6239 is economically feasible⁷⁶. The negative coefficient indicates that prices are mean reverting. For instance if a large buy order enters the market and pushes the price up by a unit or alternatively, a large sell order

⁷⁵ Although the results are not reported in this chapter, the analysis was repeated several times, with each independent trial including an additional price change into the model. Up to ten price changes prior to the price-setting trade return negative coefficients that are all statistically significant.

⁷⁶ Refer to Duffy, Frino and Stevenson (1998) and also appendix 1.

hits the market and as a result the price falls by a unit, prices will revert by 0.6239 on average.

Table 5.12: Morning Profits and Afternoon Price Permanence

Table 5.12 reports the results of a regression relating the morning profits of locals at the SFE to longer-term afternoon price volatility. The regression has the basic form,

$$P_{t+5} - P_t = \alpha + \beta_{P1}\Delta P_1 + \beta_{P2}\Delta P_2 + \beta_{P3}\Delta P_3 + \beta_{IP1}I(\pi_{i,t}^M > 0)\Delta)_1 + \beta_{IP2}I(\pi_{i,t}^M > 0)\Delta)_2 + \beta_{IP3}I(\pi_{i,t}^M > 0)\Delta)_3$$

The sample contains 3646 trader-days. Price-setting trades are identified as trades by locals that result in a shift in the SPI by at least one unit from the previous price.

Independent Variables	Dependent Variable	
	$P_{t+5} - P$	$P_{t+5} - P$
α	-0.0110	-0.0117
T-stat	(-0.50)	(-0.53)
β_{P1}	-0.6239	-0.6534
T-stat	(-70.80)***	(-41.81)***
β_{P2}	-0.3815	-0.3765
T-stat	(-34.81)***	(-19.32)***
β_{P3}	-0.1872	-0.1813
T-stat	(-18.83)***	(-10.65)***
$I\beta_{P1}$		0.0429
T-stat		(2.26)**
$I\beta_{P2}$		-0.0066
T-stat		(-0.28)
$I\beta_{P3}$		-0.0080
T-stat		(-0.38)
R-square	0.1658	0.1660
F-stat	1696.55***	849.98***

* significant at 0.10 level.

** significant at 0.05 level.

*** significant at 0.01 level.

The results of (ii) show there is no evidence that suggests morning profitability affects afternoon price permanence. That is, prices revert on average by the same amount irrespective of a local trader's morning profit or loss. Table 5.12 confirms the findings from the tables above.

As a possible explanation of the results, price-setting trades placed by locals might occur during periods of rapid expansion or contraction in the market. Since local traders generally want to trade large amounts of inventory on small price movements (bid-ask bounce) they will buy when the market is moving up and sell when it is moving down. Therefore, trades that are deemed to be responsible for shifting the SPI futures contract could potentially be mistaken as being of a price-setting nature when in actual fact it is other extraneous variables influencing market movements.

5.5 Summary

In their summary, Barberis and Thaler (2003) deem behavioural finance theory to be much nearer the start than the finish despite the abundance of literature that has surfaced, especially over the last decade. Much of the research, however, is experimental and there is a plea for more empirical studies to expand current models so they have the capacity to include more than just one of the elements of behavioural finance, namely limits to arbitrage or psychology.

There is little published work examining the effect of behavioural biases on asset prices. In a recent paper, Coval and Shumway (2005) test this hypothesis directly amongst proprietary traders at the Chicago Board of Trade. Their results suggest that traders' psychological inconsistencies affect short-term afternoon price volatility but have no impact on longer-term price volatility.

Specifically, traders with morning losses purchase contracts at higher prices and sell contracts at lower prices in the afternoon. This behaviour impacts upon short-term volatility. However, more informed traders are aware of this behaviour and realise that it's generated by a 'want' to win back previous losses. For this reason, they have no hesitation in trading rigorously against them. This more than offsets the short-term

afternoon price volatility and disseminates any long-term price permanence resulting from traders exhibiting loss aversion.

This chapter contributes to the literature by examining the affect of behavioural biases, of local traders at the Sydney Futures Exchange, on prices. Further tests are performed to determine whether the irrational behaviour of local traders creates profitable opportunities for other market participants.

The results provide extensive evidence of local traders' behavioural biases affecting short-term afternoon price volatility. Specifically, the results suggest that local traders are more than willing to purchase contracts at higher prices and sell contracts at lower prices in the afternoon after incurring profits in the morning. The results are robust for price-setting trades that are responsible for shifting the SPI futures contract by one, two and three units, respectively and after controlling for bid-ask bounce.

There is insufficient evidence, however, of morning profits affecting longer-term afternoon price volatility. Overall prices revert by approximately 0.4 units on average irrespective of whether a trader records a gain or a loss in the morning. When examined independently, a similar result holds for both price reversals and price continuations, although the magnitude of the price change is approximately two units. The results also document that trade directions, long or short, do not influence the results.

Unlike Coval and Shumway (2005) this research provides additional support for the house money effect. It contributes to the literature by showing that morning profits can, in much the same way as morning losses, influence short-term afternoon price volatility.

Chapter 6 : Conclusion

In three separate sections, this thesis presents strong evidence of a behavioural bias amongst local traders at the Sydney Futures Exchange that is consistent with the house money effect.

“The House Money Effect and Local Traders at the Sydney Futures Exchange”, finds that locals are more willing to increase their risk-taking behaviour in afternoon trading sessions following profitable mornings. The fact that the house money effect is more pronounced than loss aversion is contradictory to the work of Coval and Shumway (2005) and Locke and Mann (2004; 2005). Each study reports strong evidence of loss aversion amongst professional traders at the Chicago Board of Trade and the Chicago Mercantile Exchange, respectively.

One of the main reasons the results of this research might differ is that gains and losses are treated as separate and distinct psychological drivers of performance as opposed to one overall profit variable. If profit is not bisected in this way, its influence on subsequent risk-taking may be self-cancelling. Whether this behaviour is costly to local traders is less clear. The findings suggest there is a turning point up to which the overconfidence created by morning profits assists locals in trading profitably in the afternoon. Surprisingly, traders most influenced by morning profits, take the largest risk in the afternoon but typically incur losses. This result supports the findings of Odean (1998b; 1999) who reports that excessive trading is correlated with overconfidence but the costs associated with this bias reduces trading profits. In contrast, Locke and Mann (2005) find no costs associated with their traders’ behavioural bias.

“Trading Horizons and Behavioural Biases: Does Time Matter?”, reports that locals exhibit the strongest trading irrationality when they evaluate their performance over high frequency time intervals. Specifically, locals are more inclined to increase their risk-taking behaviour in a cycle, if in the previous cycle a profit was recorded. Surprisingly, the results show that locals rely more on profit per trade and inventory

per trader as measures of performance within a trading cycle, than profit alone. Further evidence suggests that profit earned in the afternoon does not influence risk-taking behaviour in the subsequent morning. It's difficult to directly compare these results with those from the existing literature, given that the unique trading horizons introduced in this paper have not been analysed in previous work. Other findings suggest that profit earned today bears no impact on the risk-taking behaviour of locals over the subsequent trading day. Coval and Shumway (2005) report a similar finding amongst proprietary traders at the Chicago Board of Trade. In contrast, Locke and Mann (2004) report strong evidence of loss aversion amongst traders at the Chicago Mercantile Exchange. Specifically, profits earned over the past k days, where $k = 1, 2, 3, 4$ or 5 weigh negatively on the risk-taking behaviour of floor traders today. One possible explanation of the differences in the results is that each study is conducted on a different exchange and where professional traders trade different futures contracts. Locke and Mann (2004) analyse floor traders trading agricultural futures contracts at the Chicago Mercantile Exchange, whereas Coval and Shumway (2005) describe the behaviour of proprietary traders trading Treasury bill futures contracts at the Chicago Board of Trade. This paper focuses on the behaviour of locals trading the Share Price Index at the Sydney Futures Exchange.

“Professional Futures Traders, Profits and Prices”, finds that locals with morning profits place more price-setting trades in the afternoon than those with morning losses. Consistent with the house money effect, the ‘bravado’ or confidence attributable to trading profitably in the morning seems to encourage traders to buy contracts at higher prices and sell contracts at lower prices in the afternoon. This behaviour is highly correlated with afternoon price moves of one, two and three units in the futures contract, respectively. There is insufficient evidence to suggest that longer-term price permanence is sustained. Overall, prices revert by 0.4 units in the five-minute period following the price-setting trade. This result does not change when price reversals and price continuations are evaluated independently, although the size of the reversion is much larger at approximately two units. Neither trade direction, long or short, nor morning profitability, impact upon the results. These findings are consistent with Coval and Shumway (2005) who report that loss-averse behaviour amongst professional traders at the Chicago Board of Trade can be used to explain

short-term afternoon price volatility but has no impact on longer-term price permanence.

Overall, this thesis provides strong evidence which suggests that local traders at the Sydney Futures Exchange behave in a manner that is inconsistent with the rational expectations framework of traditional finance theory. Instead, local traders are psychologically affected by money they make through their individual trading regimes, which subsequently influences their risk-taking attitudes and impacts upon short-term prices. The results show that local traders become risk-seeking in afternoon trading sessions following profitable mornings, which acts as support for the emerging behaviour finance theory. This behaviour is consistent with the house money effect, an idea that was initially proposed by Thaler and Johnson (1990) that describes the propensity of individuals to become somewhat risk-seeking immediately following some form of windfall gain.

This research aims to narrow the gap between experimental psychology and behavioural modelling by using real-world trading data to increase our knowledge of the trading behaviour of locals at the Sydney Futures Exchange. It belongs to a larger part of literature and provides additional potential implications for further research to explore. For example, the research methodology in this thesis relies upon a static approach to model the effect of profits on risk-taking. A more accurate and insightful method would be to develop a dynamic model whereby, risk and profit are modelled as they change throughout each trading day. Furthermore, during the sample period in this thesis, the Sydney Futures Exchange was floor traded and also closed for lunch between 12:30p.m. and 2:00p.m. It is now a fully automated exchange without lunchtime closure. The question of whether the structure of the financial market setting impacts upon the trading behaviour of professional traders is yet to be explored?

This work has a more general application for future research also. For example, this thesis provides extensive evidence of the house money effect, which is contradictory to existing work (Coval and Shumway, 2005; Frinio et al., 2004; Locke and Mann, 2004; 2005). Future work could apply the same research methodology to other international futures markets such as the London International Financial Futures

Exchange (LIFFE) or the Swiss-German European Derivatives Exchange (EUREX) to determine how professional traders behave in a European market setting. Additionally, future work could also aim to test whether institutions, such as banks and fund managers, as well as stockbrokers behave rationally in the context of the investment decisions and respective trading horizons. Another potential area for further research is in stock markets and options markets. For example, do market participants, in either of these market settings, exhibit psychological biases in their trading behaviour and if so, do they affect prices?

Reiterating, for behavioural finance theory to develop further and gain the recognition it deserves from advocates of traditional finance theory, more empirical research using real-world trading data to examine the behaviour of investors in the context a real financial market setting is needed.

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Appendix 1: Frequency of One-Minute Absolute Price Changes in SPI Futures Contract

The following table reports a summary of the frequency, percent, cumulative frequency and cumulative percent of the range of one-minute absolute price changes in the SPI futures contract (measured in ticks, which represent an absolute change in the value of the Share Price Index) over the sample period 24th July, 1997 to 4th October, 1999. Ticks 0-8 represent an absolute change in the SPI of 0-8 respectively, while Tick 9 incorporates all absolute changes in the SPI greater than 8.

Ticks	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	118869	53.34	118869	53.34
1	58094	26.07	176963	79.41
2	21472	9.64	198435	89.04
3	9787	4.39	208222	93.44
4	5222	2.34	213444	95.78
5	3005	1.35	216449	97.13
6	1802	0.81	218251	97.94
7	1165	0.52	219416	98.46
8	865	0.39	220281	98.85
9	2569	1.15	222850	100.00

Appendix 2: Logistic Regression Calculations

Total Dollar Risk:

If a trader makes a morning profit;

$$\begin{aligned} X'\beta &= \alpha + \beta_{\pi} I(\pi_{i,t}^M > 0) + \beta_I |INV_{i,t}^M| + \beta_{\pi I} I(\pi_{i,t}^M > 0) |INV_{i,t}^M| + \beta_R Risk_{i,t}^M \\ &= -0.8659 + (0.1845)(1) + (0.1138)(-0.044) + (0.0897)(-0.044) + (0.6630)(0.007) \\ &= -0.6857 \end{aligned}$$

$$\begin{aligned} \therefore \text{Prob}(I[Risk_{i,t}^A] > 0) &= \frac{e^{-0.6857}}{1 + e^{-0.6857}} \\ &= 0.335 \end{aligned}$$

If a trader makes a morning loss;

$$\begin{aligned} X'\beta &= \alpha + \beta_{\pi} I(\pi_{i,t}^M > 0) + \beta_I |INV_{i,t}^M| + \beta_{\pi I} I(\pi_{i,t}^M > 0) |INV_{i,t}^M| + \beta_R Risk_{i,t}^M \\ &= -0.8659 + (0.1845)(0) + (0.1138)(0.072) + (0) + (0.6630)(-0.011) \\ &= -0.8649994 \end{aligned}$$

$$\begin{aligned} \therefore \text{Prob}(I[Risk_{i,t}^A] > 0) &= \frac{e^{-0.8649994}}{1 + e^{-0.8649994}} \\ &= 0.296 \end{aligned}$$

This represents an increase in $\text{Prob}(I[Risk_{i,t}^A] > 0)$ of $\frac{0.335 - 0.296}{0.296} = 13.18\%$

To calculate the likelihood of traders taking above average afternoon risk, the slope coefficients from Table 3.3 were used in conjunction with the averages in Table 3.1.

Trade Size:

If a trader makes a morning profit;

$$\begin{aligned} X'\beta &= \alpha + \beta_{\pi} I(\pi_{i,t}^M > 0) + \beta_I |INV_{i,t}^M| + \beta_{\pi I} I(\pi_{i,t}^M > 0) |INV_{i,t}^M| + \beta_R Risk_{i,t}^M \\ &= -0.6990 + (0.1382)(1) + (0.0759)(-0.044) + (0.1007)(-0.044) + (0.6405)(-0.003) \\ &= -0.5705 \end{aligned}$$

$$\begin{aligned} \therefore \text{Prob}(I[Risk_{i,t}^A] > 0) &= \frac{e^{-0.5705}}{1 + e^{-0.5705}} \\ &= 0.3611 \end{aligned}$$

If a trader makes a morning loss;

$$\begin{aligned} X'\beta &= \alpha + \beta_{\pi} I(\pi_{i,t}^M > 0) + \beta_I |INV_{i,t}^M| + \beta_{\pi I} I(\pi_{i,t}^M > 0) |INV_{i,t}^M| + \beta_R Risk_{i,t}^M \\ &= -0.6990 + (0.1382)(0) + (0.0759)(0.072) + (0) + (0.6405)(0.005) \\ &= -0.6903 \end{aligned}$$

$$\begin{aligned} \therefore \text{Prob}(I[Risk_{i,t}^A] > 0) &= \frac{e^{-0.6903}}{1 + e^{-0.6903}} \\ &= 0.334 \end{aligned}$$

This represents an increase in $\text{Prob}(I[Risk_{i,t}^A] > 0)$ of $\frac{0.3611 - 0.334}{0.334} = 8.11\%$

Number of Trades:

If a trader makes a morning profit;

$$\begin{aligned} X'\beta &= \alpha + \beta_{\pi} I(\pi_{i,t}^M > 0) + \beta_I |INV_{i,t}^M| + \beta_{\pi I} I(\pi_{i,t}^M > 0) |INV_{i,t}^M| + \beta_R Risk_{i,t}^M \\ &= -0.7211 + (0.2926)(1) + (0.0758)(-0.044) + (0.1563)(-0.044) + (0.6259)(0.036) \\ &= -0.4162 \end{aligned}$$

$$\begin{aligned} \therefore \text{Prob}(I[Risk_{i,t}^A] > 0) &= \frac{e^{-0.4162}}{1 + e^{-0.4162}} \\ &= 0.3974 \end{aligned}$$

If a trader makes a morning loss;

$$\begin{aligned} X'\beta &= \alpha + \beta_{\pi} I(\pi_{i,t}^M > 0) + \beta_I |INV_{i,t}^M| + \beta_{\pi I} I(\pi_{i,t}^M > 0) |INV_{i,t}^M| + \beta_R Risk_{i,t}^M \\ &= -0.7211 + (0.2926)(0) + (0.0758)(0.072) + (0) + (0.6259)(-0.058) \\ &= -0.7519 \end{aligned}$$

$$\begin{aligned} \therefore \text{Prob}(I[Risk_{i,t}^A] > 0) &= \frac{e^{-0.7519}}{1 + e^{-0.7519}} \\ &= 0.3204 \end{aligned}$$

This represents an increase in $\text{Prob}(I[Risk_{i,t}^A] > 0)$ of $\frac{0.3974 - 0.3204}{0.3204} = 24.03\%$

Appendix 3: SAS Programs

```
libname sasdb 'c:\Documents and Settings\jgrant\My Documents\SAS Output Data  
Sets';
```

```
data sasdb.phd;  
    infile 'c:\Documents and Settings\jgrant\My Documents\PhD Data\On Market  
        Trades\1997SPITRADES.txt' dlm = ',';  
    input date time time. contract $ price vol b_id s_id;  
    date = date;  
run;
```

```
data sasdb.phd2;  
    infile 'c:\Documents and Settings\jgrant\My Documents\PhD Data\On Market  
        Trades\1998SPITRADES.txt' dlm = ',';  
    input date time time. contract $ price vol b_id s_id;  
run;
```

```
data sasdb.phd3;  
    infile 'c:\Documents and Settings\jgrant\My Documents\PhD Data\On Market  
        Trades\1999SPITRADES.txt' dlm = ',';  
    input date time time. contract $ price vol b_id s_id;  
run;
```

```
data sasdb.phd4;  
    set sasdb.phd sasdb.phd2 sasdb.phd3;  
run;
```

```
data sasdb.analyse;  
    set sasdb.phd4;  
  
    if b_id = 0 and s_id = 0 then  
        delete;  
    if b_id > 224 and s_id > 224 then  
        delete;  
    if b_id < 225 and s_id < 225 then  
        delete;  
    if b_id < 0 or s_id < 0 then  
        delete;  
  
    if b_id > 0 and b_id < 225 then  
        id = b_id;  
    else  
        id = -(s_id);  
  
    a_id = abs(id);
```



```

    if id < 0 then
        vol = -(vol);
    amt = vol * price;

    if date = 19971224 or date = 19971231 or date = 19980409 or date = 9981224
    or date = 19981231 or date = 19990401 or date >= 19991004 then
        delete;
run;

proc sort data = sasdb.analyse;
    by a_id date time;
run;

proc summary data = sasdb.analyse nway;
    class a_id;
    output out = sasdb.trader_counts1 (drop = _type_ rename = (_freq_ = count));
run;

data sasdb.profit_method1;
    set sasdb.analyse;
    retain neg 0 group 0;

    if (neg = 1) and (vol > 0) then
    do;
        neg = 0;
        group + 1;
    end;

    else if (neg = 0) and (vol < 0) then
    do;
        neg = 1;
        group + 1;
    end;
run;

data sasdb.raw;
    set sasdb.profit_method1;
    by a_id date;

    vol2 = abs(vol);
    n = 1;

    if time <= 46800 then
        time_var = 1;
    else
        time_var = 2;
    if time <= 45000 then
        time_var = 1;

```

```

else if time >= 50400 then
    time_var = 2;
else if time > 45000 and time <= 46800 then
    time_var = 3;
else if time > 46800 and time < 50400 then
    time_var = 4;

if time_var = 4 then
    delete;
run;

proc sort data = sasdb.raw;
    by date time a_id;
run;

data sasdb.risk;
    set sasdb.phd4;
    by date time;
    retain lastvar lastvar2 lasttime newlast newlast2;

    ltime = lag(time);
    time_diff = (time - ltime) / 60;
    lprice = lag(price);
    if time_diff >= 2 then
    do;
        do i = 1 to time_diff;
            if i = 1 then
            do;
                newlast = price;
                newlast2 = date;
            end;
            output;
            time = lasttime + (60 * i);
            price = lastvar;
            date = lastvar2;
            if i = time_diff then
            do;
                lastvar = newlast;
                lastvar2 = newlast2;
            end;
        end;
    end;
else
do;
    output;
    lastvar = price;
    lastvar2 = date;
end;
lasttime = time;
keep date time price;

```

```

run;

proc sort data = sasdb.risk;
    by date time;
run;

data sasdb.risk2;
    set sasdb.risk;
    lt = lag(time);
    td = time - lt;
    keep date time price td;
run;

proc freq data = sasdb.risk2;
    table td;
run;

data sasdb.risk3;
    set sasdb.risk;
    by date time;
    retain counter;

    if first.date then
        price_chg = 0;

    price2 = lag(price);
    time2 = lag(time);
    time_d = time - time2;

    if time_d = 0 then
        delete;
    else if time_d = 60 then
        price_chg = price - price2;

    y = abs(price_chg);

    if y > 8 then
        y = 9;

    ticks = y;

    x1 = lag(y);
    x2 = lag(x1);
    x3 = lag(x2);
    x4 = lag(x3);
    x5 = lag(x4);

    if first.date then
        do;
            x1=0;

```

```

        x2=0;
        x3=0;
        x4=0;
        x5=0;
        counter=1;
    end;
else if not first.date then
    do;
        counter+1;
        if counter=2 then
            do;
                x2=0;
                x3=0;
                x4=0;
                x5=0;
            end;
        else if counter=3 then
            do;
                x3=0;
                x4=0;
                x5=0;
            end;
        else if counter=4 then
            do;
                x4=0;
                x5=0;
            end;
        else if counter=5 then
            do;
                x5=0;
            end;
        end;
    end;

    array time_pt (118:198) d118-d198;
    do k = lbound(time_pt) to hbound(time_pt);
        if ceil(time/300) = k then
            time_pt(k) = 1;
        else
            time_pt(k) = 0;
        end;
    end;

    f = 1;
    keep date time y ticks x1-x5 time_d d118-d198 f price_chg;
run;

proc freq data = sasdb.risk3;
    table ticks time_d;
run;

```

```
proc logistic data = sasdb.risk3 outest = sasdb.ord_log_reg;
    freq f;
    model y = x1-x5 d118-d198/ rsquare;
run;
```

```
data sasdb.risk4;
    set sasdb.risk;
    by date time;
    retain counter;

    if first.date then
        price_chg = 0;

    price2 = lag(price);
    time2 = lag(time);
    time_d = time - time2;

    if time_d = 0 then
        delete;
    else if time_d = 60 then
        price_chg = price - price2;

    y = abs(price_chg);

    if y > 8 then
        y = 9;

    x1 = lag(y);
    x2 = lag(x1);
    x3 = lag(x2);
    x4 = lag(x3);
    x5 = lag(x4);

    if first.date then
        do;
            x1=0;
            x2=0;
            x3=0;
            x4=0;
            x5=0;
            counter=1;
        end;
    else if not first.date then
        do;
            counter+1;
            if counter=2 then
                do;
                    x2=0;
                    x3=0;
                    x4=0;
```

```

        x5=0;
    end;
    else if counter=3 then
        do;
            x3=0;
            x4=0;
            x5=0;
        end;
    else if counter=4 then
        do;
            x4=0;
            x5=0;
        end;
    else if counter=5 then
        do;
            x5=0;
        end;
    end;
end;

```

```

x_price_chg = (-0.1560*x1) + (-0.1046*x2) + (-0.0857*x3) + (-0.0847*x4) +
              (-0.0839*x5);

```

```

p0 = 0.7324 + x_price_chg;
p1 = 2.2697 + x_price_chg;
p2 = 3.1188 + x_price_chg;
p3 = 3.7324 + x_price_chg;
p4 = 4.2312 + x_price_chg;
p5 = 4.6513 + x_price_chg;
p6 = 5.0043 + x_price_chg;
p7 = 5.3117 + x_price_chg;
p8 = 5.6138 + x_price_chg;

```

```

prob0 = exp(p0) / (1 + exp(p0));
prob1 = (exp(p1) / (1 + exp(p1))) - prob0;
prob2 = (exp(p2) / (1 + exp(p2))) - (prob0 + prob1);
prob3 = (exp(p3) / (1 + exp(p3))) - (prob0 + prob1 + prob2);
prob4 = (exp(p4) / (1 + exp(p4))) - (prob0 + prob1 + prob2 + prob3);
prob5 = (exp(p5) / (1 + exp(p5))) - (prob0 + prob1 + prob2 + prob3 + prob4);
prob6 = (exp(p6) / (1 + exp(p6))) - (prob0 + prob1 + prob2 + prob3 + prob4 + prob5);
prob7 = (exp(p7) / (1 + exp(p7))) - (prob0 + prob1 + prob2 + prob3 + prob4 + prob5 + prob6);
prob8 = (exp(p8) / (1 + exp(p8))) -
        (prob0 + prob1 + prob2 + prob3 + prob4 + prob5 + prob6 + prob7);
prob9 = 1 - (prob0 + prob1 + prob2 + prob3 + prob4 + prob5 + prob6 + prob7 +
            prob8);

```

```

exp_price_chg = (0*prob0)+(1*prob1)+(2*prob2)+(3*prob3)+(4*prob4)+(5*prob5)+
                (6*prob6)+(7*prob7)+(8*prob8)+(9*prob9);

```

```

exp_price_chg = abs(exp_price_chg);

```

```

        if x_price_chg = 0 then
            exp_price_chg = 0;

        keep date time y x1 x2 x3 x4 x5 x_price_chg p0 p1 p2 p3 p4 p5 p6 p7 p8
            prob0 prob1 prob2 prob3 prob4 prob5 prob6 prob7 prob8 prob9

            exp_price_chg;
run;

data sasdb.check;
    merge sasdb.raw(in = a) sasdb.risk4(in = b);
    by date time;
    if a;
    risk = vol2 * exp_price_chg;
run;

proc sort data = sasdb.check;
    by a_id date time;
run;

proc summary data = sasdb.check nway noprint;
    by a_id date;
    class group time_var;
    var vol amt risk vol2 n;
    output out = sasdb.runs (drop=_type__freq_) sum = vol_sum amt_sum
        risk_sum vol2_sum n_sum idgrp(max(time) out(time) = time);
run;

data sasdb.check2;
    set sasdb.runs;
    by a_id date;
    retain cum_vol_sum wac;

    if first.a_id or first.date then
        cum_vol_sum = vol_sum;
    else
        cum_vol_sum = cum_vol_sum + vol_sum;
        lcum_vol_sum = lag(cum_vol_sum);

    if first.a_id or first.date then
        do;
            wac = amt_sum / vol_sum;
            prev_wac = 0;
        end;
    else
        do;
            prev_wac = wac;

            if abs(cum_vol_sum) > abs(lcum_vol_sum) and (cum_vol_sum < 0) and
                (lcum_vol_sum < 0) then

```

```

        wac = (amt_sum + (lcum_vol_sum * prev_wac)) / cum_vol_sum;
    else if abs(cum_vol_sum) > abs(lcum_vol_sum) and (cum_vol_sum > 0)
    and (lcum_vol_sum > 0) then
        wac = (amt_sum + (lcum_vol_sum * prev_wac)) / cum_vol_sum;
    else if (cum_vol_sum <= 0) and (lcum_vol_sum > 0) or (cum_vol_sum >
    0) and (lcum_vol_sum <= 0) then
        wac = amt_sum / vol_sum;
    else if (lcum_vol_sum = 0) then
        wac = amt_sum / vol_sum;
end;

if first.a_id or first.date then
    category = '!';
else if (lcum_vol_sum > 0) and (cum_vol_sum < 0) then
    category = 1;
else if (lcum_vol_sum < 0) and (cum_vol_sum > 0) then
    category = 2;
else if (lcum_vol_sum < 0) and (cum_vol_sum < 0) then
do;
    if abs(lcum_vol_sum) > abs(cum_vol_sum) then
        category = 3;
    else
        category = 4;
end;

else if (lcum_vol_sum > 0) and (cum_vol_sum > 0) then
do;
    if (lcum_vol_sum) > (cum_vol_sum) then
        category = 8;
    else
        category = 5;
end;

else if (lcum_vol_sum = 0) then
    category = 6;
else if (cum_vol_sum = 0) and (lcum_vol_sum < 0) then
    category = 7;
else if (cum_vol_sum = 0) and (lcum_vol_sum > 0) then
    category = 9;

if category = 1 then
    run_prof = (wac - prev_wac) * lcum_vol_sum;
else if category = 2 then
    run_prof = (wac - prev_wac) * lcum_vol_sum;
else if category = 3 then
    run_prof = (wac - (amt_sum / vol_sum)) * vol_sum;
else if category = 4 or category = 5 then
    run_prof = '!';
else if category = 7 then
    run_prof = ((amt_sum / vol_sum) - prev_wac) * lcum_vol_sum;

```



```

        else if category = 6 then
            run_prof = '!';
        else if category = 8 then
            run_prof = (wac - (amt_sum / vol_sum)) * vol_sum;
        else if category = 9 then
            run_prof = (wac - prev_wac) * lcum_vol_sum;
        else if category = '.' then
            run_prof = '!';
run;

proc sort data = sasdb.check2;
    by a_id time_var date;
run;

proc means data = sasdb.check2 noprint;
    by a_id time_var date;
    var run_prof risk_sum vol2_sum n_sum vol_sum;
    output out = sasdb.sums (drop = _type_ _freq_) sum = w x y z a;
run;

proc freq data = sasdb.sums;
    tables time_var;
run;

data sasdb.nice1(rename = (w = morn_prof x = morn_risk y = morn_inv z =
    morn_no_trades time_var = morn a = out_morn_inv))
sasdb.nice2(rename = (w = aft_prof x = aft_risk y = aft_inv z = aft_no_trades
    time_var = aft a = out_aft_inv));
    set sasdb.sums;
    by a_id time_var date;

    if time_var = 1 then output sasdb.nice1;
    if time_var = 2 then output sasdb.nice2;
run;

data sasdb.sums;
    merge sasdb.nice1 sasdb.nice2;
    by a_id date;

    if morn_prof = '.' or morn = '.' then
        delete;
    else if morn_prof = 0 then
        delete;
    else if morn_prof ^= 0 and aft = '.' then
        do;
            aft = 2;
            aft_prof = 0;
            aft_risk = 0;
            aft_inv = 0;
            aft_no_trades = 0;

```

```

        out_aft_inv = 0;
end;

else if aft_prof = '.' then
    aft_prof = 0;

    out_morn_inv = abs(out_morn_inv);
    out_aft_inv = abs(out_aft_inv);
    morn_prof_per_trade = morn_prof / morn_no_trades;

    if morn_prof < 0 then
        morn_loss = 1;
    else if morn_prof > 0 then
        morn_loss = 0;
run;

proc sort data = sasdb.sums;
    by a_id morn_loss;
run;

proc means data = sasdb.sums noprint;
    by a_id;
    var morn_prof morn_risk morn_inv morn_no_trades out_morn_inv
        morn_prof_per_trade aft_prof aft_risk aft_inv aft_no_trades out_aft_inv;
    output out = sasdb.check3 (drop = _type__freq_) mean = a b c d e f g h i j k
        stddev = p q r s t u v w x y z;
run;

data sasdb.check5;
    merge sasdb.sums sasdb.check3;
    by a_id;

    if p = 0 or q = 0 or r = 0 or s = 0 or t = 0 or y = 0 or z = 0 or u = 0 or x = 0 or
        v = 0 or w = 0 then
        delete;

    else if p = '.' or q = '.' or r = '.' or s = '.' or t = '.' or u = '.' or v = '.' or w = '.' or x = '.' or
        y = '.' or z = '.' then
        delete;

    morn_norm_prof = (morn_prof) / p;
    morn_norm_risk = (morn_risk - b) / q;
    morn_norm_inv = (morn_inv - c) / r;
    morn_norm_no_trades = (morn_no_trades - d) / s;
    out_norm_morn_inv = (out_morn_inv - e) / t;
    morn_norm_prof_per_trade = (morn_prof_per_trade - f) / u;

    aft_norm_prof = (aft_prof) / v;
    aft_norm_risk = (aft_risk - h) / w;
    aft_norm_inv = (aft_inv - i) / x;

```

```

aft_norm_no_trades = (aft_no_trades - j) / y;
out_norm_aft_inv = (out_aft_inv - k) / z;

drop a b c d e f g h i j k p q r s t u v w x y z;

if morn_norm_prof < 0 then
    morn_loss = 1;
else if morn_norm_prof > 0 then
    morn_loss = 0;
else
    delete;

loss = 0;
gain = 0;
if morn_norm_prof < 0 then
    loss = morn_norm_prof;
else if morn_norm_prof > 0 then
    gain = morn_norm_prof;

int1 = morn_norm_prof * out_norm_morn_inv;

if morn_norm_prof <= -2.5 then
    dum1 = 1;
else if morn_norm_prof > -2.5 and morn_norm_prof < 0 then
    dum1 = 0;
if morn_norm_prof >= 2.5 then
    dum2 = 1;
else if morn_norm_prof < 2.5 and morn_norm_prof > 0 then
    dum2 = 0;

ind = 0;
if morn_norm_prof > 0 then
    ind = 1;
int2 = ind * out_norm_morn_inv;
    td_risk = 1;
if aft_norm_risk < 0 then
    td_risk = 0;
inv = 1;
if aft_norm_inv < 0 then
    inv = 0;
no_trades = 1;
if aft_norm_no_trades < 0 then
    no_trades = 0;
run;

proc summary data = sasdb.check5 nway;
    class a_id;
    output out = sasdb.trader_counts2 (drop = _type_ rename = (_freq_ = count));
run;

```

```

proc means data = sasdb.trader_counts2 noprint;
    var count;
    output out = sasdb.summary_stats (drop = _type_ _freq_) mean = a median =b
        stddev = c;
run;

data sasdb.check6;
    set sasdb.check5;
    by a_id;

    drop morn_norm_prof morn_norm_risk morn_norm_inv
        morn_norm_no_trades out_norm_morn_inv morn_norm_prof_per_trade
        aft_norm_prof aft_norm_risk aft_norm_inv aft_norm_no_trades
        out_norm_aft_inv gain loss int1 dum1 dum2 ind td_risk inv no_trades;
run;

proc means data = sasdb.check6 noprint;
    by a_id;
    var morn_prof morn_risk morn_inv morn_no_trades out_morn_inv
        morn_prof_per_trade aft_prof aft_risk aft_inv aft_no_trades out_aft_inv;
    output out = sasdb.check7 (drop = _type_ _freq_) mean = a1 b c d e f g h i j k
        stddev = p q r s t u v w x y z;

data sasdb.check8;
    merge sasdb.check6 sasdb.check7;
    by a_id;

    if p = 0 or q = 0 or r = 0 or s = 0 or t = 0 or y = 0 or z = 0 or u = 0 or x = 0 or
v = 0 or w = 0 then
        delete;
    else if p = '.' or q = '.' or r = '.' or s = '.' or t = '.' or u = '.' or v = '.' or w = '.' or x = '.' or
y = '.' or z = '.' then
        delete;

    morn_norm_prof = (morn_prof) / p;
    morn_norm_risk = (morn_risk - b) / q;
    morn_norm_inv = (morn_inv - c) / r;
    morn_norm_no_trades = (morn_no_trades - d) / s;
    out_norm_morn_inv = (out_morn_inv - e) / t;
    morn_norm_prof_per_trade = (morn_prof_per_trade - f) / u;

    aft_norm_prof = (aft_prof) / v;
    aft_norm_risk = (aft_risk - h) / w;
    aft_norm_inv = (aft_inv - i) / x;
    aft_norm_no_trades = (aft_no_trades - j) / y;
    out_norm_aft_inv = (out_aft_inv - k) / z;
run;

proc tabulate data = sasdb.check5;
    class a_id morn_loss;

```

```

var morn_norm_prof aft_norm_prof aft_norm_risk aft_norm_inv
    aft_norm_no_trades;
table a_id * morn_loss all, (morn_norm_prof aft_norm_prof aft_norm_risk
    aft_norm_inv aft_norm_no_trades)*((n sum mean std)*f=8.4);
run;

proc sort data = sasdb.check5;
    by morn_loss;
run;

data sasdb.check9;
    set sasdb.check5;
    by a_id;
    retain cum_day_prof;

    if first.a_id then
        cum_day_prof = morn_prof + aft_prof;
    else
        cum_day_prof = cum_day_prof + morn_prof + aft_prof;

    lcum_day_prof = lag(cum_day_prof);

    if first.a_id then
        lcum_day_prof = 0;

    prof_diff = cum_day_prof - lcum_day_prof;
    lprof_diff = lag(prof_diff);

    if first.a_id then
        lprof_diff = 0;
run;

proc means data = sasdb.check9 noprint;
    by a_id;
    var lprof_diff;
    output out = sasdb.sick1 (drop = _type__freq_) stddev = a;

data sasdb.check10;
    merge sasdb.check9 sasdb.sick1;
    by a_id;

    std_prof = lprof_diff / a;
    ldate = lag(date);
    date_diff = date - ldate;

    if date_diff ^= 1 then
        delete;
run;

proc ttest data = sasdb.check5;

```

```

        paired (morn_prof morn_risk morn_inv morn_no_trades):(aft_prof aft_risk
            aft_inv aft_no_trades);
run;

proc reg data = sasdb.check10;
    model aft_norm_no_trades = morn_norm_prof out_norm_morn_inv int1
        morn_norm_no_trades/ rsquare collin corrb covb
        tol vif;
run;

proc print data = sasdb.check10;
run;

```