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Essays on Equity Portfolio Management

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The University of Sydney

Business School

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

Doctor of Philosophy

2015

Originality Statement

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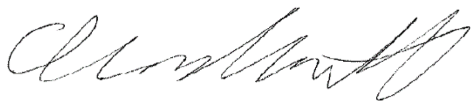

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Adam Corbett

Abstract

This dissertation contains three essays involving empirical research in the area of equity portfolio management. Specifically, two of the essays contribute to the existing funds management literature by examining issues concerning portfolio performance evaluation and asset allocations. These being, equity fund benchmark mismatching, and equity fund industry allocations during the Australian mining boom. The third essay investigates issues relating to socially responsible investing.

The first essay uses Australian equity fund data to examine the appropriateness of equity funds' self-reported benchmarks. Given the lack of regulation surrounding the benchmarking of Australian managed funds and the absence of publicly available equity style indices, this essay explores if fund benchmarks are able to adequately capture passive investment styles and whether funds are better suited to alternative benchmarks. This essay further explores if funds with inappropriate benchmarks are able to outperform relatively, on account of the strategic nature of managers to report underperforming benchmarks, and whether this influences asset flows. Despite Australian equity funds reporting an array of different investment styles, this essay shows that managers largely self-report broad-market based indices as their benchmarks. Whilst this suggests that funds are largely benchmarked to style-inappropriate indices, a large majority are found as being best suited to their self-reported benchmarks. The funds that are style-mismatched, however, are shown to be better matched to alternative S&P/ASX indices instead of passive style-specific indices. These funds are also unable to achieve superior benchmark-relative performance. The findings from this essay therefore refute those from previous studies, such as Sensoy (2009), who suggests that benchmark mismatching will be prevalent

amongst funds in industries where regulations concerning benchmarking are not stringent. The implication of these findings is that Australian equity fund investors should remain confident when relying on a fund's self-reported benchmark to sufficiently capture passive style returns.

The second essay of this dissertation also investigates the asset allocation and performance evaluation of Australian equity funds. Using the Australian mining boom as an experimental setting, the performance of funds based on their exposure to mining stocks is examined. The findings reveal that funds, on average, increased their exposure to mining-related stocks across the mining boom in relative and absolute terms. This essay further shows that funds with relatively higher exposures to mining stocks were unable to outperform funds that were less exposed, in terms of both raw and risk-adjusted returns. The mining exposure-performance relationship is shown to be more adverse amongst wholesale funds (relative to retail funds), as they are found to underperform with increasing levels of mining exposure. Nevertheless, both retail and wholesale funds that exhibit higher levels of mining-stock exposure are able to attract increased fund flows. These findings indicate that fund managers are unable to capture industry outperformance. However, the positive impact that fund mining exposure has on flows is consistent with investors being attracted to hot investment styles and misinterpreting industry allocation as fund skill.

In light of prevalent literature having argued that socially responsible investment (SRI) underperforms 'non-SRI', the rapid growth in SRI in recent years suggests that some form of non-financial satisfaction is being derived by investors who incorporating such mandates into their investment strategies. As such, the final essay of this dissertation provides a measure for the value of this non-financial satisfaction that accrues to individuals from investing in a socially responsible manner.

This non-financial benefit is referred to as the “psychic dividend” of SRI. Previous studies attempt to quantify this value as the difference in certainty equivalent returns of SRI and non-SRI portfolios. This chapter extends the definition of certainty equivalence to consider constant relative risk aversion and loss aversion. Constructing portfolios of ‘socially responsible’ and ‘socially irresponsible’ stocks using U.S equity data from 2000 to 2013 shows that non-SRI is unable to outperform SRI on a raw or risk-adjusted basis. However, the psychic dividend is measured as being at least four basis points per month for a long-only portfolio of socially responsible stocks and at least 85 basis points per month (10.2% p.a.) for a portfolio that is long socially-responsible stocks and short socially-irresponsible stocks. This psychic dividend is shown to increase with investor risk aversion and also during economic recessions. Consequently, due to this non-financial satisfaction that accrues to investors, asset managers could be free to incorporate SRI mandates into their investment practices without the repercussion of asset outflows resulting from possible portfolio underperformance.

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Chapter 1. Introduction

1.1 Motivation of the Dissertation

The value of Australia's funds management industry is estimated at $2.34 trillion as at March 2014. This represents a 15 fold increase from $153.2 billion in June of 1988, thus making Australia the fastest growing and fourth largest funds management industry in the world behind the U.S., Luxembourg and France despite having the 12th largest economy. [1] [2] The size of this industry is largely attributed to the growth in the superannuation (pension) sector over the last two decades due to government initiatives of introducing compulsory contributions and concessional taxation rates. The introduction of these initiatives has seen net funds under management from this sector increase by an average of 14.5 per cent per annum since 1990 (Nanda, Wang and Zheng, 2009). Nevertheless, the non-superannuation sector, which includes, amongst other investment vehicles; life insurance funds, public offer unit trusts, exchange traded funds (ETFs) and hedge funds, are responsible for a substantial portion of this growth.

[1] Statistics sourced from the Australian Bureau of Statistics (ABS) website: http://www.abs.gov.au/ and from the Australian Trade Commission-Investment Management Industry in Australia: http://www.austrade.gov.au/ArticleDocuments/2792/Investment-Management-Industry-in-Australia.pdf.aspx.

[2] Economy size is measured in AUD using nominal GDP.

The ownership of Australian funds management companies has been largely dominated by life insurance companies, domestic banks and international financial groups, with many medium size fund companies (whose assets under management range from $5 billion to $15 billion) having merged or been acquired by these larger companies.[3] Nevertheless, there has been a recent emergence of small (boutique) fund companies into the Australian market that manage a concentrated range of assets and are targeted towards wholesale investors. The most common of these non-superannuation Australian domiciled funds are opened-ended investment trusts. As of May 2014, there were 3,174 of these funds available to retail (household) and wholesale investors, which account for $732 billion in assets under management. Of these 3,174 funds, 751 are classified as 'Australian equity-only' funds, with combined assets under management of $190 billion.[4] This market segment makes up a modest portion of the total Australian equity market which has a market capitalisation of $1.6 trillion.[5] The relative size of this funds management sector, in addition to the assets under management held in Australian equities by multi-sector (diversified) funds, demonstrates the notable preference that Australian investors have for domestic equities. Given this abundance of managed funds that are available to Australian (and international) investors, it is important to be able to accurately evaluate them in order for appropriate investment decisions to be made, whether it be from a financial perspective, or from some other 'non-financial' perspective.

When a fund reports its past returns it is almost always disclosed alongside a benchmark index, suggesting that the benchmark should form an important component

[3] Refer to the Reserve Bank of Australia (RBA) Bulletin – *'Australian Funds Management: Market Structure and Fees'*, sourced from; http://www.rba.gov.au/publications/bulletin/2003/feb/pdf/bu-0203-3.pdf
[4] These statistics are retrieved from the Morningstar *Direct* database on 12th June 2014.
[5]ASX News, "ASX's Market Statistics": http://www.asx.com.au/about/asx-news.htm.

of the portfolio performance evaluation process. Whilst benchmarks may be useful for investors when evaluating performance, if poorly selected, they may hinder the evaluation process resulting in inaccurate assessments of portfolio performance. The first essay of this dissertation therefore explores the ability of a fund's benchmarks to serve as an appropriate performance evaluation tool. The Australian funds market provides an interesting setting to examine benchmark reporting due to the absence of regulations governing this practice. Subsequently, benchmarking decisions are ultimately left in the hands of the fund manager. Furthermore, the public reporting of portfolio holdings by fund managers is voluntary. An appropriate benchmark will therefore be even more important when evaluating performance. Considering the quantity of funds that are benchmarked against broad-market indices such as the S&P/ASX300 despite being advertised as subscribing to a specific 'non broad-market' investment style, it is suspected, prima facie, that a majority of managers fail to report an appropriate benchmark. Fund portfolios may therefore be unknowingly exposed to certain systematic risk factors that are unable to be captured by their benchmarks, hence resulting in the inaccurate evaluation of performance. As such, Chapter 2 explores how fund exposures to systematic style characteristics are captured by their benchmark indices and whether it is advantageous for managers to deviate their portfolio exposures away from these benchmarks.

Despite passive style indices being commonly used as benchmarks by U.S. equity funds, there are currently no equity style indices publicly available within the Australian market. A sample of investable Australian value/growth-size indices are constructed and tested to identify if they are more appropriate at serving as fund benchmarks compared to the S&P/ASX indices. This chapter then examines the style characteristics of equity funds that are likely to be mismatched from their self-reported benchmarks to determine whether managers distort fund performance through inappropriate benchmark reporting. To identify if self-reporting an inappropriate benchmark is advantageous for managers, the relationship between performance, flows and benchmark appropriateness is also investigated.

The findings from Chapter 2 show that investors can generally rely on a fund's self-reported benchmark to adequately capture passive style returns, and therefore can be used to accurately evaluate performance. This finding contests those from previous studies that argue that benchmark mismatching will be widespread amongst funds in industries where regulations concerning benchmarking are not stringent. Given that a large proportion of funds are found to be appropriately matched to their benchmarks, this chapter does not advocate the necessity of equity style indices being made publicly available for the Australian market. From a fund manager's perspective, this chapter suggests that outperforming a benchmark may not be as important as initially expected (at least for retail funds) given the absence of a relationship being found between fund flows and benchmark-relative performance. As such, managers should focus on maximising alternative performance measures, such as raw returns or alpha, in order to improve fund flows. Potential avenues for future research are also discussed in Chapter 2. Specifically, further investigation should be conducted into whether actively managed Australian equity funds are in fact correctly classified with respect to their advertised investment style objectives, or whether they should instead be re-classified as having a broad-market style objective.

The concept of active portfolio management largely involves portfolio rotations towards (or away) from particular assets, styles, industries, markets, or asset classes based on expectations of future performance. Specific events likely to influence markets could result in active managers altering portfolio exposures in attempts to capture some of the benefits associated with these events. Such an event, for example, could include industry booms. Arguably the most famous industry boom and subsequent bust of modern times was that of the U.S. information technology (IT) industry during the late 1990s and early 2000s. Several studies have shown that a significant proportion of fund managers actively altered their portfolio exposure during this period in an attempt to capture the upside of the boom, however not all being successful.[6] A more recent example of an industry boom witnessed over a prolonged period of time that has similarly influenced an entire equity market is what has now become known as, 'the Australian Mining Boom'.

The commencement of the Australian mining boom is considered a consequence of the rapid industrialisation and urbanisation of emerging economies in Asia, particularly China and India over the last decade, which has led to substantial investments in infrastructure, buildings and machinery in these countries and subsequent increased demand for raw commodities, especially coal and iron ore (Kearns and Lowe, 2011). The abundance of these resources and Australia's relatively close proximity to China has made it a prime source for these resources. This subsequently resulted in Australia's heightened production and investment across a broad range of mining-related sectors from around 2005 onwards and ultimately ensued this mining boom (Connolly and Orsmond, 2011). This boom assisted the Australian economy through the Global Financial Crises of the late 2000s, experiencing a milder downturn relative to other developed nations. The economic slowdown in China in recent years however has seen a decline in the mining industry

[6] A detailed discussion of the performance of funds in relation to the U.S. IT bubble is provided in Chapter 3, Section 3.3.c.

asset prices from about 2012 onwards, suggesting that the peak of this boom is behind us.

Unlike the IT boom, the Australian mining boom did not eventuate in a crash of asset prices. However, this boom provides us another opportunity to examine the reactions and implications of funds during periods of industry outperformance. As the application of industry-level analysis is considered a key component of active portfolio management for those who prescribe to the top-down approach of investing, the second essay explores how portfolio exposures of Australian funds are influenced by industry booms and the subsequent effect that these exposures have on fund performance and flows. Specifically, this essay strengthens our understanding of whether funds are able to capture industry outperformance and the effect that exposure to a booming industry has on fund investors.

The findings presented in this essay show that fund exposures to the mining industry increased in absolute and relative terms across the mining boom period, indicating that equity fund managers are attempting to outperform their benchmarks by chasing industry outperformance. However, funds with higher exposure to this mining industry (especially wholesale funds) are unable to outperform relative to those funds with lower exposures when measured using raw or risk-adjusted returns and controlling for fund-specific factors. Nevertheless, this essay shows that funds with higher mining exposure are successful in attracting greater funds inflows, which indicate that the investment decisions of fund investors are also influenced by industry booms. This result is consistent with investors being attracted to hot investment styles and misinterpreting industry allocation as fund skill.

An investment ‘style’ that has gained popularity amongst portfolio management in recent years has become known as Socially Responsible Investing (SRI). SRI is a broad concept used to describe the practice of screening investments based on some criteria that encourages environmental, corporate governance, social justice or any other non-financial related screen that is generally seen as being ‘good’ for society (Baker and Nofsinger, 2012). An SRI investor, for example, may invest solely in firms that promote renewable energy or human rights, or alternatively avoid firms that are related to the production or distribution of tobacco, nuclear power or firearms. As definitions of environmental and social responsibility traditionally stems from moral, cultural, historical, or religious beliefs, there is no clear distinction as to what can or cannot be considered as SRI. As such, the definition of SRI can vary significantly from one individual to another.[7] Incorporating SRI into the investment process however has become increasingly popular amongst individuals and institutions in recent years. Increasing awareness and support of SRI has resulted in regulatory bodies requiring mandatory disclosure of certain environmental factors by listed companies in many markets around the world, particularly within Australia. This global demand for greater social responsibility by firms has led to the inclusion of a range of SRI policies into investment mandates for an increasing proportion of managed funds, with a significant number now being managed primarily from an SRI standpoint (USSIF, 2012). Currently, there are over 500 signatories to the United Nations Principles for Responsible Investment (UN PRI) across the globe. These funds collectively hold over US$18 trillion in assets under management. Australia represents the largest signatory body to the PRI, representing about 17 percent of the total number

[7] See, for example Domini (2001), Sparkes (2010), and Fung, Law, and Yau (2010) for further discussion on socially responsible investing.

of global signatories. Furthermore, over half of all funds under management in Australia are estimated to be committed to operating in accordance with the major principles outlined by UNPRI.[8]

There is currently a vast range of products available to investors that are based on a wide spectrum of SRI guidelines, which incorporate either negative or positive screens or both into their investment mandates. Specifically, the U.S. funds management industry has seen a dramatic rise in number of funds that incorporate at least one SRI screen, with $3.74 trillion in assets under management as at 2012. This industry has seen almost a fivefold increase in SRI-screened funds since 1995, representing 11 percent ($3.74 trillion) of all institutional assets under management as at 2012 (USSIF, 2012). This growth in U.S. SRI funds under management is not only attributed to the fund sector, but is also largely attributed to other funds including venture capital funds, hedge funds, private equity funds and property funds that have also prescribed to specific SRI mandates (USSIF, 2012). Such global growth in SRI may be attributed to increasing awareness of environmental and social issues by individuals and investors along with heightened social conscience that is exhibited by society as a result of becoming wealthier (Joseph, 1989). The last essay of this dissertation (0) subsequently moves from traditional performance evaluation to examine other non-financial benefits that investors can obtain.

Traditionally, it is thought that constraining a portfolio will result in sub-optimal diversification and performance for the wealth-maximising investor relative to an unconstrained portfolio [see, for example Rudd (1981), Grossman and Sharpe

[8] Australian Trade Commission-Investment Management Industry in Australia: http://www.austrade.gov.au/ArticleDocuments/2792/Investment-Management-Industry-in-Australia.pdf.aspx.

(1986), Hall (1986) and Diltz (1995)]. A large body of literature has therefore emerged that examines the performance differential between ‘SRI-constrained’ and unconstrained ‘non-SRI’ portfolios. Whilst the literature does not unequivocally find that investors are punished in terms of financial performance for holding SRI portfolios, it is unlikely that there is not a financial cost associated with investing in SRI. In order to explain the continued and rapid growth of this “investment style” in recent times, significant non-financial satisfaction must be accruing to SRI investors. This non-financial satisfaction must be valued at an amount that is at least as large as the financial cost that is yielded from holding SRI. The last essay of this dissertation therefore measures the value of this non-financial benefit, and is referred to as the “psychic dividend” of SRI.

Psychic dividends are measured in this essay from loss aversion utility functions that use return distributions that are representative of an SRI and non-SRI investor’s portfolio. Socially responsible and socially irresponsible portfolios are constructed from monthly U.S. equities data using industry classifications as the basis for screening stocks into either portfolio. From these portfolios, this chapter shows that SRI does not underperform (or outperform) non-SRI when measured using raw or risk-adjusted returns regardless of economic or market conditions. Geczy, Stambaugh, and Levin (2005) attempt to measure this cost of SRI using differences in certainty equivalence returns between SRI and non-SRI screened portfolio. This essay extends their definition of certainty equivalence from the limiting case of exponential utility to more general cases that include constant relative risk aversion and loss aversion. The findings from this essay show that the psychic dividend to SRI is valued at an amount that is at least four basis points per month for a long-only portfolio of socially responsible stocks and at least 85 basis points per month for a portfolio that is long socially-responsible stocks and short socially-irresponsible stocks. This psychic dividend is shown to increase with investor risk aversion and also during economic recessions.

The remainder of this dissertation is organised as follows: Chapter 2 presents the first essay, entitled '*Equity Fund Benchmark Appropriateness, Performance and Flows*'. Chapter 3 presents the second essay, '*Prospecting for Alpha: Equity Fund Performance, Flows and the Mining Boom in Australia*' and the last essay, entitled *'Psychic Dividends of Socially Responsible Investors'* is presented in 0. The dissertation is concluded in Chapter 5.

1.2 Presentations and Papers Arising from this Dissertation

Certain work from this dissertation has been produced into working papers and/or presented at conferences. A working paper, titled '*The Appropriateness of Equity Funds' Self-designated Benchmarks,'* that is co-authored with Andrew Ainsworth and Kerry Pattenden and has been produced that is based on the work contained in Chapter 2. This paper was presented at the 2013 Asian Financial Management Association (AFMA) Meeting in Shanghai, China.

A working paper co-authored with Andrew Ainsworth, titled *"Equity Fund Performance, Flows and the Mining Boom in Australia",* has been produced that is based on the work contained in Chapter 3. This paper was presented at the 2013 SIRCA Young Researchers Workshop in Sydney, and has been accepted into the 2014 Southern Finance Meeting in Key West, USA.

A working paper, titled *"Psychic Dividends of Socially Responsible Investors"*, that is co-authored with Steve Satchell and Andrew Ainsworth has been produced that is based on the work contained in 0.

Chapter 2. Equity Fund Benchmark Appropriateness, Performance and Flows

2.1 Introduction

The benchmarking of a portfolio to an index is considered an important element of the fund performance evaluation process, as has been illustrated by the thousands of passive indices used to track the returns of securities in the hundreds of markets throughout the world. The ability to accurately evaluate fund performance has been a topic of interest since Sharpe (1966) and Jensen (1968). They both stress the importance of using appropriate benchmarks when measuring performance. For a benchmark to be considered a useful evaluation tool, it should be able to capture the passive component of a portfolio's returns whilst recognising a manager's stock selection ability through their active share of investments. An inappropriate benchmark may therefore be ineffective in assisting investors to make good investment decisions, adequately manage risk, or properly measure fund performance (Anderson, 2009). In order to adjust for the passive position of a portfolio and to adequately capture active variations in returns, a benchmark should be capable of adequately mimicking the passive style of the portfolio that it is attempting to evaluate. If a fund is found to be closet-indexing an alternative benchmark then it should not be assessed as possessing skill, and instead be scrutinised for charging active management fees for effectively being passively managed.[9] Similarly, fund managers should not be rewarded for outperforming a benchmark if they persistently tilt their portfolios exposures to an extent such that they track the returns of an alternative index closer than their own benchmark.

There is a large quantity of Australian equity funds advertised as subscribing to specific style objectives despite being benchmarked against broad-market indices. Given the absence in regulations surrounding fund benchmarking and holdings reporting in Australia, this chapter investigates several issues concerning the appropriateness of equity fund benchmarking. These issues include; whether Australian equity funds are adequately style-matched to their self-reported benchmarks, whether the returns of these funds are better captured by alternative passive indices, and whether funds with inappropriate benchmarks are able to outperform and attract increased flows.

The findings from this chapter assist in identifying if regulations concerning fund benchmark reporting should be more stringent to ensure that benchmarks can reliably be used to evaluate performance. These findings additionally assist in determining whether style indices should be made publicly available within Australia to allow practitioners greater capacity to compare passive portfolio returns accruing to a variety of investment styles. This chapter further identifies whether fund investors can rely on self-reported benchmarks to adequately identify passive returns and to compare funds amongst their peer group. From a manager's perspective, this chapter

[9] Closet indexing refers to the practice of passively managing a portfolio (tracking a benchmark index) of a fund that is believed by investors to be actively managed and whose fees are charged at higher 'active' rates compared to passive funds [see, for example Taylor (2004), Cremers and Petajisto (2009) and Cremers, Ferreira, Matos, and Starks (2013) for further discussion on closet indexing].

establishes if outperforming a benchmark influences asset flows, and whether this is affected by the appropriateness of the fund's benchmark.

Using Morningstar Direct data for a sample of 460 Australian actively-managed equity funds over the period from 2000 to 2012, benchmark-mismatched funds are determined using the approach of Levene (1960) to test for homogeneity of tracking error volatilities from a sample of passive equity indices. Returns-based factor analysis is then applied to identify how well value/growth, size and momentum style characteristics are captured by funds' self-reported benchmarks. Given the absence of publicly available 'style' indices within the Australian equity market, a basket of passive value/growth-size style indices is constructed and tested to determine whether these are more appropriate at serving as a benchmark index than currently available S&P/ASX indices. To assist in identifying if managers purposefully misallocate inappropriate benchmarks in attempts to outperform their peers, fund performance is examined using regression analysis to test the hypothesis that funds with inappropriately matched benchmarks outperform those with suitably matched benchmarks. This chapter then lastly examines how fund benchmark mismatching influences investor asset flows, and if managers who have assigned mismatched benchmarks are successful at attracting greater inflows.

Despite the abundance of Australian equity funds that prescribe to specific investment styles, this chapter finds that an overwhelming number of managers self-report broad-market based indices (i.e., the S&P/ASX 200 or the S&P/ASX 200 All Ordinaries) as their benchmarks. Whilst this pre-emptively suggests that funds largely assign style-inappropriate benchmarks, almost all are found to be suitably matched to their self-reported benchmarks, and only a small minority tilt their portfolios away from a particular style characteristic relative to their benchmark. For those few funds that are mismatched, they do not group to any one particular style relative to their benchmark. Furthermore, these funds are unable to achieve superior benchmark-relative performance and do not benefit from increased inflows. This implies that, as a whole, Australian equity fund managers do not (or are unable to) take advantage of the lack of benchmarking regulations in Australia by allocating indices that are easily outperformed. These findings do not support the requirement of style indices being made publicly available.

The remainder of this chapter is organised as follows: Section 2.2 provides a review of the current literature that explores fund benchmarking and style mismatching, section 2.3 describes the hypotheses that are empirically tested in this chapter and section 2.4 describes the data used in this chapter. Section 2.5 explains the methodology for testing for benchmark mismatching and evaluating fund performance and flows, section 2.6 reports and discusses the empirical findings and section 2.7 concludes.

2.2 Literature Review

2.2.a Introduction

In practice, funds are often evaluated alongside a benchmark index that is self-reported by the fund manager. Bailey (1992) suggests that an effective benchmark should be, amongst other qualities, unambiguous, tradeable, measurable, specified in advance, reflective of current investment opinions, and appropriate (i.e., the benchmark must reflect the manager's style). Meschke (2007) argue that a good benchmark should evaluate the performance resulting from the active risks taken by managers while controlling for externalities that are unable to be controlled by the manager. Sensoy (2009) describes that in order for an index to serve as a suitable benchmark, it should be adequately matched to the fund's unique investment style so as to capture common variations in returns.

Ferris and Yan (2007) argue that it is important when evaluating a manager's skill that fund performance be measured relative to that of a benchmark index. They show that a vast majority of performance evaluation studies fail to provide a realistic evaluation of managerial skill because they assume that the appropriate performance benchmark is one that is estimated from a market implicit factor model such as the Fama and French (1993) three-factor model, or Carhart (1997) four-factor model. Ferris and Yan (2007) subsequently show that failing to incorporate a fund's benchmark into the evaluation process will result in a biased measure of risk-adjusted performance that will mismeasure manager skill. For example, "ignoring the manager's self-reported benchmark would incorrectly classify as timing, changes in factor exposures which merely reflect the manager's effort to track the time-varying sensitivities of her benchmark" (p.1760). Cremers, Petajisto, and Zitzewitz (2012) show that commonly used passive benchmarks such as the S&P 500 and Russell 2000 are assigned large and noisy alphas estimates as well as non-zero and significant exposure to systematic risk factors by standard factor models, which ultimately result in misleading and biased measures of fund performance. Consequently, when fund performance is evaluated by risk-adjusting excess returns over a self-reported benchmark, it is expected to provide a more realistic measure and improved level of managerial skill than employing an implicit benchmark defined from a standard risk factor model. This argument is also supported by Kuenzi (2003) and Belden and Waring (2001), who argue that using inappropriate benchmarks leads to built-in tracking errors that hinder the evaluation process.

2.2.b Investment Styles

The investment style of a fund can generally be determined by the set of investment philosophies, objectives and strategies adhered to by the fund manager that govern the portfolio's asset allocation and ultimately influences its performance (Sharpe, 1992). Similarly, style can be referred to as the "subset of the investment universe in which a manager is constrained to operate, such as small capitalisation stocks versus large stocks, or value versus growth firms" (Ferson, 2010, p. 211). Rekenthaler, Gambera, and Charlson (2006) on the other hand argue that "investment styles are often used as a proxy for risk and the value of such an approach depends on a correct initial assessment of style" (p.6). An abundance of studies show that the investment styles of funds appear to vary significantly from those reported by the fund. Kim, Shukla, and Tomas (2000), for example, find that more than half of all U.S. funds report investment objectives as defined by the funds' characteristics, investment style, and risk/return attributes that are significantly different from their actual holdings. This result confirms the earlier findings of diBartolomeo and Witkowski (1997) and Brown and Goetzmann (1997), who argue that a large proportion of U.S. funds are misclassified with respect to their stated investment objectives. In the context of Australian managed funds, Allen, Phoon, Watson, and Wickramanayake (2010), using a Sharpe (1992) returns-based style analysis over a six year period from 2003 to 2008, find that up to 77 percent of Australian multi-sector funds are misclassified according to their investment styles.

Chan, Chen, and Lakonishok (2002) argue that a major cause of funds reporting misleading investment style objectives is due to temporary deviations in style exposures by managers who attempt to time the market. Chan, Dimmock, and Lakonishok (2006) suggest that managers may instead report inaccurate investment styles in an attempt to disguise the risk associated with a fund's actual style exposure. Frost (2004) alternatively shows that the style mismatching of funds may arise due to the incentive that managers have of placing past performance in the best possible light given that retail investors are often shown to use past fund performance to assess managerial skill. By presenting performance in the best possible light, managers hope to attract investors and thus improve fee revenue from increased fund inflows (Barber and Odean, 2000). Gallo, Phengpis, and Swanson (2007) and Brown, Harlow, and Zhang (2009) show that the failure to abide by a consistent investment style can ultimately lead to inferior performance. Allen, *et al.* (2010) dispute this, arguing that the misclassification of a fund's investment style has no significant effect on its performance. The evidence from these studies suggests that at any point in time it is reasonable to expect that not all funds will contain securities that match the styles stated by their investment objectives.

A benchmark should ideally be constructed from a universe of stocks that match the style objectives advertised by the underlying fund. diBartolomeo and Witkowski (1997) reveal that if the reported investment style of a fund is inconsistent with its actual style, then the fund's benchmark is also likely to be inadequately style matched. In terms of equity funds, style may be defined by the characteristics of the stocks that the fund invests in. Given the specificity of stock characteristics, Clarke and Ryan (1994) indicate that no one-specific benchmark will suit all funds. Furthermore, Frost (2004) suggests that if regulatory standards for evaluating fund performance are not stringent then fund managers will be inclined to misrepresent performance. Managers may therefore attempt to exaggerate past performance by benchmarking fund returns against indices that have performed poorly, regardless of how well (or how poorly) the index matches the style objectives of the fund.

2.2.c Benchmark Mismatching

The incentive for fund managers to outperform their benchmark is argued by Ippolito (1989), who demonstrate that fund flows are positively related to benchmark-excess returns. This relationship is suggested to be the result of investors being more likely to allocate funds based on simple performance measures, such as benchmark-relative returns, instead of more complicated metrics such as alpha [see, for example Sirri and Tufano (1998), Chevalier and Ellison (1997) and Del Guercio and Tkac (2002)]. Sensoy (2009) argues that it is because of this flow-performance incentive that fund managers will strategically report benchmarks that are relatively easy to outperform. He shows that managers may achieve this by reporting a benchmark with an investment style that has traditionally underperformed the style of the fund, and further shows that when funds outperform a 'style-mismatched' benchmark, they are able to attract greater fund inflows.

Wermers (2011) suggests that "managers should be rewarded for bets not easily replicated by uninformed investors; that is, managers should not be rewarded for easy bets that represent passive or known simple mechanical strategies" (p.538). Cremers, *et al.* (2012) also argue that regardless of whether or not a certain style factor is priced, it should be included in the benchmark model because there are extended periods of time when certain styles significantly outperform others. Incorporating such style factors into the benchmarking process will therefore provide a more accurate estimate of portfolio performance relative to a passive style-portfolio. When attempting to generate abnormal performance, Wermers (2011) shows that fund managers may participate in 'static' factor allocation, a strategy that involves persistently tilting the weight of their portfolio towards a specific systematic risk factor that is expected to exhibit a risk premium. For instance, if value stocks have historically outperformed growth stocks, a manager may attempt to exploit this premium by purposefully reporting a growth-styled benchmark yet tilt their portfolio persistently towards value stocks. On the other hand, managers may use a dynamic factor allocation approach to generate superior benchmark-relative performance, which involves temporarily tilting a portfolio towards a particular style that is expected to outperform others over the short run. Wermers (2011) stresses the importance of distinguishing between static and dynamic factor allocation. He shows that while static factor allocation can be a valuable strategy for managers, significant static exposure to known risk factors may be easily replicated by low-cost allocations to passive style indices in a buy-and-hold portfolio. This may result in scepticism of a manager's rationale to charge active management fees. Passive fund replication, however, may only be possible for those certain types of investment styles where passive indices exist, such as for size and value/growth style characteristics. As such, identifying a fund's static factor exposure may subsequently be useful when characterising a fund's investment style while identifying any persistent manager bias in a fund's portfolio relative to its benchmark (Wermers, 2011).

Sensoy (2009) argues that almost a third of all U.S. equity fund managers report benchmarks that are mismatched from the fund's reported style characteristics. He further argues that the self-reported benchmark of almost a third of the total sample of funds are unable to capture the exposure to a fund's size and value-growth characteristics as well as alternative published indices. These funds are predominantly overexposed from their benchmarks in the direction of small and value stocks, which may be an attempt to strategically achieve positive benchmark-adjusted returns by taking advantage of size and value premiums.[10] The findings from Sensoy (2009) confirm those of Elton, Gruber, and Blake (2003), who reveal that despite the prevalence of published style-indices, a large quantity of U.S. equity funds contain self-reported benchmarks that are mismatched from their investment styles. Specifically, Elton*, et al.* (2003) show that funds contain exposures to size and value-growth characteristics that are not reflected in their benchmarks.

Using a holdings-based approach, Cremers and Petajisto (2009) find that fund managers deliberately report benchmarks that are style-mismatched. They find that a large majority of U.S. funds that generate positive benchmark-adjusted returns, both before and after expenses, hold securities that vary significantly from those reflected in the composition of their benchmarks. Funds that maintain holdings that closely matched their benchmark, on the other hand, are shown to underperform after expenses. Beaumont (2003) also argues that for those "portfolio managers concerned primarily with matching a benchmark, mismatches would be rather small, yet for portfolio managers concerned with outperforming a benchmark, larger mismatches are common" (p.164). Subsequently, the incentive to outperform a benchmark may encourage some managers to select certain style-indices that traditionally underperform the underlying style of their fund. These incentives may persuade fund managers to deviate their style from that of their allocated benchmark, or alternatively, to strategically select a misrepresentative benchmark so as to increase their chances of consistently beating it. However, a misleading benchmark may simply be due to the unavailability of an index that adequately captures the style characteristics of a fund. This argument is expressed by Ansell, Moles, and Smart (2003), who suggest that

[10] See, for example Fama and French (1992), Davis, Fama, and French (2000), Fama and French (2006), O'Brien, Brailsford, and Gaunt (2010) and Morey and O'Neal (2006) for a discussion on the Value premium and Banz (1981), Roll (1983), Gaunt (2004) and O'Brien*, et al.* (2010) on the size premium.

benchmarks should not be treated as "one-size-fits-all". Blake, Lehmann, and Timmermann (2002) also find that it is often difficult to determine an appropriate benchmark for a managed fund. They find this to be the result of the difficulty in defining investment styles, given that fund managers often have considerable discretion in the asset allocation of their portfolios. On a similar note, Kuenzi (2003) argue that for those 'sophisticated' managers that utilise specialised investment strategies, a published index would be unable to serve its purpose of capturing the fund's exposure to common style factors. Consequently, such funds will require customised benchmarks in order to accurately evaluate fund performance.

2.2.d Alternative Explanations to Benchmark Mismatching

A main cause for benchmarks being unable to capture the styles of their underlying funds is argued to be the result of portfolio style drift.[11] Funds may follow crowds by rotating from their stated styles to mimic funds that have recently been successful. Chan, *et al.* (2002) find that funds are generally consistent in maintaining their reported styles and that style drift is most common amongst funds with poor past performance and especially in poorly performing value funds. Sensoy (2009) rejects the notion that style drift is typically responsible for funds being style mismatched from their self-reported benchmarks. He shows that the proportion of mismatched funds at the beginning of his sample in 1994 is almost identical to the proportion of funds that are overall found to be mismatched from 1994 to 2004. This evidence further supports the argument that benchmark mismatching is a result of managers attempting to distort fund performance.

[11] See, for example Arrington (2000), Barberis and Shleifer (2003), Idzorek and Bertsch (2004), Chen and Wermers (2005), Ainsworth, Fong, and Gallagher (2008) and Wermers (2012) on style drift.

2.3 Hypothesis Development

Broad market-based indices such as the S&P/ASX 300 may serve as an appropriate benchmark for funds with corresponding broad-market style. However, these indices may not be able to adequately capture common variations in returns for those funds with narrowly defined styles. For example, it may not be appropriate to evaluate the performance of a fund that is heavily exposed to value stocks using a benchmark constructed from growth stocks, since any systematic return attributed to this value characteristic might incorrectly be recognised as managerial skill. If a manager is able to identify an investment style that is expected to outperform, then overexposing her portfolio to this style should produce attractive benchmark-relative returns as long as her benchmark is not also exposed to this investment style. This practise may be prevalent amongst Australian funds due to the voluntary reporting of portfolio holdings by fund managers. If benchmarks are intentionally style mismatched then it is expected that these funds will exhibit greater benchmark-relative exposure towards investment styles that are expected to outperform. Furthermore, If benchmark-excess performance has little effect on fund flows, then the ability to beat the benchmark, and in turn, ensuring that funds are appropriately matched to their benchmarks may not be so important. If however, fund flows are related to benchmark-relative returns, then it is expected that managers will strive to outperform their benchmarks whether it be through managerial skill or through simply reporting a sub-optimal benchmark. Given that the benchmarking of equity funds is unregulated in Australia, it is expected that a large proportion of funds will be inappropriately matched to their benchmarks, and that managers will strategically select benchmarks that traditionally underperform in attempts to appear more attractive. However, others managers, especially in Australia, may have a mismatched benchmark simply due to the unavailability of a benchmark that suitably captures the underlying passive style of a fund's portfolio. It is therefore expected that value and growth funds will be more susceptible to mismatching due to these styles being inadequately captured by the current S&P/ASX indices.

If fund managers recognise that retail investors use simple performance metrics such as benchmark-excess returns instead of more complicated risk-adjusted measures such as alpha when allocating assets, then retail managers will have greater incentive and therefore be more inclined to allocate a mismatched benchmark that is easily outperformed. Wholesale managers on the other hand, recognising that their investors use more sophisticated performance metrics when allocating funds, may be less inclined to report an inappropriate benchmark index if the asset flows associated with outperforming a benchmark are negligible. Subsequently, it is expected that retail funds will be more prone to benchmark mismatching.

Funds that are identified as being mismatched from their benchmarks are expected to produce higher benchmark-relative returns compared to appropriately-matched funds. Nevertheless, this performance difference is likely to disappear after alternative 'better-suited' benchmarks are assigned to these funds. This is due to the performance differential being a result of the 'sub-optimal' benchmark, and not due to the performance of the underlying fund.

Whilst the argument that investors base their fund allocation decisions using simple performance metrics such as benchmark-adjusted returns, this may only be the case for retail investors who are generally considered as being less-sophisticated, household investors. James and Karceski (2006) argue that wholesale and retail investors use different criteria when allocating assets across funds. They show that wholesale fund investors do not chase past raw returns in the same manner as retail investors but instead use more sophisticated, risk-adjusted, performance metrics when selecting funds. Del Guercio and Tkac (2002) reach a similar conclusion when examining the behaviour of pension and retail fund investors. Subsequently, compared to retail investors, wholesale investors are expected to be less influenced by benchmark-excess fund returns when allocating assets across funds and hence benchmark mismatching will not affect flows into these as much as it will for retail funds.

2.4 Data

2.4.a Stock-Related Data

Month-ending stocks prices, market capitalisations and Global Industry Classification Standards (GICS) sector codes for all companies listed on the Australian Securities Exchange (ASX) from 2000 to 2012, along with the 13-week Treasury Note rate are retrieved from the Securities Industry Research Centre of Asia-Pacific Share Price and Price Relative Database (SIRCA SPPR). Data on firm-level book value of assets is retrieved from Aspect Huntley. Month-ending prices for all S&P/ASX Accumulation indices are retrieved from the Thomas Reuters Tick History (TRTH) database.

Zero-investment factor mimicking portfolios for the two Fama and French (1992) factors, size (*SMB*) and value/growth (*HML*), are constructed by dividing stocks into a 2x3 size-by-book-to-market (BM) matrix using two independent sorts, calculating the value-weighted average returns for the stocks in the six portfolios, and then constructing its factors using equal-weighted differences between these portfolio returns. Specifically, the size factor, *SMB* (Small minus Big), is defined as (Small-

Low + Small-Medium + Small-High)/3 minus (Big-Low + Big-Medium + Big-High)/3. The value/growth factor, *HML* (high book-to-market minus low book-to-market), is defined as (Small-High + Big-High)/2 minus (Small-Low + Big-Low)/2.[12] The Jegadeesh and Titman (1993) momentum factor (*UMD)* is constructed by investing long in stocks with positive previous-six month returns and short in stocks with negative previous-six month returns following research on momentum in Australia by Demir, Muthuswamy, and Walter (2004). The return on the SIRCA SPPR value-weighted Australian share index is used as the Australian market return and the 13-week Treasury Note rate is the risk-free return.

2.4.b Australian Equity Fund-Related Data

All fund-related data used throughout Chapter 2 and Chapter 3 are sourced from the Morningstar Direct database and include; net fund returns, net dollar value of assets under management, inception date, net flow of funds as a percentage of assets under management, primary prospectus benchmark index, wholesale/retail classifications and investment style classifications for all Australian actively managed open-ended equity funds measured at a monthly frequency. Size is calculated as the natural log of the dollar value of net assets under management by the fund in each month. Fund return is the total percentage return calculated by Morningstar as the change in monthly assets under management (AUM) after reinvesting all income and capital-gains distributions during that month and subtracting management, administrative and other fees taken from fund assets then dividing by the starting

[12] The two Fama and French (1993) factors are constructed following the approach of Fama and French (1993). However, unlike their approach, which excludes financial-sector stocks, I include financials given the importance that this industry plays in the Australian Market.

AUM.[13,14] Reinvestments are made using actual reinvestment AUM and daily payoffs are reinvested monthly. Fund asset flows (hereinafter referred to as flow) is measured by Morningstar as the percentage change in AUM over the prior month after subtracting the change in funds under management that is related to its past return, given by the formula:

$$Flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}(1+r_{i,t})}{AUM_{i,t-1}}, \qquad (2.1)$$

where $Flow_{i,t}$ is the net percentage flow of assets under management to fund *i* across period *t*. $TNA_{i,t}$ is the total net assets under management of fund *i* at the end of period *t* and $r_{i,t}$ is the raw return of fund *i* over time *t*. Flows are winsorised at 5 percent and 95 percent levels following Barber, Odean, and Zheng (2005) to avoid effects due to measurement errors or extreme observations.

Net Style Flows are calculated from the aggregate flow of assets under management into all funds with the same Morningstar investment style classification, *s*, as fund *i*, from the following formula:

$$Net\ Style\ Flow_{s,i,t-1} = \frac{\sum_{i=1}^{N_s} AUM_{i,s,t-1} - \sum_{i=1}^{N_s} AUM_{i,s,t-2}(1+r_{i,s,t-1})}{\sum_{i=1}^{N_s} AUM_{i,s,t-2}}, \qquad (2.2)$$

where *N* is the number of equity funds with investment style *s* during month *t-1* and $\sum_{i=1}^{N_s} AUM_{i,s,t}$ is the value of total net assets asset under management for all funds with investment style classification, *s*, at time *t*.

[13] Front-end loads, deferred loads and redemption fees are excluded from the calculation of fund returns.
[14] Morningstar data may be is prone to containing funds that have duplicate return series but different identifiers. To control for this occurrence, a fund should be deleted if it has a 50% overlap in returns with another fund.

Fund excess return, $r_{i,t} - r_{f,t}$, is measured as fund raw total return in month *i*, $r_{i,t}$ minus the monthly return on the 13-week Treasury Note. Fund age is calculated as the natural logarithm of the number of months since its inception date. Fund volatility, $\sigma_{i,t}$, is measured as the the historical standard deviation of a fund's monthly raw returns over the previous 12 months beginning in month *t-12*, from the equation:

$$\sigma_{i,t} = \sqrt{\frac{\sum_{t=1}^{T}(r_{i,t} - \overline{r_{i,}})}{T-1}} \text{ , } T=0, \quad (2.3)$$

where $\overline{r_i}$ is the mean return of fund *i* from month *t* = *-12* to *T*.

Morningstar classifies Australian equity funds into seven style categories; *Large-Value*, *Mid/Small-Value*, *Large-Growth*, *Mid/Small-Growth*, *Large-blend*, *Mid/Small-blend*, and *Other*.[15] Fund investment style dummies are constructed that take on values of one if a fund is classified as having that respected style, or zero otherwise.

A wholesale dummy variable is constructed that takes on a value of one for funds that are classified by Morningstar as being a wholesale fund, or zero for a retail fund. Wholesale funds are identified by Morningstar as those that are intended for well-informed/professional investors or institutions (i.e., banks, insurance companies or superannuation funds) and generally require an initial investment amount of no less than $100,000AUD. The associated fees of wholesale funds are generally cheaper due to their lower cost structures resulting from less frequent and larger transactions as well as streamlined administrative and reporting requirements. Retail funds on the other hand are intended for less-informed/household investors (Sawicki, 2001).

[15] The '*Other'* investment style category includes all funds that are considered by Morningstar as either; *Large Geared*, *Derivative Income, Other* or '*Unclassified*'.

Time-varying Carhart (1997) four-factor alpha (hereinafter referred to as Carhart alpha) are calculated at the fund level using rolling regressions estimated across 24-month horizons from the model:

$$r_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{1,i,t}(Rm_t - r_{f,t}) + \beta_{2,i,t}SMB_t + \beta_{3,i,t}HML_t + \beta_{4,i,t}UMD_t + \varepsilon_{i,t} \, , \tag{2.4}$$

where $r_{i,t} - r_{f,t}$ is the excess-return of fund *i* at time *t* above the risk-free rate . $\alpha_{i,t}$ is the Carhart alpha of fund *i* estimated over the previous 24 months from time *t-25*. *Rm-rf, SMB, HML* and *UMD* are the monthly returns from the standard Carhart (1997) four factors at time *t*, $\beta_{1,i,t} \dots \beta_{4,i,t}$ are the estimated coefficients on each of the respected four factors and $\varepsilon_{i,t}$ is the error term of fund *i* at time *t*. Time-varying CAPM alphas are also estimated using the same approach, calculated as the intercept, $\alpha_{i,t}$, from the following regression model across 24-month rolling windows:

$$r_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{1,i,t}(r_{m,t} - r_{f,t}) + \varepsilon_{i,t}, \tag{2.5}$$

where the variables are as previous described.

Fractional performance variables are used in linear piecewise regressions, when estimating flow-performance models that capture the asymmetric relationship between fund returns and flows.[16] To allow for different flow sensitivities across various levels of performance, three fractional performance variables ($LowPerf_{i,t}$, $MidPerf_{i,t}$ and $HighPerf_{i,t}$) are constructed by first calculating the percentile return rank, $rank_{i,t}$, for each fund of month *t* by sorting the sample in ascending order according to fund return in the previous month then dividing by the total number of funds in the sample (i.e., the fund with the highest return each month will have a rank

[16] See, for example Ippolito (1992), Gruber (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998) and Huang, Wei, and Yan (2007) on asymmetric fund flow-return relationships.

value of one). 33%-33%-33% breakpoints are used to then calculate performance terciles from the percentile ranks, such that:

$$rank_{i,t} = LowPerf_{i,t} + MidPerf_{i,t} + HighPerf_{i,t},$$

where,

$$LowPerf_{i,t} = \begin{cases} rank_{i,t}, & if\ rank_{i,t} < 0.33 \\ 0.33, & if\ rank_{i,t} \geq 0.33\ , \end{cases}$$

$$MidPerf_{i,t} = \begin{cases} rank_{i,t} - LowPerf_{i,t}, & if\ \ rank_{i,t} < 0.66 \\ 0.33, & if\ rank_{i,t} \geq 0.66, \end{cases}$$

$$HighPerf_{i,t} = \begin{cases} 0\ , & if\ \ rank_{i,t} < 0.66 \\ rank_{i,t} - 0.66, & if\ rank_{i,t} \geq 0.66. \end{cases} \tag{2.6}$$

2.4.c Fund Benchmark Data

The primary prospectus benchmark data for a sample of 784 Australian equity funds used throughout this chapter are sourced from the Morningstar Direct database, which contains benchmark data on 461 of these funds. For the remaining 304 funds that do not report a benchmark to Morningstar, 157 are hand collected from product disclosure statements or from the fund company websites. The remaining 147 funds whose benchmarks are unable to be retrieved are eliminated from the sample.[17] The sample of funds is further limited to those that are benchmarked against the S&P/ASX 50, S&P/ASX 100, S&P/ASX 200, S&P/ASX 200 Industrials, S&P/ASX 300, S&P/ASX 300 Industrial, S&P/ASX 300 Resources, S&P/ASX All Ordinaries, S&P/ASX Small Resources and S&P/ASX Small Ordinaries. The funds benchmarked to these indices account for approximately 97 percent of the sample. All passively-

[17] Those funds whose benchmarks are unable to be retrieved predominantly belonged to the same fund company. The difference in mean returns between the funds with and without benchmarks is 0.073 percent per month. This difference is insignificant (t-statistic = 1.12).

managed (index) funds and funds with less than 24 months of return observations are eliminated from the sample. This reduces the final sample size to 460 funds.

Table 2.1: Australian Equity Fund Sample Size

This table reports the sample size of actively managed Australian equity funds, refined from the aggregate sample of Australian domiciled funds contained in the Morningstar Direct database from January 2000 to December 2011.

	No. of Funds
Managed Funds domiciled in Australia	3,338
Equity Funds Domiciled in Australia	1,730
Australian Equity Funds	784
Actively Managed Australian Equity funds	765
Equity funds with benchmarks supplied by Morningstar	316
Funds with handed collected Benchmarks	+157
Funds with insufficient return observations	-13
Total Sample Size	**460**

2.4.d Passive Investable Style Index Construction

Six investable passive value/growth-size style indices are constructed using monthly return data from the largest 300 stocks according to their one month-lagged market capitalisation. These stocks are sorted according to their one-month lagged book-to-market ratios, with the top 30 percent (90 stocks) being classified as value stocks and the bottom 30 percent as 'growth' stocks.[18] The *Growth* index is constructed from the monthly value-weighted returns of all growth stocks. The *Value* index is constructed from the monthly value-weighted returns of stocks that are considered value stocks. The *Large-Value* index is constructed from the monthly value-weighted returns of stocks that are considered both a value stock and whose one-month lagged market capitalisation is also amongst the top 50 percent (150) of the *Top*

[18] As a robustness test when constructing the value and growth style indices, a top 50 percent and bottom 50 percent cut off is used when sorting stocks by their book-to-market ratios into Value and Growth categories, respectively. Descriptive statistics of these indices are reported in Table A.1 in Appendix A. The results obtained from the empirical analysis when using these alternative style indices are qualitatively similar.

300 stocks in the Australian equity market by market capitalisation. The *Large-Growth* index is constructed from the monthly value-weighted returns of stocks that are considered both a growth stock and whose one-month lagged market capitalisation is amongst the top 50 percent of stocks contained in the 300 by market capitalisation. The *Small-Value* index is constructed from the monthly value-weighted returns of stocks that are considered both a value stock and whose one-month lagged market capitalisation falls within in the bottom 50 percent of the *Top 300* stocks by capitalisation. Lastly, the *Small-Growth* index is constructed from the monthly value-weighted returns of stocks that are considered both a growth stock and whose one-month lagged market capitalisation is also amongst the bottom 50 percent of the largest 300 stocks in the Australian market by capitalisation. Two additional passive style indices are also constructed for this chapter, these being a *Large-Core* index and *Small-Core* index. The *Large-Core* index comprises the remaining stocks that are included in the largest 150 stock by market capitalisation, but not included in either of the *Large-Value* or *Large-Growth* index. Similarly, the *Small-core* index constitutes the remaining stocks from the lowest 150 stocks by market capitalisation of the *Top 300* that is not included in the *Small-Value* or *Small-Growth* indices. These two indices are also value-weighted from one-month lagged market capitalisation values and constructing using the same approach as the other style indices.[19, 20]

Despite evidence suggesting the presence of momentum in the Australian market [see, for example Demir, *et al.* (2004), Durand, Limkriangkrai, and Smith

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[19] The style indices are constructed in a value-weighted manner instead of equal-weighted as this is the standard approach used by the major publicly available indices, such as Standard and Poors and NASDAQ, as well as by all U.S. style indices constructed by Russell Investments.

[20] Correlation coefficients of the monthly returns between each of the eight passively-constructed Australian size-value/growth equity style indices as well as for each of the S&P/ASX accumulation indices that serve as benchmarks are reported in Table A.2 in Appendix A.

(2006), Gaunt and Gray (2003), Hurn and Pavlov (2003) and Brailsford and O'Brien (2008)], indices based on this characteristic are not constructed within this chapter. This is due to momentum not being prominently recognised as an investment style within the Australian funds market as of yet. This is evident as observation into the investment objectives of Australian equity funds' PDS's and prospectuses' show that the style dimensions of funds almost entirely only consist of size and/or value-growth classifications. Furthermore, Morningstar currently only consider size and value-growth as the only two dimensions in their style box classifications. Similarly within the U.S. market, the prominent publicly available style indices are only constructed on size and value/growth characteristics despite evidence of momentum also being observed in U.S. stock returns. Subsequently, prevalent literature on style benchmarking in the U.S., such as Sensoy (2009), only use size and value/growth dimensions as style characteristics.

2.5 Methodology

2.5.a Testing for Benchmark Matching

Fund level active management is measured using the tracking error volatility (*TE*) of a fund's returns from its benchmark index and is used to explain how well a benchmark reflects the passive style returns of a fund (Cremers and Petajisto, 2009). The lower the *TE* of a fund, the more capable its benchmark is at capturing its time-series variations in returns. A passively managed fund for example, would have a *TE* close to zero. The most appropriate benchmark for a fund is therefore considered the index that produces the lowest tracking error volatility, as calculated below:

$$TE_{i,b} = \sqrt{\frac{\sum_{t=1}^{N}\left(r_{i,t}-r_{b,t}\right)^2}{N-1}}, \quad b = 1,2,\dots,K, \qquad (2.7)$$

where $TE_{i,b}$ is the tracking error volatility of fund *i* relative to index *b*. $r_{i,t}$ is the return of fund *i* at time *t* and $r_{b,t}$ is the return of index *b* at time *i*. *K* is the number of passive indices used to test for fund *i*'s best-suited index. For this study, 24 passive indices are used to test for a fund best-suited benchmark index, these include; the S&P/ASX 20, S&P/ASX 50, S&P/ASX 100, S&P/ASX 100 Industrials, S&P/ASX 100 Resources, S&P/ASX 200, S&P/ASX 200 Resources, S&P/ASX 200 Industrials, S&P/ASX 300, S&P/ASX 300 Resources, S&P/ASX 300 Industrials, S&P/ASX All Ordinaries, S&P/ASX Small Ordinaries, S&P/ASX Small Resources, S&P/ASX Small Industrials and the S&P/ASX MidCap 50, and the eight passive investable style indices (Value, Growth, Large-Value, Large-Growth, Small-Value, Small-Growth, Small-Core and Large-Core) that are described in section 2.4.d.[21,22] A fund's *best-suited* benchmark is identified from the index that produces the lowest tracking error volatility:

$$TE_{i,best} = min\left[TE_{i,1}, \dots, TE_{i,K}\right], \qquad (2.8)$$

where $TE_{i,best}$ is the tracking error volatility of fund *i* measured relative to its '*best-suited'* benchmark, *best*.[23] A Levene (1960) test for multiple population variances

[21] For further information on the S&P/ASX indices used in this chapter, please see http://www.asx.com.au/products/indices.htm.
[22] The six alternative value/growth style indices, constructed using an alternative method (described in footnote 16) are used as a robustness measure when identifying a funds best-suited index. The results are identical to those that are found when using the original passive value/growth-constructed style indices.
[23] It is possible that funds will change their benchmarks over time (howbeit unlikely given that managers will typically introduce a new fund instead). Nevertheless, given that time-series benchmark data is not accessible, a limitation to the analysis undertaken in this chapter is presented. Whilst time-series analysis may still have been implemented (in terms of estimating *TE* across rolling windows), this approach may incorrectly identify a fund as possessing a mismatched benchmark over certain periods of time. This issue is raised in Wermers (2012), whereby fund managers may temporarily deviate their portfolios away from their stated investment styles over the short run to capture the expected outperformance of a particular style, then an alternative style over the subsequent period. Yet, over extended periods of time these deviations, on average, may balance out such that they correctly correspond to the reported style of the fund. As such, Wermers (2012) stresses the importance of differentiate between, what they refer to as, 'static' and 'dynamic' factor allocation. Subsequently, to ensure that the static factor allocation of a fund is captured, and is not biased by its dynamic allocation, this chapter refrains from estimating tracking-error volatilities across a time-series when identifying a fund's appropriate benchmark.

being equal (homogeneity of variance) is then applied to determine if the tracking error volatility of fund i (when benchmarked against its *best-suited* index) is significantly lower than the *TE* of fund i when benchmarked against its self-reported index[24].

Suppose a variable Y, with sample size N, divided into k subgroups, where N_i is the sample size of the i-th subgroup, the Levene (1960) test statistic, W, is defined as:

$$W = \frac{(N-k)}{(k-1)} \frac{\sum_{i=1}^{k} N_i(\bar{Z}_{i.} - \bar{Z}_{..})^2}{\sum_{i=1}^{k} \sum_{j=1}^{N_i} (\bar{Z}_{i,j} - \bar{Z}_{i.})^2},$$

where,

$$Z_{i,j} = |Y_{i,j} - \bar{Y}_i|.$$

$\bar{Y}_i$ is the mean of the *i-th* sub-group. $\bar{Z}_{i.}$ is the group mean of $\bar{Z}_{i,j}$ and $\bar{Z}_{..}$ is the overall mean of the $Z_{i,j}$.[25] For the purpose of this analysis, k is set equal to two, where the first sub-group ($i = 1$) is the self-reported benchmark-excess return series of a fund and the second sub-group ($i = 2$) is the benchmark-excess return series of the same fund when benchmarked against its *best-suited* index. N_i is the number of monthly benchmark-excess return observations for each subgroup, i. The null hypothesis tests whether the *TE* of a fund when benchmarked against its self-reported index is equal to the *TE* when benchmarked against its best-suited index:

$$\text{H}_0: \quad TE_{i,selfreported} = TE_{i,best},$$

$$\text{H}_1: \quad TE_{i,selfreported} > TE_{i,best}.$$

[24] Fong, Gallagher, and Lee (2008) similarly rely on the Levene (1960) test to identify differences in the tracking-error volatilities between funds and multiple benchmarks.

[25] Variations of the Levene (1960) test use median or trimmed mean values of the *i-th* subgroup when defining $\bar{Y}_i$ depending on the shape of the distribution. This chapter applies mean values which is considered most appropriate when testing for homogeneity of variance of Gaussian distributions [sourced from *'Engineering Statistics Handbook'*: http://www.itl.nist.gov/div898/handbook/eda/section3/eda35a.htm].

A fund is considered mismatched from its self-reported benchmark if the null hypothesis from the Levene (1960) test is rejected,

$$W > F_{\alpha,k-1,N-k},$$

where $F_{\alpha,k-1,N-k}$ is the upper critical value from an F distribution with $k-1$ and $N-k$ degrees of freedom at a significance level for α. Values of α equal to 0.10, 0.05 and 0.001 are used in this chapter when testing if funds are better matched to alternative benchmark indices[26].

2.5.b Four-Factor Style Characteristics Analysis

There are various methods that can be used to accurately determine a managed fund's investment style without having to rely on what is stated in its product disclosure statement. A returns-based approach is therefore applied to identify whether the style characteristics of Australian equity funds are adequately captured by their benchmark indices. The size and value/growth factors of Fama and French (1992), along with the market factor from the traditional CAPM, are said to explain a major proportion of the time-series variations in portfolio returns. Chan, *et al.* (2002) argue that these two factors can serve as useful characteristics when classifying the investment styles of portfolios. Chan, *et al.* (2002) further show that a model based on these factors (in addition to the market factor) will do just as well as more complicated high-dimensional models when determining fund styles. Carhart (1997) in turn, shows that a stock-price momentum factor, developed in Jegadeesh and Titman (1993), along with

[26] Despite a potential "philosophical" issue surrounding the self-selection of fund benchmarks reported *ex ante*, this study recognises a fund's "appropriate" benchmarks on an *ex post* basis. The rationale behind this approach is that: investors should be "getting what they paid for". Even if a fund significantly outperformed its peers, as a result of following a style different to that reported by its benchmark, this fund, ex ante, is not what the investor expected. Hence it is appropriate to identify a fund's correct benchmark on an *ex post* basis.

the three Fama and French (1992) factors do a better job of explaining time-series variations in stock returns than the three factor model. Whilst Chan, *et al.* (2002) find that the majority of U.S. mutual funds tend to closely mimic the styles of broad market indices such as the S&P 500 index, the funds that do deviate their style from the market index tend to lean towards growth stocks and momentum stocks. Applying these three factors (size, value/growth and momentum) along with the market factor, as style characteristics, a 'benchmark-excess' Carhart (1997) four-factor style regression approach is used to determine how the investment styles of funds compare to the styles of their self-reported benchmarks. This is achieved by estimating the following regression from the equation:

$$r_{i,t} - r_{b,i,t} = \alpha_{i-b} + \beta_{1,i-b}\left(R_{M,t} - R_{f,t}\right) + \beta_{2,i-b}SMB_t + \beta_{3,i-b}HML_t + \beta_{4,i-b}UMD_t + \varepsilon_{i-b,t}\,, \tag{2.9}$$

where $R_{i,t} - R_{b,i,t}$ is the excess return of fund *i* above its self-reported benchmark at time *t*, $R_{M,t} - R_{f,t}$, SMB_t, HML_t and UMD_t are the standard Carhart (1997) four factors, α_{i-b} is the intercept term, and $\varepsilon_{i-b,t}$ is the random error term at time *t.* The factor loadings, $\beta_{1,i-b}$ ... $\beta_{4,i-b}$, represent the differences between fund *i* and fund *i*'s benchmark's average exposure towards each of the respected style factors across the sample period and are estimated from the difference in the loadings from the two Carhart (1997) regressions, estimated from the following equations:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i}\left(R_{M,t} - r_{f,t}\right) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}UMD_t + \varepsilon_{i,t}, \tag{2.10}$$

and

$$r_{bench,i,t} - r_{f,t} = \alpha_b + \beta_{1,b}\left(R_{M,t} - r_{f,t}\right) + \beta_{2,b}SMB_t + \beta_{3,b}HML_t + \beta_{4,b}UMD_t + \varepsilon_{b,t}\ , \tag{2.11}$$

such that,

$$\alpha_{i-b} = \alpha_{1,i} - \alpha_{1,b},$$
$$\beta_{1,i-b} = \beta_{1,i} - \beta_{1,b},$$
$$\beta_{2,i-b} = \beta_{1,i} - \beta_{1,b},$$
$$\beta_{3,i-b} = \beta_{1,i} - \beta_{1,b}\ \text{, and}$$
$$\beta_{4,i-b} = \beta_{1,i} - \beta_{1,b}. \tag{2.12}$$

The factor loadings, $\beta_{1,i\text{-}b}$, $\beta_{2,i\text{-}b}$, $\beta_{3,i\text{-}b}$ *and* $\beta_{4,i\text{-}b}$ are used to identify the deviation of fund *i* from its benchmark's average systematic risk exposure towards; excess market sensitivity, size, value/growth and momentum style characteristics, respectively. The statistical significance of these factor loadings determine how well a fund's style characteristics are able to be captured by its benchmark indices. The intercept term, α_{i-b}, represents the benchmark-excess abnormal return of fund *i*.

2.5.c Characteristics of Mismatched Funds

To determine the effect that specific fund characteristics have on the probability of a manager reporting a mismatched benchmark, probit regressions are estimated from the following model:

$$Mismatch_i = \alpha_{i,t} + \beta_{1,i}Wholesale_i + \beta_{2,i}Size_{i,t} + \beta_{3,i}Age_{i,t} + \beta_{4,i}Expense\ Ratio_i + \beta_{5,i}X_i + \varepsilon_{i,t}\ , \tag{2.13}$$

where $Mismatch_i$ is a dummy variable that takes on a value of one if fund i is considered mismatched from its self-reported benchmark, or zero otherwise. Funds are considered mismatched at ten, five and one percent significant levels as determined from the Levene (1960) for homogeneity of variance from fund tracking error volatilities, described in section 2.5.a. The explanatory variables include: a wholesale fund dummy, $Wholesale_i$, which takes on a value of one for funds that are classified by Morningstar as being a wholesale fund, or zero for a retail fund. The natural log of a fund's size measured from its assets under management $Size_{i,t}$, the natural log of the number of months since a fund's inception date, $Age_{i,t}$, fund expense ratio, $Expense\ Ratio$, and a vector of style dummies, X_i, that include; Large-Value, Mid/small-Value, Large-Growth, Mid/small-Growth, Large-Blend, Mid/small-Blend and 'Other' investment styles (with Large-Value style being the reference variable) which take on values of one if fund *i* reports the respective style, or zero otherwise.

2.5.d Performance Regression Analysis

To investigate the effect that benchmark appropriateness has on fund performance, several multivariate performance regression models are estimated using monthly fund-level panel data over the period from 2000 to 2011. Specifically, the set of regressions identify whether funds with mismatched benchmarks differ in performance from funds with 'appropriately-matched' benchmarks after controlling for a range of characteristics that affect fund performance. The regression model is:

$$Perf_{m,i,t} = \alpha_i + \beta_{1,m}Mismatch_i + \beta_{2,m}Wholesale_i + \beta_{3,m}Mismatch_i * Wholesale_i + \beta_{5,m}Z_{i,t} + v_t + s_t + \varepsilon_{m,i,t}, \tag{2.14}$$

where $Perf_{m,i,t}$ is the performance of fund *i* across time *t* measured using metric *m*, which include; fund excess-return, $r_{i.t} - r_f$, self-reported benchmark-excess return, r_i - r_b, *CAPM alpha* and *Carhart alpha*. The explanatory variable of interest is the benchmark mismatch dummy, $Mismatch_i$, as previously defined. The regressions also include a vector of control variables, $Z_{i,t}$, comprising; fund *Size*, fund *Age*, return *Volatility*, fund *flows*, and net flows into each investment style category. All control variables are lagged by one-month and all regressions are estimated with style-fixed effects, s_t, and time-fixed effects, v_t.

2.5.d.i Justification of the Use of Factor Models to Evaluate Performance

The existence of the size and value anomaly, along with momentum, and the application of the Fama and French (1993) and Carhart (1997) models have been well documented using U.S. and international data. There is, however, considerably less examination of this topic across the Australian market. Consequently, conflicts over the validity of these models still remain due to the unconsolidated results that have been produced. Brown, Keim, Kleidon, and Marsh (1983), Beedles, Dodd, and Officer (1988), Gaunt, Gray, and McIvor (2000) and Durand, Juricev, and Smith (2007) find results consistent with the U.S. on the existence of a size premium in Australia, whilst Gaunt (2004), Gharghori, Chan, and Faff (2006) and Halliwell, Heaney, and Sawicki (1999) show evidence of a value premium in Australian stock returns. The existence of a momentum anomaly however is less clear. Bird, Chin, and McCrae (1983) argue that superannuation funds do not exhibit performance persistence. These results are supported by Bilson, Frino, and Heaney (2005), who fail to find persistence in the performance of superannuation funds over 3 year periods after adjusting for risk. Hallahan (1999), however, argue that persistence only exists in fixed-interest funds, but not in any other type of fund. Sawicki and Ong (2000) are similarly unable to show evidence of long-term (three year) persistence whereas Humphrey and O'Brien (2010) do not to find persistence for any funds over any length of time once size, value and momentum factor are taken into account. Refuting these findings of the absence of performance persistence in the Australian market are the findings of Demir, *et al.*

(2004), Durand, *et al.* (2006), Gaunt and Gray (2003), Hurn and Pavlov (2003) and Brailsford and O'Brien (2008), who argue that stock return persistence does exist and is strongest across six months horizons. These findings suggest that similar to the U.S, these variables may proxy for systematic risk.

The findings on the existence of anomalies in Australia has subsequently bought about tests of the validity of the Fama and French (1993) three factor model. Whilst earlier studies provide support for the CAPM (see, for example Ball, Brown, and Officer (1976), Halliwell, *et al.* (1999), and Durack, Durand, and Maller (2004) show that the Fama and French (1993) model provides marginal improvement over the CAPM in explaining the cross-section of Australian stock returns. However, they argue that this improvement is primarily due to the SMB factor, as the HML factor is insignificant in explaining cross-sectional returns. Faff (2001), Faff (2004) and Gaunt (2004) produce similar findings, in that the Fama and French (1993) model provides an improvement over the CAPM, yet are unable to show that HML is a priced factor. Faff (2001) and Faff (2004) also show that the sign on the SMB factor is significantly negative, instead of the expected positive, as in U.S. studies. However, he attributes this result to a reversal in the size premium over recent years. Whilst Gharghori, *et al.* (2006) also argue that the Fama and French (1993) three-factor model provides increased explanatory power over the CAPM, they conversely show that this is primarily due to the HML factor and that the explanatory power of the SMB factor is inconclusive. Durand, *et al.* (2006) and O’Brien (2007) provide the most convincing argument for the Fama and French (1993) model, showing that both SMB and HML factors are important in explaining the cross-section of portfolio returns in Australia and that the model provides significant improvement over the CAPM. Despite conflicting results concerning the validity of the use of these factor models in Australia, prevalent fund performance literature has accepted, and applied, the Carhart (1997) four-factor model when evaluating the performance of Australian funds [see, for example Capocci and Hübner (2004), Bauer, Otten, and Rad (2006), Ainsworth, *et al.* (2008), and Ferreira, Keswani, Miguel, and Ramos (2012)].

2.5.e Flow Regression Analysis

To examine the effect that having a mismatched benchmark has on fund flows, flow-performance regressions are estimated using panel data from the equation:

$$Flow_{i,t} = \alpha_i + \beta_1 Mismatch_i + \beta_2 Wholesale_{i,t-1} + \beta_3 Mismatch_i * Wholesale_{i,} + \ \beta_1 \, R_{i,t-1} + X_{i,t-1} + v_t + s_t + \varepsilon_{i,t}. \qquad (2.15)$$

The explanatory variable of interest is the dummy variable that identifies fund *i* as having a mismatched benchmark, $Mismatch_{i,t}$. $Flow_{i,t}$ is the net flow of assets under management of fund *i* at time *t*. This dummy is interacted with the wholesale dummy, $Mismatch_i * Wholesale_i$. The regression also includes a vector of controls, $X_{i,t}$, comprising; fund *Size*, *Age*, return *Volatility*, *Lagged Flow*, and the *Net Style Category Flows*.[27] All control variables are lagged one-month and all regressions are estimated with time-fixed effects, v_t, and style-fixed effects, s_t.

Whilst estimating panel regressions using lagged independent variables may give rise to estimation bias, or omitted-variable bias, as discussed in Flannery and Hankins (2013), I maintain to estimate flow-performance regressions using lagged independence variables so as to eliminate endogeneity resulting from potential look-ahead bias. This approach to estimating panel regressions appears to be the standard

[27] These control variable are commonly used throughout prevalent literature that examine the flow-performance relationship of mutual funds [see, for example Chevalier and Ellison (1997), Sirri and Tufano (1998) and Barber, *et al.* (2005)].

practise adopted by the prevalent fund flow-performance literature [see, for example Chevalier and Ellison (1997), Sirri and Tufano (1998), Del Guercio and Tkac (2002), Barber, *et al.* (2005) and Cooper, Gulen, and Rau (2005)].

Linear piecewise flow-performance regressions, following Sirri and Tufano (1998), are additionally estimated in this chapter. These regressions allow for different flow sensitivities to fund mining exposure across varying levels of performance and apply three fractional performance variables (*Low Perf*$_{i,t}$, *Mid Perf*$_{i,t}$ *and High Perf*$_{i,t}$) based on the percentile rank of the one-month lagged raw returns from the sample of funds.[28] The asymmetric relationship shown to exist between fund performance and flows can therefore be captured from these piecewise regressions. The full regression model is:

$$Flow_{i,t} = \alpha_i + \beta_1 MinExp_{i,t-1} + \beta_2 Wsale_{i,t-1} + \beta_3 LowPerf_{i,t-1} + \beta_4 MidPerf_{i,t-1} + \beta_5 HighPerf_{i,t-1} + \beta_6 X_{i,t-1} + s_i + v_t + \varepsilon_{i,t}\ , \quad (2.16)$$

where $LowPerf_{i,t-1}$, $MidPerf_{i,t-1}$ and $HighPerf_{i,t-1}$ are fractional performance variables, defined as the percentile rank of fund *i's* raw returns relative to the entire sample of funds for time *t-1* for low-, middle- and high-performing funds, respectively. All other variables are as previously defined.

2.6 Results

This section presents and discusses the empirical findings from this chapter. Descriptive statistics of the key variables and benchmark indices used in the analysis are first reported in section 2.6.a. Section 2.6.b examines the performance of indices that are self-reported as benchmarks as well as the self-constructed style indices. This

[28] Construction of the three fractional performance variables is described in detail in section 2.4.b.

section then determines whether funds are appropriately style-matched or mismatched from their self-reported benchmark indices. Section 2.2.c investigates the characteristics of funds that report mismatched benchmarks and identifies the indices that these mismatched funds are better suited to. The findings from this section assist in identifying whether benchmarking regulation should be made more stringent and whether passive style indices should be made publicly available for benchmarking. The performance of funds with mismatched benchmarks and correctly-matched benchmarks are then compared in section 2.6.d. The final component of the analysis, presented in section 2.5.e, examines the effect that benchmark mismatching has on fund flows, and subsequently identifies if managers have an incentive to self-report inappropriate benchmarks.

2.6.a Descriptive Statistics

Descriptive statistics are presented in Table 2.2 for the key variables used throughout the analysis of this chapter. The frequency of funds benchmarked to each index along with the investment styles of these funds are reported in Table 2.3. Table 2.4 reports returns statistics for the eight passively constructed investable style indices as well as for the indices that are reported as benchmarks by the funds contained in the study sample.

Table 2.2: Descriptive Statistics

Descriptive statistics for all variables used in the analysis throughout Chapter 2 are reported in this table. Fund return, benchmark return, risk-free return, market return, *SMB*, *HML*, *UMD*, CAPM alpha Carhart alpha, return volatility and net style return are all expressed as monthly percentages. Fund age is measured as the natural log of the number of months since a fund's inception date. Fund size is measured as the natural log of to the dollar value of assets under management. Fund flows are measured as a percentage of fund assets under management. All data is measured at a monthly frequency from January 2000 to December 2011.

	Mean	**Min**	**Median**	**Max**	**St. Dev.**	**Skewness**	**Kurtosis**
Fund Return	0.799	-39.290	1.830	27.700	4.945	-1.017	5.690
Benchmark Return	0.023	-26.406	-0.037	20.253	1.824	-0.344	16.899
Risk-free Return	0.424	0.217	0.433	0.594	0.098	-0.273	2.386
Market return	0.690	-13.113	1.755	7.603	4.114	-1.011	3.999
SMB	0.697	-20.526	0.530	15.176	5.548	0.058	3.081
HML	0.215	-8.822	0.747	5.939	2.945	-0.597	3.023
UMD	0.326	-12.483	0.234	9.337	2.541	-0.663	5.852
CAPM Alpha	0.020	-2.066	-0.028	4.038	0.422	1.069	9.270
Carhart Alpha	0.047	-2.249	0.018	3.114	0.392	0.512	7.125
Fund Size	18.248	7.626	18.397	23.107	1.923	-0.260	3.033
Fund Age	4.073	0.000	4.234	6.363	0.971	-0.843	3.885
Return Volatility	4.030	1.108	3.731	17.016	1.853	1.611	7.212
Net Style Return	-0.325	-5.552	-0.261	5.988	1.053	-0.096	6.448
Fund Flow	0.506	-5.571	-0.092	9.765	3.462	0.939	4.102
Expense Ratio	1.559	0.000	1.310	5.640	0.792	1.127	5.065

Table 2.3: Fund Investment Styles and Benchmark Indices

The frequency of Australian actively managed equity funds contained in the study sample used throughout this chapter that subscribe to each investment style objective and benchmarked against each of the ten respected S&P/ASX accumulation index is reported in this table.

	Large Value	Mid/Small Value	Large Growth	Mid/Small Growth	Large Blend	Mid/Small Blend	Other	Total
S&P/ASX 300	36	2	30	1	105	1	15	190
S&P/ASX 200	20	0	29	0	76	1	15	141
S&P/ASX Small Ordinaries	0	5	0	26	0	43	0	74
S&P/ASX 100	0	0	2	13	0	0	12	27
S&P/ASX 300 Industrials	9	0	1	0	0	0	0	10
S&P/ASX All Ordinaries	2	1	1	1	3	1	1	10
S&P/ASX 50	0	3	0	0	0	0	2	5
S&P/ASX 200 Industrials	1	0	0	0	0	0	0	1
S&P/ASX 300 Resources	0	0	0	0	0	0	1	1
S&P/ASX Small Resources	0	0	0	0	0	0	1	1
Total	68	11	63	41	184	46	47	460

A large portion of funds from the sample (40 percent) are shown in Table 2.3 to possess a Large-Blend investment style. Almost all of these Large-blend funds are benchmarked against either the S&P/ASX 300 or the S&P/ASX 200 index. This result is as expected given that these two indices are considered broad market-based indices. As such, these indices serve as the two most popular benchmarks, from which 41 percent and 31 percent of the 460 funds within the sample are benchmarked against, respectively. A substantial portion of funds that are benchmarked against these two broad-market indices however are classified as having either a value or growth investment style, suggesting that if these funds possess such style, then not all can be appropriately style-matched to their benchmarks. Table 2.3 additionally shows that a large proportion of the total sample of funds (about 40 percent) is classified as having some form of value or growth style. This finding is interesting given that none of their reported benchmark indices are considered to be of value or growth orientation. This result further supports the presumption that not all Australian equity funds will be appropriately style-matched to their benchmark indices. The analysis that follows seeks to identify if such fund benchmarks are in fact style-mismatched.

Table 2.4 Index Return Descriptive Statistics

Descriptive statistics for the monthly returns of the S&P/ASX accumulation indices that serve as benchmarks for the Australian equity funds contained in the sample are reported in the following table along with six size/value-growth investable style indices. The sample period is from January 2000 to December 2011.

Index	Mean	Min	Median	Max	St. Dev.	Skewness	Kurtosis
S&P/ASX 100	0.746	-11.624	1.441	8.018	3.773	-0.753	0.605
S&P/ASX 200	0.738	-12.605	1.563	8.007	3.83	-0.838	0.916
S&P/ASX 200 Industrials	0.531	-11.73	1.165	9.345	3.824	-0.674	0.856
S&P/ASX 300	0.741	-12.884	1.625	8.07	3.859	-0.856	0.992
S&P/ASX 300 Industrial	0.525	-11.899	1.044	9.38	3.846	-0.688	0.917
S&P/ASX 300 Resources	1.68	-20.626	1.832	15.306	5.947	-0.649	1.430
S&P/ASX 50	0.72	-10.344	1.511	8.128	3.774	-0.637	0.211
S&P/ASX All Ordinaries	0.749	-13.921	1.618	8.051	3.92	-0.971	1.391
S&P/ASX Small Ordinaries	0.758	-24.811	1.753	13.519	5.421	-1.301	3.687
S&P/ASX Small Resources	1.981	-31.756	2.222	16.684	7.537	-0.93	2.776
Value	1.695	-21.103	2.384	18.563	5.274	-0.917	3.69
Growth	0.468	-17.277	1.137	8.216	4.402	-1.191	2.418
Large Value	1.754	-35.134	2.293	21.256	7.945	-0.642	2.806
Large Growth	0.287	-15.204	1.193	13.055	4.86	-0.534	1.298
Large Core	0.977	-16.269	1.826	14.724	4.653	-0.482	1.174
Small Value	1.918	-22.705	2.637	21.136	5.754	-0.717	3.539
Small Growth	0.011	-28.431	0.637	16.105	6.533	-0.901	2.814
Small Core	1.128	-28.336	1.877	14.493	5.341	-1.602	7.150

2.6.b Benchmark Performance

For a fund manager to be provided with an incentive to report an inappropriate benchmark, the performance difference between possible benchmarks must be significant. The performance of funds' self-reported benchmark indices are therefore analysed in this section, along with the performance of the style-constructed indices, to identify potential advantages that benchmark mismatching can generate. The performance of these indices is examined in Table 2.5, Table 2.6 and Table 2.7 using raw and risk adjusted returns (Carhart alpha) to identify if holding passive portfolios can serve as an attractive investment strategy if benchmarked against an alternative index.

Table 2.5: Index Return Rankings

The difference between the mean monthly raw returns for each of the S&P/ASX benchmark indices contained in the study sample (as well as for eight investable Australian style-constructed size/value-growth indices) and the S&P/ASX 300 accumulation index are reported. The Benchmarks are sorted from highest to lowest in terms of their return difference and the sample period is from January 2000 to December 2011. T-statistics are displayed in parentheses and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Rank	Index	Mean Return	Return Difference from S&P/ASX 300
1	S&P/ASX Small Resources	1.981	1.24*** (2.644)
2	Small Value	1.918	1.178*** (3.911)
3	Large Value	1.754	1.024* (1.724)
4	Value	1.695	0.955*** (3.561)
5	S&P/ASX 300 Resources	1.680	0.94*** (2.73)
6	Small Core	1.128	0.388 (1.472)
7	Large Core	0.977	0.237 (1.106)
8	S&P/ASX Small Ordinaries	0.758	0.0175 (0.073)
9	S&P/ASX All Ordinaries	0.749	0.008 (0.323)
10	S&P/ASX 100	0.746	0.006 (0.246)
11	S&P/ASX 200	0.738	-0.002 (-0.312)
12	S&P/ASX 50	0.720	-0.020 (-0.44)
13	S&P/ASX 200 Industrials	0.531	-0.209* (-1.854)
14	S&P/ASX 300 Industrials	0.525	-0.216* (-1.931)
15	Growth	0.468	-0.272 (-1.203)
16	Large Growth	0.287	-0.454 (-1.453)
17	Small Growth	0.011	-0.73* (-1.862)

Mean monthly returns for four of the nine S&P/ASX indices and four of the eight style indices are reported in Table 2.5 to be significantly differ from the S&P/ASX 300. Index returns are compared to the S&P/ASX 300 as this is the most common benchmark used by Australian equity funds. The best performing index, the S&P/ASX Small Resources, is shown to significantly outperform the S&P/ASX 300 at the one percent level (t-stat = 2.644) by an average of 1.24 percent per month.[29] This suggests that a passive *Small-Resources* fund style exposures that are benchmarked against the S&P/ASX 300, will achieve a benchmark-excess return of 1.24 percent per month greater than if they were appropriately benchmarked. On the other hand, if funds with styles that suit the S&P/ASX 300 Industrials are benchmarked against the S&P/ASX 300, benchmark-excess return would be significantly lower, by 0.216 percent per month relative to its 'correct' benchmark-excess return. These results demonstrate that benchmark-excess fund returns can vary substantially based on the selection of the benchmark.

Investigating the return differences of the style-constructed indices shows that benchmark-excess performance can be greatly affected from the passive style exposures of a fund. Following a passive value style, whether it is Value, Large-Value or Small-Value, for example, is shown in Table 2.5 to significantly outperform the S&P/ASX 300. This result is further pronounced if funds were to be benchmarked against a passive growth benchmark given the underperformance of these indices relative to the S&P/ASX 300, as shown in Table 2.5. The returns of these indices conform with the well reported value premium, and to a lesser extent, the size

[29] The outperformance of the S&P/ASX Industrials indices is likely a result of the mining boom, for which this index is largely constituted of mining-related firms.

premium.[30] An alternative strategy would be to hold a broad-market passive portfolio yet be advertised as possessing an active strategy and be benchmarked against a passive growth index. This in turn would result in significantly positive mean benchmark-adjusted returns. These findings subsequently show that index selection can have a significant effect on the benchmark-excess return of a fund and if selected correctly can pose significant advantages, however if the incorrect index is reported, the effect on fund performance can be detrimental.

The differences in returns of these indices are shown in Figure 2.1 below which illustrate the differences between the S&P/ASX Small Resources and the S&P/ASX 300 Resources to be substantially greater than all other S&P/ASX indices across the sample period from January 2000 to December 2011. Passive style returns are illustrated below in Figure 2.2 for the style-constructed indices, where substantial differences between the three value indices relative to the three growth indices are observed across most of the sample period.[31]

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[30] See, for example Fama and French (1992), Davis, *et al.* (2000), Fama and French (2006), O'Brien, *et al.* (2010) and Morey and O'Neal (2006) for a discussion on the value premium and Banz (1981), Roll (1983), Gaunt (2004) and O'Brien, *et al.* (2010) on the size premium.

[31] Index prices for the six 'alternative' passive style-constructed indices, used in the robustness analysis, are displayed in Figure A.1 of Appendix A. Results are similar in that the value indices largely outperform the growth indices over the duration of the sample period.

Figure 2.1: S&P/ASX Index Prices

Monthly prices from January 2000 to December 2011 for the S&P/ASX Accumulation indices that serve as benchmarks for the sample of Australian actively managed equity funds used throughout this chapter are displayed in the following chart. Each index has a base value of 100 points at the beginning of the period.

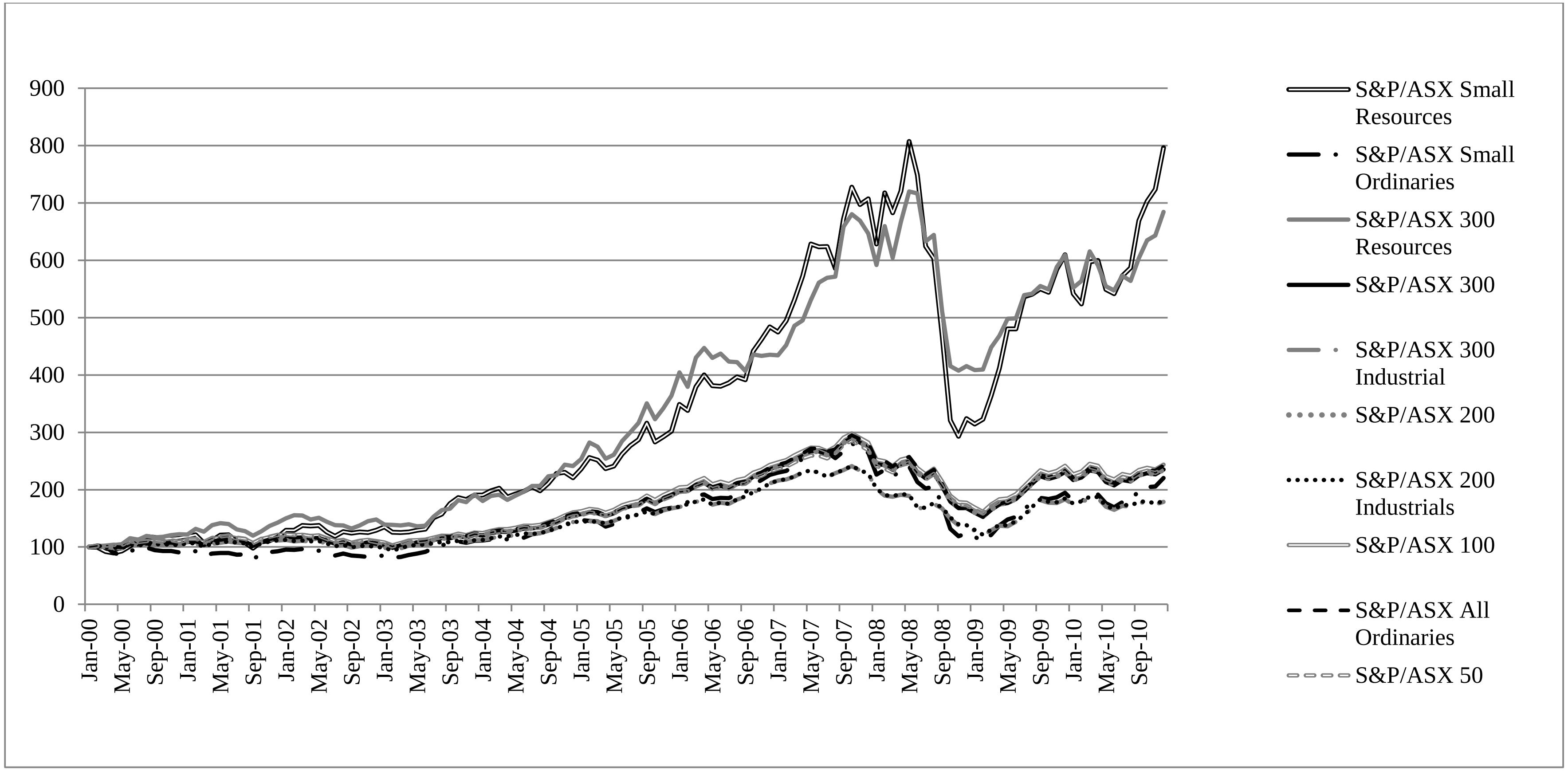
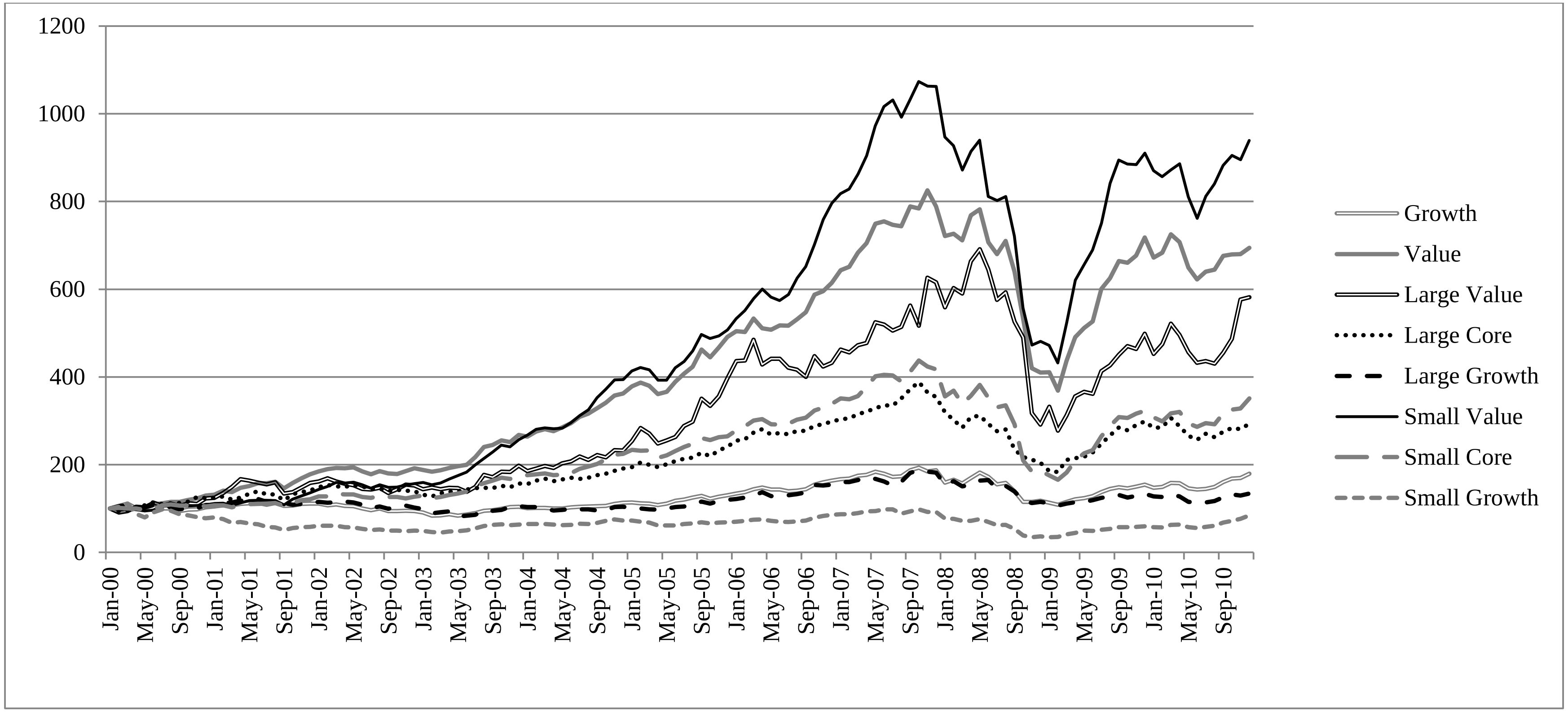


Figure 2.2: Style Index Prices

Monthly prices from January 2000 to December 2011 for eight passively constructed investable size-value/growth equity style indices used throughout this chapter are displayed in the following chart. Each index has a base value of 100 points at the beginning of the period. Indices are constructed from the universe of the largest 300 Australian equity stocks by market capitalisation with book-to-market values of equity used to define the value/growth dimension and market capitalisation for the size dimension. The indices are also value-weighted and rebalanced monthly. The construction of these indices is described in detail in section 2.4.d.



Estimating Carhart four-factor regressions for the S&P/ASX indices used as fund benchmarks over the eleven year sample period provides an indication of the style exposures of these benchmarks and their risk-adjusted returns (Carhart alpha). It is expected that any difference in performance of the indices will be attributed to the difference in their style risk exposures and that the risk-adjusted returns of these indices will be zero. The findings presented in Table 2.6 however, reveal that half of the indices exhibit significant non-zero risk-adjusted returns, indicating that relative superior (and adverse) returns displayed by some of these indices are not entirely due to systematic style exposures. The S&P/ASX 300 Resources and the S&P/ASX Small Resources for example, display significantly positive alphas over this sample period (t-stat = 3.308 and 2.614, respectively). Subsequently, a manager that passively tracks this index may potentially be assessed as possessing active skill. Alternatively, the S&P/ASX 200 Industrials, S&P/ASX 300 Industrials and the S&P/ASX Small Ordinaries all exhibit significantly negative Carhart alphas, implying that passive funds that track these indices could be assessed as possessing inferior benchmark-relative risk-adjusted returns. These preliminary findings illustrate the importance of being correctly benchmarked, as passively managed funds can appear to be exhibiting superior (or inferior) managerial skill if benchmarked against an inappropriate index. Ferris and Yan (2007) argue that fund performance should be evaluated relative to a benchmark, otherwise the value added by the manager will be either over- or underestimated. In this instance, the performance of funds that are mismatched to either the S&P/ASX 300 Resources or S&P/ASX Small Resources indices will be underestimated given the positive abnormal returns exhibited by these benchmarks.[32]

[32] A possible explanation as to why these indices are exhibiting a non-zero alpha is argued by Cremers, *et al.* (2012) to be the result of an inappropriate method used to construct the Carhart (1997) factor portfolios used in the four-factor regression. This is considered to be the result of the disproportionate

Consequently, a proportion of the abnormal performance generated by these funds will simply be attributed to the abnormal return achieved by the passive style of the fund. These findings illustrate the importance of assigning appropriate benchmarks to funds and using benchmark-relative performance metrics in the evaluation process.

It is widely acknowledged that alpha (from the Carhart (1997) 4-factor model) indicates manager skill, or 'abnormal' return. As such, if a portfolio, or in the case of table 2.6 and 2.7, a passive index, is estimated as having a significantly positive alpha, then it would be widely accepted, *prima facie*, that this portfolio has exhibited abnormal return. Nevertheless, by definition, passive indices should have zero abnormal return. Consequently, any non-zero abnormal return, exhibited by these indices should only result due to a "bad model." However, given that the Carhart (1997) model has been widely accepted in the literature and by practitioners [see, for example Demir, *et al.* (2004), Durand, *et al.* (2006), Gaunt and Gray (2003), Hurn and Pavlov (2003) and Brailsford and O'Brien (2008)], then such abnormal returns (alpha) generated by this "Bad" model may very well be "misinterpreted as a sign of skill."

weight the that the Fama-French factors place on small value stocks which have performed well, and from the value-weighted market index which is a downward-biased benchmark for U.S. stocks.

Table 2.6: Four-Factor S&P/ASX Index Exposures

Carhart (1997) four-factor regressions are estimated for the S&P/ASX accumulation indices that are reported as benchmarks by the mangers of Australian actively managed equity funds that are contained in the sample used throughout this chapter. The regressions are estimated using monthly returns over the period from January 2000 to December 2011. The dependant variables are the excess-return of the respected indices over the risk-free rate. The Carhart (1997) regressions identify index risk-adjusted returns (alpha) and exposures towards the market-risk premium (Rm-Rf), the value factor (*HML*), the size factor (*SMB*) and the momentum factor (*UMD*). The market return is the return on the SIRCA SPPR value-weighted Australian share index. Regressions are estimated with robust standard errors. T-statistics are displayed in parentheses and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	S&P/ASX 50	S&P/ASX 100	S&P/ASX 200	S&P/ASX 300	S&P/ASX All Ordinaries	S&P/ASX 200 Industrials	S&P/ASX 300 Industrials	S&P/ASX 300 Resources	S&P/ASX Small Ordinaries	S&P/ASX Small Resources
Alpha	0.0544	0.0456	0.0115	0.00692	0.00321	-0.261**	-0.274**	1.097***	-0.298*	1.074**
	(0.631)	(0.696)	(0.200)	(0.124)	(0.061)	(-2.004)	(-2.124)	(3.308)	(-1.779)	(2.614)
R_m-r_f	0.988***	1.001***	1.020***	1.026***	1.036***	0.983***	0.990***	1.163***	1.261***	1.424***
	(40.836)	(56.947)	(65.968)	(68.576)	(73.893)	(28.210)	(28.631)	(13.102)	(28.023)	(12.903)
SMB	-0.0842***	-0.0657***	-0.0484***	-0.0395***	-0.0149	-0.0503**	-0.0431*	-0.0191	0.234***	0.233***
	(-5.166)	(-5.614)	(-4.615)	(-3.895)	(-1.601)	(-2.127)	(-1.839)	(-0.317)	(7.815)	(3.169)
HML	-0.0704**	-0.0322	-0.0152	-0.0142	-0.0207	0.173***	0.177***	-0.459***	0.166***	-0.349**
	(-2.219)	(-1.339)	(-0.717)	(-0.692)	(-1.078)	(3.619)	(3.734)	(-3.763)	(2.701)	(-2.314)
UMD	0.0165	0.00372	0.00249	0.00223	-0.00972	0.0255	0.0259	-0.0971	-0.0450	-0.316**
	(0.470)	(0.172)	(0.124)	(0.115)	(-0.564)	(0.562)	(0.577)	(-0.840)	(-0.813)	(-2.330)
Observations	128	128	128	128	128	128	128	128	128	128
R-squared	0.944	0.965	0.974	0.976	0.980	0.870	0.874	0.648	0.889	0.659

Considering the style exposures of these passive indices, if a manager is able to predict which investment styles will underperform, then selecting a benchmark with a corresponding style exposure is likely to improve benchmark-relative performance. The style characteristics of the ten S&P/ASX indices used as benchmarks by the sample of funds are subsequently identified from the factor loading estimated from the Carhart (1997) four-factor regressions reported in Table 2.6. The size exposures (represented by the *SMB* coefficient) are as expected, i.e., this coefficient for S&P/ASX 50 is significantly negative at the one percent level (t-stat = -5.166) Expressing its exposure to large cap stocks, whereas the coefficient of this factor for the S&P/ASX Small Ordinaries index is significantly positive at the one percent level (t-stat = 7.815), consistent with its exposure to small market capitalisation stocks. The exposures of these indices to the value (*HML*) factor, on the other hand, reveal somewhat more interesting results. Despite not specifically recognising value (or growth) dimensions, six of the ten S&P/ASX indices demonstrate significant exposures to either value or growth stocks instead of possessing a form of 'blend' style orientation. Specifically, the industrials indices and the S&P/ASX Small Ordinaries have significant exposure to value stocks as recognised from their significantly positive *HML* coefficients, whilst the resources and S&P/ASX50 indices are shown to have significant growth orientations, as illustrated by their significantly negative coefficients from the *HML* factor. These findings suggest that the publicly available S&P/ASX indices, from which funds are benchmarked against, have considerable exposure to typical value-growth/size style dimensions, hence potentially providing sufficient opportunity for style-orientated funds to be appropriately benchmarked against.

Table 2.7: Four-Factor Style Index Exposures

Carhart (1997) four-factor regressions are estimated for each of the eight passively-constructed investable size-value/growth equity style indices that are used in the analysis throughout this chapter. The regressions are estimated using monthly returns over the period from January 2000 to December 2011. The dependant variables are the excess-return of the respected indices over the risk-free rate. The Carhart (1997) regressions identify index risk-adjusted returns (alpha) and exposures towards the market-risk premium (R_m-R_f), the value factor (*HML*), the size factor (*SMB*) and the momentum factor (*UMD*). Construction of these style indices are described in detail in section 2.4.d. Regressions are estimated with robust standard errors. T-statistics are displayed in parentheses and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	Growth	Value	Large Value	Large Growth	Small Value	Small Growth	Large Core	Small Core
Alpha	-0.233	0.710***	0.771	-0.164	0.754***	-1.134***	0.259	0.0921
	(-1.044)	(2.863)	(1.303)	(-0.558)	(3.379)	(-4.123)	(1.167)	(0.476)
R_m-r_f	0.954***	1.251***	1.247***	0.880***	1.277***	1.206***	1.088***	1.190***
	(13.492)	(18.779)	(7.866)	(11.142)	(21.314)	(16.329)	(18.230)	(22.900)
SMB	0.0641*	0.0335	-0.0424	-0.0335	0.302***	0.479***	-0.174***	0.265***
	(1.828)	(0.756)	(-0.399)	(-0.638)	(7.584)	(9.742)	(-4.393)	(7.662)
HML	-0.130	0.300***	0.0239	-0.423***	0.434***	0.0921	-0.108	0.197***
	(-1.542)	(3.297)	(0.110)	(-3.912)	(5.292)	(0.912)	(-1.318)	(2.766)
UMD	0.127	-0.197**	-0.205	-0.0341	-0.176**	0.0624	0.0406	-0.192***
	(1.287)	(-2.405)	(-1.049)	(-0.351)	(-2.391)	(0.686)	(0.552)	(-2.997)
Observations	128	128	128	128	128	128	128	128
R-squared	0.752	0.753	0.351	0.577	0.828	0.793	0.741	0.849

Similar to the Carhart regression estimated for the S&P/ASX indices in Table 2.6, not all of the passive investable style indices are found to exhibit zero risk-adjusted return. The *Value* and *Small-Value* indices are found to produce positive Carhart alphas of 0.710 percent and 0.754 percent per month, respectively, over the sample period. These returns are significant at the one percent level (t-stat = 2.863 and 3.379, respectively) which suggest that holding a passive portfolio that mimic such styles will appear to be managed more skilfully than other Australian passive style portfolios such as a *Small-Growth* or *Large-Growth* portfolio. The exposure of the style indices to size and Value/Growth characteristics, as indicated by the *SMB* and *HML* coefficients on the Carhart (1997) factors in Table 2.7 are somewhat consistent with their expressed investment styles. The *Small-Value* and *Small-Growth* indices for example, are the only style benchmarks that have significant exposure to small market capitalisation stocks (as expressed by their significantly negative *SMB* factor loadings). The *Value* and *Large-Value* indices exhibit positive exposures to the *HML* factor at the one percent significance level and the *Small-Value* index at the five percent significance level. The *Large-Growth* index is the only index with exposure to growth stocks according to its significantly negative *HML* factor exposure (t-stat = -3.912). Similar to the S&P/ASX indices, none of the style indices exhibit significant exposure to momentum stocks, as illustrated from the statistically insignificant coefficients on the *UMD* factor. The Carhart (1997) factor exposures of these style indices indicate that they may provide a closer match for funds with corresponding style objectives compared to the 'broad-market' based S&P/ASX indices previously discussed.[33]

[33] Carhart (1997) four-factor regressions results, estimated for the six 'alternative' passively-constructed investable size-value/growth style equity indices, are reported in Table A.3 in Appendix A. Results are qualitatively similar to those reported in Table 2.7.

Preliminary results from this chapter have so far revealed that benchmark-excess returns can vary significantly for a fund based on the selected benchmark and that a fund can appear to perform substantially better (or worse) relative to its benchmark in terms of both raw and risk-adjusted benchmark-excess returns if the incorrect index is selected.

2.6.c Benchmark Mismatching

Whilst it can be advantageous for managers to report an inappropriate benchmark, in that if selected wisely, a fund will appear substantially more attractive when evaluated alongside its benchmark. The following set of analysis examines whether funds are in fact style-mismatched from their self-reported benchmark indices, and upon which indices these 'mismatched' funds should be appropriately benchmarked against. Differences in the tracking error volatility between 'benchmark-mismatched' and 'appropriately-matched' funds are also examined, along with benchmark-relative style exposures of the mismatched funds to identify the style characteristics upon which these funds are most commonly mismatched. The characteristics of funds that are likely to affect the probability of having a mismatched benchmark is then lastly explored in the following set of analysis.

Table 2.8: Fund Benchmark Mismatches

The quantity of Australian equity funds that are mismatched from each self-reported benchmark index, at 10%, 5%, and 1% significant levels are reported in the following table. Funds are considered mismatched from their self-reported benchmarks if the tracking-error volatility with respect to their self-reported benchmark is significantly greater than the tracking-error volatility relative to their best-suited index, as determined from a Levene (1960) test for homogeneity of variances. This table also reports the quantity of mismatched funds and the benchmark indices to which these funds are best suited to, at each respected level of mismatch significance.

10% Significance Mismatched				**5% Significance Mismatched**				**1% Significance Mismatched**			
Original Benchmark	No. Funds	Revised Benchmark	No. Funds	Original Benchmark	No. Funds	Revised Benchmark	No. Funds	Original Benchmark	No. Funds	Revised Benchmark	No. Funds
ASX 50	3	ASX50	1	ASX 50	3	ASX All Ords	1	ASX50	2	ASX 300 Ind.	3
ASX All Ords	2	ASX All Ords	1	ASX All Ords	1	ASX 100	1	ASX200	4	ASX Small Ind.	1
ASX 100	2	ASX20	1	ASX200	7	ASX 300 Ind.	9	ASX300	1	ASX Small Ords	3
ASX 200	10	ASX100	1	ASX300	4	ASX Midcap 50	1				
ASX 300	5	ASX300 Ind.	11	Small Ords	5	ASX Small Ind.	4				
ASX Small Ords	5	Midcap50	1			ASX Small Ords	3				
		ASX Small Ind.	5			ASX 100 Indus.	1				
		ASX Small Ords	4								
		ASX 100 Ind.	2								
Total	27		27		20		20		7		7
	5.6%		5.6%		4.2%		4.2%		1.5%		1.5%

Using a Levene (1960) test for homogeneity of variances amongst benchmark-relative tracking error volatilities to identify funds that are 'mismatched' from their self-reported benchmark indices, Table 2.8 shows that 27 (5.6 percent) of the 460 funds within the sample are considered mismatched from their benchmark at a ten percent significance level. The proportion of funds shown to be mismatched funds at the five percent and one percent significance levels is even less, accounting for 20 (4.2 percent) and seven (1.5 percent) of funds, respectively. These proportions are surprisingly small, considering the relatively large number of funds that subscribe to a specific style dimension yet are benchmarked against broad-market based indices (as shown in Table 2.3). Furthermore, all of the revised benchmarks (the indices for which the benchmark-mismatched funds are found to be best-suited to) are S&P/ASX indices, and none being the passively constructed value-growth/size style indices. This result is evident across all levels of *mismatch* significance. Furthermore, of the 27 funds with benchmarks that are mismatched at the ten percent significance level, eleven are classified as being wholesale and the other 16 as retail funds. Similar proportions of wholesale and retail funds are also mismatched at the five and one percent significant levels. Specifically, nine of the 20 funds mismatched at the five percent level and three of the seven funds mismatched at the one percent level are wholesale. Given that approximately a third of the sample (157 funds) consist of wholesale funds, with the other two thirds (307 funds) being retail, wholesale managers are therefore almost twice as likely to have reported a mismatched benchmark compared to retail managers.

This finding suggests that either these mismatched funds do not actually possess such style characteristics as described from their investment objectives, or alternatively, the style dimensions exhibited by the S&P/ASX indices are able to sufficiently capture the style exposures of these funds.[34] Nevertheless, these results demonstrate that style-specific indices are not necessarily required within the Australian funds market for benchmarking purposes.

The next set of analysis undertaken in this section examines the tracking error volatility (*TE*) of funds to identify how the returns of mismatched funds deviate from their benchmark, relative to those that are considered ‘appropriately matched’. The *TE* of benchmark-mismatched funds with ‘revised’ benchmarks (i.e., mismatched funds whose benchmarks are respecified to the best-fit index) is also investigated.

[34] Benchmark-relative style characteristics of funds are further investigated later in this chapter to identify the style dimensions upon which these funds are mismatched.

Table 2.9: Tracking Error Volatility Differences

Mean tracking-error volatilities (*TE*) of funds with appropriate benchmarks, mismatched benchmarks and revised benchmarks, calculated from a sample of Australian actively managed equity funds over the period from January 2000 to December 2011 are reported in the following table. *TE* is measured at the fund-level over previous 24-month rolling windows. A fund's benchmark is considered appropriate, mismatched or revised, at 10%, 5% and 1% significant levels as determined from a Levene (1960) test for homogeneity of variance on tracking error volatilities. The Differences in mean tracking-error volatilities between these groups of funds are also measured. T-statistics are displayed in parentheses and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Mean TE			**Mean TE Difference**		
Mismatch Significance	Funds with Appropriate Benchmarks	Funds with Revised Benchmarks	Funds with Mismatched Benchmarks	Appropriate - Mismatched	Mismatched - Revised	Appropriate - Revised
10%	1.499	1.908	2.588	-1.089***	0.68***	-0.409*
				(-4.806)	(9.373)	(-1.82)
5%	1.525	1.731	2.414	-0.889***	0.683***	-0.21
				(-3.364)	(7.714)	(-0.783)
1%	1.550	1.521	2.416	-0.865*	0.895***	0.029
				(-1.949)	(4.569)	(0.066)

The average *TE* of funds with appropriately-matched benchmarks is shown in Table 2.9 to be significantly lower than the *TE* of mismatched funds across all levels of mismatch significance. This initially indicates that the returns of mismatched funds deviate significantly more from their benchmarks compared to funds with appropriately matched benchmarks, suggesting that mismatched funds, prima facie, are managed more actively. However, as expected, the average *TE* of funds drop significantly after the benchmarks of mismatched funds are revised to their best-suited indices such that average *TE* is almost indifferent to the *TE* of funds with appropriately-matched benchmarks. Subsequently, the apparent heightened activeness of mismatched funds can be almost entirely attributed to these funds having reported a mismatched benchmark.

The following set of analyses examines the specific style characteristics upon which funds deviate from their benchmarks and identify if benchmark-mismatched funds benefit from exploiting specific style premiums. The four Carhart (1997) factors are used as investment style characteristics such that benchmark-excess four-factor regressions, estimated at the fund level from the model described in equation 2.9, is able to determine the extent to which benchmarks are able to capture the style characteristics of their funds. The regression results are reported in Table 2.10.

Table 2.10: Benchmark-Excess Four-Factor Fund Exposures

This table reports the number and percentage of funds with appropriate, mismatched and revised benchmarks that exhibit significantly positive, negative and zero coefficients from the factors of a benchmark-excess Carhart (1997) four-factor regressions, given by the equation; $R_{i,t} - R_{b,t} = \alpha_i + \beta_{1,i}\left(R_m - R_f\right)_t + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{UMD,i}UMD_4 + \varepsilon_{i,t}$. Factor loadings are considered different from zero at a five percent significance level. A fund's benchmark is determined as being either appropriate or mismatched using a Levene (1960) test for homogeneity of variance upon fund tracking-error volatility. Regressions are estimated at the fund-level using monthly returns over the period from January 2000 to December 2011 for a sample of Australian actively managed equity funds. Factor loadings that are significantly greater than zero indicates that a fund is overexposed to the respect factor relative to its respected benchmark, whereas a factor loadings significantly less than zero is considered relatively underexposed. The intercept term, α_i, is a fund's benchmark-excess risk-adjusted return.

	Benchmark-appropriate Funds					Benchmark-mismatched Funds					Funds with Revised Benchmarks				
Factor	No. Funds	% Funds	Mean Factor Loading	Mean T-stat	Mean P-value	No. Funds	% Funds	Mean Factor Loading	Mean T-stat	Mean P-value	No. Funds	% Funds	Mean Factor Loading	Mean T-stat	Mean P-value
$\alpha < 0$	39	9.0%	-0.281	-2.691	0.016	0	0.0%	0.000	0.000	0.000	0	0.0%	0.000	0.000	0.000
$\alpha = 0$	375	86.6%	-0.012	-0.120	0.483	26	96.3%	0.006	-0.068	0.621	27	100%	0.142	0.555	0.447
$\alpha > 0$	19	4.4%	0.630	3.027	0.018	1	3.7%	1.074	2.788	0.039	0	0.0%	0.000	0.000	0.000
$\beta_{Rm-rf} < 0$	156	36.0%	-0.143	-3.912	0.009	15	55.6%	-0.203	-3.185	0.010	10	37.0%	-0.131	-2.882	0.014
$\beta_{Rm-rf} = 0$	241	55.7%	-0.008	-0.208	0.408	6	22.2%	-0.021	-0.472	0.540	15	55.6%	-0.038	-0.500	0.453
$\beta_{Rm-rf} > 0$	36	8.3%	0.604	9.747	0.008	6	22.2%	0.431	8.015	0.006	2	7.4%	0.636	7.925	0.000
$\beta_{SMB} < 0$	6	1.4%	-0.139	-3.654	0.029	1	3.7%	-0.257	-4.045	0.010	1	3.7%	-0.256	-3.152	0.003
$\beta_{SMB} = 0$	375	86.6%	0.016	0.333	0.517	21	77.8%	0.048	0.665	0.386	20	74.1%	0.019	0.472	0.354
$\beta_{SMB} > 0$	52	12.0%	0.136	2.853	0.019	5	18.5%	0.291	4.384	0.007	6	22.2%	0.182	2.766	0.021
$\beta_{HML} < 0$	66	15.2%	-0.164	-3.254	0.011	1	3.7%	-0.181	-2.908	0.033	6	22.2%	-0.177	-2.942	0.006
$\beta_{HML} = 0$	279	64.4%	0.006	0.008	0.460	12	44.4%	0.124	1.045	0.315	20	74.1%	0.045	0.363	0.560
$\beta_{HML} > 0$	88	20.3%	0.191	2.842	0.015	14	51.9%	0.319	3.155	0.011	1	3.7%	0.093	2.405	0.018
$\beta_{UMD} < 0$	4	0.9%	-0.304	-2.420	0.024	0	0.0%	0.000	0.000	0.000	0	0.0%	0.000	0.000	0.000
$\beta_{UMD} = 0$	413	95.4%	0.013	0.324	0.496	26	96.3%	-0.007	-0.088	0.469	24	88.9%	0.038	0.354	0.603
$\beta_{UMD} > 0$	16	3.7%	0.114	2.501	0.018	1	3.7%	0.302	2.098	0.039	3	11.1%	0.256	2.460	0.028

From the sample of 460 Australian actively managed equity funds, Table 2.10 shows that a large proportion are exposed to one or more style characteristics that are not adequately captured by their self-reported benchmark. This is most evident for the market sensitivity ($\beta_{Rm\text{-}rf}$) of funds, with 8.3 percent (36 percent) of benchmark-appropriate funds being significantly over (under) exposed to the market than that of their benchmark. In terms of the size characteristics of these funds, 1.4 percent (12 percent) are significantly overexposed to large (small) capitalisation stocks relative to their benchmark, whereas 20.3 percent (15.2 percent) of these funds exhibit value (growth) style exposures that are unable to be captured by their benchmark. These results suggest that only a relatively small proportion of fund managers take advantage of the value or size premium that was observed in section 2.6.b, by actively tilting portfolio exposures towards small or value stocks in an attempt to achieve superior benchmark-relative performance. Table 2.10 also shows that 0.9 percent (3.7 percent) of benchmark-appropriate funds are found to be significantly overexposed to past winner (loser) stocks according to the average loading on the *UMD* factor relative to their benchmarks, indicating that it is uncommon for a manager to apply a momentum trading strategy in an attempt to outperform their benchmark.

The above results differ only marginally for benchmark-mismatched funds, with the exception of market sensitivity, whereby a substantially higher proportion (56 percent) of funds are shown as having significantly less market exposure relative to their benchmark. Furthermore, 22.2 percent of these mismatched funds are also significantly more sensitive to the market than their self-reported benchmark. Similarly, a larger proportion of mismatched funds (52 percent) are found to be overexposed to value stocks relative to their benchmark. The difference in the proportion of mismatched and appropriately matched funds with momentum and size characteristics that significantly differ from their self-reported benchmarks is also negligible. This finding suggests that the majority of funds with mismatched benchmarks do not attempt to strategically outperform their benchmarks by taking advantage of style characteristics that are not captured by their benchmark indices. Furthermore, after revising the benchmark of the mismatched funds to their 'best-fit' index, the differences in style-characteristic exposures largely disappear, however, slightly more of these mismatched funds become over-exposed to small capitalisation stocks, value stocks and momentum stocks relative to their 'best-fit' benchmark.

Examination of the benchmark-adjusted Carhart alpha of funds with appropriately-matched benchmarks shows that only 4.4 percent (nine percent) of funds produce abnormal returns above (below) their benchmarks, compared to 3.7 percent (four percent) of funds with mismatched benchmarks. This implies that benchmark-mismatched funds on average are slightly less successful than appropriately-matched funds at outperforming their benchmarks on a risk-adjusted basis. Consequently, any evidence that suggests that managers are able to consistently outperform their benchmarks may simply be a result of their portfolios being over exposed to systematic risk factors that are not captured by their benchmark indices. The effect and extent to which specific characteristics have on the probability of a fund having a mismatched benchmark is next examined using the probit regression models described in equation 2.13, with results reported in Table 2.11.

Table 2.11: Determinants of Benchmark-Mismatched Funds

Probit regressions that describe the probability of a fund having a mismatched benchmark index are estimated in the following table. The dependant variable is a binomial variable which takes the value of one if a fund has a mismatched benchmark, or zero otherwise. A Levene (1960) test for homogeneity of variance of fund tracking-error volatilities is used to identify whether funds are appropriately matched or mismatched to their self-reported benchmarks at ten percent, five percent or one percent significance levels. The explanatory variables include; A wholesale dummy, $Wholesale_i$, which takes on the value of one if fund i is classified as a wholesale fund or zero if it is a retail fund, the natural log of a fund's total net assets, $Size_{i,t-1}$, the natural log of the number of months since fund i's inception date, Age_{t-1}, Style dummies are represent large value, mid/small value, large growth, mid/small growth, large blend and mid/small blend investment styles, respectively as classified by Morningstar. All regressions are estimated using monthly data from January 2000 to December 2011 for a sample of Australian actively managed equity funds. Z-statistics are displayed in parentheses and *, ** and *** denote significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	**Benchmark-mismatched** *(at 10% significance level)*	**Benchmark-mismatched** *(at 5% significance level)*	**Benchmark-mismatched** *(at 1% significance level)*
Constant	-0.858***	-1.295***	-3.971***
	(-7.018)	(-9.710)	(-16.411)
Wholesale	0.893***	0.751***	0.642***
	(24.978)	(19.595)	(16.450)
Size	-0.0824***	-0.0729***	0.0930***
	(-11.231)	(-8.860)	(7.505)
Age	0.0969***	0.169***	-0.0238
	(4.781)	(7.305)	(-0.783)
Expense Ratio	0.440***	0.364***	0.0410**
	(23.437)	(18.820)	(2.454)
Mid/Small Value Style	0.873***	0.995***	1.556***
	(15.928)	(18.521)	(25.909)
Large-Blend Style	-1.279***	-1.268***	-0.668***
	(-35.015)	(-30.744)	(-12.648)
Mid/Small-Blend Style	-0.589***	-0.386***	-0.158***
	(-15.423)	(-10.599)	(-2.847)
Other Style	-1.432***		
	(-29.032)		
Observations	28,142	25,206	25,206
Pseudo R-squared	0.2458	0.248	0.2707

Identifying the characteristics of funds with mismatched benchmarks from the probit regression estimates reported in Table 2.11 shows that smaller, older, more expensive, wholesale funds with a mid/small value style tilt are observed as being more likely to report a benchmark index that is mismatched at the ten percent or five percent significant levels. Funds with a Large-blend style, Mid/small blend, or 'Other' style tilt on the other hand are more likely to be appropriately matched to their benchmarks as indicated by the statistically significant coefficients on the respective factors from these probit regression estimates. Similar results are also found for fund's that report benchmarks that are considered mismatched at the one percent significance level, except for the fund size, which is found to inversely relate to probability of a fund reporting a benchmark that is mismatched. Observing the style objectives of these funds reveal Large-blend, Mid/Small-blend or '*Other*-styles' are the only style objectives that describe whether funds have mismatched benchmarks (mismatched at the 10 percent significance level). The Large-Value, Mid/Small Value, Large-Growth and Mid/Small-Growth style objectives on the other hand are shown to have insignificant explanatory power when determining if a fund has a mismatched benchmark.

2.6.d Performance of Benchmark Mismatched Funds

The following analysis examines whether managers who are observed as reporting a mismatched benchmark are successful at exploiting these performance differences by reporting underperforming benchmarks. Monthly average returns and benchmark-excess returns of funds with mismatched and appropriately-matched benchmarks are examined in Table 2.12 to identify any differences that may exist between these groups of funds. Multivariate regressions results are then reported in Table 2.13 which more formally identifies how benchmark-mismatching affects fund performance after controlling for common factors that are shown to influence fund performance.

Table 2.12 Appropriately Matched and Mismatched Return Comparisons

The difference in mean monthly raw returns and benchmark-excess returns of funds with appropriately matched self-reported benchmarks, mismatched self-reported benchmarks and funds, whose mismatched benchmarks have been respecified to their best-suited benchmarks, are reported in the following table. Funds are considered mismatched from their benchmark at a five percent significance level as determined from a Levene (1960) test for homogeneity of variance on fund-benchmark tracking-error volatilities. Mean returns are calculated at the fund level from January 2000 to December 2011 for a sample of actively managed Australian equity funds. T-statistics are displayed in parentheses and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Appropriately-matched Funds	Mismatched Funds	Revised-Benchmark Funds	Difference
Mean Raw Return	0.803	0.720		0.083
				(0.579)
Mean Benchmark-excess Return	0.022	0.036		-0.014
				(-0.205)
	0.022		0.199	-0.176***
				(-3.387)
		0.036	0.199	-0.163***
				(-3.083)

The difference in average raw returns between appropriately-matched and mismatched benchmarked funds is shown in Table 2.12 to be statistically insignificant, suggesting that any difference in benchmark-excess return between these two types of funds is a result of their benchmarks and not a consequence of the inherent characteristics of the underlying funds. Monthly average benchmark-excess returns of mismatched and appropriately-matched funds are shown to be insignificantly different from one another, implying that managers with mismatched benchmarks do not (or are unable to) enhance the appearance of fund performance through the allocation of an underperforming ‘inappropriate’ benchmark.

Revising the benchmarks of the mismatched funds to their ‘best-suited’ indices results in their benchmark-excess returns increasing by an average of 0.163 percent per month. This difference is statistically significant at the one per cent level (t-stat =

3.083), indicating that the performance of benchmark mismatched funds-funds, in terms of their benchmark-excess returns, is worse when benchmarked against their self-reported 'mismatched' index. Furthermore, once these benchmarks are revised, mismatched funds are shown to achieve benchmark-excess returns of 0.176 percent per month greater than the average appropriately-matched fund. This return difference is also statistically significantly at the one percent level (t-stat = -3.387). Consequently, by reporting a mismatched benchmark, managers are effectively placing themselves at a disadvantage in terms of their benchmark-excess returns than if they were to report their best-suited index as a benchmark.

To more formally examine the effect that benchmark-mismatching has on fund performance, multivariate regressions, estimated from equation 2.14, using various fund performance metrics are conducted. The regression results are reported in Table 2.13. The relationship between benchmark-mismatching an fund performance is identified in these regressions from the *Mismatch* dummy variable, which takes on a value of one if a fund is considered mismatched from its benchmark (at a ten percent significance level), or zero otherwise.[35]

[35] Fund performance regressions applying mismatch dummy variables that consider funds to be mismatched from their benchmarks at one and five percent significant levels are reported in Table A.4 in Appendix A. Results are qualitatively similar to those reported in Table 2.13.

Table 2.13: Fund Performance and Benchmark Mismatching

The relationship between fund performance and benchmark mismatching are estimated using monthly panel data from January 2000 to December 2011 for a sample of Australian actively managed equity funds. The dependent fund performance variables include; Benchmark-excess returns, r_i-r_b, excess returns, r_i-r_f, CAPM Alpha and Carhart alpha. The explanatory variables include a binomial *Mismatch* variable which takes a value of one if a fund is considered mismatched from its benchmark (at a ten percent significance level as determined from a Levene (1960) test for homogeneity of variance on fund-benchmark tracking-error volatilities), or zero otherwise. A binomial wholesale variable that takes a value of one if a fund is classified as a wholesale fund, or zero for a retail fund is also included. A mismatch-wholesale interaction variable is additionally included. A vector of control variables which comprise of; the natural log of a fund's total net assets, *Size*, the natural log of the number of months since a fund's inception date, *Age*, return *Volatility* (measured as the historical standard deviation of monthly raw returns over the previous 12 months), lag flow of assets under management, *Lag Flow*, and the Net flow of assets under management into all funds with the same investment style, *Net Style Flows,* are contained in the regressions. All control variables are lagged one-month and regressions are estimated with time-fixed effects (month dummies) and style-fixed effects (style dummies). Robust standard errors are clustered at the fund level and t-statistics are displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	r_i-r_b	r_i-r_f	CAPM Alpha	Carhart Alpha
Variables	(1)	(2)	(3)	(4)
Constant	-0.657***	-1.599***	-0.283*	-0.414***
	(-2.709)	(-5.693)	(-1.934)	(-2.899)
Mismatch	-0.142	-0.185*	-0.0557	0.0225
	(-1.306)	(-1.750)	(-1.185)	(0.345)
Wholesale	0.0762***	0.0764***	0.0602***	0.0658***
	(3.041)	(2.823)	(2.691)	(2.834)
*Mismatch*Wholesale*	0.207	0.282**	0.169*	0.107
	(1.334)	(1.969)	(1.750)	(0.875)
Size	-0.0227***	-0.0230***	-0.00295	0.00331
	(-2.817)	(-2.601)	(-0.542)	(0.604)
Age	0.0455**	0.0348	0.0514**	0.0262
	(1.973)	(1.405)	(2.489)	(1.231)
Volatility	0.130***	0.128***	-0.00906	0.0124
	(4.395)	(4.153)	(-0.496)	(0.741)
Lag Flow	0.00491	0.00457	0.0178***	0.0169***
	(1.423)	(1.112)	(6.245)	(6.287)
Net Style Flow	0.101***	0.00955	0.0210***	0.0111*
	(4.291)	(0.419)	(2.662)	(1.664)
Style Dummies	Yes	Yes	Yes	Yes
Time-fixed Effects	Yes	Yes	Yes	Yes
Observations	15,824	15,824	12,468	12,468
R-squared	0.081	0.867	0.284	0.217

The regression results presented in Table 2.13 show that reporting a mismatched benchmark has mostly a negligible effect on the performance of both wholesale and retail funds. This result is illustrated, for retail funds (with the exception of the excess-returns performance regression) by the statistically insignificant coefficients on the *Mismatch* dummy variable. Similar results are observed for wholesale funds, as demonstrated from the statistically insignificant coefficients from the linear combination of the *Mismatch* dummy and *Mismatch*Wholesale* interaction variables, which are insignificant at the ten percent level (t-stats = 0.56, 0.91, 1.29 and 1.20) for benchmark-excess returns, excess-returns, CAPM alpha and Carhart alpha performance regressions, respectively. Retail funds with mismatched benchmarks, on the other hand, are shown to produce excess returns that are on average 0.185 percent per month less than funds that are considered appropriately matched to their benchmarks. This result is significant at the ten per cent level (t-stat = -1.750), suggesting that retail managers with mismatched benchmarks perform worse than managers of appropriate-matched funds. This performance difference, however, disappears after returns are risk-adjusted, as shown by the insignificant coefficients on the *Mismatch* dummy from regressions three and four. These results further confirm that managers who report inappropriate benchmarks fail to select indices that underperform and hence are unsuccessful at enhancing benchmark-excess performance. The results also show that the performance ability of managers who report mismatched benchmarks is largely indifferent from funds with appropriately-matched benchmarks.

2.6.e Flow-Performance of Benchmark Mismatched Fund

The final component of analysis undertaken in this chapter investigates how benchmark mismatching affects investor decisions to allocate assets across funds, and subsequently identifies if managers are able to benefit (through increased fund flows) from reporting a mismatched benchmark. The findings from this chapter have so far revealed that benchmark-mismatched managers do not select indices that underperform and that they are unable to outperform relative to benchmark-appropriate funds. Consequently, it is expected that benchmark-mismatched funds should not rationally attract excess flows. Preliminary examination reveals that the average flow to funds with mismatched benchmarks is 0.254 percent of assets under management per month compared to 0.037 percent for funds with appropriate benchmarks. This difference is statistically significant at the five percent level (t-stat = 2.526).[36] This flow difference is largely attributed to wholesale funds, which exhibit a difference of 0.327 percent per month between mismatched and appropriately matched benchmarks, significant at the five percent level (t-stat = 2.260). The difference in mean flows between mismatched retail funds and appropriately matched retail funds on the other hand is 0.144 percent per month and is statistically insignificant at the ten percent level (t-stat = 1.342). These finding initially suggests that wholesale funds that have mismatched benchmarks are successful at attracting relatively more investor funds. Retail-investor flows however are indifferent to the appropriateness of the benchmark. The following analysis more formally examines if benchmark-mismatched funds attract greater fund flows by estimating multivariate flow-performance regressions that control for common fund flow factors, as described in equations 2.15 and 2.16.

[36] Funds are considered mismatched at the 10% level. The difference in mean flow between mismatched and appropriate funds is also statistically significant when funds are considered mismatched at the five percent level (t-stat = 2.00).

Table 2.14: Fund Flows and Benchmark Mismatching

Regressions that describe the relationship between fund benchmark mismatching and flows are estimated in the following table using monthly panel data for a sample of Australian actively managed equity funds over the period from January 2000 to December 2011. The dependent variable is fund-level percentage flow of assets under management, *Flow*. The explanatory variables are fund-level include a binomial benchmark mismatching variable, *Mismatch*, as well as a wholesale-mismatch interaction variable, *Mismatch*Wholesale*. The mismatch dummy takes on a value of one if the fund is mismatched from its self-reported benchmark, or zero otherwise. *Wholesale*, is a binomial variable that takes on a value of one if a fund is classified as a wholesale fund or zero if it is a retail fund. Funds are considered mismatched from their benchmarks at a ten percent significance level as determined from a Levene (1960) test for homogeneity of variance from fund benchmark-relative tracking-error volatilities. Performance control variables include; raw fund returns, *Return*, as well as three fractional performance controls ($LowPerf_{i,t}$ $MidPerf_{i,t}$ *and* $HighPerf_{i,t}$) based on the percentile ranks of monthly lagged raw fund returns and constructed using fractional 33%-33%-33% breakpoints used to define the *Low*, *Mid* and *High* fractile ranks. These performance measures are also interacted with the *Mismatch* variable. The regressions also include a vector of control variables, comprising; the natural log of a fund's total net assets, *Size*, the natural log of the number of months since a fund's inception date, *Age*, return *Volatility*, measured as the historical standard deviation of monthly raw returns over the previous 12 months for each fund, flow of assets under management during the previous month, *Lag Flow*, and the net flow of assets under management into all funds with the same investment style, *Net Style Flow*. All independent variables are lagged by one-month and regressions are estimated with time-fixed effects (month dummies) and style-fixed effects (style dummies). Robust standard errors are clustered at the fund level and t-statistics are displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	Flow	Flow	Flow	Flow
Constant	4.674***	4.695***	4.557***	4.577***
	(8.319)	(8.389)	(8.073)	(8.145)
Mismatch	-0.179	-0.145	-0.172	-0.143
	(-1.087)	(-1.039)	(-1.046)	(-1.021)
Wholesale		0.0480		0.0433
		(0.445)		(0.404)
*Mismatch*Wholesale*		-0.0946		-0.0825
		(-0.260)		(-0.227)
Return	0.0210*	0.0208*		
	(1.755)	(1.749)		
Low Return Rank			0.855**	0.848**
			(2.579)	(2.554)
Mid Return Rank			-0.172	-0.178
			(-0.681)	(-0.707)
High Return Rank			-0.0144	-0.00107
			(-0.032)	(-0.002)
Size	-0.0652**	-0.0669**	-0.0655**	-0.0671**
	(-2.283)	(-2.309)	(-2.298)	(-2.321)
Age	-0.712***	-0.711***	-0.714***	-0.713***
	(-9.367)	(-9.267)	(-9.386)	(-9.284)
Volatility	0.0554	0.0539	0.0623	0.0608
	(1.263)	(1.225)	(1.416)	(1.379)
Lag Flow	0.221***	0.221***	0.221***	0.221***
	(8.927)	(8.934)	(8.915)	(8.922)
Net Style Category Flow	0.565***	0.565***	0.566***	0.566***
	(9.893)	(9.915)	(9.905)	(9.927)
Style Dummies	Yes	Yes	Yes	Yes
Time-fixed Effects	Yes	Yes	Yes	Yes
Observations	21,797	21,797	21,797	21,797
R-squared	0.187	0.187	0.187	0.187

Conflicting with initial findings, the appropriateness of a fund's benchmark is shown to have a negligible effect on fund flows. This relationship, or lack thereof, is identified from the statistically insignificant factor loadings from the *Mismatch* and *Mismatch*Wholesale* interaction variables that are introduced into the flow-performance regressions. This finding is robust across flows regression models that capture linear and the asymmetric relationship between returns and flows for both wholesale and retail funds. Specifically, asset flows into retail funds are shown to be unaffected, regardless of the fund having a mismatched benchmark or not. This is indicated by insignificant coefficients by the *Mismatch* variable from the regressions in columns two and four of Table 2.14 (t-stats = -1.087 and -1.046). The effect that benchmark appropriateness has on the asset flows of wholesale funds is similarly shown to be negligible. This is determined from the statistical insignificant linear combination of coefficients from the *Mismatch* and *Mismatch*Wholesale* interaction variables from columns two and four of the regression estimates (t-stats = -0.70 and -0.66, respectively). These findings suggest that managers (of both wholesale and retail funds) who report mismatched benchmarks, are unable to attract additional fund flows, and subsequently do not benefit from increased revenue generated by the fees obtained from managing these funds. This result is consistent with benchmark-mismatched funds being unable to outperform appropriately-matched funds.[37]

2.7 Conclusion

An appropriate benchmark is one that can evaluate a manager's ability to generate returns beyond that of her passive investment style, and not one that can be

[37] Fund flow-performance regressions applying mismatch dummy variables that consider funds to be mismatched from their benchmarks at one and five percent significant levels are reported in Table A.5 in Appendix A. Results are qualitatively similar to those reported in Table 2.14.

easily outperformed due to a mismatch from what the she is actually invested in (Anderson, 2009). Due to the absence of publicly available style equity indices within Australia, this chapter has investigated whether the investment styles of actively managed Australian equity funds adequately capture the style characteristics of their self-reported benchmark indices, and whether managers take advantage of the lack of regulations surrounding benchmark reporting by selecting inappropriate benchmark indices. Despite a large majority of ‘style-orientated’ funds reporting broad-market based indices as their benchmark, none are significantly better matched to passive value/growth–size style indices, and that all ‘benchmark-mismatched’ funds are found to better matched to an alternative S&P/ASX index. Subsequently, this chapter does not advocate the necessity of publicly available passive style indices for the Australian funds market, and as such fund investors should remain confident when relying on a fund’s self-reported benchmark to adequately capture passive style returns. Investors, however, should be cautious if relying on a fund’s reported investment styles when making investment decisions.

Examining the characteristics of funds reveals that managers of small, inexpensive, wholesale funds are more likely to report a mismatched benchmark. Furthermore, the majority of benchmark indices are unable to adequately capture fund investment styles as characterised by market-risk, value/growth and size style factors, regardless of having appropriately-matched or mismatched benchmark indices. Nevertheless, only a minority of these funds tilt their portfolio exposures away from the style characteristics of their benchmarks in attempts to exploit documented style premiums.

This chapter has further shown that managers who report mismatched benchmarks are unable to outperform ‘appropriately-matched’ funds in terms of raw, risk-adjusted, or benchmark adjusted performance, thus implying that attempts to make fund performance appear more attractive through the misallocation of benchmarks go unrewarded. Despite prevalent literature showing the benefits of benchmark outperformance, those funds with mismatched benchmarks are also unsuccessful at attracting excess fund flows relative to appropriately-benchmarked funds. This finding is evident for both wholesale and retail funds. The findings from this chapter therefore refute those from previous studies that suggest that benchmark mismatching will be prevalent amongst funds in industries where regulations concerning benchmarking are not stringent.

Chapter 3. Prospecting for Alpha: Equity Fund Performance, Flows and the Mining Boom in Australia

3.1 Introduction

The top-down approach to investment management suggests that if fund managers are able to identify industries that will outperform in the future then they should earn higher returns. The ability to identify industries that will experience a boom in the future should yield even higher returns. Kacperczyk, Sialm, and Zheng (2005) find that funds with higher industry concentrations are capable of outperforming funds with lower industry concentrations. However, identifying economic settings where hypotheses about the effect of an industry boom on funds management can be tested are relatively rare. One such natural experimental setting was the IT bubble experienced in the U.S. during the late 1990s and early 2000s. Brunnermeier and Nagel (2005), Dass, Massa, and Patgiri (2008), Greenwood and Nagel (2009) and Griffin, Harris, Shu, and Topaloglu (2011) provide confilicting results concerning the performance and the exposure to IT stock of U.S funds during this bubble. Using the sample of Australian equity managed fund data described in Chapter 2, this chapter examines an independent sample from the recent mining boom in the Australian equity market. This chapter provides an opportunity to strengthen our understanding of whether funds can capture industry outperformance and what effect exposures to booming industries have on managed fund investors.

The stocks in the mining industry experienced average monthly returns of 1.16 percent between 2003 and 2012, compared to the average monthly market return of 0.60 percent. It is anticipated that funds with higher mining exposure are able to capture some of the return benefits. In addition, the question of how investors respond to differences in mining exposures across funds is addressed. If funds are able to earn abnormal returns through their industry allocations then a rational response from investors would be to increase their investments into funds with high mining exposure. Alternatively, funds may be attracted by the industry returns of a 'hot' industry (i.e., an industry that is experiencing prolonged high abnormal return relative to other industries). Frazzini and Lamont (2008) argue that fund investors are attracted to past style returns, however, basing investment decisions on past style returns is shown to lead to an erosion of wealth. Cooper, *et al.* (2005) find that fund flows are affected by funds that change names to reflect the current 'hot' investment style. In a market with a dominant, booming industry, investors could potentially over-expose themselves to this industry, without considering any rational performance-motivated factors in their investment decision.

A returns-based approach is applied to measure fund-level mining industry exposures using monthly data from January 2003 to January 2012. This approach finds that significant differences in mining industry allocations exist amongst equity funds. In contrast to expectations, no evidence is found that funds with a higher exposure to the mining industry outperform over this period. The findings indicate that investors misinterpret industry allocation decisions by fund managers as representing skill and increase investments in those funds with a high exposure to this ‘hot’ industry. Flows are significantly higher for funds that have a higher exposure to the mining industry, despite the fact that there are no performance benefits that accrue to investors.

This chapter relates to studies that have examined the IT bubble in the U.S.. The results support the findings of Greenwood and Nagel (2009) in that fund managers are not able to extract abnormal returns from industry outperformance. Similarly, those funds with the highest exposure to the booming industry receive increased inflows. By contrast, Brunnermeier and Nagel (2005) show that hedge fund managers were able to capture most of the upside of the IT bubble. This chapter does not find evidence to suggest that long-only fund managers exhibit skill with respect to industry allocation. The implications of these findings are that investors should not misinterpret fund allocations to ‘popular’ assets as representing skill and instead other factors should be examined when attempting to select funds that will outperform in the future.

The remainder of this chapter is organised as follows: Section 3.2 provides an overview of the Australian mining boom. Section 3.3 reviews the current literature relating to industry booms on fund performance and flows. Section 3.4 develops the hypotheses that are empirically tested. Section 3.5 reports the data and describes the construction of key variables used in the empirical analysis throughout this chapter. Section 3.6 explains the methodology used to measure fund exposures to mining stocks and the approach used to measure the effect that that this exposure has on fund performance and flows. Section 3.7 presents the empirical results and section 3.8 concludes.

3.2 Background to the Australian Mining Boom

The reliance on the extraction of natural resources and lack of investment in the IT and communications industries throughout the 1990s had previously caused concern for the Australian economy due to falling relative prices of commodities and weak potential productivity gains. Yet, by the end of the 2000s Australia was experiencing economic growth backed by the largest mining boom since European settlement of Australia during the 18th century (Battellino, 2010). Up until the middle of the 2000s, business investment in non-mining sectors was the main driver of economic growth as the real price of Australia's key export commodities stagnated throughout the 1980s and 1990s being at their lowest in more than a century (Kearns and Lowe, 2011). Despite increased demand for raw commodities by China during the early 2000s, low commodity prices largely discouraged investment in the mining sector and as a result many Australian mining companies merged with multinationals in attempts to offset diminishing profitability (Connolly and Orsmond, 2011).[38] However, the rapid industrialisation and urbanisation of emerging economies in Asia, particularly in China and India over the last decade, resulted in Asia's (excluding Japan) share of world GDP increasing from ten percent in 2000 to 17 percent in 2010. This growth eventuated in substantial investment in infrastructure, buildings and machinery, with China alone accounting for almost half of the world's production of steel and half of the world's coal consumption in 2010 (Kearns and Lowe, 2011). Subsequently, their demand for raw commodities, especially coal and iron ore, which are the primary resources used in the production of steel, saw a sharp rise during the mid-2000s. This benefitted Australia not only because of its abundance of these

[38] Of the top 20 mining companies listed on the Australian securities exchange (ASX) in 2000, only seven of were still listed by the end of 2005 (Connolly and Orsmond, 2011).

resources but also because of its relatively close proximity to China and the subsequent lower shipping costs associated with exportation (Connolly and Orsmond, 2011). Demand for these commodities, especially iron ore and coal saw an increase from three percent of the value of Australia's exports in 2003 to 17 percent by 2010. Similarly, the contribution of coal as a percentage of net exports increased from seven percent in 2003 to ten percent in 2010, representing a significant contribution of the nearly 60 percent rise in Australia's terms of trade over the same period. Much of the increase in these resource exports can be directly attributed to China. By 2009, China accounted for over 55 percent of Australia's exports of ores and metals, up from 13.3 percent in 2000 (Huang and Wang, 2011). [39]

The inability of the mining industry to initially meet the demand for these resources, due to a lack of investment, exacerbated the surge in commodity prices. This subsequently led to heightened growth in production and investment not only in iron ore and coal mining but across a broad range of mining-related sectors such as oil and thermal coal (Battellino, 2010). Since 2000, mining investment increased from \$10 billion to about \$58 billion by the end of the decade, representing over a two fold increase in mining investment as a percentage of both total private business investment and as a percentage of GDP (Connolly and Orsmond, 2011). Mining revenue also increased from six percent of GDP in 2000 to 14 percent by the end of the decade (Connolly and Orsmond, 2011). In relation to the market value of mining companies, relative to the Australian stock market (ASX), the price of mining equities increased by around 180 percent over the 2000s. Based on the behaviour of commodity prices

[39] Figure B.1 in Appendix B displays a time-series chart of the number of *Top 300* constituent stocks belonging to each industry over the period from January 2000 to December 2011. This figure shows the proportion of mining stocks contained in the *Top 300* increasing drastically over this period.

and the change in the level mining investment, the current mining boom is said to be dated from about 2005 onwards (Battellino, 2010).

The onset of the Global Financial Crisis (GFC) during the latter half of 2008, however, resulted in a steep decline in global commodity prices. By May of 2009 the Reserve Bank of Australia (RBA) commodity price index fell by over 30 percent from its October 2008 level (Kearns and Lowe, 2011). However, sustained growth by emerging economies such as China, and their continued demand for bulk commodities, maintained Australia's export volumes. These volumes continued to grow from late 2008 onwards despite global trade volumes falling by about 20 percent over the same period. Within 18 months, commodity prices had returned to their pre-GFC levels, assisting Australia in experiencing a milder downturn than many other developed economies (Kearns and Lowe, 2011). The economic slowdown in China in recent years however, has seen a decline in mining industry-related asset prices from about 2012 onwards, thus being viewed as the beginning of the end of the boom.

3.3 Literature Review

3.3.a Introduction

Despite the economic and financial impact that the mining boom has had on Australia, its effect on the funds management industry has not yet been investigated in the portfolio management literature. There are however numerous studies that examine concepts that are likely to explain fund manager and investor behaviour during industry booms. Specifically, the IT bubble and bust in the U.S. during the late 1990s/early 2000s which has been extensively studied, provides insight into the asset allocations and performance during abnormal periods of high industry-specific performance. Whilst the mining industry did not witness a bust in asset prices similar to that of the U.S. IT industry towards the end of the boom, there are a variety of studies that investigate the effects of industry allocations and performance allocations to funds during industry outperformance.

3.3.b Fund Industry Analysis

Barberis and Shleifer (2003) show that many investors chase past style returns. If investors allocate assets across industries in the same manner as they do across style groups, then it is likely that investors will rely on a fund's industry exposure in order to incorporate past industry performance into their investment decisions. Such an argument is supported by Frazzini and Lamont (2008), who show that investors not only chase past fund returns but also utilise past style returns when selecting funds. Frazzini and Lamont (2008) also argue that retail investors effectively destroy wealth when actively reallocating assets across funds, for which they coin the 'dumb-money' effect. Kacperczyk, *et al.* (2005) on the other hand, find that there are substantial differences between mutual funds that are industry-concentrated and those that are well diversified across industries. They show that funds with concentrated holdings tend to have positive active weights to growth and small cap stocks, and outperform funds that are more diversified at the industry level. This performance difference is argued to be the result of managers possessing the ability to successfully recognise when industries move in and out of favour and to advantageously adjust their portfolio positions accordingly.

Hoberg and Phillips (2010) investigate industry-level effects on stock performance after industry booms and busts. They examine whether factors that influence stock returns differ between competitive or concentrated industries and whether these factors differ between value and growth industries. They provide strong evidence suggesting that stocks from competitive industries, especially competitive growth industries, when in a booming phase (measured using ex-ante industry-level valuation) will likely be followed by a subsequent decline in risk-adjusted returns and cash flows. This is particularly evident when the industry is experiencing extensive new financing and investing. Hoberg and Phillips (2010), however, fail to find similar evidence amongst stocks from concentrated industries.

3.3.c The IT Bubble

Greenwood and Nagel (2009) examine the portfolio decisions of mutual fund managers during the IT bubble and argue that inexperienced managers are more likely to exhibit trend chasing tendencies. They show that inexperienced managers increased their exposure to IT stocks following quarters in which the IT industry experienced heightened returns. IT exposure was particularly shown to increase around the peak of the bubble during the early 2000s, then shown to subsequently decrease after the peak in March of 2000. More experienced fund managers on the other hand were shown by Greenwood and Nagel (2009) to maintain constant holdings of technology stocks throughout the duration of the bubble. Despite the high exposure to technology stocks by less experienced fund managers relative to their style benchmarks during the run-up of the bubble, along with their large associated abnormal fund inflows, these managers were unable to outperform more experienced managers, who maintained consistent levels of IT exposure throughout the duration of the bubble and bust (Greenwood and Nagel, 2009). In light of significant losses incurred by less experienced managers after the collapse of the IT industry, Greenwood and Nagel (2009) show that outflows of assets under management from these funds were not significantly large in relation to their peers. Consequently, due to the large abnormal returns and inflows of assets under management achieved during the run up of the bubble, the relative costs to these funds in terms of their asset outflows after the crash was much less severe than expected.

Cooper, *et al.* (2005) argue that many mutual fund managers changed the name of their fund around the time of the IT bubble, to sound more ‘IT’ orientated in an attempt to improve fund inflows. Whilst they find that those funds that changed names were successful in improving fund flows, their name changes, and subsequent inflows were argued to be unrelated to any change in actual portfolio holdings exhibited by these funds. Greenwood and Nagel (2009) further consider window dressing by fund managers as a means of increasing inflows during the IT bubble, however, they find little evidence to suggest that inexperienced managers achieved higher abnormal inflows by ‘dressing up’ their portfolios with IT stocks around reporting dates.[40]

Other studies that investigate the behaviour of investor groups during the IT bubble include Griffin, *et al.* (2011), who suggest that institutional investors, mainly hedge funds, participated in trend-chasing of NASDAQ 100 stocks on a daily and weekly basis during the run-up of the bubble. They argue that these investors were responsible for driving up the prices of IT stocks, particularly large stocks, during the months leading to the peak of the bubble by aggressively investing in technology stocks before reversing their positions in March of 2000. This ‘sophisticated’ behaviour of hedge fund managers is argued to have exacerbated the crash of the IT industry. Individual investors on the other hand are shown to have demonstrated relatively unsophisticated behaviour by actively buying during the run-up and especially after the peak of the bubble.

[40] See, for example Haugen and Lakonishok (1988), Lakonishok, Shleifer, Thaler, and Vishny (1991), Meier and Schaumburg (2004), Griffiths and Winters (2005) and Morey and O'Neal (2006) for a discussion about window dressing.

Brunnermeier and Nagel (2005) find similar results to that of Griffin, *et al.* (2011) in terms of hedge fund managers when looking at the role they played throughout the IT bubble. They find that hedge funds also adjusted their exposure to technology stocks throughout the bubble. Brunnermeier and Nagel (2005) argue that hedge fund managers were able to capture most of the upside of the bubble by overexposing their portfolios' to the IT sector relative to the market. This relative exposure was at its greatest up until about six month before the peak of the bubble, when hedge fund managers then began reducing portfolio exposures to this sector on a stock-by-stock basis before prices began to collapse. At the peak of the bubble in March 2000, 31 percent of hedge fund holdings consisted of IT stocks, whereas only 21 percent of the market portfolio was comprised of these stocks at that time. However, by the end of 2000, the weighted portfolio holdings of IT stocks for hedge funds were much closer to the weight of the market portfolio. Consequently, hedge fund managers were able to successfully adjust their holdings so as to capture the upturn of this bubble whilst avoiding much of the downturn.

Dass, *et al.* (2008) argue that mutual fund exposure to 'bubble-stocks' can be largely explained by a fund manager's contractual incentives. If a manager has lower performance incentives contained in his or her advisory contract, then they will be more likely to exhibit herding behaviour during a bubble by following other managers. Grinblatt, Titman, and Wermers (1995) and Wermers (1999) show that it is commonplace for herding to exist amongst fund managers. Herding is also shown by Scharfstein and Stein (1990) and Zwiebel (1995) to arise in funds where managers are concerned about their reputation and are uncertain of their own ability, whereas those managers who are more concerned with seeking profits rather than preserving their reputations are less likely to exhibit such herding behaviour. Consequently, Dass, *et* *al.* (2008) argue that the degree of herding is ultimately influenced by the compensation structure of the fund during the IT bubble, mutual fund managers with low incentive contracts were more likely to herd by investing in bubble stocks given their lack of incentive to deviate from the crowd. Those funds with larger contractual incentives however were shown to hold fewer IT stocks during the bubble as it is argued to be more advantageous for them to invest in 'old economy' stocks in an attempt to outperform the 'herding' funds. The smaller the holdings in technology stocks of these 'high-incentive' funds, the poorer they performed relative to 'low-incentive' funds during the run up of the bubble and vice-versa after the peak.

3.3.d Conclusion

A variety of studies have argued that the industry-exposures of managed funds are likely to be sensitive to industry outperformance, and that these exposures will influence fund performance and flows. Whilst mixed evidence has been produced relating to this topic, this research largely stems from the U.S. technology industry during the IT bubble of the late 1990s/early 2000s. The recent Australian mining boom therefore affords us a rare opportunity to further explore, in a natural experimental setting, the effects that industry booms have on the funds management industry.

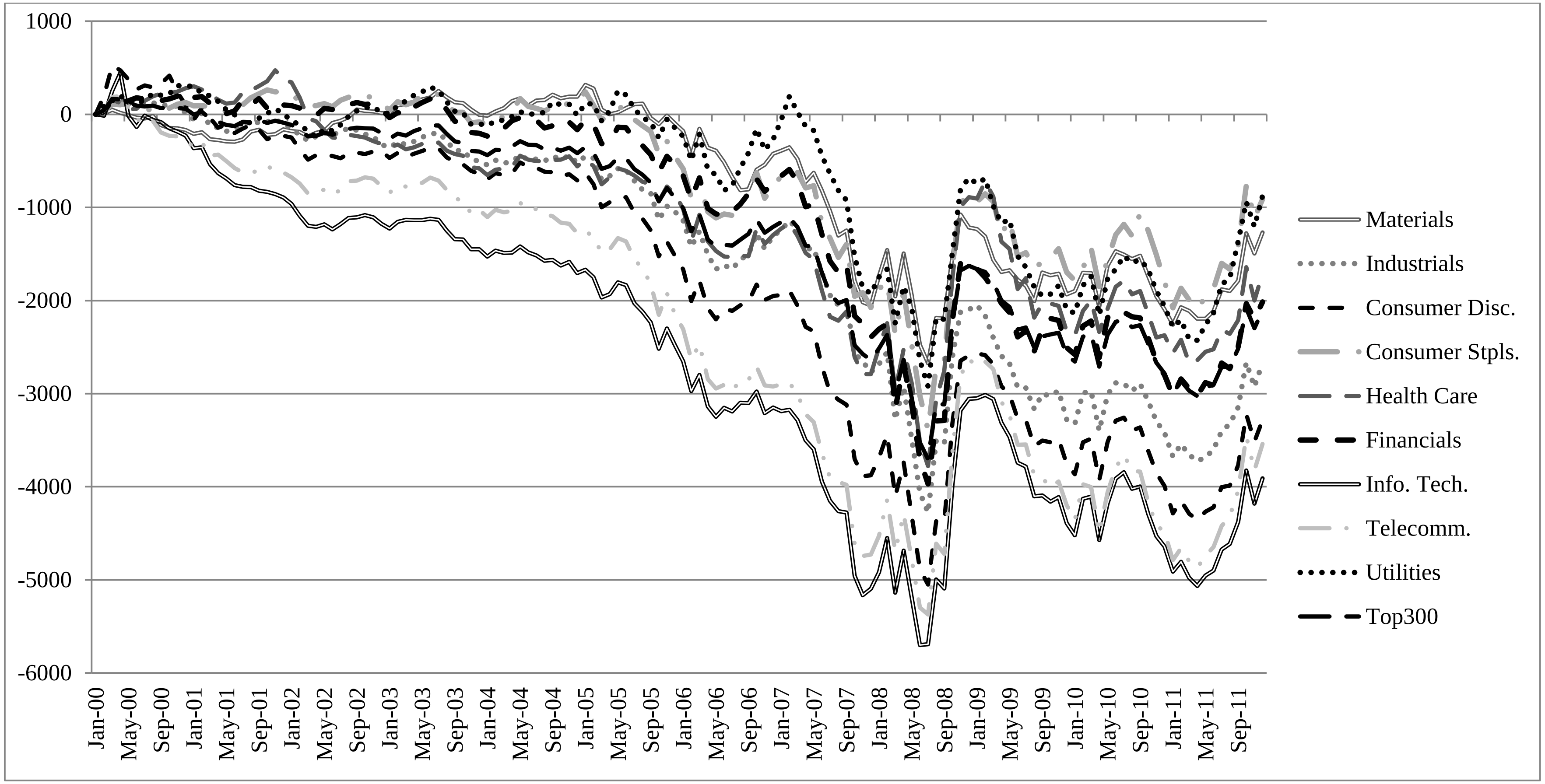
3.4 Hypothesis Development

There are key differences between the IT bubble in the U.S. and the mining boom in Australia. The rapid rise, and subsequent decline, in the prices of IT stocks in the U.S. has since been termed a bubble, whereas the rise in prices of mining stocks in Australia was based on economic fundamentals, resulting largely from the rapid increase in demand of bulk commodities from emerging Asian economies such as China and India. The effect that this increase in demand had on the value of mining companies can be illustrated from the mining industry-relative sector returns displayed in Figure 3.1. This chart shows how the mining industry significantly outperforms all other nine industries over the latter part of the sample period. Despite the rapid decline in this industry around the market crash of August 2008, the mining industry still manages to outperform all other industries over the remainder of the decade based on its initial outperformance prior to the crash. For example, the mining industry, on average, outperformed the market index by 0.559 percent per month while outperforming the Materials sector by 0.278 percent per month, Industrials by 0.704 percent, Consumer Discretionary by 1.006 percent, Consumer Staples by 0.350 percent, Health Care by 0.386 percent, Financials by 0.494 percent, Information Technology by 1.435 percent, Telecommunications by 1.233 percent and Utilities by 0.204 percent per month.[41]

[41] Refer to Figure B.2 in Appendix B for a time-series chart of monthly industry index prices across period from January 2000 to December 2011.

Figure 3.1: Mining-Relative Industry Index Prices

Monthly industry index prices relative to the price of a mining industry index are displayed across period from January 2000 to December 2011. The indices are constructed from the top 300 Australian stocks by market capitalisation using tier one and two GICS categories to group stocks into one of nine industries. The industries include Materials (excluding Metals-and-mining), Consumer Staples, Consumer Discretionary, Industrials, Telecommunications, Utilities, Information Technology and Health Care. A market index is also included that is constructed from the largest 300 Australian stocks by market capitalisation. All indices are value-weighted and rebalanced monthly and begin with a base price of 100 points at the start of the sample period.



This chapter primarily examines whether fund managers possess skill in generating abnormal returns from industry expansions. Greenwood and Nagel (2009) argue that inexperienced managers were more likely to exhibit trend chasing tendencies during the IT boom in the late 1990s/early 2000s in the U.S.. More experienced fund managers on the other hand are shown to maintain their holdings of IT stocks throughout the duration of the bubble. Inexperienced managers underperformed their more experienced counterparts indicating an absence of superior stock selection skill (Greenwood and Nagel, 2009). Brunnermeier and Nagel (2005) show that hedge fund managers are able to capture most of the upside of the IT bubble. Consequently, this chapter contributes to these studies by examining whether funds with higher exposures to the mining industry are able to outperform funds with lower exposures during a defined period of mining industry outperformance.

This chapter also explores the effects that fund exposures to a booming industry have on flows of assets under management. It is expected that investors will be attracted to funds that have higher exposures to booming industries regardless of how well they perform. This is based on the presumption that a booming industry will continue to outperform other industries and that funds with higher exposure to this industry will also be expected to continually outperform funds that are less exposed until such time that the boom subsides. As equity funds are largely defined by their investment styles, investors are likely to, at least partially, form investment decisions based on the fund style classifications. Frazzini and Lamont (2008) find that individuals will chase the past returns of funds as well as past style returns. However, retail investors are shown to effectively destroy wealth when actively reallocating assets across managed funds. If the boom in the stock prices of mining companies can arguably represent an investment style in the Australian market, then investors may be enticed to reallocate assets into funds with high exposures to this industry. Cooper, *et al.* (2005) show that many mutual fund managers merely changed the name of their fund around the time of the bubble in an attempt to attract asset inflows. They also find that the effect of these name changes on asset flows is unrelated to the change in holdings of the funds. It is therefore expected that fund flows will be related to the booming industry, with those funds observed as having higher exposures to the mining industry experiencing relatively higher fund inflows.

I incorporate the clients that each fund services into the analysis to identify whether retail or wholesale funds, or the investors in these funds, lead to differences in the performance and flow relationship. In contrast to retail investors, wholesale investors are often well-informed professionals who make use of consultancy services that provide extensive performance monitoring and advice on selecting fund managers (Sawicki, 2001). James and Karceski (2006) argue that wholesale and retail investors use different criteria when allocating assets between funds. They show that wholesale fund clients do not chase past raw returns in the same manner as retail investors, but instead use more sophisticated, risk-adjusted, performance metrics when selecting funds. Del Guercio and Tkac (2002) reach a similar conclusion when examining the behaviour of pension and retail mutual fund investors. If wholesale and retail fund investors differ in terms of their sophistication, then it can be argued that these two types of investors could allocate funds differently based on the industry exposure of a fund during an industry boom. A more sophisticated wholesale investor, for example, regardless of their preference towards mining-boom stocks, may be more capable of identifying funds with high exposures to mining stocks and thus allocate their funds accordingly. Less sophisticated (retail) investors, on the other hand, are more likely to be unaware of the industry concentration of funds. Nevertheless, wholesale investors may not be swayed by funds that are simply overexposed to 'hot' stocks from booming industries but instead may use more sophisticated performance metrics when selecting funds. Consequently, if the sophistication of a fund's clients is considered an indicator of the relationship between a fund's exposure to mining stocks and its asset flows, then such relationship may be largely affected by the wholesale/retail classification of the fund.

3.5 Data

3.5.a Industry Index Construction

Ten industry-classified indices are constructed from the monthly returns of the largest 300 stocks by market capitalisation listed on the Australian Securities Exchange (hereinafter referred to as the *Top 300)*. These indices are primarily used as factors in a Sharpe (1992) constrained regression analysis described in section 3.6.a to identify fund-level industry exposures. The construction of the indices initially involves sorting the *Top 300* into ten industry groups according to their Tier one Global Industry Classification Standards (GICS) codes each month. The Tier one GICS codes classify stocks belonging to either one of; *Energy*, *Materials*, *Consumer Staples*, *Consumer Discretionary*, *Industrials, Telecommunications, Utilities, Information Technology*, *Financials* or *Health Care* industries. To accurately capture a fund's exposure to stocks that are directly influenced by the Australian mining boom, a '*Mining'* index is constructed by adjusting both the Energy and Materials industry groups. This is attained by extracting the tier two '*Metals and Mining*' stocks from the tier one, Materials industry, and including them within the tier one Energy group. As a result, the constituent stocks of this index include only those that are considered to be directly affected by the mining boom. The eight remaining tier one industry groups remain unchanged. The ten industry indices used throughout this study are therefore constructed using stocks classified as Mining (including Metals and Energy), Materials (excluding Metals and Mining), Consumer Staples, Consumer Discretionary, Industrials, Telecommunications, Utilities, Information Technology, Financials and Health Care.[42]

The sum of the holdings of the ten industry indices is equal to the holdings of the *Top 300*. This is to ensure that the Sharpe (1992) constrained regressions are able to wholly capture fund return exposure to each industry in the market.[43] Furthermore, in order for the constrained regression to accurately estimate industry exposures, the industry index returns must not be highly correlated.[44] Monthly returns for these ten industry indices are determined by summing the value-weighted returns from the constituent stocks in each industry index using one-month lagged market capitalisation values and rebalancing monthly. Descriptive return statistics for these ten industry indices are presented in Figure 3.1. All other data and data sources used throughout this chapter are listed and described in Chapter 2.4.

[42] The industries and sub-industries contained in each tier one GICS sector category can be found at http://www.standardandpoors.com/indices/gics/en/au.
[43] Industry indices are constructed using the largest 300 stocks by market capitalisation as this is the universe in which Australian equity fund managers are generally benchmarked against (Ainsworth, *et al.*, 2008).
[44] Correlation coefficients of the monthly returns between each of the ten industry indices are reported in Table B.1 in Appendix B.

Table 3.1: Industry Index Descriptive Statistics

Descriptive statistics for the monthly returns of ten accumulation industry indices across the period from January 2000 to December 2011 are reported in this table. The indices are constructed from the top 300 Australian listed stocks by market capitalisation using tier one and two GICS categories to group stocks into one of ten industries. The industries include Mining, Materials (excluding Metals-and-mining), Consumer Staples, Consumer Discretionary, Industrials, Telecommunications, Utilities, Information Technology and Health Care. A market index is also included (Top 300 Market) that is constructed from the largest 300 Australian stocks by market capitalisation. All indices are value-weighted and rebalanced monthly.

Industry Index	**Mean**	**Min**	**Median**	**Max**	**St. Dev.**	**Skewness**	**Kurtosis**
Mining	1.403	-20.438	2.163	20.621	5.790	-0.349	4.642
Materials	1.031	-22.536	0.891	12.909	5.839	-0.708	4.548
Utilities	0.923	-12.435	1.322	10.152	3.910	-0.783	4.492
Consumer Staples	0.881	-12.325	1.194	12.909	3.430	-0.492	5.136
Financials	0.653	-13.182	1.473	12.797	4.379	-0.510	4.077
Health Care	0.639	-10.601	0.607	16.510	4.525	0.228	4.115
Industrials	0.455	-20.541	0.726	13.308	5.038	-0.923	5.443
Consumer Discretionary	0.189	-16.492	0.524	17.055	5.853	-0.214	3.447
Telecommunications	-0.070	-10.896	0.461	10.965	4.597	-0.271	2.675
Information Technology	-0.421	-34.673	-0.185	24.494	7.867	-0.227	5.543
Top 300 Market	0.586	-13.089	1.348	7.593	3.713	-0.858	4.100

3.6 Methodology

3.6.a Time-varying Mining-Industry Fund Exposures

To identify fund exposures to mining boom stocks, returns-based constrained regressions, following Sharpe (1992), are estimated from the equation:

$$R_{i,t} = \alpha_{i,t} + \sum_{j=1}^{N} \beta_{i,t,j} R_{j,t} + \epsilon_{i,t}\,, \qquad (3.1)$$

$$s.t.\ \sum_{j=1}^{N} \beta_{i,j} = 1 \text{ , and}$$

$$\beta_{i,t,j} \geq 0, \quad \text{j} = 1, \dots, N$$

where $R_{i,t}$ is the return on fund *i* at time *t*, $R_{j,t}$ is the return on industry index *j* at time *t*, $\beta_{i,t,j}$ is the coefficient on the industry index return factor, $R_{j,t}$, of industry *j* at time *t*, constrained to be greater than or equal to zero and that $\beta_{i,t,1}$ to $\beta_{i,t,N}$ sum to equal one, which can be interpreted as the fraction of fund *i*'s portfolio that is exposed to industry *i* at time *t*.

Horst, Nijman, and de Roon (2004) refer to the application of both constraints in the Sharpe style regression as being a *strong* form of the returns-based style analysis (RBSA). The relaxing of the short selling constraint (i.e., when short selling is permitted) is referred to semi-strong RBSA, whereas omitting both constraints is referred to as *weak* RBSA. In weak RBSA, the style exposures are estimated from the factor loading using least squares regression. However, when the equality constraint (all coefficients sum to one) and the short-sale constraint (all coefficients are non-negative) is included, ordinary least squares regression is unable to estimate the factor exposures, $\beta_{i,t,1,\dots,}\ \beta_{i,t,N}$, and instead quadratic programming algorithms are necessary to obtain these estimates [see Sharpe (1987)]. A strong version of RBSA is applied throughout this chapter given that Australian equity fund managers are largely prohibited in their use of short selling.[45] When the coefficients of the RBSA regressions are constrained to sum to one, the exposures can be interpreted as portfolio holdings (Horst, *et al.*, 2004; Swinkels and Van Der Sluis, 2006). Nevertheless, the objective of the RBSA is not to identify the actual holdings of the funds, but to identify the exposure to the specific risks associated with each of the factors included in the model (Sharpe, 1992). In the case of this chapter, it is the fund exposure to the risks associated with mining stocks that are of interest. The fund-level factor exposures to the mining industry index obtained from these regressions are therefore used throughout this chapter as a measure for fund mining stock exposure.

An inherent problem of the Sharpe (1992) RBSA model is that it unrealistically assumes that portfolio exposures remain constant over the sample period. To address this issue, regressions are estimated over rolling windows (sub-samples) to obtain time-varying factor exposures. Subsequently, the constrained regressions described in equation 3.1 are estimated over 36-month windows using monthly return data to obtain a time-series of fund-level industry exposures. Returns data used in these regressions begin in January 2000, and as such the first factor exposures are observed at January 2003 and extend until December 2012. The length of the rolling windows used to identify time-varying factor exposures from Sharpe (1992) constrained regressions in previous studies range from 18 months (McGuire, Remolona and Tsatsaronis, 2005) to 60 months (Drew and Stanford, 2003). Lucas and Riepe (1996) recommend a 36-month rolling window as it is short enough to capture significant style movements yet long enough to avoid excessive noise. This window length is commonly used throughout related studies when estimating time-series style exposures [see, for

[45] For regulations concerning short selling by Australian managed funds see, '*Australian Securities & Investment Commission (ASIC) Regulatory Guide 196: Short Selling'*, *April 2011*.

example Bateman and Thorp (2007), Bryan, Ham, Rafferty, and Yoon (2009), Lesseig, Long, and Smythe (2002) and Papadamou and Siriopoulos (2004)].

Time-varying industry exposures of the *Top 300* market index, estimated across 18, 24, 30, 36 and 42-month rolling windows, are compared against the industry weights of this index to test which window length best suits the data. The correlation between the actual and 'implied' weights, when estimated using a 36-month window length is about 0.90 for the mining industry, with tracking-error volatilities averaging 2.8 percent across all industries. The mean absolute differences between the implied and actual weights of the *Top 300* index is also shown to be around 2.3 percent, which produced the closest fit when compared to the exposures estimated across the other window lengths. As such, a 36-month rolling window is selected as it is considered the most appropriate at predicting industry exposures as it balances timely shifts in portfolios exposures whilst retaining sufficient degrees of freedom. The correlations between implied and actual industry weights for estimated using different rolling lengths in reported in Table 3.2. Time-series plots of implied mining industry weights against the actual market weight of the mining industry are reported in Figure 3.3.

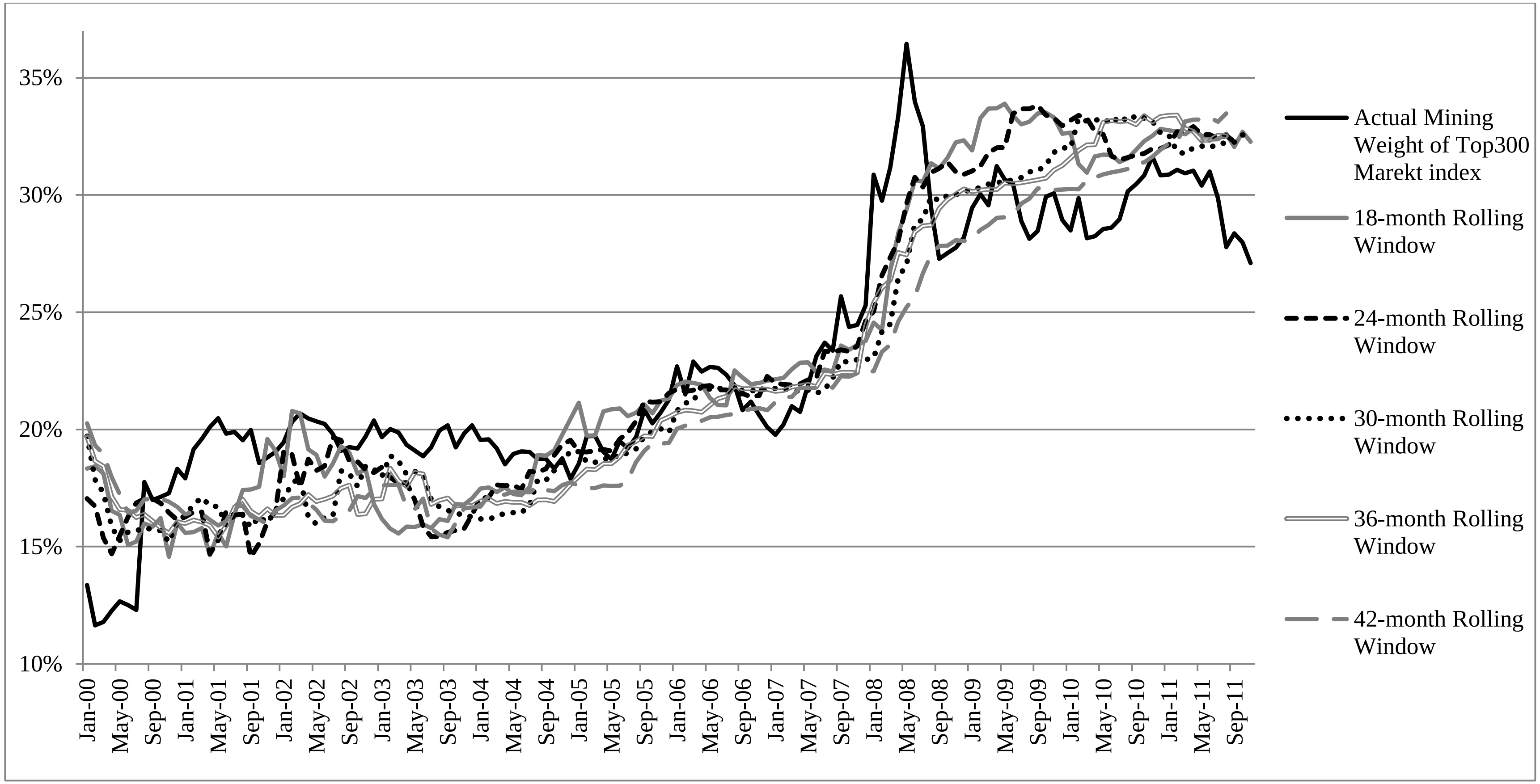
Table 3.2: Industry Index Correlations of Actual and Implied Market Weights

Correlation coefficients between the industry weights of the *Top 300* Market index, measured monthly across the period from January 2003 to December 2011, and the respected implied industry weights, estimated from Sharpe (1992) constrained regressions over 18-, 24-, 30-, 36- and 42-month rolling windows, are reported.

	Rolling Window Length (Months)				
Industry Index	18	24	30	36	42
Mining	0.899	0.901	0.899	0.889	0.869
Materials	0.083	0.003	-0.252	-0.471	-0.598
Industrials	0.197	0.413	0.443	0.487	0.609
Consumer Discretionary	0.688	0.751	0.761	0.740	0.688
Consumer Staples	0.144	0.200	0.309	0.357	0.322
Health Care	-0.050	0.021	0.026	0.003	-0.154
Financials	0.397	0.544	0.629	0.704	0.737
Information Technology	0.422	0.380	0.395	0.355	0.311
Telecommunications	0.849	0.783	0.682	0.640	0.622
Utilities	-0.232	-0.149	-0.070	-0.123	-0.213

Figure 3.2: Actual and Implied Mining Industry Market Weights

Actual monthly market capitalisation weights of the mining index relative to the Top 300 market index are displayed alongside implied monthly mining index weights of the Top 300. Implied weights are estimated using a Sharpe (1992) constrained regression framework over 18-, 24-, 30-, 36- and 42-month rolling windows from January 2000 to December 2011.



3.6.b Portfolio Analysis

To investigate the performance, flows and characteristics of funds with different mining-boom exposures, fund portfolio analysis is conducted. The sample of actively managed Australian equity funds are first sorted into decile portfolios according to their one-month lagged mining index exposures, with decile one containing funds with the highest exposure to mining stocks and decile ten containing the lowest mining-exposed funds. Portfolios are equally-weighted and are rebalanced monthly. Two long-short portfolio are also constructed that are long decile one and short decile ten, and long deciles one and two and short deciles nine and ten. Average monthly fund mining exposure, raw return, flow, size and age for funds contained in each decile (and long-short portfolios) are pooled across the sample period from January 2000 to December 2011.

Style factor exposures and risk-adjusted performance of fund with varying levels mining exposure are investigated by estimating Carhart (1997) four-factor regressions, from the decile fund portfolios across the sample. The Carhart (1997) regressions are estimated from the equation:

$$r_{p,t} - r_{f,t} = \alpha_p + \beta_{1,p}\left(r_{m,t} - r_{f,t}\right) + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}UMD_t + \varepsilon_{p,t}\,, \tag{3.2}$$

where $r_{p,t} - rf_t$ is the excess return of portfolio *p* at time *t*. α_p is the Carhart alpha of portfolio *p*. R_m-r_f, *SMB, HML* and *UMD* are the monthly returns from the standard Carhart (1997) factors at time *t*, $\beta_{1,i,t} \ldots \beta_{4,i,t}$ are the estimated coefficients on each of the respected four factors and $\varepsilon_{p,t}$ is the error term of portfolio *p* at time *t*.

3.6.c Regression Analysis

Whilst the portfolio analysis approach is used to provide a preliminary indication of the effect that fund mining exposure has on performance and flows, this approach does not control for other fund-specific characteristics that may influence fund performance or flows. To provide more rigorous statistical evidence in support of the hypothesis, the relationship between mining exposure, performance and flows is examined using multivariate regressions models that are estimated from fund-level monthly panel data for the sample of Australian equity funds across the period from January 2003 to December 2011.

3.6.c.i Mining Exposure-Performance Relationship

Regressing various fund performance metrics against fund mining exposure and a vector of control variables using monthly fund-level panel data, the effect that a fund's exposure to mining stocks has on its performance during the mining-boom is examined. This regression is described from the equation:

$$Perf_{m,i,t} = \alpha_{m,i} + \beta_{1,m} MinExp_{i,t} + \beta_{2,m} Wsale_i + \beta_{3,m} MinExp_{i,t} * Wsale_i + \beta_{5,m} X_{i,t} + s_i + v_t + \varepsilon_{m,i,t}, \quad (3.3)$$

where $Perf_{i,t}$ is the performance of fund *i* during period *t* using metric *m*, $MinExp_{i,t}$ is the percentage exposure of fund *i* to the mining index time *t*, $Wsale_i$ is a binary dummy variable that is equal to one if a fund is classified as wholesale fund, or zero if it is a retail fund. $MinExp_{i,t} * Wsale_i$ is an interaction term between fund *i*'s mining exposure and its wholesale dummy value at time *t*. This interaction is used to control for differences that could exist in the fund flow-mining exposure relationship between wholesale and retail funds. The vector of control variables, $X_{i,t}$, includes *Age*, *Size*, *Volatility* and *Flow*. All control variables are lagged one month. s_i are fund style-fixed effects and v_t are month-fixed effects. The performance metrics, *m*, include; market-excess returns (r_i-r_m), *CAPM alpha* and *Carhart alpha*. Construction of these metrics and explanatory variable are described in detail in Chapter 2.4.b.

3.6.c.ii Mining Exposure-Flow Relationship

The portfolio analysis framework described in the previous section provides a means of identifying the flows of funds with different levels of mining exposure. However, to identify the relationship between these two variables during the mining boom, multivariate regression analysis is conducted. The regression model is estimated from the following equation:

$$Flow_{i,t} = \alpha_i + \beta_1 MinExp_{i,t-1} + \beta_2 Wsale_i + \beta_3 MinExp_{t-1} * Wsale_i + \beta_4 Return_{i,t-1} + \beta_5 MinDum_{i,t-1} * Return_{i,t-1} + \beta_6 X_{i,t-1} + v_t + \varepsilon_{i,t} , \tag{3.4}$$

where $Flow_{i,t}$ is the net percentage flow of assets under management into fund *i* during month *t.* A mining industry dummy, $MinDum_{i,t}$, is created that is equal to one for fund *i* at time *t* if its exposure to mining stocks, $MinExp_{i,t}$, is above the median level of mining exposure for all funds in the sample during month *t*, or zero otherwise. This variable is also interacted with lagged fund return, $MinDum_{i,t-1} * Return_{i,t-1}$. All other variables are as previously defined.

Linear piecewise flow-performance regression are also incorporated into this fund flow model to allow for different flow sensitivities to fund mining exposure across varying levels of performance. These piecewise regression apply the same three fractional performance variables ($Low\ Perf_{i,t}$, $Mid\ Perf_{i,t}$ *and* $High\ Perf_{i,t}$) that are based on the percentile rank of the one-month lagged raw returns from the sample of funds.[46] These fractional performance variables are also each interacted with a lagged fund mining exposure dummy variable, $MinDum_{i,t-1}$, to capture the nonlinearity of the flow-performance relationship when explaining the effect that fund mining exposure has on fund flows. The full regression model is:

$$Flow_{i,t} = \alpha_i + \beta_1 MinExp_{i,t-1} + \beta_2 Wsale_{i,t-1} + \beta_3 MinDum_{i,t-1} * Wsale_{i,t-1} + \beta_4 LowPerf_{i,t-1} + \beta_5 MinDum_{i,t-1} * LowPerf_{i,t-1} + \beta_6 MidPerf_{i,t-1} + \beta_7 MinDum_{i,t-1} * MidPerf_{i,t-1} + \beta_8 HighPerf_{i,t-1} + \beta_9 MinDum_{i,t-1} * HighPerf_{i,t-1} + \beta_{10} X_{i,t-1} + v_t + \varepsilon_{i,t} \ , \qquad (3.5)$$

where $LowPerf_{i,t-1}$, $MidPerf_{i,t-1}$ and $HighPerf_{i,t-1}$ are fractional performance variables, defined as the percentile rank of fund *i's* raw returns relative to the entire sample of funds at time *t-1* for low, middle and high return ranking funds, respectively. All other variables are as previously defined.

3.7 Results

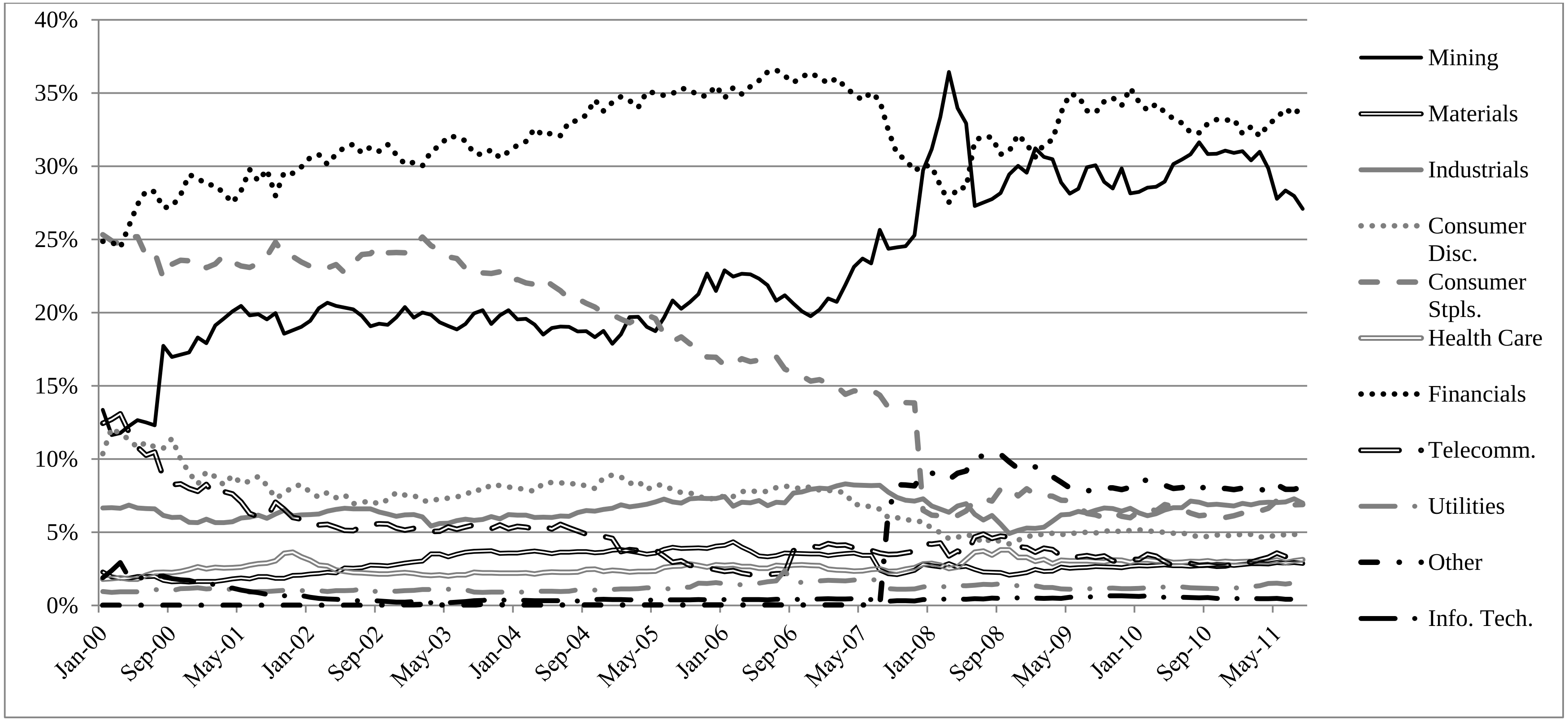
3.7.a Descriptive Statistics

The market weight of mining stocks relative to other industry weights increases substantially over the period from January 2000 to January 2012 (Figure 3.3). The market weights of the other industries has either remained stable or declined over the same period, whereas mining stocks have increased from 13 percent in January 2000 to 27 percent of the total weight of the *Top 300* in December 2011, peaking in June of 2008 with an index weight of 36 percent. The total number of mining stocks contained in the *Top 300* has increased from 41 to 87 over the same period, with a maximum of 100 stocks contained in the *Top 300* during January 2011.

[46] Construction of the three fractional performance variables is described in detail in section 2.4.b.

Figure 3.3: Industry Index Market Weights

A time-series of market capitalisation weights as a percentage of the Top 300 market index for each industry index is displayed at a monthly frequency from January 2000 to December 2011. The industries are Mining, Materials (excluding Metals-and-mining), Consumer Staples, Consumer Discretionary, Industrials, Telecommunications, Utilities, Information Technology, Health Care and Other.[47] The indices are constructed from the top 300 Australian listed stocks by market capitalisation using tier one and two GICS categories to group stocks into one of ten industries. All indices are value-weighted and rebalanced monthly.



[47] The "Other" industry category consists of stocks not classed in any of the other Tier one or two GICS categories and is likely to consist mainly of exchange traded funds.

The number of open-ended Australian equity managed funds included in the study sample increases from 343 at the beginning of the sample in January 2003 to 712 funds by the end of the sample in December 2011. The average fund size decreases over time from $393 million at the beginning of the sample to $236 million by the end of the sample, reflecting new entrants with smaller amounts of assets under management. Descriptive statistics for the other key variables used in the analysis throughout this study are reported in Table 3.3. The expansion of the mining industry as a result of the boom has influenced managers' portfolio allocations such that the portfolio exposure to mining stocks for the average fund increases from 10.5 percent in January 2003, to a peak of 28 percent in December of 2011. The average exposure to mining across the full sample is just over 21 percent.[48]

[48] Descriptive monthly return statistics for these industry indices and the market index (Top 300) are reported across mining-boom, non-mining boom and global financial crisis (GFC) sub-periods from January 2000 to December 2011 in Table B.6 within Appendix B. Mining-boom and non-boom sub-periods are also defined in Appendix B.

Table 3.3: Descriptive Statistics

Descriptive statistics are reported for all variables used in the analysis throughout Chapter 3. The statistics are measured using monthly data at the fund level for the sample of actively managed Australian equity funds over the period from December 2003 to December 2011. *Mining Exposure* is the fund level percentage exposure of a fund's portfolio to mining-related stocks, calculated using a returns-based constrained regression approach over a 36-month rolling windows, *Return*, *Market-Excess Returns*, *CAPM Alpha* and *Carhart Alpha* are fund-level performance metrics. The two alpha metrics are calculated over a 24-month rolling window. *Size*, is the value of the Total Net Assets under management for a fund and *Age* is the number of month since a fund's inception date. *Volatility* is measured as the historical standard deviation of fund monthly raw returns over the previous 12 months. *Net Style Flow* is the net flow of assets under management into all funds with the same investment style category. *Flow* is the net monthly flows of assets under management into each fund. The market return is the SIRCA SPPR value-weighted share index and the Risk-free rate is the 13-week Treasury Note rate. *SMB*, *HML* and *UMD* are the returns from the standard size, value and momentum Carhart (1997) factors, respectively.

Variable	**Mean**	**Min**	**Median**	**Max**	**Std. Dev.**	**Skewness**	**Kurtosis**
Mining Exposure	21.049	0.000	21.262	100.000	13.101	1.268	8.593
Return	0.781	-39.290	1.810	27.700	4.931	-1.010	5.762
Market-Excess Return	0.067	-26.177	0.005	25.432	2.013	-0.361	15.519
CAPM Alpha	0.003	-2.281	-0.040	4.038	0.413	0.993	9.611
Carhart Alpha	0.027	-3.440	0.003	4.890	0.389	0.399	9.063
Size ($ million)	345	0.00	80.50	10,800	811.00	6.015	52.487
Age (months)	84	0	68	580	72.780	1.691	8.170
Volatility	4.020	1.076	3.733	17.016	1.831	1.641	7.552
Net Style Category Flow	-0.332	-5.552	-0.274	5.988	1.054	-0.077	6.578
Flow	0.551	-5.571	-0.069	9.765	3.499	0.921	4.002
Market Return	0.691	-13.113	1.755	8.000	4.108	-1.004	3.987
Risk-free Rate	0.423	0.217	0.432	1.364	0.098	-0.129	3.260
SMB	0.709	-20.526	0.530	22.365	5.557	0.059	3.082
HML	0.227	-9.456	0.747	14.953	2.944	-0.590	3.056
UMD	0.325	-12.483	0.234	11.561	2.542	-0.664	5.888

3.7.b Fund Mining Exposure and Fund Characteristics: Portfolio Analysis

The portfolio analysis results, reported in Table 3.4, shows a significant dispersion in the average mining exposure between the most and least exposed portfolios. The difference between the highest and lowest mining-exposed portfolios each month is on average 42 percent, with the high mining-exposed portfolios having an average exposure of 43 percent and the low mining-exposed having an average mining exposure of one percent. Time-varying mining exposures of these decile portfolios are illustrated in Figure 3.4.

The performance of funds measured from monthly raw returns is insignificantly different between the two extreme decile portfolios. The high decile portfolio does not significantly outperform the low decile portfolio, on average. This result also holds when looking at the difference in average returns between the top two and bottom two deciles, which is further illustrated in Figure 3.5. Given the sizeable appreciation in the relative value of the mining industry, this result indicates that funds are unable to capture the returns to the mining industry in a meaningful way that yields outperformance relative to their peers. These results, however, do not control for fund risk-exposures or other fund-specific factors that influence performance. More rigorous fund-level performance analysis is therefore conducted later in this chapter.

Table 3.4: Mining-Exposed Decile Fund Portfolios

Average monthly Mining Exposure, Returns, Flows, fund Size, and fund Age, for equal-weighted decile portfolios constructed from a sample of Australian actively managed equity funds over the period from January 2003 to December 2011 are reported. Funds are sorted equally into decile portfolios each month based on their one-month lagged mining-exposure and rebalanced monthly. Decile one (ten) contains funds with the highest (lowest) exposure to mining stocks. Differences in average Mining Exposure, Returns, Flows, fund Size, and fund Age, between the High and Low and average of top two and bottom two portfolios over the sample period are also reported. Fund-level mining exposure is measured from a Sharpe (1992) constrained regression approach across 36-month rolling windows and expressed as a percentage, Return is average raw fund return in percentage per month, Flow is the net monthly percentage flow of assets under management, Size is the net value of assets under management in $millions and Age is the number of months since inception date. T-statistics are displayed in parentheses and *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Decile	Mining Exposure	Return	Flow	Size	Age
1 [High]	43.193	0.730	1.061	204.040	78.577
2	30.362	0.650	0.829	238.798	87.842
3	26.822	0.565	0.483	276.388	95.433
4	24.705	0.588	0.485	340.032	99.805
5	22.948	0.537	0.571	374.561	97.544
6	21.096	0.585	0.242	398.211	98.599
7	18.523	0.514	0.391	374.415	87.851
8	13.969	0.582	0.541	292.323	85.223
9	8.001	0.597	0.479	343.637	84.363
10 [Low]	1.367	0.648	0.424	602.928	79.938
Decile Average	21.094	0.599	0.551	344.533	89.518
Av. (1 + 2)	36.778	0.690	0.945	221.419	83.209
Av. (9 + 10)	4.662	0.623	0.451	473.283	82.150
High - Low	41.826***	0.082	0.637***	-398.888***	-1.361
	(170.739)	(0.757)	(8.29)	(-16.3)	(-0.99)
Av.(1+2) - Av.(9+10)	32.115***	0.067	0.493***	-251.864***	1.059
	(210.798)	(0.917)	(9.387)	(-17.6)	(1.079)

The difference between the average monthly fund flows for the high and low mining exposure deciles is positive and significant. Although flows do not change monotonically as fund mining exposure changes, the two high mining exposure portfolios experience substantially higher average flows relative to the remaining eight decile portfolios. Fund in the highest decile experience, on average, a 0.637 percent greater inflow of assets per month than funds contained in the lowest mining exposures decile. This finding suggests that during the mining boom period, investors were significantly attracted to funds that exhibited high levels of exposure to mining stocks, despite these funds being unable to outperform their peers. This result is consistent with Cooper et al. (2005) and Greenwood and Nagel (2009), who show that increased investor assets flowed to funds with high IT exposure during the U.S. IT boom. Similarly, the result that high mining-exposed funds attract higher flows also supports the findings of Frazzini and Lamont (2008), who show that investors chase past style returns.

The portfolio analysis shows that fund size is inversely related to mining exposure. The difference between the top and bottom deciles indicates that funds with the highest exposure to mining boom stocks, over the period from 2003 to 2011, are on average $399 million smaller than the least mining-exposed funds. A similar conclusion can be drawn when examining the difference between the average size of the top two and bottom two deciles. This result is largely driven by the lowest mining-exposure portfolio (decile ten), which contains funds that are much larger, on average, than the funds in all other decile portfolios. This size of funds in this decile is on average about $205 million larger than the funds in the next largest portfolio (decile six). Differences in average fund age across the portfolios are also reported in Table 3.4 with no clear pattern emerging. That is, fund age does not appear to affect a fund manager's preference for mining-boom stocks.[49, 50]

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[49] Average monthly fund mining exposure, returns, flows and size, for the equal-weighted decile portfolios are reported across calendar-year sub-periods from January 2003 to December 2011 in Table B.2, Table B.3, Table B.4 and Table B.5, respectively, within Appendix B.

[50] Average monthly fund mining exposure, returns, flows, size, and age, for the equal-weighted decile portfolios across mining-boom and non-mining boom sub-periods are reported within Table B.7 in Appendix B.

Figure 3.4: Mining Exposures of Decile Fund Portfolios

A time series of average mining exposures of funds contained in decile portfolios from January 2003 to December 2011 is displayed in this figure. Decile portfolios are constructed from sorting a sample of Australian actively managed equity funds equally into groups each month based on their one-month lagged mining-exposure and rebalanced monthly. Decile one (ten) contains funds with the highest (lowest) exposure to mining stocks. Fund-level mining exposure is measured from a Sharpe (1992) constrained regression approach across 36-month rolling windows and expressed as a percentage.

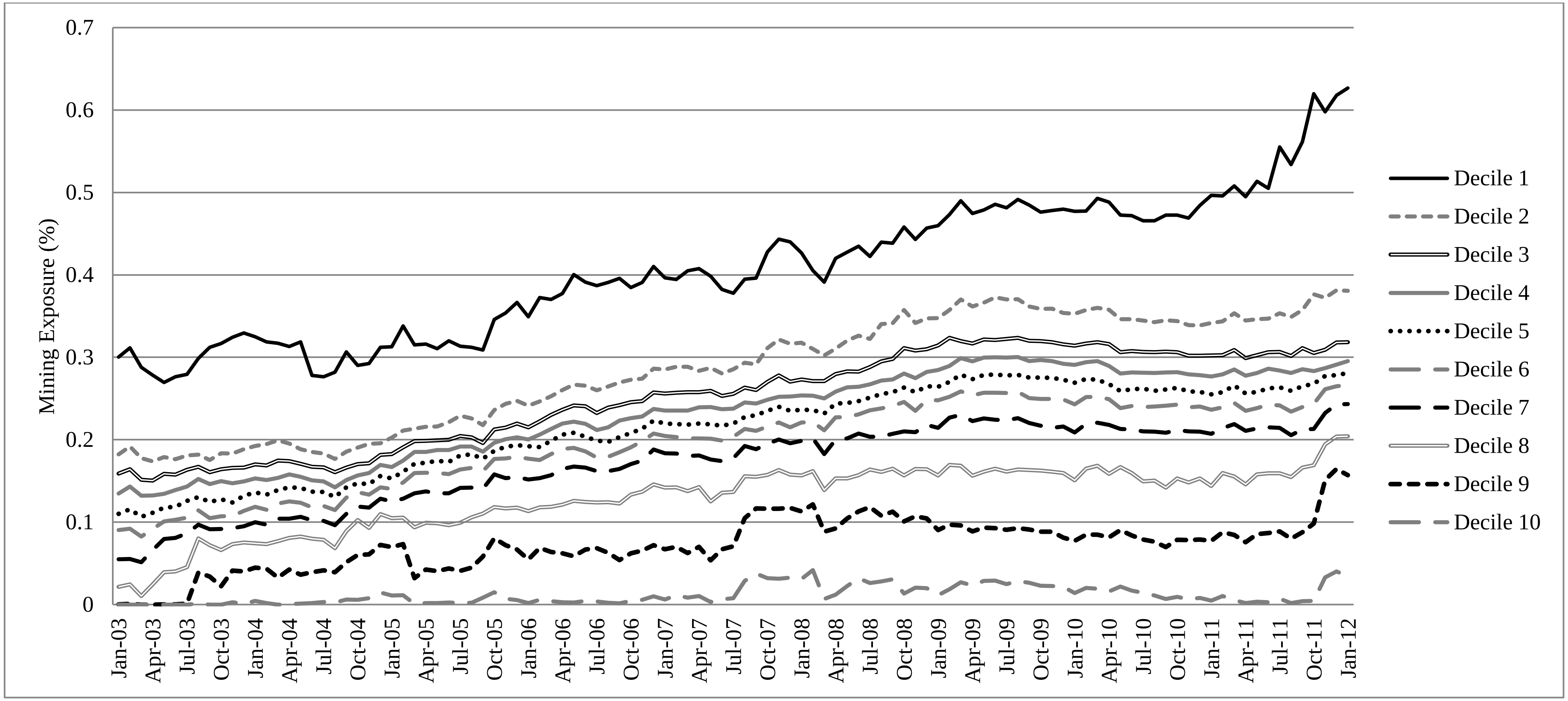
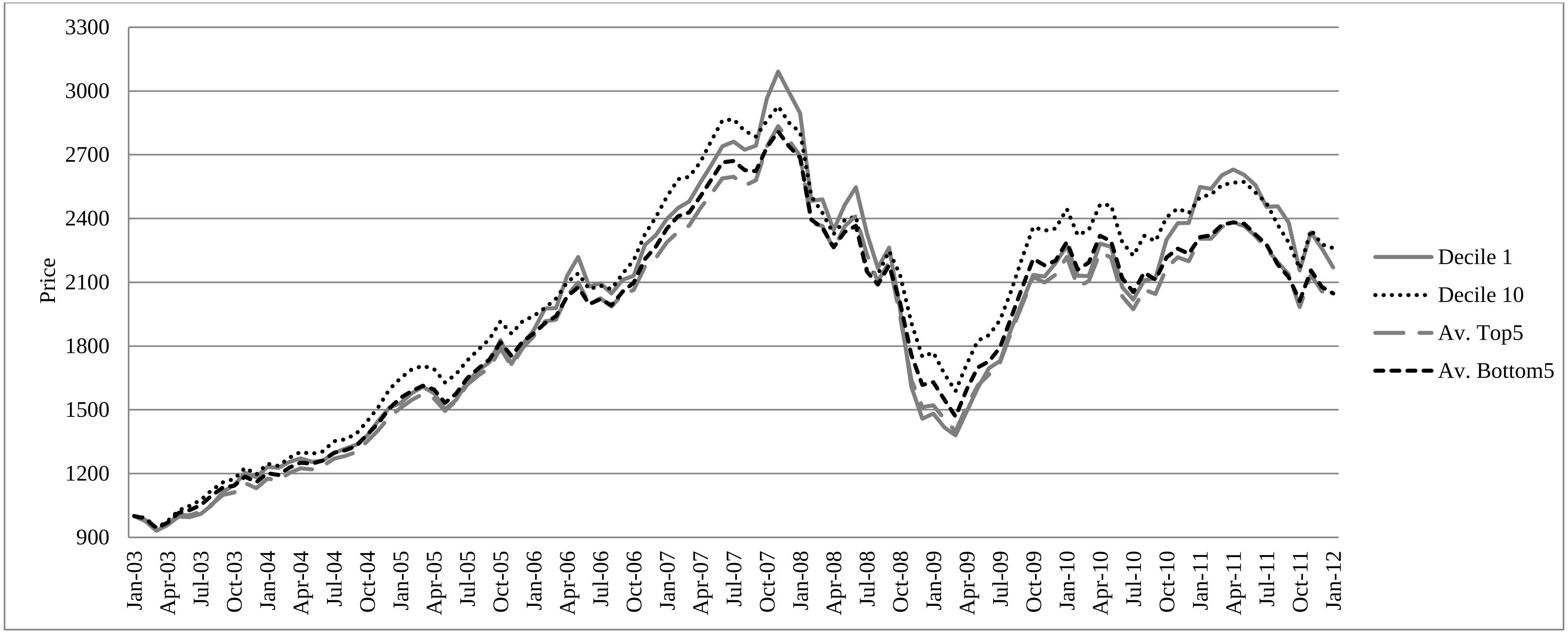


Figure 3.5: Decile Fund Portfolio Prices

Time series plots of monthly prices for the highest and lowest equal-weighted decile portfolio of funds (decile one and decile 10) and the average for the top and bottom five portfolios (Av. Top 5 and Av. Bottom 5) are displayed from January 2003 to December 2011. Decile portfolios are constructed from a sample of Australian actively managed equity funds sorted equally according to their one-month lagged mining-exposure and rebalanced monthly. Fund-level mining exposure is measured from a Sharpe (1992) constrained regression approach across 36-month rolling windows. All portfolios begin with a base value price of 1000 points at the beginning of the sample period.



To better understand the relationship between performance, risk and fund mining exposure, Carhart (1997) four-factor regressions are estimated from the monthly returns for each of the decile portfolios along with the portfolio that is long 'high mining-exposed' funds and short 'low mining-exposed' funds. The regression results, presented in Table 3.5, show a near monotonic relationship between the decile portfolios' market beta and exposure to mining stocks. I.e., funds in the highest mining exposure decile on average have the highest market beta. The highest mining decile (Decile one) is on average slightly overexposed to the market relative to the market ($\boldsymbol{\beta}_{\mathbf{Rm\text{-}Rf}}$ =1.185), whereas Decile 10 is slightly underexposed to the market ($\boldsymbol{\beta}_{\mathbf{Rm\text{-}Rf}}$ =0.949). The difference in the market factor between the High and Low deciles is therefore shown as being significantly different at the one percent level (t-stat = 2.656).This result suggests that the higher mining-exposed funds hold stocks that are, on average, more exposed to the market than the stocks held by the "less mining-exposed" funds. This finding may be attributed to the mining industry being more sensitive to the market during the mining boom relative to the remaining industries.

The loadings on the size factor, are shown to exhibit a U-shape pattern across the deciles as both the High and Low mining-exposure portfolios have significantly positive loadings whilst the mid deciles have statistically insignificant loadings. This indicates that the two extreme deciles (and decile nine) are significantly overexposed to small-sized stocks, whereas the remaining deciles contained mid-sized stocks, or a blend of both large and small stocks. This finding suggests that during the mining boom, mining-concentrated funds may have been confident of the growth potential of small stocks in this industry and as such were adventurous in holding a higher proportion of these stocks. Similarly, deciles nine and ten may have been concentrated amongst industries other than mining, and subsequently contained the ability to identify mispriced stocks, which were also evidently small stocks. The significantly negative *SMB* factor exposure for the High-Low portfolio (t-statistic = -2.947) indicates that this long-short portfolio is relatively overexposed to large firms.

The portfolios of funds with lower mining exposures (deciles seven, eight, nine and ten) are shown to have a significant value tilt, as indicated by the statistically significant loadings on the *HML* factor. This suggests that the stocks held by funds with the least mining exposure were value orientated. Conversely, portfolios of high mining–exposed funds did not, on average, have a significant net exposure to value or growth stocks as shown by the statistically insignificant loadings on the *HML* factors. This result is surprising given that the *HML* loadings of the High–Low portfolio is significantly negative, indicating that high mining-exposed funds tend to be more growth orientated relative to the least mining-concentrated funds..

The statistically insignificant coefficients on the *UMD* factor for each of the decile portfolios reported in Table 3.5 suggest that funds of all levels of mining-exposure, on average, do not implement momentum strategies. Furthermore, there does not appear to be a net difference in momentum exposure between funds with high mining exposure and low mining exposure as indicated by the statistically insignificant coefficients on the two long-short portfolios.

The Carhart alphas reported for each decile portfolio in Table 3.5 are statistically insignificant. This indicates that long-only portfolios of funds, constructed according to level of mining-exposure, on average, were unable to produce significant abnormal returns over the mining boom. In other words, funds with high (or low) exposure to mining stocks, on average, did not achieve significantly positive risk-adjusted returns. The Carhart alphas of the two long-short portfolios in Table 3.5, however, shows a more interesting result. The High-Low portfolio suggests that constructing a portfolio that is long funds with high mining-exposure and short fund with low mining exposure will produce an average risk-adjusted return of 24 basis points per month (significant at the one-percent level). However, the second long-short portfolio [Av. (1 and 2) - Av. (9 and 10)] indicates that such a strategy will result in a negative risk adjusted return of 54 basis point per month (also significant at the one percent level). [51] Subsequently, Carhart alpha does appear to be systematic across levels of fund mining-exposure. This result provides initial indication that fund managers who held relatively higher proportions of mining stocks in their portfolios throughout the mining boom were unable to outperform their peers.

[51] Table B.8 in Appendix B reports Carhart (1997) four-factor regressions estimated for the equal-weighted decile portfolios across mining boom and non-boom defined sub-periods. Results are qualitatively similar to the full-period regressions reported in Table 3.5.

Table 3.5: Four-Factor Decile Fund Portfolio Exposures

Carhart (1997) four-factor regressions are estimated for equal-weighted decile portfolios constructed from a sample of Australian actively managed equity funds over the period from January 2003 to December 2011. Funds are sorted equally into decile portfolios each month based on their one-month lagged mining-exposure and rebalanced monthly, with decile one (ten) containing funds with the highest (lowest) exposure to mining stocks. Equal weighted monthly portfolio returns are then calculated for each decile over the sample period. Fund-level mining exposure is measured from a Sharpe (1992) constrained regression approach across 36-month rolling windows. Carhart (1997) regressions are also estimated for long-short portfolios constructed from decile one and decile ten, as well as for a portfolio that is long deciles one and two and short deciles nine and ten. T-statistics are displayed in parentheses and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Decile	$\beta_{Rm\text{-}Rf}$	β_{SMB}	β_{HML}	β_{UMD}	Carhart Alpha
1 [High]	1.185***	0.086***	-0.045	-0.009	0.008
	(34.43)	(3.787)	(-0.91)	(-0.165)	(0.078)
2	1.113***	0.018	-0.014	0.031	0.02
	(46.84)	(1.333)	(-0.443)	(0.872)	(0.263)
3	1.082***	-0.015	0.03	-0.06	0.024
	(38.946)	(-1.316)	(0.924)	(-1.614)	(0.372)
4	1.04***	-0.012	0.021	0.002	0.028
	(67.804)	(-1.119)	(1.087)	(0.072)	(0.502)
5	1.017***	-0.006	0.022	-0.004	-0.005
	(82.643)	(-0.656)	(0.973)	(-0.168)	(-0.083)
6	1.005***	-0.015	0.024	0.022	0.04
	(44.975)	(-1.282)	(0.907)	(0.694)	(0.667)
7	1.057***	0.003	0.061**	-0.05*	-0.06
	(61.205)	(0.281)	(2.481)	(-1.857)	(-0.995)
8	1.05***	0.025*	0.131***	-0.063*	0.062
	(56.664)	(1.834)	(5.205)	(-1.894)	(0.937)
9	0.963***	0.052***	0.158***	-0.026	0.104
	(24.526)	(2.714)	(3.628)	(-0.441)	(1.005)
10 [Low]	0.949***	0.054**	0.204***	-0.011	0.128
	(19.586)	(2.566)	(3.53)	(-0.144)	(0.944)
High - Low	0.242***	-0.559***	0.037	0.009	0.24***
	(2.656)	(-2.947)	(1.067)	(0.076)	(3.394)
Av. (1 and 2) - Av. (9 and 10)	0.197***	0.004	-0.204***	0.036	-0.541***
	(3.211)	(0.153)	(-2.707)	(0.373)	(-3.356)

Preliminary investigation into the difference between wholesale and retail funds in relation to their portfolio exposures to mining stocks reveals a statistically significant difference at the one percent level (t-stat = -6.018), with the average mining exposure of wholesale funds being 20.59 percent compared to 21.62 percent for retail funds. This result, however, appears to be economically insignificant, suggesting that these two types of managers do not differ greatly from one another in terms of their preference for mining stock. Despite having lower exposure to mining stocks, wholesale funds on average outperform retail funds across the sample period in terms of raw returns (by 0.14 percent per month), CAPM alpha (by 0.054 percent per month) and Carhart alpha (by 0.0664 percent per month). These performance differences are statistically different at the ten, one and one percent significance level, respectively (t-stats = 1.875, 8.454 and 10.797, respectively). Fund flows are on average 0.375 percent of assets under management per month for wholesale funds and 0.365 percent per month for retail funds. This difference is statistically insignificant (t-stat = 0.200). The effect that mining stock exposure has on the performance and flows of wholesale/retail funds is examined in further detail in the following section through the application of regression analysis.

3.7.c Performance and Mining Exposure: Regression Analysis

Multivariate regression models that examine the relationship between fund exposure to mining stocks and fund performance during the mining boom are estimated in Table 3.6. Initial results show that the level of exposure to mining stocks does not affect fund perfomance across the mining boom (when performance is measured using market-excess returns, CAPM alpha or Carhart alpha). This is demonstrated from the statistically insignificant coefficients on the *MiningExposure* variables from the regressions in colums one, three and five. Examining this performance-mining exposure relationship closer, by separating funds into their wholesale and retail categories, reveals more interesting findings.

The effect that mining exposure has specifically on retail funds is identified from the coefficients on the *MiningExposure* variables from the regressions in columns two, four and six of Table 3.6. The linear combination of the *MiningExposure* and *MiningExposure*Wholesale* variables in these regressions subsequently identifies the relationship between mining exposure and wholesale fund performance during the mining boom. The statistically insignificant coefficient on the mining exposure variable from the regression in column two suggests that a retail fund's exposure to mining stocks does not significantly influence its market-excess returns. The lack of relationship between mining exposure and this performance metric is also observed for wholesale funds, as indicated by the statistically insignificant coefficient from the linear combination of respective variables (t-statistic = -0.83) in regression two.

The regression from column four in Table 3.6 shows that when adjusting for market risk, a retail fund's exposure to mining stocks is able to positively influence its returns (as measured from CAPM alpha). This is demonstrated from the significance of the *MiningExposure* coefficient at the five percent level (t-statistic = 2.384). Consequently, when the exposure to mining stocks of a retail fund increases by one standard deviation (12.53 percent) its CAPM alpha is expected to increase by an average of 4.74 basis points per month. This relationship, however, is not observed for wholesale funds, as indicated by the insignificant coefficient from the linear combinations of the respected variables, equalling -0.00207 (t-statistic = -0.94) in regression four.

Adjusting the CAPM alpha for additional risk factors not included in the CAPM, the Carhart alpha is able to further identify if increased exposures to mining stocks by funds during the mining boom results in superior performance. The significantly positive relationship between abnormal returns and mining exposure, observed for retail funds when measured using CAPM alpha, disappears when performance is measured using Carhart alpha. This is shown from the insignificant

MiningExposure coefficient in regression six (t-statistic = -0.972). This finding implies that the premium resulting from increased exposure to mining stocks was a consequence of retail funds capturing risk factors that are absent from the CAPM. As such, solely increasing portfolio exposure to mining stocks during the boom is unlikely to result in improved performance for retail funds.

When performance is measured using Carhart alpha, the insignificant relationship observed for wholesale funds between their level of mining exposure and performance is shown in regression six, from the linear combination of the *MiningExposure* and *MiningExposure*Wholesale* variables, to be significantly negative at the ten percent level (t-statistic = -1.85). This counterintuitive result implies that wholesale funds were adversely affected, in terms of their risk-adjusted returns, when mining exposure increased during the mining boom. A one standard deviation increase in a wholesale fund's exposure to mining stocks (10.49 percent) for example, is therefore expected to decrease its Carhart-adjusted return by an average of 4.37 basis points per month.

The regression estimates for each of the control variables are also consistent across each of the regressions in Table 3.6, in that small, older, more volatile funds, with past positive flows achieve significantly better performance than their counterpart funds. Accordingly, the findings from these performance regressions suggest that for Australian equity mutual funds, in general, that have increased expoures to mining stocks during the Australian mining boom are unable to generate enhanced performance. Whilst mining exposure seems to be positivly related to a retail fund's risk–adjusted returns, this relationship is observed as being a result of their mining exposure picking up some unboserved risk factor that is not priced in the CAPM. The performance of wholesale funds during the mining boom however, is shown to be adversly affected from an increase in the expoure to mining stocks after controling for Carhart risk-factors. These results are robust to controlling for factors that are shown to influence fund performance. Subsequently, these findings suggest that attempts by managers to outperform by exploiting the mining boom go unrewarded for retail funds and, are in fact, detrimental for wholesale funds.

Table 3.6: Fund Mining-Exposure Performance Relationship

Regressions are estimated using monthly panel data from January 2003 to December 2011 for a sample of Australian actively managed equity funds to describe the relationship between fund performance and fund mining exposure. The dependent fund performance variables include; market-excess fund return, where the monthly market return is the return on the CRSP value weighted share index, *CAPM alpha* and *Carhart alpha*, measured across prior 24-month rolling windows. The explanatory variables are fund-level mining-stock exposure, *MiningExposure*, determined as the percentage exposure of a fund's portfolio to mining-related stocks, calculated using a Sharpe (1992) returns-based constrained regression approach across 36-month rolling windows, a wholesale fund dummy, *Wholesale*, which takes on a value of one if a fund is classified as a wholesale fund, or zero if it is a retail fund, and a wholesale-mining exposure interaction variable, *MiningExposure*Wholesale*. A vector of control variables which comprise of; the natural log of a fund's total net assets, *Size*, the natural log of the number of months since a fund's inception date, *Age*, return *Volatility* (measured as the historical standard deviation of monthly raw returns over the previous 12 months) and lag flow of assets under management, *Lag Flow*, are contained in the regressions. All control variables are lagged one-month and regressions are estimated with time-fixed effects (month dummies) and style-fixed effects (style dummies). Robust standard errors are clustered at the fund level and t-statistics are displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Market-Excess Return		**CAPM Alpha**		**Carhart Alpha**	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.278	-0.296	-0.246**	-0.276***	-0.317***	-0.321***
	(-1.291)	(-1.342)	(-2.305)	(-2.618)	(-3.110)	(-3.258)
Mining Exposure	0.000783	0.00246	0.00216	0.00378**	-0.00216	-0.00128
	(0.377)	(1.148)	(1.431)	(2.384)	(-1.617)	(-0.927)
Wholesale		0.202**		0.202***		0.137**
		(2.357)		(3.558)		(2.482)
Mining Exposure Wholesale*		-0.00574		-0.00586**		-0.00289
		(-1.371)		(-2.367)		(-1.229)
Size	-0.0165**	-0.0209***	0.00193	-0.00195	0.00526	0.00146
	(-2.134)	(-2.606)	(0.412)	(-0.412)	(1.112)	(0.309)
Age	0.0366	0.0426**	0.0523***	0.0584***	0.0356*	0.0414**
	(1.643)	(1.964)	(2.645)	(3.143)	(1.782)	(2.167)
Volatility	0.111***	0.110***	0.00531	0.00452	0.0299**	0.0285**
	(3.485)	(3.465)	(0.306)	(0.263)	(2.060)	(1.976)
Lag Flow	0.00919**	0.00965**	0.0142***	0.0144***	0.0140***	0.0140***
	(2.429)	(2.550)	(5.774)	(5.918)	(6.032)	(6.079)
Style fixed-effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Month fixed-effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	19,739	19,739	15,569	15,569	15,569	15,569
R-squared	0.084	0.085	0.257	0.271	0.203	0.214

3.7.d Fund Flows and Mining Exposure: Regression Analysis

Funds with higher exposures to mining stocks during the mining boom are anticipated to attract greater inflows of assets under management, and that the flow-performance relationship will be strongest amongst high mining-exposed funds. Estimating multivariate flow-performance regressions to investigate the relationship between fund mining exposure and flows, illustrated in Table 3.7, identifies a strong positive relationship between these two variables. This relationship is robust across linear and asymmetric flow-performance regression models. Separating funds according to the clients they service, namely wholesale and retail investors, the preference for mining-exposed funds by these investors are also examined in this analysis.

Table 3.7: Fund Mining-Exposure Flow Relationship

Regressions are estimated using monthly panel data from January 2003 to December 2011 for a sample of Australian actively managed equity funds to describe the relationship between fund flows and fund mining exposure. The dependent variable is fund-level percentage flow of assets under management, *Flow*. The explanatory variables are fund-level mining-stock exposure, *MiningExposure*, determined as the percentage exposure of a fund's portfolio to mining-related stocks and calculated using a Sharpe (1992) returns-based constrained regression approach across 36-month rolling windows, a wholesale fund dummy, *Wholesale*, which takes on a value of one if a fund is classified as a wholesale fund, or zero if it is a retail fund, and a wholesale-mining exposure interaction variable, *MiningExposure*Wholesale*. Performance control variables include; raw fund returns, *Return*, as well as three fractional performance controls ($LowPerf_{i,t}$ $MidPerf_{i,t}$ *and* $HighPerf_{i,t}$) based on the percentile ranks of monthly lagged raw fund returns and constructed using fractional 33%-33%-33% breakpoints used to define the *Low*, *Mid* and *High* fractile ranks. All performance measures are interacted with a fund mining exposure dummy, *Mining Dummy*, which takes a value of one if the mining exposure of a fund is greater than the median mining exposure for the sample of funds in that month, or zero otherwise. The regressions also include a vector of control variables, comprising; the natural log of a fund's total net assets, *Size*, the natural log of the number of months since a fund's inception date, *Age*, return *Volatility*, measured as the historical standard deviation of monthly raw returns over the previous 12 months for each fund, flow of assets under management during the previous month, *Lag Flow*, and the net flow of assets under management into all funds with the same investment style, *Net Style Flow*. All independent variables are lagged by one-month and regressions are estimated with time-fixed effects (month dummies) and style-fixed effects (style dummies). Robust standard errors are clustered at the fund level and t-statistics are displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	**Flow** [1]	**Flow** [2]	**Flow** [3]	**Flow** [4]
Constant	6.083***	6.229***	5.792***	5.926***
	(9.779)	(10.158)	(9.170)	(9.525)
Mining Exposure	0.0127***	0.00771*	0.00906**	0.00534
	(2.883)	(1.821)	(2.012)	(1.269)
Lag Return	0.0199	0.0213		
	(1.470)	(1.572)		
*Mining Dummy*Lag Return*	-0.0110	-0.0117		
	(-1.115)	(-1.185)		
Wholesale		-0.341*		-0.319*
		(-1.776)		(-1.678)
Mining Exposure Wholesale*		0.0187**		0.0167**
		(2.271)		(2.078)
Low Return Rank			1.239***	1.227***
			(3.073)	(3.033)
Mid Return Rank			-0.375	-0.356
			(-1.084)	(-1.032)
High Return Rank			-0.399	-0.292
			(-0.459)	(-0.337)
*Low Return Rank*Mining Dummy*			0.384	0.303
			(0.921)	(0.744)
*Mid Return Rank*Mining Dummy*			0.298	0.266
			(0.555)	(0.497)
*High Return Rank*Mining Dummy*			-1.896	-1.875
			(-1.465)	(-1.465)
Size	-0.0991***	-0.101***	-0.0991***	-0.100***
	(-3.152)	(-3.157)	(-3.173)	(-3.149)
Age	-0.864***	-0.864***	-0.874***	-0.875***
	(-10.486)	(-10.378)	(-10.614)	(-10.478)
Volatility	-0.0242	-0.0240	0.0151	0.0132
	(-0.686)	(-0.696)	(0.433)	(0.384)
Lag Flow	0.173***	0.172***	0.171***	0.170***
	(6.495)	(6.458)	(6.400)	(6.368)
Net Style Flow	0.540***	0.538***	0.539***	0.538***
	(9.430)	(9.354)	(9.457)	(9.395)
Time-fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*
Observations	19,739	19,739	19,739	19,739
R-squared	0.155	0.156	0.157	0.158

The relationship between a fund's mining exposure and flows, shown in regression one of Table 3.7, indicates that a one standard deviation (12.02 percent) increase in a fund's mining exposure will result, on average, in a 0.153 percent per month increase in its asset flows. The sensitivity of mining exposure to fund flows is greater for wholesale funds than retail funds, as shown by the significantly positive coefficients from the mining exposure-wholesale interaction variables presented in regressions two and four of Table 3.7. From regression two, a one standard deviation increase in a retail fund's mining exposure is shown to increase flows by an average of 9.3 basis points per month. Whereas the same increase in a wholesale fund's mining exposure results result in a 31.7 basis point increase per month (t-statistic = 2.88) when combining the wholesale and wholesale-mining exposure interaction variables. This indicates that wholesale fund investors have a preference towards investing in funds with higher exposures to mining stocks and are sophisticated enough to identify the level of mining exposures for such funds. Retail investors on the other hand, are either less influenced by a fund's level of mining exposure or alternatively do have a preference for such funds but are less successful at identifying those that are either over- or underexposed to mining stocks. This result conflicts with the findings of Del Guercio and Tkac (2002) and James and Karceski (2006), who suggest that wholesale investors use sophisticated 'risk-adjusted' performance measures when allocating assets across funds. Nevertheless, despite high-mining funds having been shown (in section 3.7.c) to be unable to outperform, wholesale investors still appear to be attracted to such funds. The significantly negative coefficients on the wholesale dummy variable (in regressions two and four), on the other hand, suggest that wholesale funds, on average, attract about 2 percent less in flows (per month) than their retail counterparts after controlling for other fund characteristics. This finding is robust across all regressions.

Regressions one and two in Table 3.7 show that the flow-performance sensitivity of funds is not significantly influenced by their mining exposure, as indicated by the coefficients for the fund Mining Dummy-Return interaction, $MiningDummy_{i,t-1}*LagReturn_{i,t-1}$, variable. These findings are robust across different model specifications. The fractional performance variables ($LowPerf_{i,t-1}$, $MidPerf_{i,t-1}$ and $HighPerf_{i,t-1}$) shown in regressions three and four of Table 3.7 indicate that only the lowest performing funds will benefit from improved fund flows from increased returns. For example, in regression three, a one percent increase in the performance rank of the bottom performing funds results in a 1.623 percent expected increase in flows per month. Flows to mid and high performing funds however are insignificantly different after experiencing a change in performance. The interactions between these fractional performance variables and the mining dummy, $MinDum_{i,t-1}$, are all statistically insignificant. This result indicates that fund mining exposure does not influence the flow-performance relationship of funds at any levels of performance. This finding suggests that despite achieving potentially higher inflows as a result of having a relatively higher exposure to mining stocks, an improvement in relative fund performance does attract new assets under management. These findings add to our understanding of the behaviour of managed fund investors by highlighting how portfolio exposure to industry-booming stocks affects the fund flow-performance relationship.

The coefficients on fund size, age, return volatility, lagged fund flow and net flows to style groups are all significant and in the direction that is expected, with the exception of lagged fund flows, which has no significant effect on current period fund flows. This relationship is consistent across all regression, indicating that smaller, younger, less risky funds that experienced high net flows to their respected style groups will attract greater flows than their counterparts. Lagged net flows to a fund's investment style group is shown to have the greatest effect on fund flow, demonstrating that a one percent increase in the net flow to each style group per month will result, on average, in about a 0.54 percent per month increase in fund flows. The direction and significance of these control variables in the flow-performance regression are consistent with results from Chevalier and Ellison (1997), Sirri and Tufano (1998), Del Guercio and Tkac (2002), Barber, *et al.* (2005) and Cooper, *et al.* (2005).

3.8 Conclusion

A unique setting is identified to provide further evidence on how industry booms impact fund performance and fund flows. A returns-based approach to measure fund-level mining industry exposures is used to measure Australian equity funds' exposures to the mining industry in Australia. The mining industry has experienced a boom during the last decade, more than doubling the average monthly returns of the market. This chapter shows that equity funds that have a higher exposure to the mining industry are not able to outperform funds that have a lower exposure to this industry on a risk-adjusted basis. The results also indicate that funds with higher exposures to the mining industry are able to attract relatively more inflow. This is more pervasive amongst wholesale funds relative to retail funds, despite increased mining exposure being detrimental to the performance of wholesale funds.

This inflow may be attributed to investors mistaking industry allocation for fund skill and that they are attracted to invest in the ‘hot’ industry [see Cooper, *et al.* (2005) and Frazzini and Lamont (2008)]. The results support the findings of Greenwood and Nagel (2009) on the IT bubble as fund managers are not able to extract abnormal returns from industry outperformance and funds with the highest exposure to the booming industry receive increased inflows. This chapter suggests that investors should be wary during times of industry expansions as industry allocation is not a substitute for stock selection skill.

Chapter 4. Psychic Dividends of Socially Responsible Investors

4.1 Introduction

The increased demand for socially responsible investments (SRI) in recent years has resulted in a shift towards greater environmental and social governance (ESG) by firms throughout global markets, and more noticeably, a rise in the number of managed funds that incorporate SRI mandates into their investment strategies. As SRI extends to include an increasing range of products across a variety of asset classes, its popularity is illustrated by the $3.74 trillion of institutional funds under management in the U.S. that are managed using at least one or more ESG screens. These funds represent 11 percent of total institutional assets under management in the U.S. as of 2012. This value has grown from $161.8 billion in 1995, demonstrating both a relative and absolute increase compared to the growth in aggregate institutional assets under management over the same period (USSIF, 2012). The rise in popularity of SRI is also illustrated by the increased number of managed funds subscribing to particular ESG objectives, increasing from 55 funds with $12 billion in assets under management in 1995 to 333 with $640.5 billion in assets under management as of 2012 (U.S. Social Investment Forum, 2012). The growth in alternative investment funds (also referred to as social venture capital, double or triple bottom line private equity, hedge, and property funds) that incorporate some form of ESG screen has also outgrown all other non-SRI alternative investment funds, increasing from 177 funds with total assets of $37.8 billion under management in 2010, to 301 fund in 2012 and $132 billion in assets under management (USSIF, 2012).

The growth in global SRI is a likely consequence of increased awareness of environmental and social issues by investors along with heightened social consciousness that is exhibited by society as a result of becoming wealthier (Joseph, 1989). If individuals are able to derive non-financial utility from investing in SRI, then they may be content with accepting suboptimal returns in exchange for being socially responsible. This chapter subsequently provides a measure of what I term *"psychic dividends"* to socially responsible investors. The broadest definition of psychic returns covers any asset whereby there is a stream of positive (or negative) benefits conferred by ownership of a non-material kind. Other definitions are contextual. In the context of employment, psychic income is defined as the level of satisfaction derived from a job rather than the salary earned from doing it.[52] An alternative definition, relating to an activity, is the subjective value of the nonmonetary satisfaction gained from undertaking the activity.[53] The psychic dividend accruing to an SRI investor can be assumed to stem from a sense of satisfaction derived by the individual from knowing they are contributing to the preservation of the environment or to the legitimacy of society. Or alternatively, this dividend may eventuate for an individual from the 'clear conscience' of having not supported a firm that is destructive to the environment or to society. Previous work by Srivastava, Pownall, and Satchell (2013) illustrates how psychic dividends can be calculated in an heterogeneous capital asset pricing framework where the equilibrium asset class weights are known. In the work that

[52] This definition of psychic dividend is sourced from http://www.qfinance.com.
[53] This definition of psychic dividend is sourced from; Economic Essays, University of North Carolina.

follows, the proportion of investible wealth held in SRI is unknown, and as such, an alternative approach is followed.

This chapter follows the work of Geczy, *et al.* (2005), who considers the cost to mutual fund investors for being socially responsible as the difference in certainty equivalent returns between an optimal portfolio of an unconstrained universe of mutual funds and an optimal SRI-constrained portfolio of mutual funds. This chapter, however, extends the definition of certainty equivalence from the limiting case of exponential utility to more general cases that include constant relative risk aversion and loss aversion. Geczy, *et al.* (2005)'s concept of 'cost' can therefore be interpreted as our concept of psychic dividend. Subsequently, this chapter shows that non-SRI portfolios are unable to outperform SRI on a raw or risk-adjusted basis. However, the psychic dividend to SRI is measured as being at least four basis points per month for a long-only portfolio of socially responsible stocks and at least 85 basis points per month for a portfolio that is long socially-responsible stocks and short socially-irresponsible stocks. This psychic dividend is also shown to increase with investor risk aversion and also during economic recessions.

The remainder of this chapter is organized as follows: Section 4.2 defines socially responsible investing, section 4.3 reviews the literature on the financial cost and benefit SRI, section 4.4 develops the hypothesis and section 4.5 describes the data and method used to examine the performance of SRI portfolios and outlines the approach used to measure psychic dividend. Section 4.6 presents the empirical findings and section 4.7 concludes.

4.2 Socially Responsible Investment

The Social Investment Forum considers SRI to be "an investment process that considers the social and environmental consequences of investments, both positive and negative, within the context of rigorous financial analysis" (USSIF, 2012). SRI is also more generally regarded in other contexts as being the process of incorporating any non-financial criteria into the investment process that seek to encourage environmental or social good. This may include the investment in assets that promote human rights or consumer protection, or alternatively, avoids investments in assets that are associated with practices considered unethical, anti-social, or damaging to the environment (i.e., investments in firms or industries related to alcohol, tobacco, gambling, pornography or weapons) (Sparkes and Cowton, 2004). Whilst historic, religious, cultural and moral beliefs largely influence what asset managers and individuals consider SRI, the constant evolution and lack of consensus amongst its interpretation has led to a degree of ambiguity surrounding its definition. SRI is therefore often used synonymously with terms such as 'green', 'clean', 'ethical', 'sustainable', 'socially conscious' or 'triple-bottom-line' investing. Subsequently, many SRI-screens adopted by institutions and individuals may either complement one another or remain mutually exclusive to one another.

Kinder, Lydenberg, and Domini, Research and Analysis Inc. (KLD), a third-party provider of firm-level quantitative SRI classification data, profile companies using positive and negative SRI criteria to provide ESG ratings for over 3000 of the largest publicly listed U.S. firms. The positive SRI criteria assess firm based on their involvement in practices that promote or sustain environmental or corporate responsibility, whereas negative SRI criteria assess firms based on practices that adversely affect the environment or society. These criteria are based on several major

ESG dimensions including; employee relations, diversity, community relationships, human rights, environment, governance, and controversial issues. Each indicator within the major dimensions is assigned a binary score, and the sum of scores across all ESG dimensions provides the company with its final ESG rating. Subsequently, no firms are considered 'perfectly' socially responsible or irresponsible. Furthermore, firms with the same overall ESG rating may differ substantially from one another in terms of their individual ESG characteristics, thereby being perceived differently from one another in terms of their social responsibility (Chen and Delmas, 2011). KLD are also responsible for maintaining the MSCI KLD 400 Social Index, a market capitalisation-weighted index constructed from the universe of the MSCI USA Investable Market Index and constitutes the highest 400 ESG-screened companies according to KLD's ESG ratings. The ESG ratings are based on a culmination of five key categories, including; environment, community and society, employees and supply chain, customers, and governance and ethics, while also excluding companies involved in the production and distribution of alcohol, tobacco, firearms, gambling, nuclear power or military weapons. This index is designed to assist investors track the performance of socially responsible portfolios.

The difficulty of classifying an investor as being 'socially responsible' is demonstrated in Geczy, *et al.* (2005). To identify such investors, Geczy, *et al.* (2005) construct SRI portfolios of mutual funds using information sourced from the current literature as well as from the asset management industry. These sources include, the Social Investment Forum (2001), Morningstar, newspapers, magazines and journals, fund prospectuses and websites, as well as from direct contact with fund managers. Geczy, *et al.* (2005) use this information to identify 20 positive and 20 negative screens in which to categorise mutual funds. The positive screens are; Renewable

Energy, Community Involvement/Investment, Human Rights, Environment, Diversity and Animal Rights. The negative screens consist of; alcohol, tobacco, gambling, nuclear power, firearms, defence contracting (military) weapons, irresponsible foreign operations (i.e., investment in oppressive regimes such as Burma or China and mistreatment of indigenous peoples), abortion/birth control, usury (i.e., predatory lending, bonds, fixed-income securities) and pornography. To measure the psychic dividend earned by SRI investors, this chapter defines SRI in a broad sense that does not impose a specific definition, but incorporates all general screens commonly used throughout the prevalent literature that characterise a firm's environmental or social governance mandates. The specific approach used to construct a portfolio that is representative of SRI and non-SRI investors is described in detail in section 4.5.a.

4.3 Background Literature

4.3.a Introduction

An abundance of studies have emerged that seek to examine the effect that SRI has on stock portfolio performance. A large proportion of these studies investigate the financial cost of SRI by comparing SRI-screened portfolio performance against the performance of unscreened of 'non-SRI' screened portfolios. The findings from these studies, however, remain largely unconsolidated as the literature proposes two competing hypotheses concerning the effect that SRI has on performance. The first suggests that by constraining the investment opportunity set to contain only SRI stocks, a portfolio will fail to be mean-variance efficient, and through the incurrence of higher costs structures, to remain socially responsible, these portfolios will ultimately underperform non-SRI portfolios. The opposing hypotheses suggests that in the long run, socially responsible stocks are able to outperform non-SRI stocks due to the avoidance of potential costs associated with reputation loss, corporate social crisis or from potential litigation costs that may arise from ignoring socially responsible practises (Renneboog, Ter Horst and Zhang, 2008). The following literature discusses the extent to which this financial cost (or benefit) impacts investors who are socially responsible.

4.3.b Financial cost from SRI

Traditionally, SRI-constrained portfolios are typically expected to underperform in the long-run. This argument has largely been supported by a body of literature using a variety of screens to evaluate the performance of SRI-constrained portfolios. Geczy, *et al.* (2005) find that the cost imposed by constraining a portfolio based on SRI criterion depends on the investors' prior beliefs about pricing models, managerial skill, as well as their proportion of wealth that is invested in SRI. They show that the cost of SRI to investors who strongly believe in the CAPM and whose portfolio is minimally invested in SRI can be as little as one to two basis points per month. However, for those with a belief in multi-factor asset pricing models, such as the Fama and French (1993) or Carhart (1997) models, or who believe that managers possess skill based on past returns, then the cost of an SRI-constrained portfolio can become economically significant. This is argued to be especially true for investors who hold a large proportion of their total portfolio wealth in socially responsible funds. Geczy, *et al.* (2005) further argue that this cost of engaging in SRI is offset by the utility derived by socially responsible investors for 'doing good'. However, they recognise that this mean-variance measure of cost does not incorporate the non-financial utility extracted by socially responsible investors that is associated with SRI investing. Consequently, the certainty equivalent cost imposed on the SRI fund portfolios is considered an overestimate of the total net cost to investors who have such investment preferences.

Using the MSCI KLD 400 Social index as an SRI indictor, Becchetti and Ciciretti (2009) examine the variance and performance of socially responsible stocks using daily data in an event study across a 14 year horizon. They show that the raw returns and unconditional volatility of SRI stocks are significantly lower than conventional stocks after controlling for industry effects, however, conditional abnormal returns of SRI stocks are found to be statistically indifferent. Becchetti and Ciciretti (2009) further argue that passive SRI stock portfolios exhibit significantly lower systematic risk.

Hong and Kacperczyk (2009) examine the performance of 'sin' (alcohol, tobacco and gaming) stocks, using time-series regressions over the period from 1965 to 2006 and find that a portfolio that is long sin stocks and short 'non-sin' stocks, of similar characteristics, produces a significantly positive Carhart alpha (of about 26 basis points per month). They also find that sin stocks have higher book-to-market value, are under-priced, have less analyst coverage and are held less by institutions, relative to non-sin stocks. Using cross-sectional regression analysis and controlling for firm characteristics including size, past returns, and market-to-book ratio, Hong and Kacperczyk (2009) also show that sin stocks are able to significantly outperform their counterparts by about 29 basis points per month. These results are also found to be robust for stocks outside of the U.S. market over the period from 1985 to 2006 for Canada, France, Germany, Italy, Netherlands, Spain, Switzerland, and the United Kingdom. Adler and Kritzman (2008) apply Monte Carlo simulation to estimate the cost of socially responsible investing. They show that this cost (when measured as the difference in raw returns between an SRI constrained portfolio and an unconstrained portfolio) is substantial, even for moderately skilled investors. Adler and Kritzman (2008) also argue that this cost increases with investor skill, cross-sectional dispersion of the fraction of the universe that is restricted, and the number of securities held in the portfolio.

4.3.c Financial benefit from SRI

The previous literature commonly argues that there is a trade-off between social responsibility and financial gain when it comes to investing. However, there is also a large body of literature suggesting that SRI is able to outperform non-SRI. This implies that investors not only benefit socially from such investments, but are also financially better off. Investigating the relationship between corporate social responsibility and corporate financial performance by conducting a meta-analysis on 52 studies, Orlitzky, Schmidt, and Rynes (2003) find that the two are positively related to each other. Their results indicate that this relationship is strongest amongst backward-looking performance measures (accounting returns) rather than with forward-looking indicators (such as shareholder returns). Derwall, Guenster, Bauer, and Koedijk (2005) support the findings of Orlitzky et al. (2003) when examining the performance of U.S. large-cap 'eco-efficient' stock portfolios constructed using eco-efficiency scores from Innovest Strategic Value Advisors over the period from 1995 to 2003. Derwall, *et al.* (2005) show that the highest eco-efficient portfolio produce a Carhart alpha significantly greater than the lowest eco-efficient portfolio (by about 6 percent per annum) after controlling for industry effects. These findings confirm those of Blank and Daniel (2002), who also argue that eco-efficient portfolios are able to outperform the S&P500 index in terms of their Sharpe ratio over the period of 1997 to 2001. Derwall, *et al.* (2005) suggest that the reason as to why SRI stocks outperform non-SRI stocks is because markets are either undervaluing environmental information, or, that SRI portfolios are capturing the premium of some risk factors that are absent in prevalent asset pricing models.

Thomas (2001) and Ziegler, Rennings, and Schröder (2002) show that the stocks of environmentally-conscious firms in UK and European markets outperform after adjusting for Fama and French (1993) and Carhart (1997) risk factors. These studies however, focus only upon the environmental aspect of SRI. Statman (2008b), on the other hand, examines the performance of SRI stocks more broadly by comparing the MSCI KLD 400 Social Index, against the S&P 500. He shows that over the period from 1990 to 2004, the KLD 400 outperformed the S&P500 in terms of raw returns, although slightly underperformed after returns are risk-adjusted. Kempf and Osthoff (2007), on the other hand, use SRI stock ratings from KLD to construct long-short SRI portfolios from the highest and lowest ten percent of SRI-scored stocks from within each industry. They show that this strategy produces a significantly positive Carhart alpha (up to 8.7 percent per annum) over the period from 1992 to 2004. In contrast to Derwall, *et al.* (2005), Kempf and Osthoff (2007) find this relationship to be insignificant for the environmental component of the SRI portfolio. Chan and Walter (2014) support Derwall, *et al.* (2005)'s findings when investigating the performance of 372 environmentally-friendly firms listed on the NYSE, AMEX, and NASDAQ during the period of 1990 to 2007. They show that portfolios of environmentally friendly firms produce significantly positive Carhart alpha of about 7 percent p.a. However, unlike Derwall, *et al.* (2005), Chan and Walter (2014) use the same environmental classifications as KLD to construct portfolios from publicly available information based on the argument of reducing search costs for environmentally-conscience investors.

4.3.d Financial Indifference from SRI

Galema, Plantinga, and Scholtens (2008) examine the Carhart alphas of socially responsible portfolios constructed according to the scores of stocks from six different social screens monitored by KLD over the period from 1992 to 2006. Galema et al. (2008) confirm the findings from earlier studies that the highest SRI-scored stocks do not significantly differ in terms of performance from the lowest scored-SRI stocks. They argue that SRI eventuates in lower book-to-market ratios, and as a result, the alphas do not capture SRI effects.

Nelling and Webb (2009) argue that the relationship between SRI and performance found by previous studies is a result of methodological limitations. They therefore examine the existence and direction of causality between stock performance and SRI, using SRI scores from the KLD Socrates database. Nelling and Webb (2009) subsequently show that this positive relationship between stock performance and SRI-classification disappears once time-fixed effects and tobit models are introduced to conventional OLS regression analysis. This argument is further supported when using Granger causality models, such that no causality from SRI score to performance is found and only weak evidence of causality running from stock performance to SRI score.

Brzeszczyński and McIntosh (2013) analyse the performance of individual SRI investors by constructing SRI portfolios using freely available information from the Global-100 list of UK SRI stocks rather than from private databases such as KLD. They similarly fail to find any evidence that these portfolios significantly outperform the FTSE100 or FTSE4GOOD indices from 2000 to 2010 when using either raw or risk-adjusted returns. Applying a proprietary dataset from the Sustainability Asset Management Group, *GmbH*, Humphrey, Lee, and Shen (2012) examine the effect that SRI has on the performance and risk of a broad sample of UK firms. They similarly find no evidence of a difference in the risk-adjusted performance of high and low SRI rated portfolios after controlling for industry and idiosyncratic risk factors. Humphrey, *et al.* (2012) further show that SRI does not affect idiosyncratic risk, though they do find some evidence that high SRI firms are larger and have lower systematic risk.

Lee, Faff, and Langfield-Smith (2009) argue that methodological limitation of past studies that examine the SRI-performance relationships of individual stocks is the cause of inconsistent findings. Such limitations are said to include a lack of relevant controls factors, the inclusion of a limited number of accounting and market performance variables, small sample sizes, short analysis periods and an over-reliance on negative screening processes to establish the sample. To account for these limitations, Lee, *et al.* (2009) employ an alternative SRI metric to rank stocks that does not preclude entire industries but includes companies perceived to be industry leaders with respect to environmental, social and economic performance. These metrics are constructed from data sourced from the Dow Jones Sustainability Indexes Group, representing stocks from across all industries and regional segments. Using cross-sectional panel analysis across a five year horizon and controlling for industry, country, size, style, risk, financial slack, R&D intensity, and liquidity, Lee, *et al.* (2009) find no evidence of a relationship between SRI and stock performance.

In addition to the above studies that focus on SRI at the stock level, there is an extensive body of literature that examines the performance of SRI at the fund level. Renneboog, *et al.* (2008) provide a review of this literature, concluding that “the existing studies hint but do not unequivocally demonstrate that SRI investors are willing to accept suboptimal financial performance to pursue social or ethical objectives” (p.1740). Based on this SRI performance literature, it cannot be said with certainty that mutual fund investors are financially punished (or rewarded) for being socially responsible.

4.3.e Non-financial Benefit from SRI

Investment decisions of individuals are not considered to be made solely on financial grounds. Webley, Lewis, and Mackenzie (2001), Schueth (2003), Michelson, Wailes, Van Der Laan, and Frost (2004) and Williams (2007) show that certain investors consider ethical and personal values when making investment decisions. Hostede and Hofstede (1991) Katz, Swanson, and Nelson (2001) and Williams and Zinkin (2005) argue that the behaviour to invest in such a manner stems from sociocultural influences on perceptions of corporate responsibility. Naber (2001) Brammer, Williams, and Zinkin (2007) and Williams and Zinkin (2008) similarly argue that religious beliefs are also responsible for investors' choice to hold SRI assets. A plethora of studies subsequently examine the characteristics of investors that make them likely to consider the ESG aspects of investments in additional to merely financial aspects [see, for example Beal and Goyen (1998), Tippet and Leung (2001), McLachlan and Gardner (2004), Williams (2007), Haigh (2008), Owen and Qian (2008) Junkus and Berry (2010) and Pérez-Gladish, Benson, and Faff (2012)]. These studies report conflicting results that demographic factors (age, gender, education, income, etc.), life style and emotional factors amongst other characteristics affect investors' level of social responsibility, and the extent to which their invested wealth is allocated to 'SRI' assets.

Statman (2004), Statman (2008a) and Sparkes (2010) argue that the motivation behind investors selecting SRI extends beyond that of solely achieving financial benefit to obtain some other benefit, of a non-financial nature, that relates to the environmental and social considerations of the investment. Knoll (2002) however, highlights that SRI is not simply achieving ESG goals, i.e. it is not about charity or giving money away, but must also require the generation of some financial return for the practise to be considered an "investment." Hence to be considered SRI, the practise must satisfy two main criteria; one) generating a positive expected financial return, and two) be able uphold a level of ESG responsibility. Lewis and Mackenzie (2000) argue that SRI investors may care more about the social responsibility aspect of their investment than the financial benefit, and as such, may be willing to forgo some financial return in exchange for holding social responsible assets. Beal, Goyen, and Phillips (2005) subsequently refer to this non-financial benefit as a "psychic return". Beal, *et al.* (2005) similarly argue that some investors will trade-off financial returns for psychic returns due to the increased utility gained from the fact that their investments possess such SRI characteristics. Beal, *et al.* (2005) also suggests that this psychic return can also be viewed as an increase in happiness and may be derived from the desire of investors for social change and hence could be linked to the knowledge that their investments do not support unethical or controversial products or practises. Webley, *et al.* (2001) support Beal, *et al.* (2005)'s concept of psychic returns by showing that socially responsible investors maintain or increase SRI holdings after the underperformance of such investments, thus suggesting that SRI investors make investment decisions based on ideology more so than financial principles.

4.3.f Conclusion

The variety of approaches used throughout the current literature that explore the cost to investors from being socially responsible generally measures this 'cost' in terms of financial loss (or gain) from either raw or risk adjusted-returns of SRI-constrained portfolios relative to some other 'non-SRI' benchmark. This literature fails to reach consensus, and as such, there is conflict as to whether investors who are socially responsible are financially better or worse off than 'non-responsible' investors. Geczy, *et al.* (2005) however, use certainty equivalent returns to measure the cost of being socially responsible. They show that there is a financial cost when investing in a socially responsible manner, yet argue that this is an overestimate of the net cost to investors for being socially responsible, as this financial cost is offset by the non-financial utility derived by investors for being socially responsible. This chapter expands the work of Geczy, *et al.* (2005) by measuring the value of this non-financial satisfaction that socially responsible investors derive from investing in such a manner, for which this chapter refers to as the *"psychic dividend"* of SRI.

4.4 Hypothesis development

4.4.a Psychic Returns and Dividends

The existing literature, at least in art economics, addresses estimates of psychic returns to art using a number of procedures which are discussed in Srivastava, *et al.* (2013). These include the rental value of art, Hedonic modelling and inferences based on the intercept of the CAPM. Whilst each of these methods seems quite plausible, they typically provide estimates of psychic returns in the order of ten to thirty percent. Taking this range of estimates together with information concerning expected capital gains for art and expected total returns for equity, Srivastava, *et al.* (2013) construct optimal portfolios for investors by allowing the psychic return parameter to vary, hence obtaining some notion as to what a plausible range of values might be. Individual psychic dividends however, which may be very high due to extreme pleasures gained from heightened aesthetic sensitivity, are likely to be much lower in an equilibrium framework when all investors are considered and whereby some of whom may not be influenced by aesthetic considerations. Likewise, SRI investors may have vastly different preferences from other investors, and without additional information, our “representative” investor will be an amalgam of the two groups. Psychic dividends calculated from such an approach are therefore likely to under-estimate the psychic dividend enjoyed by SRI investors.

4.5 Data and Method

4.5.a SRI Portfolio Construction

To measure the psychic dividend earned by SRI investors, the performance of two portfolios representative of a socially responsible investor (*Good* portfolio) and a socially irresponsible investor (*Bad* portfolio) are required. These two portfolios are constructed from the universe of the 500 largest U.S. stocks by market capitalisation. Stocks are first classified as *Good*, *Bad* or ‘*Other*’, according to their tier one Standard Industry Classification (SIC) industry category. SIC categorises U.S. stocks into one of 99 tier one industries.[54] These industries are therefore categorised into either one of these three groups. The socially responsible (*Good*) category contains 21 industries groups, which include;

> Health Services, Educational Services, Social Services, Justice Public Order & Safety, Museums Art Galleries & Gardens, Administration-Human Resource Programs, Measuring & Analysing Instruments Manufacturers, Insurance Carriers, Insurance Agents Brokers & Service, Admin-Environmental Quality Programs, Local/Suburban Transit & Highway Passenger, Agricultural Production-Crops, Communications, Miscellaneous Repair Services, Public Finance & Taxation Policy,

[54] SIC classifications are sourced from: http://www.melissadata.com/lookups/sic.asp.

Administration Of Economic Programs, Business Services and Personal Services.

The socially irresponsible (*Bad*) category comprises of 14 industries groups, which include;

Metal Mining, Coal Mining, Oil & Gas Extraction, Mining & Quarrying/Non-metallic Minerals, Tobacco Products Manufacturers, Lumber & Wood Products ex-Furniture Manufacturers, Chemicals & Allied Products Manufacturers, Petroleum Refining & Related Industrial Manufacturers, Leather & Leather Products Manufacturers, Pipelines Except Natural Gas, Amusement & Recreation Services (casinos and gaming), Agricultural Production/Livestock, Wholesale Trade-Nondurable Goods, Forestry, as well as Tobacco and Meat & Fish Markets Sub-industries.

The remaining 64 industries are classified as belonging to the '*Other*' category. The smallest ten stocks, by one-month lagged market capitalisation from the *Bad* industry category are used to construct an equal-weighted *Bad* portfolio. The portfolio is limited to ten stocks from each industry so that it is not overweighted toward any one industry relative to the industry weights of the market index. The smallest stocks from each industry (contained in the top 500 universe) are selected based on the assumption that smaller firms are less in the 'spotlight' and as such are under less pressure to operate in a socially responsible manner. The *Good* portfolio on the other hand is constructed in the same manner, yet using the largest ten stocks from each of the *Good* industries (based on the assumption that larger firms are under more pressure to behave in a more socially responsible manner). This approach is considered a 'worst-of-worst' industries and a 'best-of-best' industries approach when allocating stocks to the SRI portfolios.

The *Good* and *Bad* portfolios are readjusted monthly using one-month lagged market capitalisation values.

4.5.b Data

Monthly stock-return, market capitalisation and SIC data for all U.S. stocks from January 1990 to December 2013 are sourced from the Centre for Research in Security Prices (CRSP) database. The three Fama and French (1993) factors and Carhart (1997) momentum factor, along with the risk-free return for the U.S. market is sourced from Ken French's website.[55] The market-excess return is the value-weighted return of all CRSP firms incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of ten or eleven at the beginning of month minus the one-month Treasury bill rate. The Fama-French factors are constructed using six value-weighted portfolios formed on market capitalisation and book-to-market value of equity. Specifically, *SMB* (Small Minus Big) is the average return on the three small portfolios minus the average return on the three big portfolios, given by:

$$SMB = \frac{1}{3}[(Small\ Value + Small\ Neutral + Small\ Growth) - (Big\ Value + Big\ Neutral + Big\ Growth)].$$

HML (High Minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios:

$$HML = \frac{1}{2}[(Small\ Value + Big\ Value) - (Small\ Growth + Big\ Growth)].$$

[55] Factor returns are sourced from the Ken French website; http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

The momentum factor (*UMD*) is constructed from six value-weighted portfolios formed on size and prior two to twelve month returns. The portfolios, which are formed monthly, are the intersections of two portfolios formed on size (market capitalisation) and three portfolios formed on prior two to twelve month returns. The monthly size breakpoint is the median NYSE market equity. The monthly prior return breakpoints are the 30thand 70th NYSE percentiles. *UMD* is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios,

$$UMD = \frac{1}{2}[(Small\ High + Big\ High) - (Small\ Low + Big\ Low)].$$

The six portfolios used to construct *UMD* each month include NYSE, AMEX, and NASDAQ stocks with prior return data. Index prices for the MSCI KLD Social 400 Index is sourced from Datastream. This index is used as a robustness check for the socially responsible portfolio constructed in section 4.5.a.

4.5.c NBER Economic Cycle

SRI portfolio performance and psychic dividends of SRI investors are measured over the sample period from January 1990 to December 2013 as well as across National Bureau of Economic Research (NBER) recessionary and expansionary dates from this period.[56] Of the 287 months between January 1990 and December 2013, 255 were expansionary months and the remaining 32 were recessionary months. The performance of the *Good* and *Bad* Portfolios are also measured separately over months with positive market returns (up-market months)

[56] NBER business cycle dates are sourced from; http://www.nber.org/cycles/cyclesmain.html.

and months with negative market return (down-market months) according to the return of the market portfolio.[57]

Table 4.1: NBER Business Cycle Dates

National Bureau of Economic Research (NBER) turning point (peak and trough) dates for the U.S. economic cycle over the period from January 1990 to December 2013 are reported in this table along with the duration of the economic phase (in month) since the previous turning point.

Date	Peak / Trough	Duration (months)
1/01/1990	-	-
1/07/1990	Peak	7
1/03/1991	Trough	8
1/03/2001	Peak	12
1/11/2001	Trough	8
1/12/2007	Peak	73
1/06/2009	Trough	18
30/12/2013	-	55

4.5.d Performance Evaluation

The performance of the *Good*, *Bad* and a long-short (*Good–Bad*) portfolios are measured from the intercept term, α, of the standard CAPM and Carhart (1997) four-factor models in equations 4.1 and 4.2, respectively, using ordinary least squares regressions:

$$R_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i,t}\left(Rm_t - r_{f,t}\right) + \varepsilon_{i,t}, \tag{4.1}$$

and

$$r_{i,t} - r_{f,t} = \alpha_{i,t} + \beta_{1,i,t}\left(Rm_t - r_{f,t}\right) + \beta_{2,i,t}SMB_t + \beta_{3,i,t}HML_t + \beta_{4,i,t}UMD_t + \varepsilon_{i,t}, \tag{4.2}$$

where $r_{i,t} - r_{f,t}$ is the excess return of portfolio *i* at time *t*. $\alpha_{i,t}$ is CAPM or Carhart alpha of portfolio *i*. R_m-R_f, *SMB, HML* and *UMD* are the monthly returns from the

[57] The returns from the CRSP value-weighted market index is used to identify up-market and down-market months from the market.

standard Carhart (1997) factors at time *t*, $\beta_{1,i,t} \ldots \beta_{4,i,t}$ are the estimated coefficients on each of the four factors, respectively, and $\varepsilon_{i,t}$ is the error term of portfolio *i* at time *t*.

4.5.e Calculation of Psychic Dividends

Given a utility function, U, and initial wealth, W_0, and SRI returns, r, the certainty-equivalence, ce, of SRI returns can be defined additively or multiplicatively, i.e.:

$$E\left[U\left(W_0(1+r)\right)\right] = U\left(W_0(1+ce)\right), \text{ and}$$

$$E\left[U\left(W_0(e^r)\right)\right] = U(W_0 e^{ce}), \text{ respectively.}$$

To separate the value of ce from the level of W_0 (which seems practical, if only because of data limitations), homogeneous (in wealth) utility functions are proposed, such as power utility. If we let,

$$U(W) = \frac{W^{1-\alpha}}{1-\alpha},$$

using the additive form, investible wealth can be set equal to one. This framework considers long-only strategies, which avoids the consideration of bankruptcy issues.

4.5.e.i The Long – only Strategy

Consider the function:

$$\frac{V_T}{1-\alpha} = \frac{1}{T}\sum_{t=1}^{T} \frac{(1+r_{i,t})^{1-\alpha}}{1-\alpha},$$

where V_T is the sample estimate of expected utility. $r_{i,1} \ldots r_{i,T}$, are the sample returns to portfolio *i* from time *t*=1 to *T*, and α is the risk-aversion coefficient that takes a value of 3, 5 or 7, which correspond to typical values used in the current literature[58]. When expressed in terms of certainty equivalent returns, *ce,* this function becomes,

$$\frac{(1+ce)^{1-\alpha}}{1-\alpha} = \frac{V_T}{1-\alpha}\,.$$

We then simplify to arrive at an expression for *ce*,

$$(1+ce)^{1-\alpha} = V_T,$$

$$(1+ce) = V_T^{\frac{1}{1-\alpha}},$$

rearranging yields:

$$ce = V_T^{\frac{1}{1-\alpha}} - 1. \qquad (4.3)$$

It is therefore evident that *ce* depends only upon V_T and α.

To compute implied psychic returns, it is necessary that the portfolios considered are indistinguishable bar this unobservable dividend, *d*, that accrues with certainty to the SRI investor. This would imply, using population moments, that:

$$V = E[(1+r)^{1-\alpha}],$$

and that the expected utility of the SRI investor is,

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[58] Despite the importance that the coefficient of relative risk aversion (CRRA) plays in many microeconomic and macroeconomic models, experimental research has provided little guidance as to how risk aversion should be modelled. Subsequently, this difficulty in empirically estimating CRRA has resulted in its value being largely disputed. Whilst CRRA is typically estimated to be around one to five, earlier studies, such as Arrow (1971), argues on a theoretically ground that it should be approximately one, Altug (1983) estimates it to be near zero. Epstein and Zin (1991) and Giovannini and Weil (1989) also empirically support this value being closer to one. Maitel (1973) suggests an estimate of CRRA of approximately 1.5. Similarly, Kydland and Prescott (1982), find that a value between one and two is required to observe the relative variability of consumption and investment whereas Friend and Blume (1975) suggest that the parameter should be around two. Recent studies, however, argue even higher aversion to risk with values in the order of five to ten being reasonable (Kaplow, 2005). Mehra and Prescott (1985) for example, impose an upper bound CRRA of ten, whereas values up to 30 are argued by Kandel and Stambaugh (1991) to be possible. Recent empirical work in the area of financial economics, indicate estimates of CRRA to be greater than two. Those that attempting to reconcile the equity risk premium with rational behaviour, indicates that individuals' CRRA's may be above 10 [See, for example Blake (1996), Brav, Constantinides, and Geczy (2002), Campbell (1996, 2003), Kocherlakota (1996), Mankiw and Zeldes (1991), and Palsson (1996)]. Similarly high estimates of CARR are also reported in studies of risk-taking behaviour in other markets [see, for example Barsky, Juster, Kimball, and Shapiro (1997)].

$$V_s = E[(1+r)^{1-\alpha}](1+d)^{1-\alpha} .$$

It follows that, if ce_s is the certainty equivalence of the SRI investor, then,

$$d = \frac{1+ce_s}{1+ce} - 1 = \frac{ce_s - ce}{1+ce}.$$

For small values of ce, d can be accurately approximated by $ce_s - ce$.

4.5.e.ii The Long–Short Strategy and Loss Aversion

In the following section, psychic dividends to SRI from long-only portfolios are computed from loss-aversion utility functions, which have been argued by numerous scholars to provide a more accurate representation of investor preferences.[59] Furthermore, these utility functions are defined over rates of return rather than wealth so as to avoid wealth measurement issues. Defining:

$$U(r_t) = \begin{cases} (r_t - r_{f,t})^{\alpha_1}, & if\ r_t \geq r_{f,t} \\ -\lambda(r_{f,t} - r_t)^{\alpha_2}, & if\ r_t < r_{f,t} \end{cases} .$$

This function can then be expressed as:

$$U(r_t) = d_t(r_t - r_{f,t})^{\alpha_1} - (1-d_t)\lambda(r_{f,t} - r_t)^{\alpha_2},$$

and thus $\widehat{U(r_t)}$ is calculated from the following equation:

$$\widehat{U(r_t)} = \frac{1}{T}\sum_{t=1}^{T}\left[d_t(r_t - r_{f,t})^{\alpha_1} - (1-d_t)\lambda(r_{f,t} - r_t)^{\alpha_2}\right],$$

where,

$$d_t = \begin{cases} 1, & if \quad r_t \geq r_{f,t} \\ 0, & if \quad r_t < r_{f,t} \end{cases},$$

[59] See Kahneman and Tversky (1979) for a discussion on the rival merits of loss aversion utility and utility that includes relative risk aversion.

$$U = \begin{cases} \left(ce - r_{f,t}\right)^{\alpha_1}, & if\ \widehat{U(r_t)} \geq 0 \\ -\lambda\left(r_{f,t} - ce\right)^{\alpha_2}, & if\ \widehat{U(r_t)} < 0 \end{cases} \quad . \tag{4.4}$$

Defining *CE* as excess certainty equivalent return:

$$CE \equiv ce - r_{f,t},$$

then *CE* can be calculated as,

$$CE = \begin{cases} U^{\frac{1}{\alpha_1}}, & if\ U \geq 0 \\ -\left(\frac{-U}{\lambda}\right)^{\frac{1}{\alpha_2}}, & if\ U < 0 \end{cases} \tag{4.5}$$

where α_1 and α_2 are coefficients that govern the attitude to upside and downside risk, respectively, and λ is the coefficient of loss aversion. This chapter considers $\alpha_1 = \alpha_2 = 0.88$ and $\lambda = 2.25$, which has become the consensus amongst the finance literature [see, for example Kahneman and Tversky (1979), Neilson and Stowe (2002), Barberis and Huang (2001) and Ang, Bekaert, and Liu (2005)].

One of the strengths of the loss-aversion approach is that it allows us to model long-short portfolios easily. Suppose a strategy is considered where we hold 100 in cash and $\theta \times 100$ in a long–short position, then,

$$r_t = r_f + \theta(r_t^+ - r_t^-),$$

$$r_t - r_f = \theta(r_t^+ - r_t^-),$$

The utility function can then be expressed as:

$$U(r_t) = d_t[\theta(r_t^+ - r_t^-)]^{\alpha_1} - (1 - d_t)\lambda[\theta(r_t^- - r_t^+)]^{\alpha_2},$$

where,

$$d_t = \begin{cases} 1, & if \quad r_t^+ \geq r_t^- \\ 0, & if \quad r_t^+ < r_t^- \end{cases}$$

and θ is the level of gearing, which is set equal to one. Then,

$$\widehat{U(r_t)} = \frac{1}{T}\sum_{t=1}^{T}\left[d_t\left(\theta(r_t^+ - r_t^-)\right)^{\alpha_1} - (1-d_t)\lambda\left(\theta(r_t^- - r_t^+)\right)^{\alpha_2}\right],$$

and thus U is calculated as:

$$U = \begin{cases} \left(ce - r_{f,t}\right)^{\alpha_1}, & if\ \widehat{U(r_t)} \geq 0 \\ -\lambda\left(r_{f,t} - ce\right)^{\alpha_2}, & if\ \widehat{U(r_t)} < 0 \end{cases} .$$

Again, if CE is defined as excess certainty equivalent return, then:

$$CE = \begin{cases} U^{\frac{1}{\alpha_1}}, & if\ U \geq 0 \\ -\left(\frac{-U}{\lambda}\right)^{\frac{1}{\alpha_2}}, & if\ U < 0 \end{cases} . \tag{4.6}$$

In the case of the long-short strategy, the difference in the certainty equivalent returns is reported as the psychic dividend. A more precise expression in terms of ex-ante expected utility remains elusive. However, in this chapter additive dividends are considered when evaluating expected utility. The reason as to why a less clear expression is obtained is due to the necessity of considering the population values for expected loss aversion.

If p is the probability that the term y is positive, then expected loss aversion, LA, is equal to,

$$LA = U^+p - \lambda U^-(1-p),$$

where,

$$U^+ = \mathrm{E}[y^{\alpha_1}|y \geq 0],$$

$$U^- = \mathrm{E}[(-y)^{\alpha_2}|y < 0],$$

Then LA is calculated as

$$LA = \begin{cases} ce^{\alpha_1}, & if\ LA \geq 0 \\ -\lambda(ce)^{\alpha_2}, & if\ LA < 0 \end{cases} .$$

To an approximation, ignoring a term of magnitude d_r,

$$U^{d+} = E[(d+y)^{\alpha_1}|y + d \geq 0],$$

$$U^{d-} = \mathrm{E}[(-d - y)^{\alpha_2} | y + d < 0],$$

Let pd be the probability that the term, $y + d$, is positive.

$$LA(d) = U^{d+}pd - \lambda U^{d-}(1 - pd),$$

and loss aversion, $LA(d)$, varies with d.

4.6 Results

4.6.a Summary Statistics

The following analysis describes the characteristics of the *Good* and *Bad* portfolios used in the calculations of the psychic dividends, as well as the factors used in the evaluation of the performance of these portfolios.

Table 4.2: Descriptive Statistics

Monthly return descriptive statistics for the market portfolio, *MKT*, risk-free rate of return, *Rf*, and the Fama and French (1993) and Carhart (1997) size, value, and momentum factors (*SMB*, *HML* and *UMD*) from January 1990 to December 2013 for the U.S. market are reported in the following table. The market return is the CRSP value-weighted portfolio and the risk-free return is the Treasury bill rate. Factor returns are sourced from the Ken French website.[60] Descriptive statistics of the returns and number of stocks contained in the socially responsible (*Good*), socially irresponsible (*Bad*), and a long-short (*Good-Bad*) stock portfolio are also reported.

	Mean	**Min**	**Median**	**Max**	**St.Dev.**	**Skewness**	**Kurtosis**
MKT	0.903	-17.150	1.460	11.340	4.394	-0.691	1.218
Rf	0.261	0.000	0.280	0.690	0.187	0.004	-1.126
SMB	0.217	-16.390	0.060	22.020	3.318	0.824	8.444
HML	0.241	-12.680	0.170	13.870	3.167	0.086	3.021
UMD	0.587	-34.720	0.650	18.390	5.007	-1.635	11.325
# stocks in *Good* Portfolio	48.537	41	48	56	2.738	0.084	0.747
# stocks in *Bad* Portfolio	47.035	33	48	55	5.432	-0.736	-0.396
R(*Good*)	0.969	-18.476	1.293	13.215	4.479	-0.552	1.328
R(*Bad*)	1.025	-21.590	1.241	16.703	4.867	-0.469	2.167
R(*Good-Bad*)	-0.056	-13.713	-0.252	11.970	3.870	-0.192	0.623

The number of stocks contained in each of the *Good* and *Bad* portfolios are approximately the same (about 48 stocks each) and remain relatively stable in quantity throughout the sample period. The monthly returns for the *Good* and *Bad* portfolios along with the return from the market portfolio are also similar to one another. The correlation between the return series of the *Good* and *Bad* portfolio is 0.6750 and the difference in variance, using a Levene (1960) test for homogeneity of variance, is insignificant (f-statistic = 0.8342). The skewness of the *Good* and *Bad* portfolio return distributions are also insignificant from one another (z-statistic equal to 0.621). The insignificant difference for the third and fourth moments between the return

[60] Ken French website; http://mba.tuck.dartmouth.edu/ pages/faculty/ken.french.

distributions of these portfolios lends support to the approach used to calculate the psychic dividends from these two portfolios.[61,62,63]

4.6.b SRI Performance Evaluation

Table 4.3: Portfolio Return Differences

Difference in mean monthly returns for the *Good*, *Bad*, and long-short (*Good-Bad*) stock portfolios, across the period from January 1990 to December 2013 are reported. Differences in mean returns are also reported across NBER U.S. economic expansion and recession sub-periods, and for Up- and Down-market months, where 'Up' represents months where the market return is positive and 'Down' are months where negative market returns are observed. The market return is the CRSP value-weighted portfolio and the risk-free return is the Treasury bill rate. T-statistics are displayed in parenthesis and *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Mean Return (% per month)				
	Entire Period	Expansion	Recession	Up-market Months	Down-market Months
Good-Market	0.066	0.050	0.067	-0.1570	0.422***
	(0.7339)	(0.5290)	(0.1933)	(-1.377)	(2.782)
Bad-Market	0.122	0.068	0.628	-0.3680	1.049***
	(0.5604)	(0.3241)	(0.7447)	(-1.515)	(2.822)
Good-Bad	-0.056	-0.018	-0.561	0.2120	-0.627**
	(-0.2441)	(-0.0817)	(-0.5823)	(0.8)	(-1.595)
(*Good-Bad*) - rf	-0.340	-0.280	-0.819	-0.0470	-0.893**
	(-1.5359)	(-1.2787)	(-0.8545)	(-0.178)	(-2.26)

The raw mean monthly return of the *Good* and *Bad* portfolios, shown in Table 4.3, are not significantly different to the market return when measured across the entire sample period as well as across expansionary and recessionary sub-periods. The *Bad* portfolio is shown to outperform the *Good* portfolio across all periods in terms of raw returns by about six basis points per month, however this difference is also insignificant (t-statistic = -0.244). The long-short portfolio, constructed from long *Good* stocks and

[61] The method of testing for equality of the third central moment is described in Appendix C.
[62] Descriptive statistics for the *Good* and Bad portfolios that are constructed as a robustness measure by removing the stock size and stock quantity-per-industry constraints from the original SRI portfolios are reported in Table C.1 in Appendix C.
[63] Descriptive statistics for the monthly returns of the MSCI KLD Social 400 index and MSCI U.S. total return index across the period from January 1990 to December 2013 are reported in Table C.5 within Appendix C.

short *Bad* stocks underperform the risk-free rate of return by about 34 basis points per month across the entire period, 28 basis points during expansionary months and 82 basis points during recessionary months. This underperformance however, is also statistically insignificant. The *Good* and *Bad* portfolios are shown to significantly outperform the market during down-market months, with the *Good* portfolio significantly outperforming the *Bad* portfolio. This results in the long-short portfolio significantly underperforming the market. These relationships are not observed during up-market months. A possible explanation of this result is that SRI may be picking up a latent factor. Without knowing the factor, I attribute it to a psychic dividend. If SRI is actually something different then that can possibly be controlled for in some portfolio sorting procedure.

Table 4.4: CAPM and Four-Factor SRI Portfolio Exposures

CAPM and Carhart (1997) four-factor regressions are estimated for the socially responsible (*Good*), socially irresponsible(*Bad*) and long short (*Good – Bad*) stock portfolios using monthly returns over the period from January 1990 to December 2013. The CAPM regressions show portfolio market-risk exposure (R_m-R_f) and the Carhart (1997) regressions identify market-risk exposure (R_m-R_f), value exposure (*HML*), size exposure (*SMB*) and momentum exposure (*UMD*). Alpha indicates portfolio risk-adjusted returns. The market return is the CRSP value-weighted portfolio and the risk-free return is the Treasury bill. Factor returns are sourced from the Ken French website. Regressions are estimated with robust standard errors and t-statistics are displayed in parentheses with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

	***Good* – Rf**		***Bad* - Rf**		***Good* - *Bad***	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.0892	0.0661	0.268	0.118	-0.179	-0.0520
	(0.968)	(0.727)	(1.320)	(0.594)	(-0.813)	(-0.238)
R_m - R_f	0.942***	0.981***	0.785***	0.858***	0.157***	0.123**
	(45.309)	(44.488)	(17.129)	(17.769)	(3.158)	(2.317)
SMB		-0.131***		-0.00164		-0.129*
		(-4.570)		(-0.026)		(-1.875)
HML		0.0176		0.353***		-0.336***
		(0.579)		(5.298)		(-4.581)
UMD		0.0381**		0.0319		0.00623
		(2.046)		(0.782)		(0.139)
Observations	287	287	287	287	287	287
R-squared	0.878	0.889	0.507	0.555	0.034	0.105

The intercept terms (alpha) from the regressions reported in Table 4.4 show that *Good*, *Bad*, and *Good-Bad* portfolios are unable to produce significantly positive (or negative) abnormal returns after adjusting for market, size, value and momentum risk factors. The *Good* and *Bad* portfolios are both found to be slightly underexposed to the market risk premium, the *Good* portfolio has greater exposure to large market capitalisation and momentum stocks whereas the *Bad* portfolio is shown to be overexposed to value stocks. The long-short portfolio is shown to have a significantly negative exposure to the value risk factor. These findings indicate that socially responsible stocks tend to be larger in size, and that socially irresponsible stocks tend to be growth oriented.[64] Similar results of insignificant risk-adjusted return are also observed for these portfolios across economic recessions and expansions, and market Up and Down sub-periods.[65,66]

Unlike Derwall, *et al.* (2005) and Chan and Walter (2014), who find evidence of eco-efficient portfolios significantly outperforming the market index and produce significantly positive risk-adjusted returns, the SRI portfolio constructed in this chapter, which also incorporates environmental screens, is unable to produce significantly positive market-excess, or risk-adjusted returns. This may be due to the stocks from other socially responsible industries that are included in the SRI portfolio underperforming. Blank and Daniel (2002), Thomas (2001) and Ziegler, *et al.* (2002) however, fail to find evidence of eco-friendly stock portfolios outperforming. The performance of the SRI portfolio is also consistent with the findings from other studies

[64] These results are robust when removing the screens to construct the *Good* and Bad portfolios, as shown in Table C.2 in Appendix C.
[65] Refer to Table C.3 and Table C.4 in Appendix C for Carhart (1997) regression estimates of the *Good* and *Bad* portfolios across economic and market sub-periods, respectively.
[66] CAPM and Carhart (1997) four-factor regressions are estimated for the MSCI KLD 400 Social index in Table C.6 in Appendix C, over NBER-dated expansionary and recessionary sub-periods. The results are qualitatively similar to the *Good* portfolio regressions in Table 4.4.

that more broadly define SRI rather than just considering environmental factors. Statman (2008b) for example, when examining the KLD social 400 index relative to the S&P500, finds that this socially responsible index is unable to significantly outperform the market index in terms of raw returns or risk-adjusted returns. Galema, Plantinga, and Scholtens (2008) similarly show that the risk-adjusted returns of a high and low SRI-scored stock portfolio are indifferent from one another, and similar to the findings from this chapter, show that high SRI-ranked stocks are relatively more growth orientated. The exposure of the *Good* portfolio to growth stocks is additionally supported by Hong and Kacperczyk (2009), who show that a sin portfolio (constructed of alcohol, tobacco and gaming stocks) largely consists of value stocks. Yet, unlike the *Good* and *Bad* portfolios used in this chapter, Hong and Kacperczyk (2009)'s portfolio that is long sin stocks and short non-sin stocks is shown to produce significantly positive risk-adjusted returns. The relative performance exhibited by the *Good* and *Bad* portfolios are also validated by other studies, including; Lee, Faff, and Langfield-Smith (2009), Brzeszczyński and McIntosh (2013), and Humphrey, *et al.* (2012). These findings lend support to these portfolios as being representative of the typical SRI and non-SRI portfolio, as such, validating the use of them in the measurement of psychic dividends.

4.6.c Psychic Dividends

Using the *Good* and *Bad* portfolios, implied psychic dividends accruing to socially responsible investors from holding SRI portfolios are measured using power utility functions and loss-aversion utility functions for long-only portfolios, in the following analysis.

Table 4.5: Psychic Dividends to SRI Investors

Psychic dividends (measured as a percentage per month) are reported as the difference in certainty equivalent returns of the *Good* and *Bad* portfolios over the period from January 1990 to December 2013 for various levels of risk aversion. U is investor utility derived by from investing in the respected portfolios and *CE* is certainty equivalent return as calculated from equation 4.5.

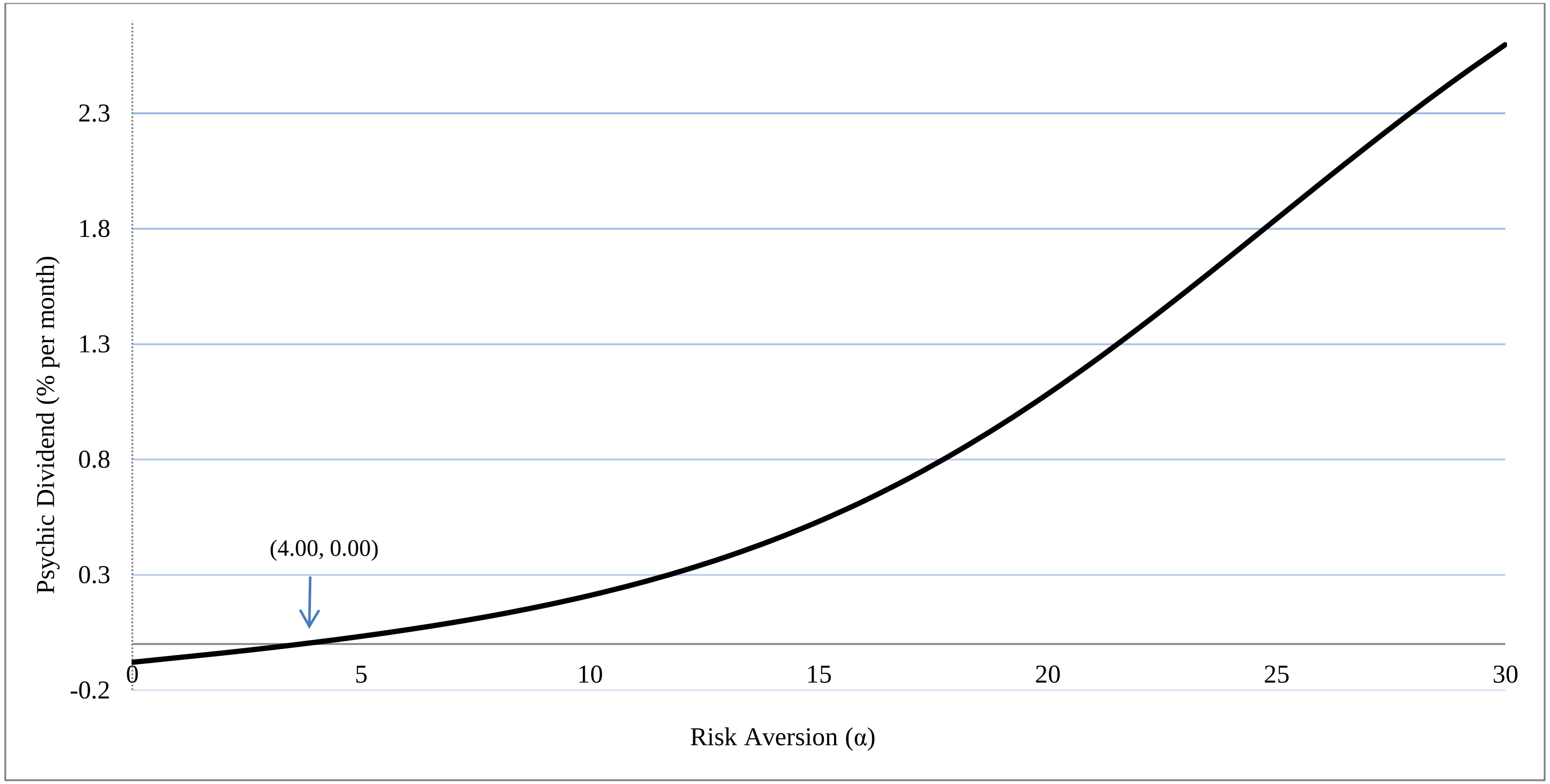
		Good Portfolio	**Bad Portfolio**	
	Risk Aversion (α)	Certainty Equivalent Return		Psychic Dividend
	3	0.65%	0.67%	-0.02%
	5	0.44%	0.41%	0.03%
	7	0.22%	0.12%	0.09%
U	-	-1.48%	-1.54%	
CE	-	-0.33%	-0.35%	0.02%

The psychic dividend earned by socially responsible investors is calculated as the difference in certainty equivalent returns (*ce*) from the *Good* and *Bad* Portfolios, where *ce* is measured from equation 4.3. This psychic dividend, reported in Table 4.5, is in the range of about negative 1.6 basis points and 9.4 basis points per month for investors with typical levels of risk aversion (α equal to three, five and seven). The relationship of how this psychic dividend changes across varying levels of investor risk aversion is further illustrated in Figure 4.1. The value of the psychic dividend when measured as the difference in *CE* (calculated from equation 4.5) between the *Good* and *Bad* portfolios is shown in Table 4.5 to be equal to two basis points per month.[67]

[67] Psychic dividends calculated from the MSCI KLD Social 400 index and the MSCI U.S. index in place of the *Good* and *Bad* portfolios, respectively, are reported in Table C.7 in Appendix C.

Figure 4.1: Risk-Aversion and Psychic Dividends to SRI

The relationship between psychic dividends (measured in percentage per month) and investor risk-aversion (α) is displayed is the following chart. Psychic dividend is measured as the difference in the certainty equivalent returns (ce) of a socially responsible (*Good*) stock portfolio and socially irresponsible (*Bad*) stock portfolio, where *ce* is calculated for both portfolios from equation 4.3 using monthly returns from across the period January 1990 to December 2013. The construction of the *Good* and bad portfolios is described in detail in section 4.5.a.



The value of the psychic dividend is shown in Figure 4.1 to increase with risk aversion in a non-linear fashion and is negative for investors with risk aversion (α) less than three. In other words, the psychic dividend accruing from SRI will for higher for socially responsible investors who are more averse to risk.[68]

The next set of analysis considers loss-aversion utility functions when computation psychic dividends to socially responsible investors. The difference in psychic returns when certainty equivalent returns, *CE*, (computed from equation 4.5) approaches zero, is interpreted as the psychic divided. Psychic returns along with *CE* for the corresponding *Good* and *Bad* portfolios are reported in Table 4.6.

Table 4.6: Certainty Equivalence of Psychic Returns

The certainty equivalent returns, *CE*, for a socially responsible (*Good*) stock portfolio and a socially irresponsible (*Bad*) stock portfolio are reported in this table across a range of psychic returns (measured as a percentage per month). The difference in the psychic return between the *Good* and *Bad* portfolios when the *CE* of both portfolios are equal to zero indicates the value of the psychic dividend to SRI.

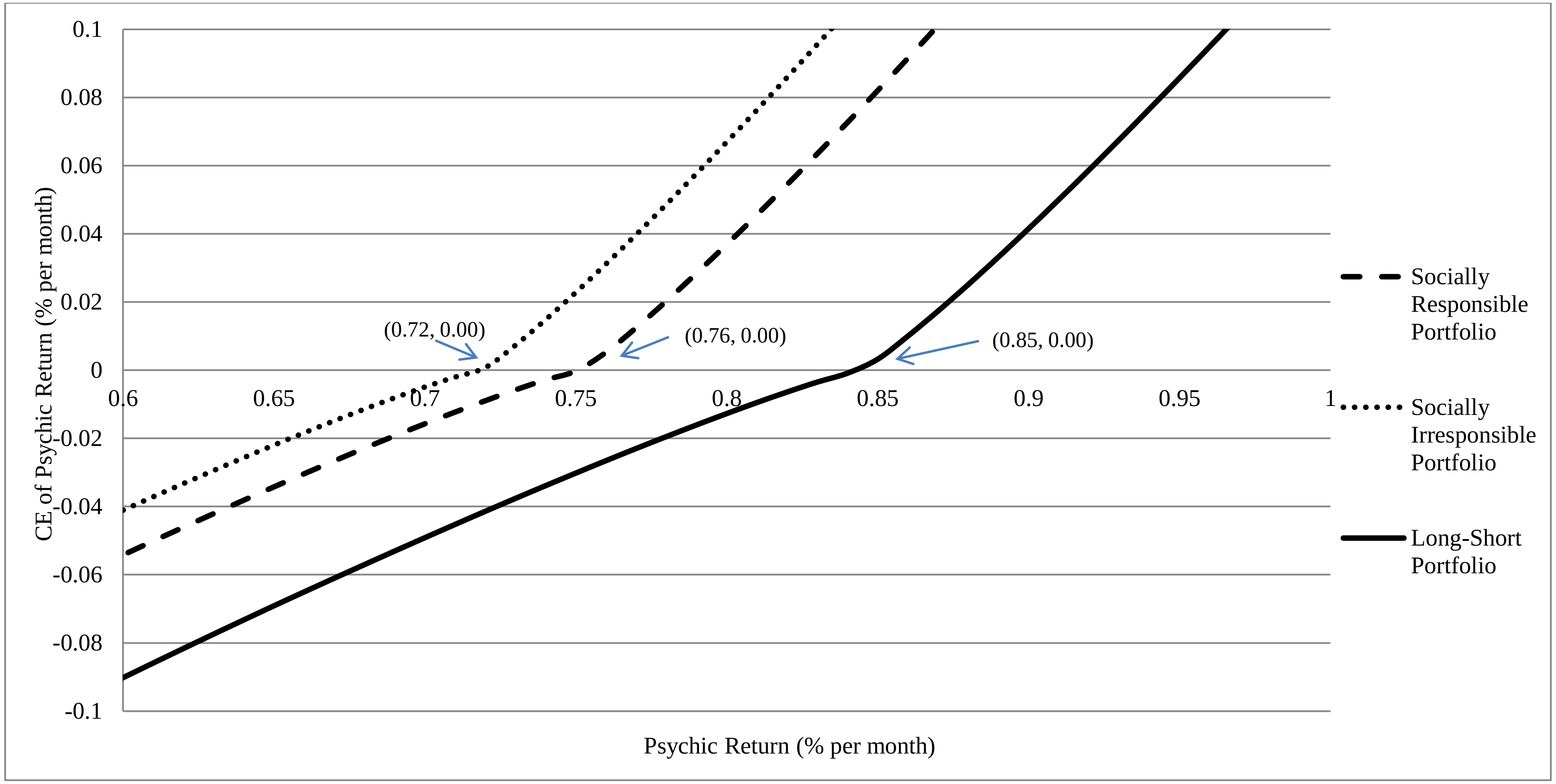
	CE of Psychic Return (% per month)	
Psychic Return	*Good* Portfolio	*Bad* Portfolio
0.69	-0.00811	-0.01924
0.7	-0.00495	-0.01571
0.71	-0.00203	-0.01228
0.72	**0.00074**	**-0.00895**
0.73	0.00729	-0.00577
0.74	0.01481	-0.00280
0.75	0.02279	-0.00024
0.76	**0.03114**	**0.00525**
0.77	0.03976	0.01247

[68] The relationship between psychic dividends and investor risk-aversion when the MSCI KLD Social 400 index and the MSCI U.S. total return are used in place of the *Good* and *Bad* portfolios, respectively, is presented in Figure C.3 in Appendix C.

The psychic return of the good portfolio is shown in Table 4.6 to be about 72 basis points per month for the *Good* portfolio and about 76 basis points per months for the *Bad* portfolio when *CE* of the respected portfolio approaches zero. The difference in the psychic return between these two portfolios equates to about four basis points per month, which can be interpreted as the relative value derived by socially responsible investors from SRI. This result is further illustrated in Figure 4.2, which show how values of *CE* for these two portfolios change across varying levels of psychic return. The relationship between *CE* and psychic returns for a long-short strategy that is long *Good* stocks and short *Bad* stocks, where *CE* is calculated from equation 4.6 in section 4.5.e.ii, is also presented in Figure 4.2.

Figure 4.2: Certainty Equivalence of Psychic Returns

The relationship between psychic returns and certainty equivalence (CE) of psychic returns, measured in percent per month, for a socially responsible (*Good*) portfolio, socially irresponsible (*Bad*) portfolio and a long-short (*Good – Bad*) portfolio of U.S. stocks is illustrated in this chart. The portfolios are constructed using monthly U.S. stock data across the period January 2000 to December 2013. The difference in psychic returns when *CE* of the *Good* and *Bad* portfolios is equal to zero (at the intersection of the horizontal axis) indicates the psychic dividend to SRI.



The intersection of the socially irresponsible (*Bad*) portfolio and the socially responsible (*Good*) portfolio curves with the psychic returns axis (when certainty *CE* of the psychic return is equal to zero) is shown in Figure 4.2 to occur at values of about 72 and 76 basis points, respectively, which implies a psychic dividend of at least four basis points per month accruing to socially responsible investors. The psychic dividend from the long-short strategy can be interpreted from the intersection of the long-short portfolio curve with the psychic return axis (at *CE* equal to zero), which occurs at a value of 85 basis points per month. This result suggests that the psychic dividend derived from investing in such a long-short strategy will be valued by investors by an amount that is at least nine basis points per month greater than if they were to invest in a long-only socially responsible portfolio, and 13 basis points per month more than investing in a socially irresponsible portfolio. During economic expansions, the psychic dividend equates to about negative 12 basis points per month, and the long-short strategy resulting in a psychic return of 1.25 percent per month. However, during recessionary phases, investors are shown to value a socially responsible portfolio by at least 52 basis points per month compared to the socially irresponsible portfolio, and derive a psychic return of 2.25 percent per month from the long-short strategy.[69,70]

4.6.d Proportion of Wealth Invested in SRI

Based on the psychic dividend values determined in the previous analysis, the optimal proportion of wealth invested in SRI and the market portfolio is able to be

[69] Refer to Figure C.1 and Figure C.2 in Appendix C for the relationship between psychic returns and *CE* for *Good*, Bad and long-short portfolios during NBER economic expansion and recession periods, respectively, and Figure C.4 for when the MSCI KLD Social 400 index and the MSCI U.S. total return indices are used in place of the *Good* and *Bad* portfolios, respectively.

[70] Figure C.4 in Appendix C displays the relationship between psychic returns and certainty equivalence (CE) of psychic returns when the *Good* and *Bad* portfolios are replaced with the MSCI KLD Social 400 index and the MSCI U.S. index, respectively.

determined when investors are left with the choice of these two assets and cash. Following the approach of Srivastava, *et al.* (2013), the ratio of wealth invested in SRI and in the market portfolio is calculated via two approaches; a portfolio construction framework (which considers there to be only one type of investor) and an equilibrium framework (which differentiate investors into two types; those who are concerned with ESG aspects of investing, and those who are not). Using the portfolio construction framework, the ratio of socially responsible investment to passive market investment, where ω_S and ω_M are the weights of the optimal portfolio invested in SRI and the passive market portfolio respectively, can be calculated as:

$$\frac{\omega_S}{\omega_M} = \frac{\sigma_M^2(\mu_S+p)-\sigma_{S,M}\mu_M}{\sigma_S^2\mu_M-\sigma_{S,M}(\mu_S+p)}, \tag{4.7}$$

where σ_M^2 and σ_S^2 is the variance of the market portfolio and socially responsible portfolio respectively and μ_M and μ_S is the excess return of the market portfolio and the socially responsible portfolio above the risk-free rate, respectively. $\sigma_{S,M}$ is the covariance between the socially responsible and market portfolios, and *p* is the psychic dividend.

Under the equilibrium-based framework of Srivastava, *et al.* (2013), the optimal proportion of wealth invested in SRI and the market portfolio in a society in equilibrium can be calculated as:

$$\frac{\omega_S}{\omega_M} = \frac{\sigma_M^2 d_1-\sigma_{S,M}d_2}{\sigma_S^2 d_2-\sigma_{S,M}d_1}, \tag{4.8}$$

where $d_1 = \left(\lambda_S^{-1} + \lambda^{-1}\right)\mu_S + \frac{p}{\lambda_S} - r_f$ and $d_2 = \left(\lambda_S^{-1} + \lambda^{-1}\right)\mu_M - r_f$. λ_s and λ_I are λ are the coefficients of loss aversion for the SRI investor and non-SRI investor, respectively, and are both set equal to 2.25. r_f is the risk-free rate of return. The optimal weights and relative proportions invested in SRI and the market portfolio across varying levels of psychic dividends for both portfolio and equilibrium approaches are reported in Table 4.7. The relationship between psychic dividends and these optimal proportions are further illustrated in Figure 4.3 and Figure 4.4, respectively.

Table 4.7: Psychic Dividends and Optimal Portfolio Proportions

The optimal relative portfolio proportions invested in a socially responsible portfolio, ω_S, and in the market portfolio, ω_M, (measured as a percentage) that correspond with varying levels of psychic dividend, *p*, (measured in percent per month) using the portfolio framework and equilibrium-based framework of Srivastava, *et al.* (2013) are reported. $\frac{\omega_S}{\omega_M}$ is the ratio of the optimal proportion of wealth invested in a socially responsible portfolio and the optimal proportion of wealth invested in the market portfolio.

	Portfolio Construction Approach			Equilibrium Approach		
p	ω_S	ω_M	$\frac{\omega_S}{\omega_M}$	ω_S	ω_M	$\frac{\omega_S}{\omega_M}$
0	2.299	-0.602	-3.818	1.711	-0.882	-1.940
0.1	4.247	-2.423	-1.753	2.576	-1.691	-1.524
0.2	6.195	-4.243	-1.460	3.442	-2.500	-1.377
0.3	8.143	-6.063	-1.343	4.308	-3.309	-1.302
0.4	10.091	-7.883	-1.280	5.174	-4.118	-1.256
0.5	12.039	-9.704	-1.241	6.040	-4.927	-1.226
0.6	13.988	-11.524	-1.214	6.905	-5.736	-1.204
0.7	15.936	-13.344	-1.194	7.771	-6.545	-1.187
0.8	17.884	-15.165	-1.179	8.637	-7.354	-1.174
0.9	19.832	-16.985	-1.168	9.503	-8.163	-1.164
1	21.780	-18.805	-1.158	10.369	-8.972	-1.156
1.1	23.728	-20.626	-1.150	11.235	-9.781	-1.149
1.2	25.676	-22.446	-1.144	12.100	-10.590	-1.143
1.3	27.624	-24.266	-1.138	12.966	-11.399	-1.137
1.4	29.572	-26.087	-1.134	13.832	-12.208	-1.133
1.5	31.520	-27.907	-1.129	14.698	-13.017	-1.129
1.6	33.468	-29.727	-1.126	15.564	-13.826	-1.126
1.7	35.417	-31.548	-1.123	16.429	-14.635	-1.123
1.8	37.365	-33.368	-1.120	17.295	-15.444	-1.120
1.9	39.313	-35.188	-1.117	18.161	-16.253	-1.117
2	41.261	-37.009	-1.115	19.027	-17.062	-1.115
2.1	43.209	-38.829	-1.113	19.893	-17.871	-1.113
2.2	45.157	-40.649	-1.111	20.759	-18.680	-1.111
2.3	47.105	-42.470	-1.109	21.624	-19.489	-1.110
2.4	49.053	-44.290	-1.108	22.490	-20.298	-1.108
2.5	51.001	-46.110	-1.106	23.356	-21.108	-1.107
2.6	52.949	-47.930	-1.105	24.222	-21.917	-1.105
2.7	54.898	-49.751	-1.103	25.088	-22.726	-1.104
2.8	56.846	-51.571	-1.102	25.954	-23.535	-1.103
2.9	58.794	-53.391	-1.101	26.819	-24.344	-1.102
3	60.742	-55.212	-1.100	27.685	-25.153	-1.101

Figure 4.3: Psychic Dividends and Optimal Relative SRI Portfolio Proportions (Portfolio Framework)

The ratio of the relative proportion of wealth invested optimally in a socially responsible portfolio, ω_S, and the market portfolio, ω_M, calculated using the portfolio construction framework of Srivastava, *et al.* (2013), is reported across varying values of psychic dividend (measured in percentage per month). The socially responsible portfolio is constructed using monthly U.S. stock data from January 1990 to December 2013 and is described in detail in section 4.5.a. The market portfolio is the CRSP value-weighted portfolio for U.S. stocks.

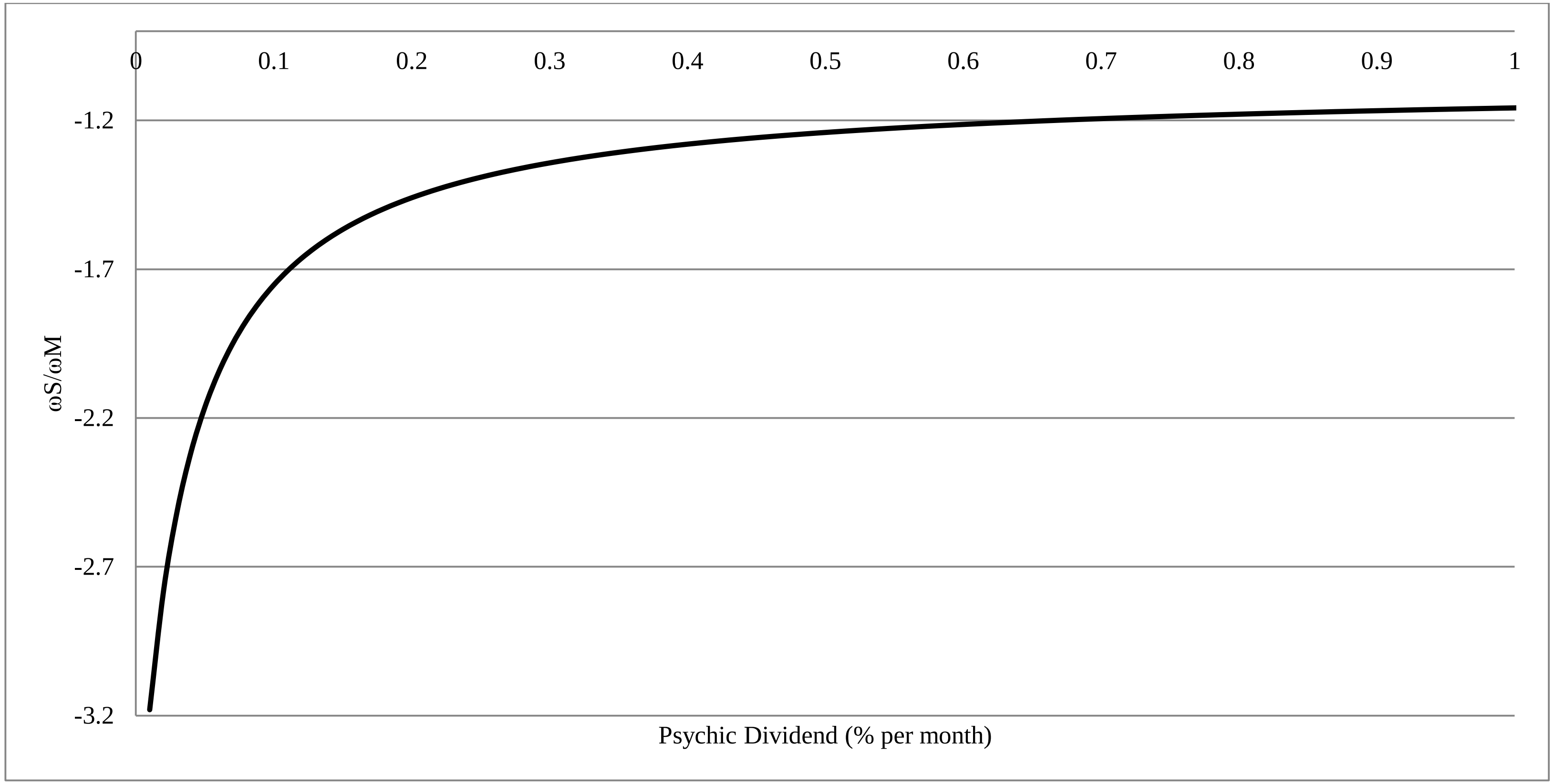


Figure 4.4: Psychic Dividends and Optimal Relative SRI Portfolio Proportions (Equilibrium-based Framework)

The ratio of the relative proportion of wealth invested optimally in a socially responsible portfolio, ω_S, and the market portfolio, ω_M, calculated using the equilibrium-based framework of Srivastava, *et al.* (2013), is reported across varying values of psychic dividend (measured in percentage per month). The socially responsible portfolio is constructed using monthly U.S. stock data from January 1990 to December 2013 and is described in detail in section 4.5.a. The market portfolio is the CRSP value-weighted portfolio for U.S. stocks.

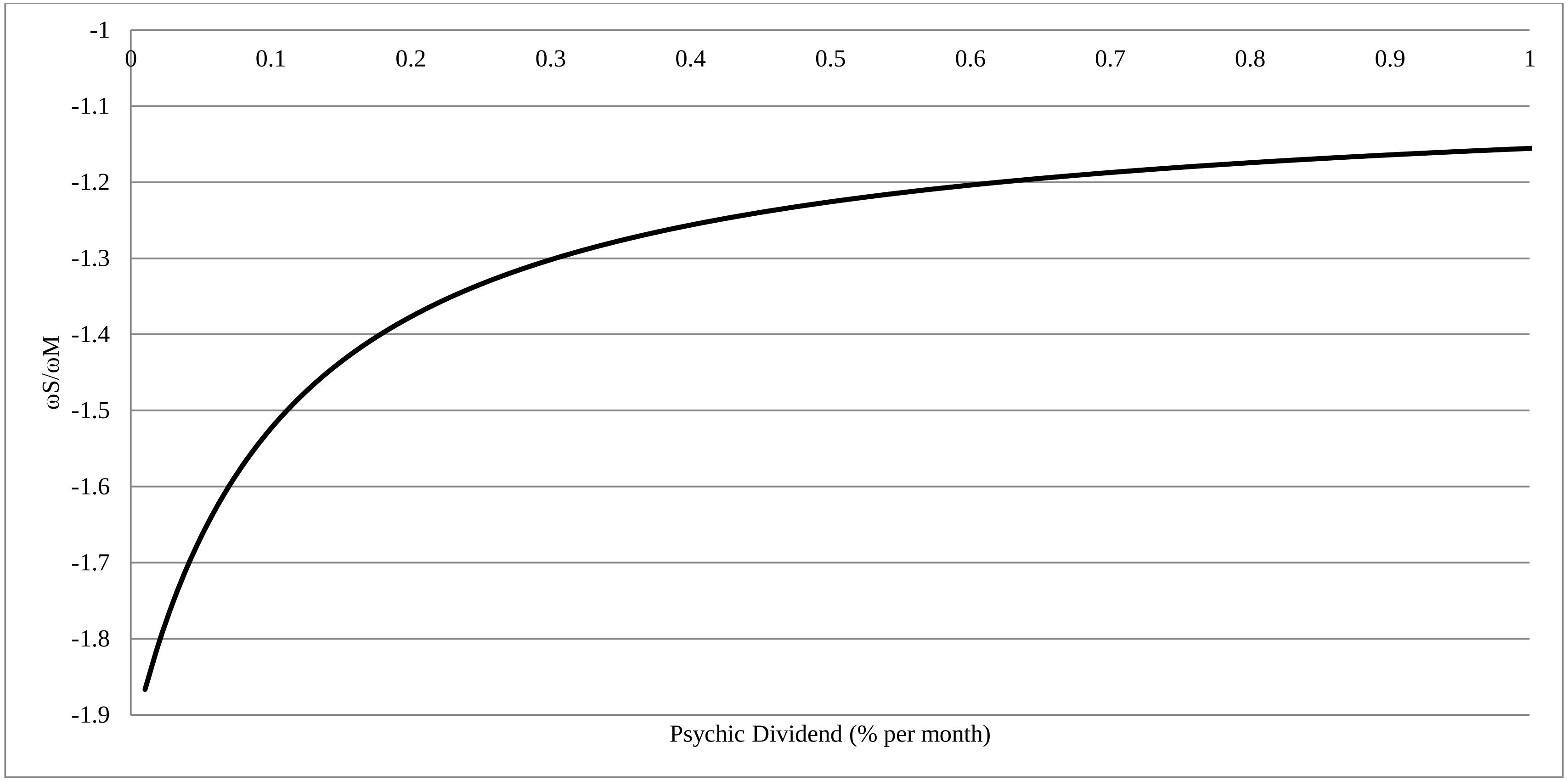


Table 4.7 reports the relative proportion of wealth invested in SRI, ω_S, and in the market, ω_M, for optimal portfolios calculated from both portfolio and equilibrium approaches across varying values of psychic dividend, *p*. These results show that when considering all types of investors, the relative proportion of the optimal portfolio invested in SRI across the same level of psychic return, decreases. For psychic dividends greater than 4.5 basis points per month, the proportion of wealth invested in SRI relative to the market for the optimal portfolio is negative under the portfolio framework. Whereas the proportion of wealth invested in SRI relative to the market is negative for psychic dividends greater than seven basis points per month under the equilibrium framework. The negative proportions are shown to result from a short position taken in market portfolio and a long position for the SRI portfolio. The short position of the market can be attributed to the SRI (*Good*) portfolio outperforming the market portfolio over the sample period. Subsequently, for socially responsible investors with a psychic dividend corresponding to negative value for ω_S/ω_M, investors are required to short sell the market and invest over 100 percent of their wealth in SRI in order to be holding an optimal portfolio. For the observed psychic dividend of four basis points per month computed in the previous analysis, the optimal proportion invested in SRI relative to the market is measured to be about 22.76 from the portfolio construction framework and 4.38 under the equilibrium framework. The relationship between psychic dividend and these optimal proportions are illustrated in Figure 4.3 and Figure 4.4, respectively.

To approximate the proportion of wealth held by investors in SRI relative to the market portfolio, net assets under management invested in U.S mutual funds that are classified as being SRI are compared to the net assets under management of all other U.S mutual funds. If these proportions of assets under management approximate the value invested in SRI and in the market portfolio by investors, then the value of the psychic dividend can subsequently be measured.

Morningstar currently identifies $125 billion in U.S funds under management classified as SRI from a total of $26,621 billion. This gives a proportion of about 0.47 percent in SRI to 99.53 percent in 'non-SRI'. Using these proportions as invested wealth results in a psychic dividend of about -1.20 percent per month (calculate from the portfolio construction method using equation 4.7). This psychic dividend increases to about -0.86 percent per month when investors are differentiated into two types as determined under an equilibrium framework (calculated from equation 4.8). This negative psychic dividend can be attributed to SRI having a much smaller proportion of net wealth invested relative to the market, despite SRI outperforming the market over the sample period. Possible explanations of this result are that the actual net proportion of wealth invested in SRI is much higher than 0.47 percent, or otherwise, the expected return to SRI estimated in this chapter have been vastly overstated.

4.7 Conclusion

The prevalent asset management literature surrounding SRI performance confounds traditional arguments that constrained portfolios underperform optimal unconstrained portfolios. Considering an aggregation of socially responsible/irresponsible screens that are commonly used in current SRI performance studies, a socially irresponsible portfolio of U.S. equity stocks is shown in this chapter to outperform a socially responsible portfolio only during economic recessions, yet is unable able to outperform when returns are risk-adjusted. In light of this performance differential (or lack thereof) that exist between SRI and non-SRI, a degree of non-financial satisfaction is assumed to accrue to some investor from holding SRI. The significance of this non-financial satisfaction is evident from the immense growth in the global SRI asset-management industry in recent years. A measure of the amount by which socially responsible investors value this non-financial satisfaction is therefore provided in this chapter. Previous studies attempt to quantify this value as the difference in certainty equivalence returns of SRI and non-SRI portfolios, this chapter extends the definition of certainty equivalence from the limiting case of exponential utility to more general cases that include constant relative risk aversion and loss aversion, and is subsequently referred to as the 'psychic dividend' from SRI. This psychic dividend is subsequently measured as being at least four basis points per month for a long-only portfolio of socially responsible stocks and at least 85 basis points per month for a portfolio that is long socially-responsible stocks and short socially-irresponsible stocks. This psychic dividend is also shown to increase with investor risk aversion and also during economic recessions.

Applying the framework developed in Srivastava, *et al.* (2013), the proportion of wealth invested in SRI relative to the market portfolio is identified. When investors are restricted to only SRI and the market and for a psychic dividend equal to four basis points per month, the proportion of wealth held in SRI is measured to be about 22.76 times greater than the proportion held in the market portfolio when there is one type of investor, and 4.38 times when investors are separated into two types. For large values of psychic dividend, the optimal portfolio requires a short position in the market portfolio and over 100% of wealth invested in SRI. This approach is also used to estimate psychic dividends using the relative proportions of aggregate assets under management invested in SRI and non-SRI U.S. mutual funds as an approximation of wealth invested in SRI and the market. This approach values psychic dividend at -1.20 percent per month and -0.86 percent per month from these two frameworks, respectively. Possible explanations of this negative psychic dividend may be attributed to the actual aggregate proportion of wealth invested in SRI, relative to the market, being substantially higher than the relative proportion of aggregate assets under management in SRI-classified mutual funds. Or, alternatively, the actual expected return to SRI is vastly overstated, implying that the market portfolio significantly outperforms SRI. The empirical evidence from this chapter therefore suggests that asset managers may be free to incorporate ESG mandates into investment practices without the repercussion of asset outflows resulting from portfolio underperformance, due to this non-financial satisfaction that is shown to accrue to individuals from investing in a socially responsible manner.

Chapter 5. Conclusion

Three essays were presented in this dissertation that examined topics related to equity portfolio management. The first two essays investigated issues concerning portfolio asset allocations and performance evaluation of Australian managed funds while the third essay investigated issues relating to socially responsible investing. Specifically, the first essay examined the appropriateness of Australian equity fund benchmarks and whether funds with inappropriate benchmarks outperform and attract increased flows of assets under management. In light of the lack of regulations surrounding the benchmarking of Australian managed funds and the absence of publicly available equity style indices, this essay finds that a large majority of funds are best suited to their self-reported benchmarks. The funds that are considered to be inappropriately benchmarked, however, are shown to be better matched to alternative S&P/ASX indices. No funds are significantly better matched to passive size-value/growth style indices despite a large majority of 'style-orientated' funds reporting broad market-based indices as their benchmark. This chapter further shows that managers who report mismatched benchmarks are unable to outperform 'appropriately-matched' funds or attract increased funds of assets under management. This implies that attempts to make fund performance appear more attractive through the misallocation of benchmarks go unrewarded. The findings from this chapter refute those from previous studies that suggest that benchmark mismatching will be prevalent amongst funds in markets where regulations concerning benchmarking are not stringent. As such, investors can generally rely on a fund's self-reported benchmark to adequately capture passive style returns and thus be used to accurately evaluate performance.

Chapter 3 of this dissertation explored how fund portfolio exposures are influenced by industry booms and the subsequent effect that these exposures have on fund performance and flows. Using the Australian mining boom as a natural experiment, this essay has strengthened our understanding of whether equity funds are able to capture industry outperformance and the effect that exposures to booming industries have on fund investors. This essay shows that Australian equity funds, on average, increased their exposure to mining-related stocks across the mining boom in relative and absolute terms. However, those funds with higher exposure to this industry were unable to outperform relative to those funds with lower exposures, in terms of both raw and risk-adjusted returns. This suggests that fund managers are not able to extract abnormal returns from industry outperformance. Nevertheless, this essay also shows that funds with higher mining exposure were successful in attracting greater funds inflows. This indicates that the investment decisions of mutual fund investors are also influenced by industry booms. This mining exposure-flow relationship is shown to be more pervasive amongst wholesale funds relative to retail funds, despite increased mining exposure being more detrimental to the performance of wholesale funds. This inflow may be attributed to investors mistaking industry allocation for fund skill and is consistent with investors being attracted to hot investment styles. Subsequently, this essay suggests that investors should be wary during times of industry expansions as industry allocation is not a substitute for stock selection skill.

The final essay of this dissertation (Chapter 4) measured the value of the non-financial satisfaction that accrues to socially responsible investors. This non-financial benefit is referred to as the "psychic dividend" of SRI. This essay shows that SRI portfolios do not significantly underperform (or outperform) non-SRI portfolios when measured using raw or risk-adjusted returns, regardless of economic or market conditions. However, the psychic dividend to SRI is valued at an amount that is at least four basis points per month for a long-only portfolio of socially responsible stocks and at least 85 basis points per month for a portfolio that is long socially-responsible stocks and short socially-irresponsible stocks. This psychic dividend is shown to increase with investor risk-aversion and also during economic recessions. An implication of identifying the value of this psychic dividend is that SRI asset managers may be free to incorporate SRI mandates into investment practices without the repercussion of asset outflows resulting from the underperformance of a portfolio by an amount that is at least as large as this psychic dividend.

Appendix A

The following charts and tables contained in this appendix support the empirical analysis conducted in the first essay (Chapter 2: Equity Fund Benchmark Appropriateness, Performance and Flows) of this dissertation.

Table A.1: Style Index Return Descriptive Statistics (II)

Descriptive statistics for the monthly returns over the period from January 2000 to December 2011 of the six alternative passive Australian size/value-growth investable equity style indices are reported in this table. These indices are constructed as a robustness check for the other size/value-growth style indices that are used in Chapter 2.

Rank	Index	Mean	Min	Median	Max	St. Dev.	Skewness	Kurtosis
1	Small Value	1.737	-21.491	2.394	18.845	5.433	-0.644	3.019
2	Value	1.193	-13.402	1.981	14.578	4.376	-0.711	1.602
3	Large Value	1.163	-13.269	2.035	14.524	4.353	-0.683	1.484
4	Large Growth	0.648	-13.960	1.407	8.999	4.122	-1.004	1.569
5	Growth	0.631	-14.397	1.480	8.953	4.172	-1.062	1.776
6	Small Growth	0.230	-30.183	1.468	14.178	6.832	-1.136	2.933

Figure A.1: Style Index Prices (II)

Monthly prices from January 2000 to December 2011 for the six 'alternative' passively-constructed investable size-value/growth equity style indices that are used as a robustness measure for the style indices used throughout Chapter 2 are displayed in the following chart. Each index has a base value of 100 points at the beginning of the period. Indices are constructed from the universe of the largest 300 Australian equity stocks by market capitalisation with book-to-market values of equity used to define the value/growth dimension and market capitalisation for the size dimension. The indices are also value-weighted and rebalanced monthly. The construction of these indices is described in detail in section 2.4.d.

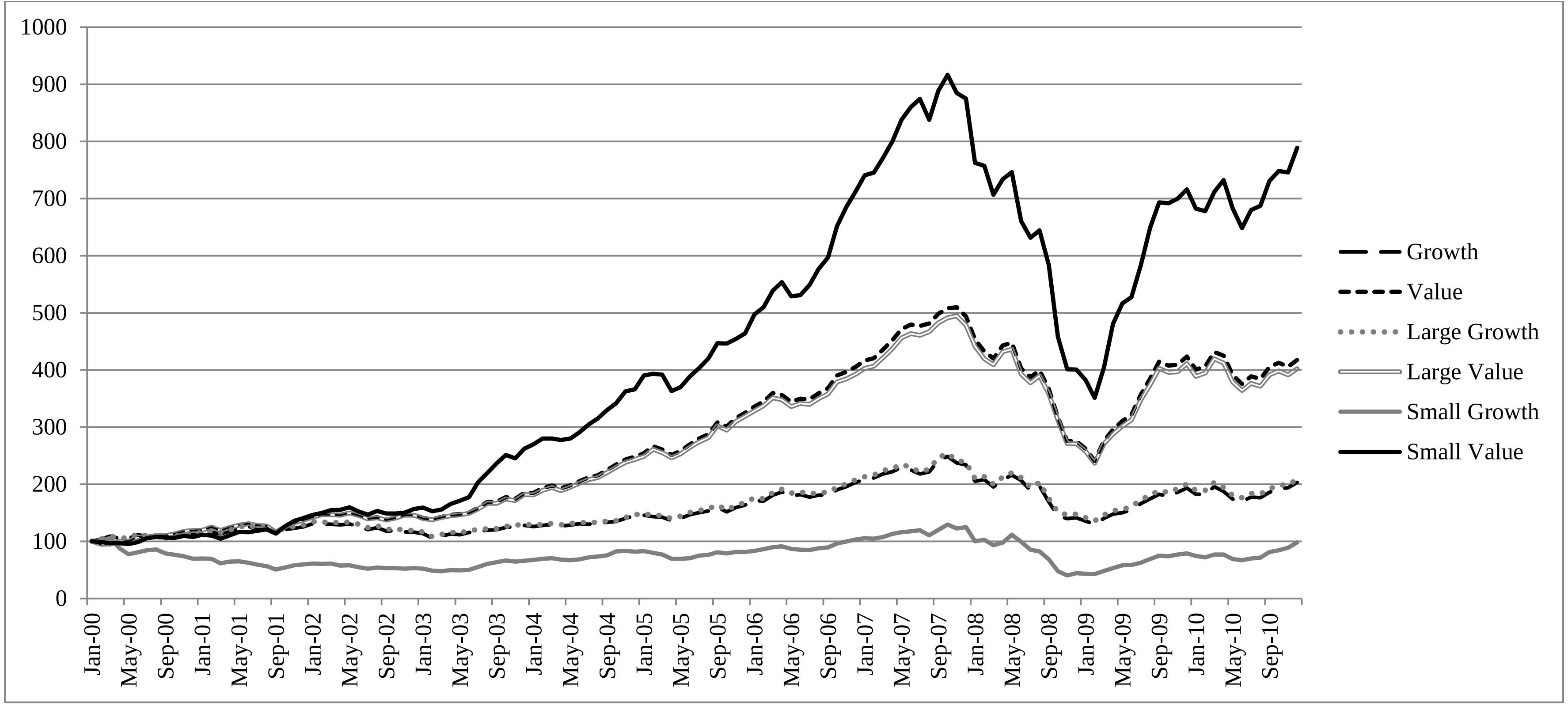


Table A.2: Index Correlations

Correlation coefficients are reported for the monthly returns between each of the eight passively-constructed Australian size-value/growth equity style indices as well as for each of the S&P/ASX accumulation indices that serve as benchmarks for the Australian equity funds contained in the sample over the period from January 2000 to December 2011.

	Growth	Value	Large Value	Large Core	Large Growth	Small Value	Small Core	Small Growth	ASX Small Res.	ASX Small Ords	ASX 300 Res.	ASX 300	ASX 300 Ind.	ASX 200	ASX 200 Ind.	ASX 100	ASX All Ords	ASX 50
Growth	1.000																	
Value	0.667	1.000																
Large Value	0.475	0.784	1.000															
Large Core	0.629	0.708	0.435	1.000														
Large Growth	0.856	0.578	0.471	0.544	1.000													
Small Value	0.685	0.845	0.497	0.655	0.509	1.000												
Small Core	0.783	0.809	0.487	0.662	0.608	0.893	1.000											
Small Growth	0.771	0.643	0.376	0.543	0.578	0.786	0.827	1.000										
ASX Small Res.	0.740	0.681	0.446	0.625	0.592	0.738	0.832	0.788	1.000									
ASX Small Ords	0.833	0.792	0.471	0.666	0.616	0.893	0.936	0.905	0.853	1.000								
ASX 300 Res.	0.728	0.707	0.615	0.725	0.636	0.608	0.693	0.630	0.825	0.706	1.000							
ASX 300	0.814	0.821	0.536	0.853	0.692	0.818	0.836	0.749	0.745	0.883	0.762	1.000						
ASX 300 Ind.	0.702	0.756	0.428	0.774	0.592	0.791	0.754	0.664	0.565	0.810	0.525	0.946	1.000					
ASX 200	0.809	0.820	0.536	0.856	0.689	0.811	0.829	0.739	0.738	0.876	0.760	1.000	0.947	1.000				
ASX 200 Ind.	0.697	0.752	0.426	0.774	0.590	0.784	0.747	0.655	0.560	0.803	0.522	0.944	1.000	0.946	1.000			
ASX 100	0.795	0.812	0.536	0.864	0.689	0.793	0.807	0.714	0.716	0.851	0.755	0.998	0.948	0.999	0.947	1.000		
ASX All Ords	0.832	0.832	0.551	0.840	0.702	0.833	0.861	0.775	0.769	0.903	0.775	0.997	0.933	0.996	0.931	0.992	1.000	
ASX 50	0.770	0.796	0.538	0.874	0.679	0.767	0.776	0.685	0.694	0.819	0.751	0.991	0.941	0.992	0.941	0.996	0.982	1.000

Table A.3: Four-Factor Style Index Exposures (II)

Carhart (1997) four-factor regressions are estimated for the six 'alternative' passively-constructed investable size-value/growth style equity indices that are used as a robustness check for the style indices used throughout Chapter 2. The regressions are estimated using monthly returns over the period from January 2000 to December 2011. The Carhart (1997) regressions identify index risk-adjusted returns (alpha) and exposures towards the market-risk premium (R_m-R_f), the value factor (*HML*), the size factor (*SMB*) and the momentum factor (*UMD*). Construction of these style indices are described in detail in section 2.4.d. Regressions are estimated with robust standard errors. T-statistics are displayed in parentheses and *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	Large Growth	Large Value	Small Growth	Small Value	Growth	Value
Alpha	-0.0267	0.292*	-0.974***	0.659***	-0.0667	0.310**
	(-0.212)	(1.818)	(-3.881)	(3.255)	(-0.547)	(1.998)
Rm-rf	1.018***	1.105***	1.328***	1.215***	1.031***	1.114***
	(30.081)	(25.619)	(19.707)	(22.347)	(31.535)	(26.751)
SMB	-0.0670***	-0.0154	0.500***	0.294***	-0.0421*	0.00168
	(-2.978)	(-0.538)	(11.149)	(8.139)	(-1.937)	(0.061)
HML	-0.202***	0.254***	0.0497	0.335***	-0.193***	0.257***
	(-4.364)	(4.298)	(0.539)	(4.505)	(-4.315)	(4.520)
UMD	0.0755*	-0.0699	-0.0240	-0.170**	0.0701*	-0.0771
	(1.813)	(-1.317)	(-0.289)	(-2.536)	(1.741)	(-1.504)
Observations	128	128	128	128	128	128
R-squared	0.893	0.846	0.844	0.843	0.903	0.858

Table A.4: Fund Performance and Benchmark Mismatching (II)

Regressions that describe the relationship between fund performance and benchmark mismatching are estimated using monthly panel data from January 2000 to December 2011 for a sample of Australian actively managed equity funds. The dependent fund performance variables include; Benchmark-excess returns, R_i-R_b, excess returns, R_i-r_f, CAPM Alpha and Carhart alpha. The explanatory variables include a binomial *Mismatch* variable which takes a value of one if a fund is considered mismatched from its benchmark (at five and one percent significance levels, as determined from a Levene (1960) test for homogeneity of variance on fund-benchmark tracking-error volatilities), or zero otherwise. A binomial wholesale variable that takes a value of one if a fund is classified as a wholesale fund, or zero for a retail fund is also included. A mismatch-wholesale interaction variable is additionally included. A vector of control variables which comprise of; the natural log of a fund's total net assets, *Size*, the natural log of the number of months since a fund's inception date, *Age*, return *Volatility* (measured as the historical standard deviation of monthly raw returns over the previous 12 months), lag flow of assets under management, *Lag Flow*, and the Net flow of assets under management into all funds with the same investment style, *Net Style Flows*, are contained in the regressions. All control variables are lagged one-month and regressions are estimated with time-fixed effects (month dummies) and style-fixed effects (style dummies). Robust standard errors are clustered at the fund level and t-statistics are displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	r_i-r_b		r_i-r_f		CAPM Alpha		Carhart Alpha	
Constant	-0.656***	-0.680***	-1.594***	-1.632***	-0.273*	-0.287*	-0.398***	-0.416***
	(-2.694)	(-2.761)	(-5.644)	(-5.745)	(-1.880)	(-1.959)	(-2.845)	(-2.940)
Mismatch (5%)	-0.116		-0.176**		-0.0390		0.0438	
	(-1.329)		(-2.000)		(-0.950)		(0.673)	
Mismatch (1%)		-0.204		-0.368		-0.124		-0.245
		(-0.608)		(-1.208)		(-1.226)		(-1.467)
*Mismatch (5%)*Wholesale*	0.150		0.242*		0.164		0.152	
	(1.018)		(1.888)		(1.463)		(1.234)	
*Mismatch (1%)*Wholesale*		0.0656		0.333		0.108		0.263
		(0.191)		(1.071)		(0.939)		(1.337)
Wholesale	0.0818***	0.0885***	0.0825***	0.0902***	0.0623***	0.0694***	0.0645***	0.0713***
	(3.176)	(3.461)	(2.980)	(3.307)	(2.812)	(3.110)	(2.799)	(3.049)
Size	-0.0230***	-0.0215***	-0.0237***	-0.0216**	-0.00332	-0.00247	0.00304	0.00378
	(-2.841)	(-2.598)	(-2.636)	(-2.380)	(-0.607)	(-0.452)	(0.554)	(0.694)
Age	0.0459**	0.0443*	0.0357	0.0345	0.0515**	0.0493**	0.0264	0.0252
	(2.015)	(1.956)	(1.459)	(1.423)	(2.503)	(2.419)	(1.241)	(1.193)
Volatility	0.129***	0.129***	0.126***	0.127***	-0.00960	-0.00892	0.0122	0.0141
	(4.380)	(4.386)	(4.133)	(4.156)	(-0.529)	(-0.489)	(0.744)	(0.846)
Lag Flow	0.00489	0.00495	0.00449	0.00460	0.0177***	0.0177***	0.0167***	0.0166***
	(1.399)	(1.413)	(1.081)	(1.107)	(6.255)	(6.249)	(6.325)	(6.254)
Net Style Flow	0.101***	0.101***	0.00973	0.00924	0.0212***	0.0213***	0.0112*	0.0114*
	(4.282)	(4.285)	(0.425)	(0.405)	(2.650)	(2.679)	(1.673)	(1.725)
Style Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,824	15,824	15,824	15,824	12,468	12,468	12,468	12,468
R-squared	0.081	0.081	0.867	0.867	0.284	0.282	0.219	0.216

Table A.5: Fund Flows and Benchmark Mismatching (II)

Regressions that describe the relationship between fund benchmark mismatching and flows are estimated in the following table using monthly panel data for a sample of Australian actively managed equity funds over the period from January 2000 to December 2011. The dependent variable is fund-level percentage flow of assets under management, *Flow*. The explanatory variables are fund-level include a binomial benchmark mismatching variable, *Mismatch*, as well as a wholesale-mismatch interaction variable, *Mismatch*Wholesale*. The mismatch dummy takes on a value of one if the fund is mismatched from its self-reported benchmark, or zero otherwise. *Wholesale*, is a binomial variable that takes on a value of one if a fund is classified as a wholesale fund or zero if it is a retail fund. Funds are considered mismatched from their benchmarks at five and one percent significance level as determined from a Levene (1960) test for homogeneity of variance from fund benchmark-relative tracking-error volatilities. Performance control variables include; raw fund returns, *Return*, as well as three fractional performance controls ($LowPerf_{i,t}$ $MidPerf_{i,t}$ *and* $HighPerf_{i,t}$) based on the percentile ranks of monthly lagged raw fund returns and constructed using fractional 33%-33%-33% breakpoints used to define the *Low*, *Mid* and *High* fractile ranks. These performance measures are also interacted with the *Mismatch* variable. The regressions also include a vector of control variables, comprising; the natural log of a fund's total net assets, *Size*, the natural log of the number of months since a fund's inception date, *Age*, return *Volatility*, measured as the historical standard deviation of monthly raw returns over the previous 12 months for each fund, flow of assets under management during the previous month, *Lag Flow*, and the net flow of assets under management into all funds with the same investment style, *Net Style Flow*. All independent variables are lagged by one-month and regressions are estimated with time-fixed effects (month dummies) and style-fixed effects (style dummies). Robust standard errors are clustered at the fund level and t-statistics are displayed in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

VARIABLES	**Flow**	**Flow**	**Flow**	**Flow**	**Flow**	**Flow**
Constant	4.662***	4.676***	4.543***	4.556***	4.637***	4.521***
	(8.280)	(8.321)	(8.027)	(8.066)	(8.260)	(8.011)
Mismatch (5% level)	-0.115	-0.174	-0.108	-0.171		
	(-0.679)	(-1.043)	(-0.640)	(-1.024)		
Mismatch (1% level)					-0.279	-0.269
					(-1.490)	(-1.442)
Wholesale		0.0342		0.0299	0.0400	0.0361
		(0.318)		(0.278)	(0.384)	(0.348)
*Mismatch*Wholesale*		0.137		0.147		
		(0.404)		(0.431)		
Return	0.0211*	0.0208*			0.0209*	
	(1.763)	(1.742)			(1.748)	
Low Return Rank			0.864***	0.860***		0.858***
			(2.608)	(2.594)		(2.589)
Mid Return Rank			-0.173	-0.176		-0.178
			(-0.684)	(-0.700)		(-0.707)
High Return Rank			-0.0334	-0.0350		-0.0225
			(-0.074)	(-0.078)		(-0.050)
	-	-	-	-	-	-
Size	0.0650**	0.0671**	0.0653**	0.0673**	0.0652**	0.0655**
	(-2.270)	(-2.302)	(-2.286)	(-2.314)	(-2.244)	(-2.259)
	-	-	-	-	-	-
Age	0.709***	0.705***	0.712***	0.708***	0.707***	0.710***
	(-9.334)	(-9.178)	(-9.354)	(-9.198)	(-9.244)	(-9.265)
Volatility	0.0515	0.0506	0.0587	0.0579	0.0507	0.0579
	(1.173)	(1.150)	(1.334)	(1.313)	(1.155)	(1.316)
Lag Flow	0.221***	0.221***	0.221***	0.221***	0.221***	0.221***
	(8.927)	(8.925)	(8.915)	(8.912)	(8.925)	(8.913)
Net Style Flow	0.565***	0.564***	0.565***	0.564***	0.563***	0.564***
	(9.866)	(9.874)	(9.878)	(9.887)	(9.865)	(9.878)
Style Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,797	21,797	21,797	21,797	21,797	21,797
R-squared	0.187	0.187	0.187	0.187	0.187	0.187

Appendix B

The following charts and tables contained in this appendix support the empirical analysis conducted in the second essay (Chapter 3: Prospecting for Alpha: Equity Fund Performance, Flows and the Mining Boom in Australia) of this dissertation.

Table B.1: Industry Index Return Correlations

Correlation coefficients are reported between the monthly returns from each of the ten industry indices and the Top 300 index over the period from January 2000 to December 2011. The indices are constructed from the largest 300 Australian stocks by market capitalisation using tier one and two GICS categories to group stocks into one of ten industries. The industries include Mining, Materials (excluding Metals-and-mining), Consumer Staples, Consumer Discretionary, Industrials, Telecommunications, Utilities, Information Technology and Health Care. A market index is also included (Top 300 Market) that is constructed from the largest 300 Australian stocks by market capitalisation. All indices are value-weighted and rebalanced monthly.

	Mining	Materials	Industrials	Consumer Discretionary	Consumer Staples	Health Care	Financials	IT	Telecomm.	Utilities	*Top 300* Market
Mining	1.000										
Materials	0.664	1.000									
Industrials	0.537	0.696	1.000								
Consumer Disc.	0.346	0.528	0.593	1.000							
Consumer Stpls.	0.457	0.572	0.579	0.444	1.000						
Health Care	0.387	0.480	0.519	0.420	0.572	1.000					
Financials	0.442	0.647	0.730	0.547	0.612	0.518	1.000				
Info. Tech.	0.319	0.332	0.402	0.466	0.217	0.360	0.294	1.000			
Telecomm.	0.165	0.235	0.223	0.291	0.253	0.202	0.259	0.203	1.000		
Utilities	0.337	0.410	0.432	0.303	0.502	0.444	0.464	0.264	0.259	1.000	
Top 300 Market	0.777	0.805	0.816	0.687	0.701	0.617	0.842	0.454	0.378	0.518	1.000

Figure B.1: Industry Index Stock Quantities

The number of constituent stocks from the *Top 300* index belonging to each of the ten industry-constructed indices is reported across the period from January 2000 to December 2011. Industry indices are constructed from tier one and tier two GICS categories of all Australian listed stocks contained in the *Top 300* index. The *Top 300* is a value-weighted accumulation index of the 300 largest Australian listed stocks by market capitalisation that is rebalanced monthly.

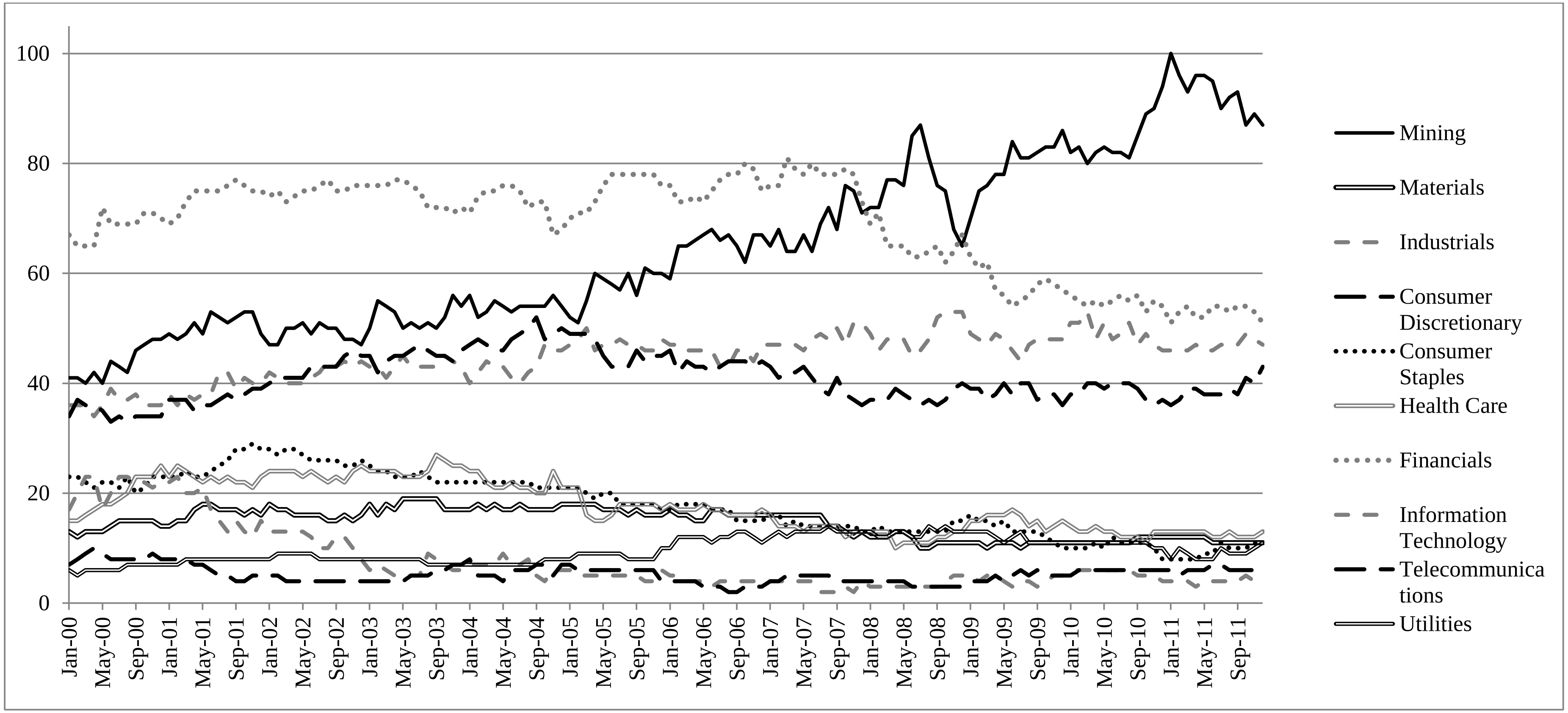


Figure B.2: Industry Index Prices

Monthly industry index prices are displayed across period from January 2000 to December 2011. The indices are constructed from the largest 300 Australian stocks by market capitalisation using tier one and two GICS categories to group stocks into one of ten industries. The industries include Mining, Materials (excluding Metals-and-mining), Consumer Staples, Consumer Discretionary, Industrials, Telecommunications, Utilities, Information Technology and Health Care. A market index is also included (Top 300 Market) that is constructed from the largest 300 Australian stocks by market capitalisation. All indices are value-weighted and rebalanced monthly and begin with a base price of 100 points at the start of the sample period.

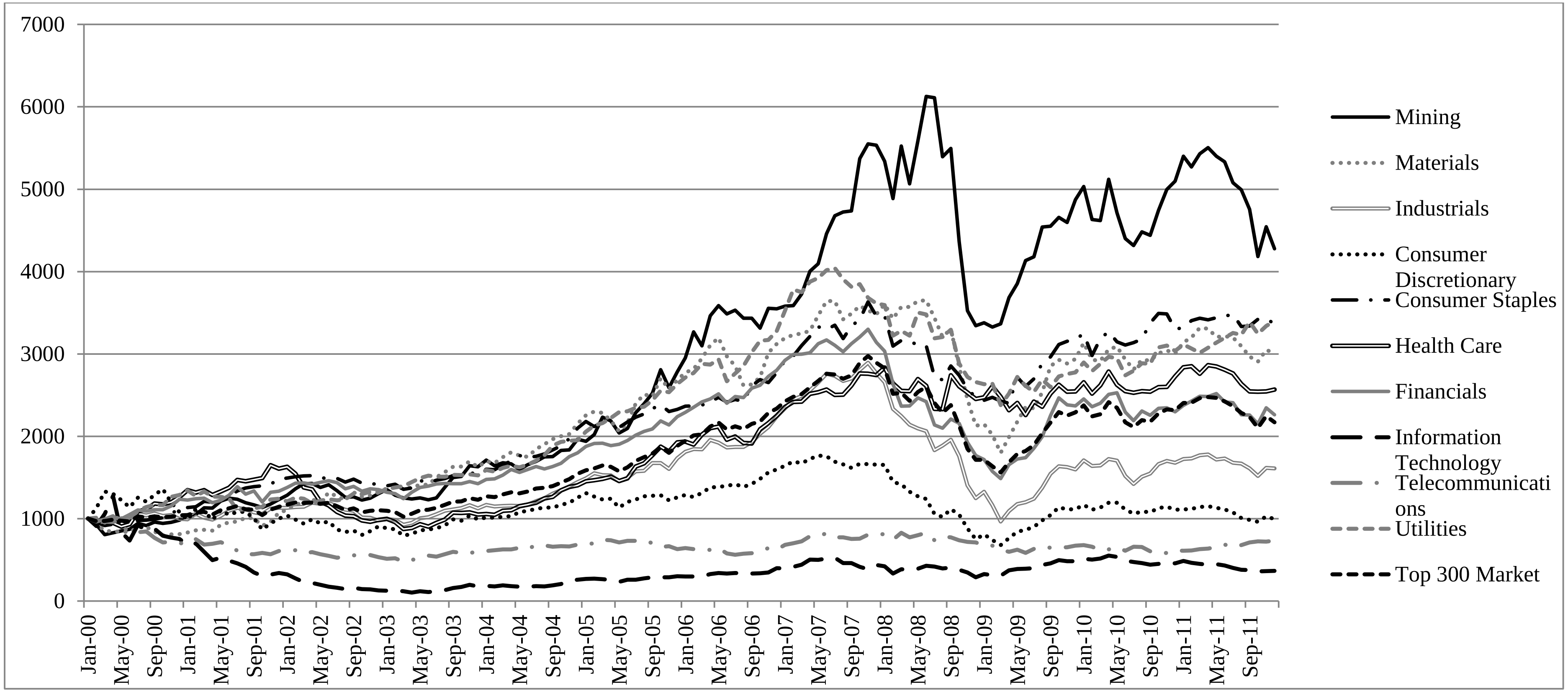


Table B.2: Decile Fund Portfolio Mining Exposures (Calendar Year Sub-Periods)

Average monthly mining exposures (measured as a percentage of total industry exposure) for equal-weighted decile portfolios constructed from a sample of Australian actively managed equity funds are reported over calendar year sub-periods from January 2003 to December 2011. Funds are sorted equally into decile portfolios each month based on their one-month lagged mining-exposure and rebalanced monthly. Decile one (ten) contains funds with the highest (lowest) exposure to mining stocks. Differences in average mining exposure between the High and Low and average of top two and bottom two portfolios over the sample period are also reported. Fund-level mining exposure is measured from a Sharpe (1992) constrained regression approach across 36-month rolling windows and expressed as a percentage. T-statistics are displayed in parentheses and *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Decile	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
1 [High]	29.90	30.21	32.64	38.53	40.52	43.02	47.94	47.57	54.24
2	18.12	19.01	22.40	26.36	29.43	32.80	36.24	34.78	35.57
3	16.08	17.02	20.22	23.76	26.15	28.89	31.97	30.90	30.62
4	14.23	15.42	18.85	21.86	24.18	26.60	29.57	28.45	28.32
5	12.07	14.07	17.71	20.38	22.49	24.90	27.49	26.37	26.39
6	10.16	12.51	16.32	18.66	20.75	23.18	25.32	24.32	24.34
7	7.95	10.72	14.11	16.52	18.56	20.35	22.16	21.26	21.67
8	4.87	8.44	10.59	12.58	14.58	15.78	16.23	15.52	16.42
9	1.55	4.70	5.55	6.33	8.60	10.71	9.07	8.02	9.73
10 [Low]	0.05	0.42	0.58	0.41	1.80	2.38	2.37	1.35	0.98
Av. Top 5	18.01	19.11	22.33	26.15	28.52	31.22	34.62	33.59	34.99
Av. Bottom 5	4.89	7.33	9.41	10.88	12.83	14.45	15.00	14.07	14.60
Decile Average	11.50	13.25	15.90	18.54	20.71	22.86	24.84	23.85	24.83
Top 300 Market	19.62	18.86	19.77	21.82	22.74	30.48	29.59	29.41	29.77
Dec Av. – *Top 300*	-8.12	-5.61	-3.87	-3.28	-2.03	-7.62	-4.75	-5.55	-4.94
High - Low	29.855***	29.794***	32.064***	38.122***	38.718***	40.637***	45.574***	46.213***	53.256***
	(28.736)	(32.204)	(38.744)	(57.115)	(63.941)	(70.84)	(86.696)	(93.594)	(85.644)
Top 5 - Bottom 5	13.118***	11.771***	12.922***	15.268***	15.696***	16.771***	19.619***	19.517***	20.39***
	(45.144)	(45.675)	(54.075)	(65.647)	(71.183)	(76.594)	(87.424)	(90.513)	(81.547)

Table B.3: Decile Fund Portfolio Returns (Calendar Year Sub-Periods)

Average monthly returns (measured as a percentage) for equal-weighted decile portfolios constructed from a sample of Australian actively managed equity funds are reported over calendar year sub-periods from January 2003 to December 2011. Funds are sorted equally into decile portfolios each month based on their one-month lagged mining-exposure and rebalanced monthly. Decile one (ten) contains funds with the highest (lowest) exposure to mining stocks. Differences in average mining exposure between the High and Low and average of top two and bottom two portfolios over the sample period are also reported. Fund-level mining exposure is measured from a Sharpe (1992) constrained regression approach across 36-month rolling windows and expressed as a percentage. T-statistics are displayed in parentheses and *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Decile	2003	2004	2005	2006	2007	2008	2009	2010	2011
1 [High]	1.917	1.860	1.756	2.137	1.670	-5.221	3.735	1.107	-1.235
2	1.386	2.101	1.801	1.750	1.623	-4.624	3.716	0.433	-1.219
3	1.486	2.268	1.758	1.774	1.346	-4.483	3.053	0.292	-0.978
4	1.330	2.173	1.614	1.776	1.317	-4.085	3.175	0.225	-0.945
5	1.327	2.245	1.761	1.790	1.219	-4.178	2.895	0.125	-0.907
6	1.372	2.115	1.726	1.765	1.165	-3.873	3.200	0.103	-0.977
7	1.264	2.058	1.622	1.849	1.123	-4.303	3.088	0.182	-0.963
8	1.784	2.195	1.591	2.120	1.306	-4.231	2.987	0.150	-0.960
9	1.944	2.260	1.301	2.183	1.222	-3.802	2.962	0.181	-1.067
10 [Low]	1.990	2.408	1.396	2.191	1.000	-3.655	2.862	0.274	-0.759
Av. top5	1.487	2.130	1.738	1.845	1.434	-4.517	3.314	0.435	-1.055
Av. bottom 5	1.673	2.208	1.527	2.022	1.163	-3.972	3.019	0.178	-0.945
Decile Average	1.580	2.168	1.633	1.934	1.299	-4.245	3.167	0.307	-1.001
Mining Index Return	2.207	1.100	3.606	1.969	3.414	-3.497	3.637	0.931	-2.241
Decile Av. - Mining Index Return	-0.627	1.068	-1.974	-0.035	-2.115	-0.749	-0.470	-0.624	1.240
High - Low	-0.073	-0.548***	0.36	-0.054	0.67***	-1.566***	0.873***	0.833***	-0.476**
	(-0.227)	(-2.638)	(1.354)	(-0.229)	(3.311)	(-3.522)	(3.029)	(3.191)	(-2.024)
Top 5 - Bottom 5	-0.186	-0.078	0.211**	-0.177**	0.271***	-0.545**	0.295**	0.257**	-0.111
	(-1.501)	(-1.04)	(2.056)	(-2.095)	(3.511)	(-3.121)	(2.411)	(2.354)	(-1.27)

Table B.4: Decile Fund Portfolio Flows (Calendar Year Sub-Periods)

Average monthly flows (measured as a percentage of assets under management) for equal-weighted decile fund portfolios constructed from a sample of Australian actively managed equity funds are reported over calendar year sub-periods from January 2003 to December 2011. Funds are sorted equally into decile portfolios each month based on their one-month lagged mining-exposure and rebalanced monthly. Decile one (ten) contains funds with the highest (lowest) exposure to mining stocks. Differences in average mining exposure between the High and Low and average of top two and bottom two portfolios over the sample period are also reported. Fund-level mining exposure is measured from a Sharpe (1992) constrained regression approach across 36-month rolling windows and expressed as a percentage. T-statistics are displayed in parentheses and *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Decile	2003	2004	2005	2006	2007	2008	2009	2010	2011
1 [High]	2.746	2.009	2.928	1.718	1.572	0.564	0.959	0.028	-0.140
2	1.691	1.425	1.674	2.084	1.578	0.810	0.810	0.027	-0.587
3	1.710	1.535	1.684	1.363	1.182	0.321	0.367	-0.285	-0.961
4	1.578	1.372	0.879	1.231	1.451	0.364	0.099	0.163	-0.699
5	0.747	0.658	1.114	1.111	1.212	0.738	1.087	0.068	-0.516
6	-0.031	0.641	0.865	0.413	0.894	0.270	0.530	-0.047	-0.610
7	0.766	0.638	0.863	1.168	1.083	-0.048	-0.116	0.371	-0.190
8	0.100	1.034	1.263	0.921	1.097	0.040	1.156	0.590	-0.600
9	0.853	0.952	1.046	0.884	1.456	-0.104	0.845	0.127	-0.488
10 [Low]	1.329	1.887	0.585	0.763	1.621	0.047	0.161	-0.034	-0.607
Av. Top 5	1.695	1.397	1.653	1.502	1.399	0.561	0.664	0.000	-0.581
Av. Bottom 5	0.608	1.039	0.927	0.830	1.227	0.042	0.512	0.202	-0.499
Decile Average	1.149	1.215	1.290	1.165	1.315	0.300	0.590	0.101	-0.540
High - Low	1.417***	0.122	2.343***	0.955***	-0.049	0.518***	0.797***	0.062	0.467***
	(3.839)	(0.358)	(7.969)	(3.744)	(-0.179)	(2.656)	(4.271)	(0.371)	(3.255)
Top 5 - Bottom 5	1.087***	0.358**	0.726***	0.672***	0.173	0.519***	0.152***	-0.201***	-0.082
	(6.833)	(2.38)	(5.591)	(6.196)	(1.585)	(6.025)	(1.89)	(-2.887)	(-1.335)

Table B.5: Decile Fund Portfolio Size (Calendar Year Sub-Periods)

Average monthly fund size, measured as total net assets under management (in $millions), for equal-weighted decile fund portfolios constructed from a sample of Australian actively managed equity funds are reported over calendar year sub-periods from January 2003 to December 2011. Funds are sorted equally into decile portfolios each month based on their one-month lagged mining-exposure and rebalanced monthly. Decile one (ten) contains funds with the highest (lowest) exposure to mining stocks. Differences in average mining exposure between the High and Low and average of top two and bottom two portfolios over the sample period are also reported. Fund-level mining exposure is measured from a Sharpe (1992) constrained regression approach across 36-month rolling windows and expressed as a percentage. T-statistics are displayed in parentheses and *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Decile	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
1 [High]	284	369	168	325	412	240	76.7	90.5	99.4
2	413	319	370	185	198	271	176	212	202
3	258	295	412	314	365	224	271	281	164
4	339	384	394	379	404	213	216	397	384
5	466	400	352	422	455	395	355	331	300
6	516	360	408	435	540	613	272	291	301
7	432	536	451	617	424	301	292	299	261
8	963	547	338	264	393	259	156	162	151
9	651	621	151	257	312	263	295	369	394
10 [Low]	392	787	1050	900	929	629	445	395	254
Av. Top 5	353	353	340	325	367	268	219	262	230
Av. Bottom 5	591	571	481	496	521	413	293	303	272
Decile Average	471.4	461.8	409.4	409.8	443.2	340.8	255.47	282.75	251.04
High - Low	-108***	-418***	-882***	-575***	-517***	-389***	-368.3***	-304.5***	-154.6***
	(-1.882)	(-3.67)	(-8.068)	(-5.691)	(-4.976)	(-5.333)	(-7.855)	(-7.718)	(-7.372)
Top 5 - Bottom 5	-238***	-218***	-141***	-171***	-154***	-145***	-74***	-41***	-42***
	(-6.184)	(-6.332)	(-4.846)	(-6.198)	(-5.472)	(-7.361)	(-5.019)	(-2.682)	(-3.16)

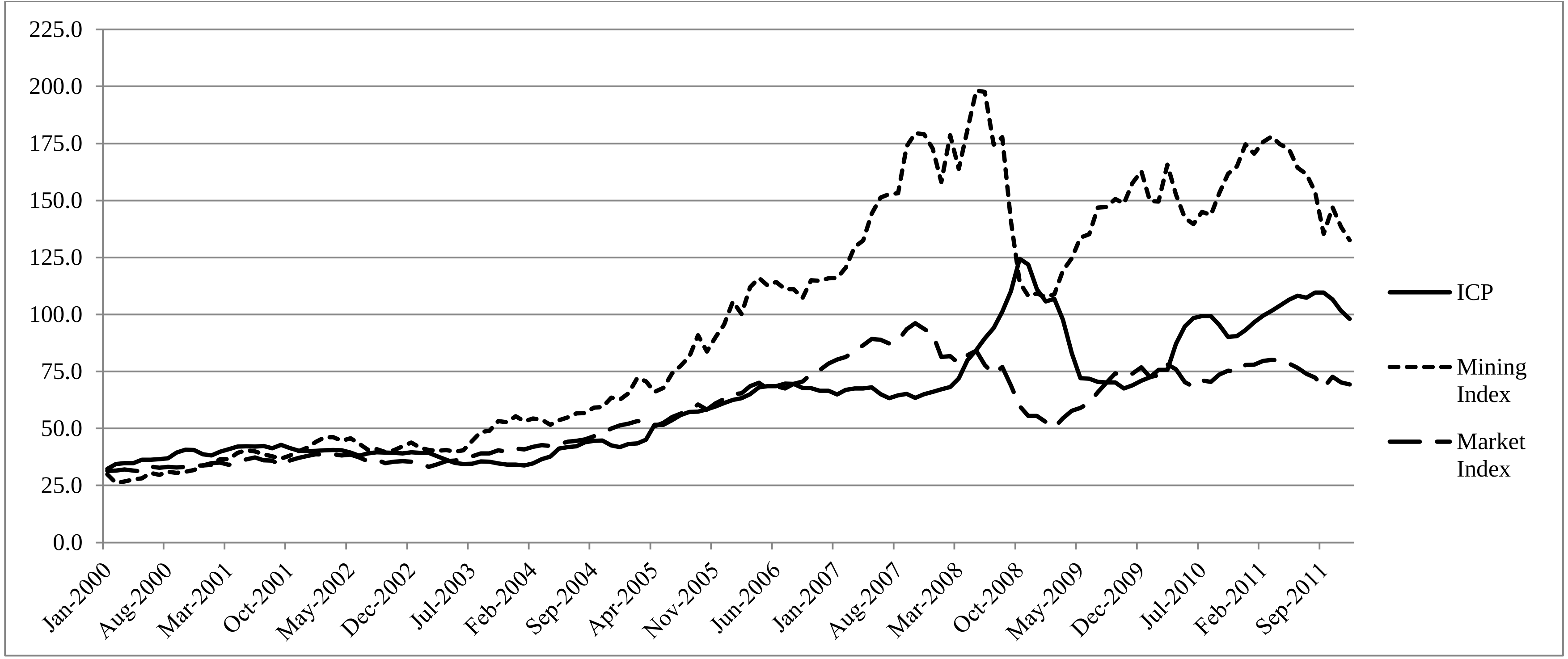
Defining the Australian Mining Boom Period

The Reserve Bank of Australia's Index of Commodity Prices (ICP) provides an indication of the prices received by Australian commodity exporters. The ICP categorises commodities into one of four groups, these being: *Rural commodities, Base metals, Bulk commodities* and *Other resources*. The *Rural commodities* consist of; Wool, Beef and Veal, Wheat, Barley, Canola, Sugar, Cotton, Milk powder, and Lamb and Mutton. The *Base metals* commodities consist of; Aluminium, Lead, Copper, Zinc and Nickel. The *Bulk commodities* contain; Iron ore, Metallurgical coal and Thermal coal. And the *Other Resources* includes; LNG, Crude oil, Alumina, Gold and Copper ore. The *Base metals, Bulk commodities* and *"Other resources"* components of the ICP are considered to provide a more accurate evaluation of the state of the mining sector when compared to the aggregated ICP given that these categories contain only *"mining"* commodities. The non-rural component of the ICP, displayed in Figure B.3 along with the Mining Industry Index and *Top 300* Market Index below, is used to identify the commencement of the Australian mining boom. This chart shows the prices of *non-rural/mining* commodities beginning to trend upwards from January 2004 before peaking in October of 2008 after the onset of the GFC in September 2008 then peaking again for a second time in September 2011. This period from January 2004 to September 2008 is therefore considered as the "mining-boom period". [71]

[71] Further data and information relating to the Index of Commodity Prices (ICP) can be found at the Reserve Bank of Australia (RBA) website; http://www.rba.gov.au/publications/bulletin/2013/mar/3.html.

Figure B.3: Index of Commodity Prices, Mining Industry Index and Top 300 Market Prices

A Time-series of monthly prices for the non-rural component of the RBA Index of Commodity Prices (ICP) are reported from January 2000 to March 2013 in the following chart alongside prices for the Mining index and the Top 300 Market index. The non-rural component of the ICP includes all commodities categorised as either a base metals, bulk commodities or 'other' resources, as defined by the RBA.[72] The Mining index is value-weighted and constructed from Australian listed stocks from the universe of the *Top 300* index and rebalanced monthly. The *Top 300* is a value-weighted accumulation index of the 300 largest Australian listed stocks by market capitalisation that is rebalanced monthly.



[72] ICP data is sourced from the Reserve Bank of Australia (RBA) website, http://www.rba.gov.au/publications/bulletin/2013/mar/3.html.

Table B.6: Industry Index Return Descriptive Statistics (Mining Boom, Non-Boom and GFC Sub Periods)

Descriptive statistics for the monthly returns of ten industry indices and a market index (Top 300) across mining-boom, non-mining boom and the global financial crisis (GFC) sub-periods from January 2000 to December 2011 are reported. The indices are constructed from the top 300 Australian listed stocks by market capitalisation using tier one and two GICS categories to group stocks into one of ten industries. The industries include Mining, Materials (excluding metals-and-mining), Consumer Staples, Consumer Discretionary, Industrials, Telecommunications, Utilities, Information Technology and Health Care. The Top 300 is constructed from the largest 300 Australian stocks by market capitalisation. All indices are value-weighted and rebalanced monthly. The mining boom period is identified The mining boom period is identified from January 2004 to September 2008 and from December 2009 until July 2011 from the RBA's non-rural component of the index of commodity prices (ICP). The non-boom period is from January 2003 until December 2003, October 2008 until November 2009 and from August 2011 onwards. The GFC period is defined from September 2008 until Differences April 2009. Mean return of the mining index and the Top 300 across each of the sub periods are also reported. T-statistics are displayed in parentheses and *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

	Entire Period			Non-booming Period			Mining Boom Period		
Industry Index	Mean	Median	St. Dev.	Mean	Median	St. Dev.	Mean	Median	St. Dev.
Mining	1.149	1.179	5.877	0.706	0.206	5.305	1.440	1.300	6.358
Materials	0.923	1.322	3.910	1.683	1.115	5.128	0.877	1.380	4.050
Industrials	0.881	1.194	3.430	0.764	0.795	3.603	0.880	1.331	3.881
Consumer Discretionary	0.856	1.238	4.922	0.735	0.749	4.710	0.783	1.466	5.252
Consumer Staples	0.653	1.473	4.379	1.110	1.357	4.100	0.565	1.693	4.682
Health Care	0.639	0.607	4.525	0.546	0.700	5.033	0.923	0.786	4.143
Financials	0.455	0.726	5.038	0.713	0.757	3.789	0.600	1.387	5.769
Information Technology	0.189	0.524	5.853	1.204	1.859	6.554	0.191	0.605	5.234
Telecommunications	-0.070	0.461	4.597	1.407	1.260	7.924	0.216	0.520	4.476
Utilities	-0.421	-0.185	7.867	0.984	0.642	9.006	0.692	0.684	5.634
Top 300 Market	0.586	1.348	3.713	0.807	0.798	3.592	0.732	1.776	4.067
Mining - *Top 300*	0.562*			-0.101			0.707*		
T-stat	(1.814)			(-0.395)			(-1.737)		

Table B.6 Continued

	GFC Period			Mining Boom Period ex. GFC		
Industry Index	Mean	Median	St. Dev.	Mean	Median	St. Dev.
Mining	2.809	1.458	4.469	1.526	2.141	7.092
Materials	0.453	-0.163	4.944	1.058	1.575	4.157
Industrials	1.717	1.147	4.726	0.892	1.659	3.821
Consumer Discretionary	1.595	2.020	8.105	0.769	1.724	5.041
Consumer Staples	1.882	1.160	7.395	0.511	2.158	4.189
Health Care	0.512	0.461	4.577	1.264	0.945	4.321
Financials	1.638	3.337	9.679	0.459	1.777	5.063
Information Tech.	2.373	4.099	8.388	-0.121	0.525	4.792
Telecommunications	-0.302	-0.070	4.595	0.345	0.401	4.545
Utilities	3.179	1.605	8.521	0.636	0.944	5.347
Top 300 Market	1.723	2.269	5.009	0.739	2.308	4.057
Mining - *Top 300*	1.086			0.788		
T-stat	(1.182)			(1.351)		

Table B.7: Mining-Exposed Decile Fund Portfolios (Mining Boom and Non-Boom Sub Periods)

Average monthly mining exposure, returns, flows, fund size and fund age for equal-weighted decile portfolios constructed from a sample of Australian actively managed equity funds across mining-boom (Boom) and non-mining boom (non-boom) sub-periods from January 2000 to December 2011 are reported. Funds are sorted equally into decile portfolios each month based on their one-month lagged mining-exposure and rebalanced monthly. Decile one (ten) contains funds with the highest (lowest) exposure to mining stocks. Differences in average Mining Exposure, Returns and Flows between the High and Low and average of top two and bottom two portfolios over the sample period are also reported. Fund-level mining exposure is measured from a Sharpe (1992) constrained regression approach across 36-month rolling windows and expressed as a percentage, Return is average raw fund return in percentage per month, Flow is the net monthly percentage flow of assets under management, Size is the net value of assets under management in $millions and Age is the number of months since inception date. The mining boom period is identified from January 2004 to September 2008 and from December 2009 until July 2011 from the RBA's non-rural component of the index of commodity prices (ICP). The non-boom period is from January 2003 until December 2003, October 2008 until November 2009 and from August 2011 onwards. T-statistics are displayed in parentheses and *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

	Mining Industry Exposure (%)			**Return (% per month)**			**Flows (% per month)**		
Decile	Entire Period	Boom	Non-Boom	Entire Period	Boom	Non-Boom	Entire Period	Boom	Non-Boom
1	43.193	41.514	47.618	0.730	0.399	1.603	1.061	1.144	0.842
2	30.362	29.441	32.791	0.650	0.303	1.566	0.829	0.947	0.516
3	26.822	26.171	28.522	0.565	0.266	1.352	0.483	0.581	0.228
4	24.705	24.134	26.208	0.588	0.279	1.400	0.485	0.642	0.065
5	22.948	22.442	24.268	0.537	0.250	1.292	0.571	0.614	0.460
6	21.096	20.663	22.238	0.585	0.267	1.424	0.242	0.318	0.040
7	18.523	18.172	19.448	0.514	0.215	1.300	0.391	0.587	-0.130
8	13.969	13.713	14.636	0.582	0.285	1.362	0.541	0.652	0.248
9	7.958	7.687	8.672	0.597	0.303	1.376	0.479	0.550	0.296
10	1.367	1.166	1.890	0.648	0.366	1.391	0.424	0.539	0.123
Av. of Top 5	29.569	28.711	31.823	0.614	0.299	1.442	0.685	0.785	0.422
Av. of Bottom 5	12.551	12.254	13.330	0.585	0.287	1.371	0.415	0.529	0.116
Average	21.049	20.472	22.566	0.599	0.293	1.406	0.551	0.658	0.269
Mining Index	24.669	24.510	25.043	1.228	1.300	1.119			
Average - Mining Index	-3.619	-4.038	-2.477	-0.629	-1.007	0.287			
Dec. 1 - Dec. 10	41.826***	40.347***	45.728***	0.082	0.033	0.212	63.705***	60.454***	71.914***
	(168.83)	(147.32)	(88.09)	(0.755)	(0.271)	(0.942)	(8.29)	(6.536)	(5.28)
Av. Top5 - Av.Bottom5	17.018***	16.457***	18.493***	0.028	0.012	0.071	26.98***	25.559***	30.643***
	(187.34)	(164.19)	(94.81)	(0.653)	(0.248)	(0.788)	(8.32)	(6.57)	(5.3)

Table B.7 Continued

	Fund Size ($ million)			Fund Age (months)		
Decile	Entire Period	Boom	Non-Boom	Entire Period	Boom	Non-Boom
1 [High]	204	236	121	78.577	78.452	78.904
2	239	247	217	87.842	85.931	92.888
3	276	298	219	95.433	93.698	99.997
4	340	370	262	99.805	96.152	109.433
5	375	378	364	97.544	94.130	106.346
6	398	429	316	98.599	98.595	98.610
7	374	403	298	87.851	84.448	96.866
8	292	286	309	85.223	82.852	91.436
9	344	340	354	84.363	79.761	96.511
10 [Low]	603	687	385	79.938	79.281	81.659
Av. of Top 5	287	306	237	91.855	89.683	97.550
Av. of Bottom 5	403	430	332	87.139	84.936	92.938
Decile Average	345	368	285	89.496	87.307	95.247
High - Low	-399***	-451***	-264***	-1.361	-0.829	-2.756
	(-16.47)	(-14.288)	(-8.25)	(-0.993)	(-0.51)	(-1.079)
Top 5 - Bottom 5	-116***	-124***	-95***	4.716***	4.746***	4.612***
	(-15.71)	(-13.49)	(-9.3)	(7.219)	(6.222)	(3.662)

Table B.8: Four-Factor Decile Fund Portfolio Exposures (Mining Boom and Non-Boom Sub Periods)

Carhart (1997) four-factor regressions are estimated for equal-weighted decile portfolios constructed from a sample of Australian actively managed equity funds across mining-boom (Boom) and non-mining boom (Non-boom) sub-periods from January 2000 to December 2011. Funds are sorted equally into decile portfolios each month based on their one-month lagged mining-exposure and rebalanced monthly, with decile one (ten) containing funds with the highest (lowest) exposure to mining stocks. Equal weighted monthly portfolio returns are then calculated for each decile over the sample period. Fund-level mining exposure is measured from a Sharpe (1992) constrained regression approach across 36-month rolling windows. Carhart (1997) regressions are also estimated for long-short portfolios constructed from decile one and decile ten, as well as for a portfolio that is long deciles one and two and short deciles nine and ten. The mining boom period is identified from January 2004 to September 2008 and from December 2009 until July 2011 from the RBA's non-rural component of the index of commodity prices (ICP). The non-boom period is from January 2003 until December 2003, October 2008 until November 2009 and from August 2011 onwards. T-statistics are displayed in parentheses and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	MKT			***SMB***			***HML***			***UMD***		
Decile	Entire Period	Boom	Non-boom	Entire Period	Boom	Non-boom	Entire Period	Boom	Non-boom	Entire Period	Boom	Non-boom
1 [High]	1.185***	1.05***	1.24***	0.086***	0.13***	0.067**	-0.045	-0.072	-0.013	-0.009	0.044	-0.01
	(34.43)	(16.417)	(34.85)	(3.787)	(3.567)	(2.351)	(-0.91)	(-0.799)	(-0.248)	(-0.165)	(0.341)	(-0.191)
2	1.113***	1.089***	1.114***	0.018	0.036	-0.004	-0.014	0.028	-0.036	0.031	0.082	0.008
	(46.84)	(30.262)	(36.3)	(1.333)	(1.479)	(-0.213)	(-0.443)	(0.335)	(-0.98)	(0.872)	(1.154)	(0.183)
3	1.082***	1.048***	1.098***	-0.015	-0.005	-0.024	0.03	-0.008	0.045	-0.06	-0.036	-0.063
	(38.946)	(33.598)	(31.099)	(-1.316)	(-0.313)	(-1.38)	(0.924)	(-0.139)	(1.112)	(-1.614)	(-0.729)	(-1.599)
4	1.04***	1.053***	1.03***	-0.012	-0.012	-0.02	0.021	0.032	0.007	0.002	0.055	-0.021
	(67.804)	(30.867)	(71.169)	(-1.119)	(-0.498)	(-1.401)	(1.087)	(0.593)	(0.297)	(0.072)	(1.06)	(-0.817)
5	1.017***	1.015***	1.017***	-0.006	-0.01	-0.005	0.022	0.032	0.022	-0.004	-0.015	0.000
	(82.643)	(44.3)	(74.094)	(-0.656)	(-0.643)	(-0.323)	(0.973)	(0.534)	(0.856)	(-0.168)	(-0.341)	(-0.012)
6	1.005***	1.042***	0.986***	-0.015	-0.02	-0.026	0.024	0.05	0.001	0.022	0.016	0.012
	(44.975)	(35.761)	(40.186)	(-1.282)	(-0.968)	(-1.434)	(0.907)	(0.781)	(0.029)	(0.694)	(0.366)	(0.345)
7	1.057***	1.093***	1.044***	0.003	0.01	-0.005	0.061**	0.055	0.049*	-0.05*	-0.09	-0.045
	(61.205)	(42.203)	(52.87)	(0.281)	(0.489)	(-0.317)	(2.481)	(1.036)	(1.774)	(-1.857)	(-1.631)	(-1.463)
8	1.05***	1.094***	1.027***	0.025*	0.02	0.019	0.131***	0.175***	0.104***	-0.063*	-0.09	-0.067*
	(56.664)	(25.763)	(53.866)	(1.834)	(0.652)	(1.149)	(5.205)	(3.14)	(3.553)	(-1.894)	(-1.287)	(-1.794)
9	0.963***	1.059***	0.914***	0.052***	0.005	0.059**	0.158***	0.253***	0.113**	-0.026	-0.094*	-0.026
	(24.526)	(37.506)	(19.458)	(2.714)	(0.24)	(2.077)	(3.628)	(6.27)	(2.011)	(-0.441)	(-1.792)	(-0.403)
10 [Low]	0.949***	1.056***	0.91***	0.054**	0.009	0.069**	0.204***	0.192**	0.192**	-0.011	-0.083	0.000
	(19.586)	(22.533)	(14.33)	(2.566)	(0.319)	(2.19)	(3.53)	(2.384)	(2.577)	(-0.144)	(-0.883)	(-0.005)
1 - 10	0.24***	-0.002	0.334***	0.037	0.122**	-0.001	-0.242***	-0.268**	-0.197*	0.009	0.132	-0.003
	(3.394)	(-0.033)	(3.799)	(1.067)	(2.495)	(-0.013)	(-2.656)	(-2.482)	(-1.733)	(0.076)	(0.989)	(-0.026)
Top 5 - Bottom 5	0.087**	-0.013	0.128***	-0.005	0.024	-0.018	-0.106**	-0.147***	-0.078	0.025	0.099*	0.014
	(2.502)	(-0.602)	(2.944)	(-0.31)	(1.089)	(-0.936)	(-2.603)	(-3.363)	(-1.552)	(0.464)	(1.946)	(0.244)

Table B.8 Continued

	Carhart Alpha		
Decile	Entire Period	Boom	Non-boom
1 [High]	0.008	0.024	-0.036
	(0.078)	(0.097)	(-0.312)
2	0.02	0.095	-0.02
	(0.263)	(0.569)	(-0.22)
3	0.024	0.091	-0.018
	(0.372)	(0.669)	(-0.233)
4	0.028	0.051	0.014
	(0.502)	(0.33)	(0.239)
5	-0.005	0.038	-0.011
	(-0.083)	(0.317)	(-0.18)
6	0.04	0.161	-0.001
	(0.667)	(1.174)	(-0.012)
7	-0.06	-0.098	-0.062
	(-0.995)	(-0.726)	(-0.902)
8	0.062	0.119	0.05
	(0.937)	(0.797)	(0.676)
9	0.104	0.389***	0.066
	(1.005)	(3.113)	(0.553)
10 [Low]	0.128	0.271	0.112
	(0.944)	(1.405)	(0.699)
1 - 10	-0.559***	-0.589**	-0.621***
	(-2.947)	(-2.129)	(-2.737)
Top 5 - Bottom 5	-0.479***	-0.451***	-0.52***
	(-5.497)	(-4.018)	(-5.013)

Appendix C

The following charts and tables contained in this appendix support the empirical analysis conducted in the third essay (Psychic Dividends of Socially Responsible Investors) of this dissertation.

Table C.1: SRI Portfolio Descriptive Statistics (II)

Descriptive statistics for the monthly returns and quantity of stocks contained in the socially responsible (*Good*) and socially irresponsible (*Bad*) U.S. stock portfolios from January 1990 to December 2013 are reported. The *Good* and *Bad* portfolios are constructed as a robustness measure for those portfolios used throughout Chapter 5 by removing the stock size and stock quantity per industry constraints.

	Mean	**Min**	**Median**	**Max**	**St. Dev.**	**Skew**	**Kurt**
# Stocks in *Good* portfolio	109.446	83	107	167	15.278	0.945	1.304
# Stocks in *Bad* portfolio	94.718	65	97	119	12.740	-0.278	-0.784
R(*Good*)	0.984	-23.655	1.218	18.768	5.127	-0.623	2.115
R(*Bad*)	1.034	-20.068	1.417	14.459	4.436	-0.607	2.250

As a robustness measure for the approach used to calculate the return series of our two SRI portfolios, both portfolios are re-constructed by removing the size and number of stocks per industry constraint. An insignificant difference is observed when comparing the portfolio returns using the two approaches despite the average number of stocks per month substantially increasing. The difference in the mean return of the two *Good* portfolios is 3.3 basis points per month (t stat = 0.311). Similarly, a negligible difference in the mean return of the two *Bad* portfolios, of 0.09 basis points per month (t-stat = 0.013) is observed.

Table C.2: CAPM and Four-Factor SRI Portfolio Exposures (II)

CAPM and Carhart (1997) four-factor regressions are estimated for a socially responsible (*Good*), socially irresponsible (*Bad*) and a long-short (*Good – Bad*) U.S. stock portfolios using monthly returns over the period from January 1990 to December 2013. The *Good* and *Bad* portfolios are constructed as a robustness measure from those used throughout Chapter 5 by removing the stock size and stock quantity per industry constraints. The CAPM regressions show portfolio market-risk exposure (R_m-R_f) and the Carhart (1997) regressions identify market-risk exposure (R_m-R_f), value exposure (*HML*), size exposure (*SMB*) and momentum exposure (*UMD*). Alpha indicates portfolio risk-adjusted returns. The market return is the CRSP value-weighted portfolio and the risk-free return is the Treasury bill. Factor returns are sourced from the Ken French website. Regressions are estimated with robust standard errors and t-statistics are displayed in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

	Good-rf		*Bad*-rf		(*Good-Bad*)	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.00875	0.0327	0.258	0.133	-0.249	-0.100
	(0.099)	(0.393)	(1.602)	(0.835)	(-1.285)	(-0.546)
R_m-r_f	1.116***	1.078***	0.802***	0.871***	0.315***	0.207***
	(56.139)	(53.346)	(22.088)	(22.515)	(7.194)	(4.646)
SMB		0.107***		-0.0534		0.161***
		(4.088)		(-1.064)		(2.774)
HML		-0.122***		0.223***		-0.344***
		(-4.356)		(4.166)		(-5.583)
UMD		0.0116		0.0657**		-0.0541
		(0.678)		(2.010)		(-1.435)
Observations	287	287	287	287	287	287
R-squared	0.917	0.930	0.631	0.660	0.154	0.283

The risk-adjusted returns are shown to be insignificant for the *Good* and *Bad* portfolios presented in Table C.2 above. The loading on the size factor for the *Good* portfolio changes from significantly negative to significantly positive, indicating that the composition of this portfolio changes from large stocks to small stocks. This also changes the sign of the size factor for the long short portfolio from significantly negative to positive. The sign of the value factor for the *Good* portfolio becomes significantly negative, indicating that this portfolio is more exposed to growth stocks. Unlike the originally-constructed *Good* portfolio, this portfolio does not capture significant exposure to momentum stocks, yet the *Bad* portfolio does. All other factor loading for these portfolios remain quantitatively similar to the original portfolio construction.

Table C.3: CAPM and Four-Factor SRI Portfolio Exposures (NBER Business Cycle Sub-periods)

CAPM and Carhart (1997) four-factor regressions are estimated for the socially responsible (*Good*), socially irresponsible(*Bad*) and long-short (*Good – Bad*) stock portfolios using monthly returns over NBER-dated economic expansion and recession sub-periods from January 1990 to December 2013. The CAPM regressions show portfolio market-risk exposure (R_m-R_f) and the Carhart (1997) regressions identify market-risk exposure (R_m-R_f), value exposure (*HML*), size exposure (*SMB*) and momentum exposure (*UMD*). Alpha indicates portfolio risk-adjusted returns. The market return is the CRSP value-weighted portfolio and the risk-free return is the Treasury bill. Factor returns are sourced from the Ken French website. Regressions are estimated with robust standard errors and t-statistics are displayed in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

	NBER Expansionary Phase						**NBER Recessionary Phase**					
	Good-rf		*Bad*-rf		*Good-Bad*		*Good*-rf		*Bad*-rf		*Good-Bad*	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	0.105	0.0501	0.299	0.000429	0.191***	0.1000*	-0.0330	0.122	0.441	0.777	0.0543	-0.0164
	(1.086)	(0.522)	(1.449)	(0.002)	(3.509)	(1.806)	(-0.094)	(0.316)	(0.507)	(0.821)	(0.369)	(-0.075)
R_m-r_f	0.941***	0.979***	0.750***	0.879***		-0.190***	0.938***	0.999***	0.884***	1.015***		0.172
	(39.370)	(39.385)	(14.650)	(17.301)		(-2.864)	(18.235)	(13.194)	(6.953)	(5.482)		(0.479)
SMB		-0.137***		0.0530		-0.462***		-0.0833		-0.255		0.189
		(-4.597)		(0.872)		(-6.246)		(-0.673)		(-0.844)		(0.686)
HML		0.0314		0.494***		0.0116		-0.0588		-0.248		-0.0229
		(0.946)		(7.269)		(0.236)		(-0.621)		(-1.068)		(-0.138)
UMD		0.0483**		0.0367	-0.194	0.0497		0.0407		0.0636	-0.474	-0.655
		(2.191)		(0.815)	(-0.885)	(0.232)		(0.714)		(0.456)	(-0.471)	(-0.583)
Observations	255	255	255	255	255	255	32	32	32	32	32	32
R-squared	0.860	0.874	0.459	0.556	0.046	0.181	0.917	0.922	0.617	0.646	0.005	0.030

Table C.4: CAPM and Four-Factor SRI Portfolio Exposures (Market Return Sub-periods)

CAPM and Carhart (1997) four-factor regressions are estimated for the socially responsible (*Good*), socially irresponsible(*Bad*) and long-short (*Good – Bad*) stock portfolios using monthly returns over Up- and Down-market sub-periods from January 1990 to December 2013. 'Up' represents months where the market return is positive and 'Down' are months where negative market returns are observed. The CAPM regressions show portfolio market-risk exposure (R_m-R_f) and the Carhart (1997) regressions identify market-risk exposure (R_m-R_f), value exposure (*HML*), size exposure (*SMB*) and momentum exposure (*UMD*). Alpha indicates portfolio risk-adjusted returns. The market return is the CRSP value-weighted portfolio and the risk-free return is the Treasury bill. Factor returns are sourced from the Ken French website. Regressions are estimated with robust standard errors and t-statistics are displayed in parentheses, with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

	Up Months						**Down Months**					
	Good-rf		*Bad*-rf		*Good-Bad*		*Good*-rf		*Bad*-rf		*Good-Bad*	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	-0.368**	-0.0694	0.0375	0.0267	0.374	-0.0592	0.00157	-0.178	-0.508	-0.127	0.273	0.438
	(-2.377)	(-0.471)	(0.178)	(0.127)	(0.929)	(-0.147)	(0.003)	(-0.306)	(-1.157)	(-0.283)	(0.436)	(0.702)
R_m-r_f	1.019***	0.968***	0.959***	0.954***	0.769***	0.921***	0.740***	0.804***	0.224**	0.121	0.224*	0.179
	(26.471)	(25.897)	(23.313)	(21.968)	(7.637)	(8.952)	(6.459)	(6.672)	(2.041)	(1.054)	(1.832)	(1.384)
SMB		-0.183***		-0.0636		0.0555		-0.0394		-0.180**		-0.0599
		(-6.857)		(-1.394)		(0.754)		(-0.311)		(-2.202)		(-0.441)
HML		-0.0999***		0.0139		0.489***		0.236**		-0.449***		-0.224**
		(-2.948)		(0.372)		(5.246)		(2.278)		(-4.327)		(-2.022)
UMD		-0.0479***		-0.0554*		0.0236		0.107		0.0331		-0.111
		(-2.893)		(-1.705)		(0.516)		(1.184)		(0.650)		(-1.152)
Observations	185	185	102	102	185	185	102	102	185	185	102	102
R-squared	0.794	0.842	0.845	0.853	0.242	0.355	0.294	0.338	0.022	0.133	0.032	0.083

Figure C.1: Certainty Equivalence of Psychic Returns (NBER Expansionary Phase)

The relationship between psychic returns and certainty equivalence (CE) of psychic returns, measured in percent per month, for a socially responsible (*Good*) portfolio, socially irresponsible (*Bad*) portfolio and a long-short (*Good – Bad*) portfolio of U.S. stocks is illustrated in this chart. The portfolios are constructed using monthly U.S. stock data across NBER-dated economic expansionary sub-periods from January 1990 to December 2013. The difference in psychic returns when *CE* of the *Good* and *Bad* portfolios is equal to zero (at the intersection of the horizontal axis) indicates the psychic dividend to SRI.

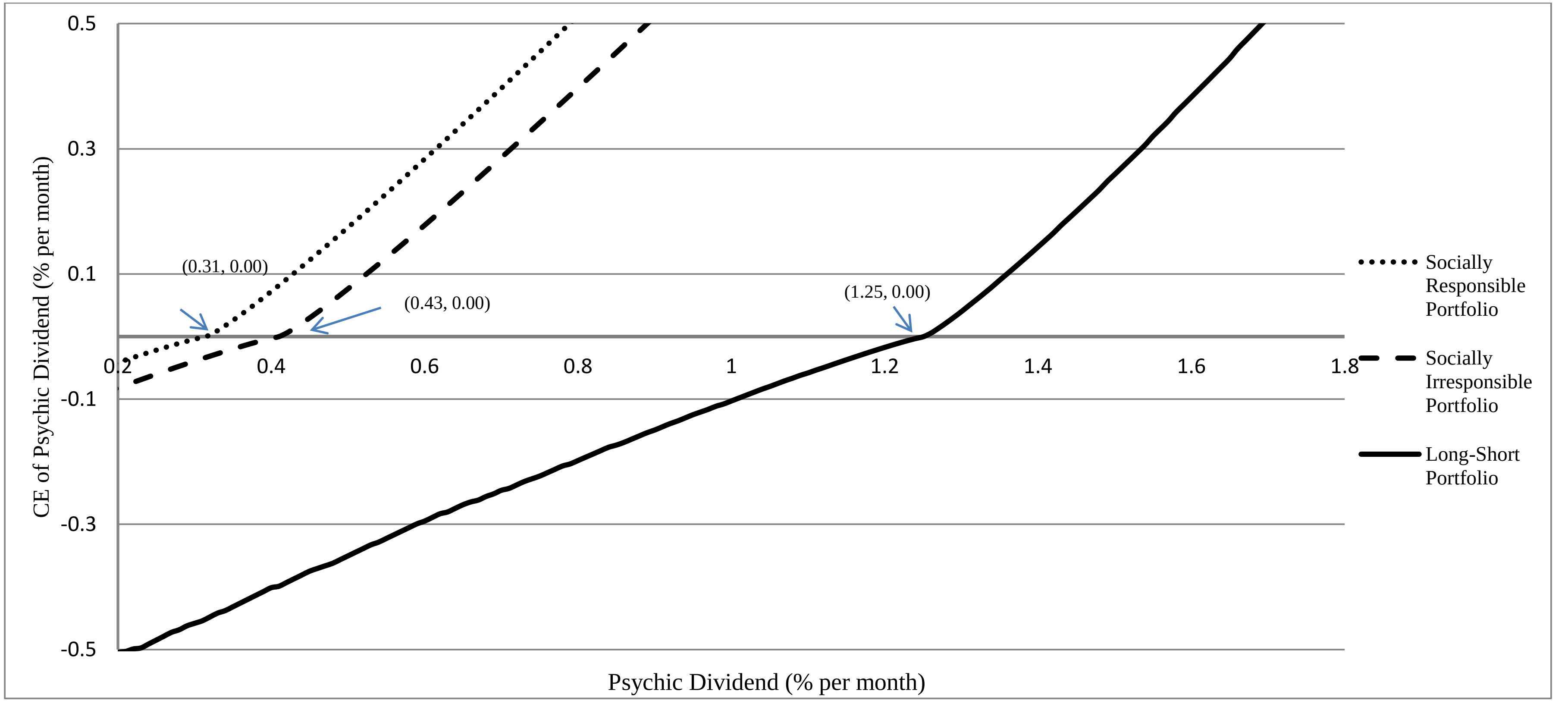


Figure C.2: Certainty Equivalence of Psychic Returns (NBER Recessionary Phase)

The relationship between psychic returns and certainty equivalence (CE) of psychic returns, measured in percent per month, for a socially responsible (*Good*) portfolio, socially irresponsible (*Bad*) portfolio and a long-short (*Good – Bad*) portfolio of U.S. stocks is illustrated in this chart. The portfolios are constructed using monthly U.S. stock data across NBER-dated economic recessionary sub-periods from January 1990 to December 2013. The difference in psychic returns when *CE* of the *Good* and *Bad* portfolios is equal to zero (at the intersection of the horizontal axis) indicates the psychic dividend to SRI.

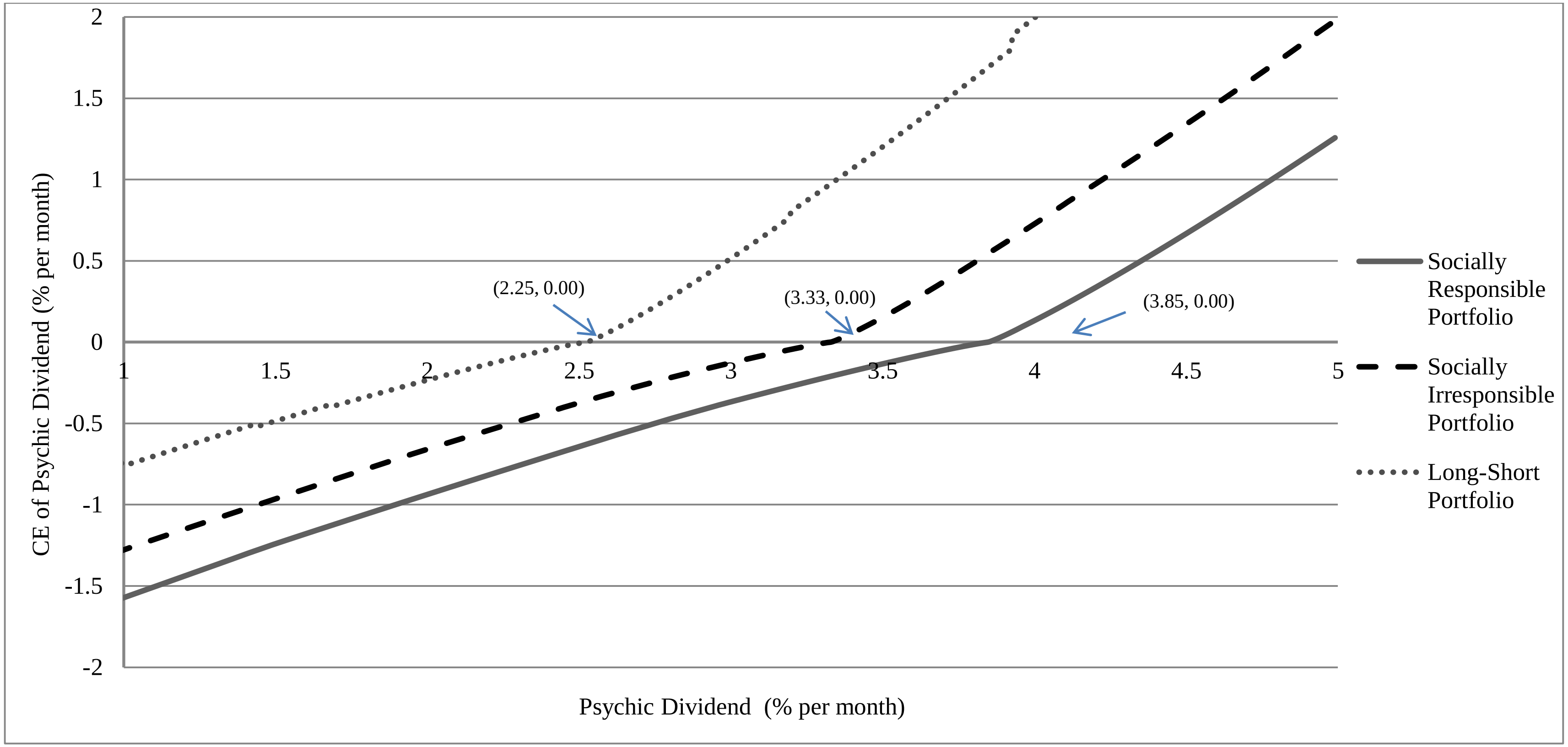


Table C.5: KLD Social 400 and MSCI U.S. Index Return Descriptive Statistics

Descriptive statistics for the monthly returns of the MSCI KLD Social 400 index and MSCI U.S. total return index across the period from January 1990 to December 2013 are reported in this table.

	Mean	**Min**	**Median**	**Max**	**Std. Dev.**	**Skew**	**Kurt**
KLD Social 400	0.775	-15.640	0.670	10.680	4.376	-0.500	0.866
MSCI U.S.	0.887	-17.102	1.291	11.426	4.292	-0.615	1.167

Table C.6: CAPM and Four-Factor MSCI KLD 400 Social Index Exposures

CAPM and Carhart (1997) four-factor regressions are estimated for the MSCI KLD 400 Social index using monthly returns over NBER expansion and recessionary sub-periods from January 1990 to December 2013. The CAPM regressions show portfolio market-risk exposure (R_m-R_f) and the Carhart (1997) regressions identify market-risk exposure (R_m-R_f), value exposure (*HML*), size exposure (*SMB*) and momentum exposure (*UMD*). Alpha indicates portfolio risk-adjusted returns. The market return is the CRSP value-weight portfolio and the risk-free return is the Treasury bill. Factor returns are sourced from the Ken French website. Regressions are estimated with robust standard errors and t-statistics are displayed in parentheses with *, **, and *** denoting significance at the 10%, 5%, and 1% level, respectively.

	Entire Period		**Expansion**		**Recession**	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	-0.0943	-0.0326	-0.0869	-0.00125	-0.169	-0.248
	(-1.233)	(-0.448)	(-1.090)	(-0.017)	(-0.572)	(-0.774)
Rm-rf	0.952***	0.958***	0.953***	0.957***	0.946***	0.908***
	(55.417)	(54.508)	(48.390)	(49.736)	(21.929)	(14.497)
SMB		-0.138***		-0.158***		0.0233
		(-6.022)		(-6.850)		(0.227)
HML		-0.0372		-0.0708***		0.105
		(-1.523)		(-2.738)		(1.341)
UMD		-0.0452***		-0.0513***		-0.0296
		(-3.042)		(-2.999)		(-0.627)
Observations	286	286	254	254	32	32
R-squared	0.915	0.928	0.903	0.923	0.941	0.946

Table C.7: Psychic Dividends to SRI Investors (Using the MSCI U.S. index and the MSCI KLD Social 400 index)

Psychic dividends (measured as a percentage per month) are reported as the difference in certainty equivalent returns of the MSCI KLD Social 400 index and the MSCI U.S. total return index over the period from January 2000 to December 2013 for various levels of risk aversion. U is investor utility derived by from investing in the respected portfolios and *CE* is certainty equivalent return as calculated from equation 4.5.

		Good Portfolio	**Bad Portfolio**	
	Risk Aversion (α)	Certainty Equivalent Return		Psychic Dividend
	3	0.48%	0.57%	-0.09%
	5	0.27%	0.37%	-0.10%
	7	0.06%	0.16%	-0.10%
U	-	-1.74%	-1.57%	
CE	-	-0.40%	-0.36%	0.04%

Figure C.3: Risk-Aversion and Psychic Dividends to SRI (II)

The relationship between psychic dividends (measured in percentage per month) and investor risk-aversion (α) is displayed is the following chart. Psychic dividend is measured as the difference in the certainty equivalent returns (ce) of the MSCI KLD Social 400 index and the MSCI U.S. total return index, where *ce* is calculated for both portfolios from equation 4.3 using monthly returns from across the period January 1990 to December 2013. The construction of the *Good* and bad portfolios is described in detail in section 4.5.a.

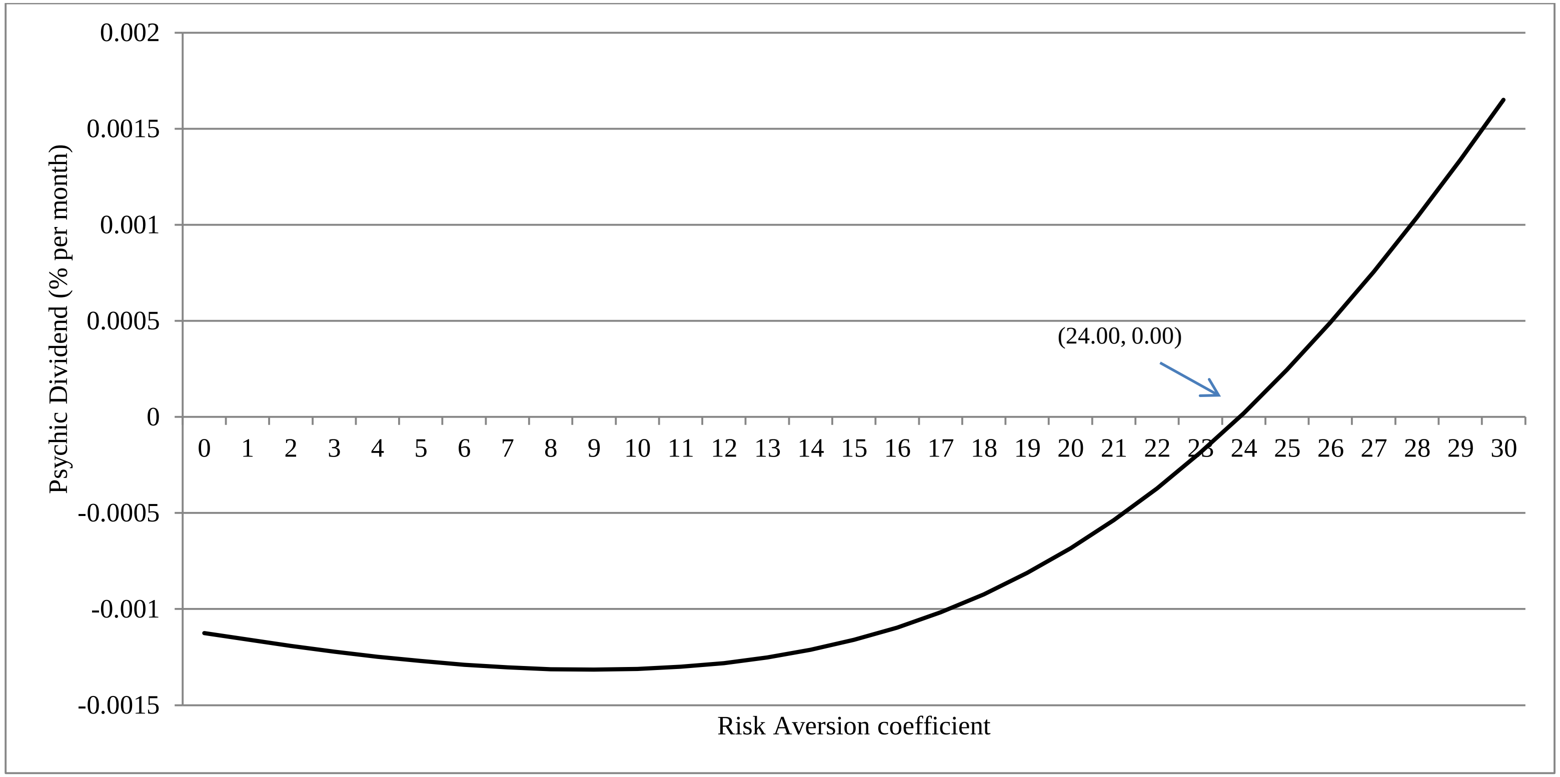
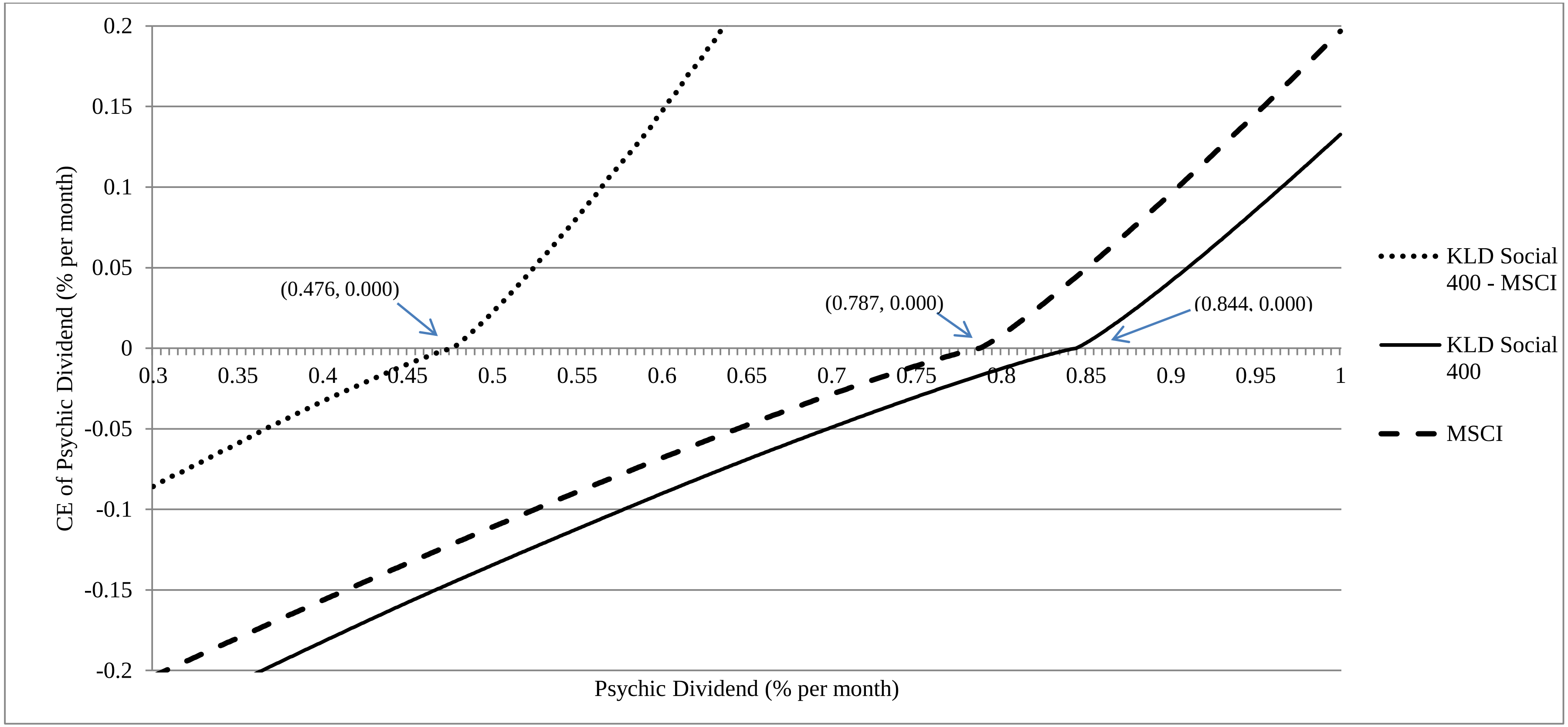


Figure C.4: Certainty Equivalence of Psychic Returns (Using the MSCI U.S. index and the MSCI KLD Social 400 index)

The relationship between psychic returns and certainty equivalence (CE) of psychic returns, measured in percent per month, for the MSCI KLD Social 400 index, the MSCI U.S. total return index and a long-short portfolio (KLD Social 400 – MSCI U.S. total return index) using monthly returns across the period from January 2000 to December 2013 is illustrated in this chart. The difference in psychic returns when *CE* of the MSCI KLD Social 400 index and the MSCI U.S. total return index is equal to zero (at the intersection of the horizontal axis) indicates the psychic dividend to SRI.



Testing for Equality of the Third Central Moment

The following approach is used to test for the difference in the third central moment of two distributions, with independent random variables *X* and *Y*,

$$\mu_3^x = \mu_3^y,$$

where,

$$\mu_3^x = E\left[\left(X - E(X)\right)^3\right].$$

It turns out that generally if we calculate,

$$m_3^x = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3,$$

that

$$Var(m_3^x) = \frac{\mu_6^x - 6\mu_4^x\mu_2^x - (\mu_3^x)^2}{n} + \text{terms in } \frac{1}{n^2}.$$

This results from taking a series expansion of the exact third moment in the general case and dropping higher order terms. The above formula in the case of normality becomes $\frac{6\sigma^4}{n}$. Note that $\mu_j^x = E\left[\left(X - E(X)\right)^j\right]$.

It therefore follows that:

$$\sqrt{n}\left(m_3^x - m_3^y\right) \xrightarrow{d} N(0, \sigma^2),$$

where,

$$\sigma^2 = \mu_6^x - 6\mu_4^x\mu_2^x - (\mu_3^x)^2 + \mu_6^y - 6\mu_4^y\mu_2^y - \left(\mu_3^y\right)^2$$

so,

$$\frac{\sqrt{n}(m_3^x - m_3^y)}{\sigma} \xrightarrow{d} N(0,1).$$

Whilst in principle we could repeat the exercise for calculating the equality of fourth moments; this would involve standard errors based on eighth moments which will be sufficiently erratic in sample as to be of questionable value.

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