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An Empirical Analysis of Asset Pricing Models in Australia

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Abstract

Fama and French (2015) develop a five-factor model with the market risk, size, book-to-market, profitability and investment factors, and find that this model has stronger explanatory power than the three-factor model of Fama and French (1993) in the U.S. markets. In addition, they find that, once the profitability and investment factors are controlled for, the book-to-market factor becomes redundant in their sample. They suggest that this redundancy might be specific to the U.S. markets. In this thesis, I analyse the performance of alternative asset pricing models in the Australian market. My findings confirm the power of the five-factor model. Furthermore, consistent with Fama and French's conjecture, the book-to-market factor is not redundant in the Australian market.

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Attestation of authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of a university of institution of higher learning, except where due acknowledgement is made in the acknowledgements.

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Abbreviations

APT	**A**rbitrage **P**ricing **T**heory
BM	**B**ook-to-**M**arket ratio
CAPM	**C**apital **A**sset **P**ricing **M**odel
FFPMU	**F**ama and **F**rench **P**rofit **M**inus **U**nprofitable (Fama and French's definition of profitability measure)
FFOP	**F**ama and **F**rench **O**perating **P**rofit
GRS	**G**ibbons, **R**oss, and **S**hanken (1989) test
HML	**H**igh **M**inus **L**ow
INV	**Inv**estment factor
MKT	The **m**ar**k**e**t** factor
NMOP	**N**ovy-**M**arx **O**perating **P**rofit
NMPMU	**N**ovy-**M**arx **P**rofit **M**inus **U**nprofitable (Novy-Marx's definition of profitability measure)
SMB	**S**mall **M**inus **B**ig
SPPR	**S**hare **P**rice and **P**rice **R**elative database obtained from SIRCA
U.S.	The **U**nited **S**tates

Chapter 1

Introduction

This thesis examines the performance of various asset pricing models, namely the CAPM, the three-, four- and five-factor models, in the Australian market. The evaluation of asset pricing models is important in finance because it will help finance manager to determine the appropriate discount rate to be used in capital budgeting. Additionally, in mutual funds, asset pricing models help to evaluate the performance of mutual funds by pricing risks correctly.

The simplest asset-pricing model is the Capital Asset Pricing Model (CAPM). The CAPM clearly demonstrates the relationship between return and risk. It is the first equilibrium asset-pricing model, which enables quantitative inspection. However, Fama and French (2004) argue that the CAPM fails in actual practice due to unrealistic assumptions. Furthermore, they point out that the CAPM fails to capture the portfolio returns sorted based on the book-to-market equity ratio.

Fama and French (1992) point out that the CAPM fails in explaining stock returns in the U.S. market. In addition, they argue that size (price times number of shares outstanding) and book-to-market equity ratio contain strong explanatory power for cross-sectional variations in returns. Fama and French (1993) propose the three-factor model, which combines the market factor with the size and book-to-market factors. The three-factor model can explain average returns in the U.S stock market and the big success of this model has made it become popular worldwide.

Recently, Novy-Marx (2013) argues that profitability, gross profit-to-asset, has roughly similar explanatory power as book-to-market ratio. Novy-Marx shows that controlling for the profitability helps to enhance the performance of the Fama and French three-factor model in explaining returns for the largest, high liquidity companies in the U.S. In a similar vein, Fama and French (2015) build a five-factor model, which includes a different profitability factor (revenue minus the cost of goods sold, the interest and the selling, general and administration cost in time t, divided by the book value of equity in the previous time period, t-1.) and the investment factor (asset growth) in addition to the three-factor model. They suggest that the five-factor model outperforms the three-factor model in explaining returns for small and unprofitable companies in the U.S. market. However, different definitions of the profitability may lead to different results. Interestingly, Fama and French (2015) argue that the HML factor seems to be redundant in their sample when profitability and investment are controlled for. Given that the three-factor model is the most prominent model which has been widely used in the asset pricing and corporate finance literature, Fama and French (2015) suggest that the redundancy of the HML factor might be sample and/or region specific.

In the spirit of Fama and French (2015) and given that Fama and French (2012) document the importance of the HML factor in capturing international returns, it is necessary to study whether the HML factor is redundant in the international market if profitability and investment are controlled. By employing the out of sample test in the Australian market, my aim is to answer two research questions: 1. Does application of the five-factor model enable us to better predict asset prices in the Australian market? 2. Is the HML factor redundant in the Australian market?

The Australian market is a good candidate for the out of sample test. It is the second largest market in the Asia-Pacific region and the eighth largest market in the world, with a total market capitalization close to $1.5 trillion (ASX website, 2015). Thus the Australian market is small enough to present out of sample evidence to the findings in the U.S. while at the same time large enough to be of interest to academia and practice. Moreover, Fama and French (1998) document the highest value premium in Australia and Fama and French (2012) find that the HML factor plays an important role in the Asia-Pacific region including Australia. Therefore, it is meaningful to test whether the HML factor is redundant in the Australian market.

This thesis provides Australian evidence for the Fama and French five-factor model by evaluating performances of alternative asset pricing models in the Australian market. In the spirit of Novy-Marx (2013) and Fama and French (2015), I test both definitions of the profitability for the five-factor model in Australia in order to check whether the model is definition sensitive. In addition, to check the validity of the five-factor model, I test whether the HML factor is redundant in the Australian market by evaluating the performance of a four-factor model (including the market, size, profitability and investment factors). If the outcomes show that the HML factor is not redundant, then it should be the evidence to support the five-factor model. To perform these empirical tests, I form test portfolios and factor mimicking portfolios based on different characteristics. Test portfolios are regressed on different mimicking factors for different models. To assess the model's goodness of fit, I look at the R^2 for each model. In addition to these, in order to compare the pricing error between models, I perform the Wald test, the Gibbons, Ross, and Shanken's (GRS) test and calculate information ratio for each model.

Overall, the GRS test cannot reject the four- or five-factor models for portfolios which are sorted by size, Novy-Marx operating profit and size-investment. Using the Fama and French profitable minus unprofitable (FFPMU) factor, the five-factor model produces higher average R^2 of 75.39%, where using the Novy-Marx profitable minus unprofitable (NMPMU) factor produces lower average R^2 of 74.93%. This suggests that the five-factor model could be definition sensitive. The t-statistics on the HML factors imply that the HML factor is still significant with extra factors. Looking at the goodness of fit between the five-factor model and the four-factor model, the five-factor model outperforms the four-factor model regardless of the definitions in terms of the profitability. Furthermore, using the FFPMU as the profitability factor produces a lower information ratio for portfolios that are sorted on size, Novy-Marx operating profit and size-investment, with information ratios of 0.334 and 0.244 respectively. These results suggest that the five-factor models provide a better measurement on the Australian stocks. Moreover, the Fama and French profitable minus unprofitable (FFPMU) factor offers a better measurement than the Novy-Marx profitable minus unprofitable (NMPMU) factor in the Australian market. In contrast to Fama and French (2015), Australian evidence shows that the HML factor is meaningful when the profitability and investment are controlled. Their findings might be sample or region specific. My study findings support the five-factor model.

My study's findings have implications for academia and practice. First, by confirming the explanatory power of the five-factor model and the HML factor this thesis adds to the debate on whether the three-factor model is no longer powerful. Second, my study findings suggest that fund managers in Australia should apply the five-factor model to price risk because the five-factor model carries better risk characteristics in the Australian market. In particular, forming portfolios based on the profitability and investment could bring values in the Australian market.

The following thesis is organized as follows: Chapter 2 includes a review of the past literature. Chapter 3 describes the data and methodology involved in this thesis. Chapter 4 and 5 discuss the empirical results and Chapter 6 is the conclusion.

Chapter 2

Literature review

This chapter reviews the literature on asset pricing from three different dimensions. I start from the evolution of the theory and models in Section 2.1. Section 2.2 and 2.3 discuss the prior research on multi-factor models in the U.S and across the world respectively. Finally, Section 2.4 discusses the existing literature on the Australian market.

2.1 Asset pricing Theory

2.1.1 Consumption-based Theory

Cochrane (2005) derives the basic asset-pricing model from the perspective of the consumption-based theory. Investors tend to make their own decisions in terms of their wealth, some would choose to consume while others choose to save. Savings can be achieved in different ways, such as depositing or investing. Here, an asset can be regarded as a normal good, which can be consumed. Consider the relationship between consumption, asset price and the economy state, during good times, for example, during an expansion, investors are rich, thus they have more money available to invest more. The increasing demand of asset causes the asset price to increase. In contrast, during the bad state, for example, in a recession, investors do not feel rich and as a result they would choose to decrease the amount they invest. In order to attract investment, the price of the asset decreases. In addition, assets perform accordingly to the economic environment.

Consumption level has a negative relationship in terms of the level of utility, hence maximizing the utility is a key objective for the investors in determining their fair consumption levels, and this causes the utility to become a key element in the consumption-based model. The simplest consumption-based model is a two period model, which is expressed as:

$$U(c_t,c_{t+1})=u(c_t)+\beta E_t[u(c_{t+1})] \tag{1}$$

wherein c_t denotes consumption at date t (current consumption); c_{t+1} denotes consumption at date t+1 (future consumption); u represents the utility people would get; β is a coefficient which represents people's level of impatience; $E(c_{t+1})$ stands for expected future consumption, investors can only estimate their future incomes based on the current level of income.

While this two-period model can be extended into the multi-period model, by adding more expectations of future consumptions. In order to explain the theory, I have only assumed the simplest two-period model. In each time period, investors can freely choose how to spend their money. And to find the best decision, they need to target the option, which brings the highest level of utility. If an investor can invest in an asset priced at p_t today with a payoff of x_{t+1} in the future, and she can freely choose the amount she would buy or sell, she can calculate the desired trading amount in order to maximize her utility:

$$\begin{gathered} \max_{\{\xi\}} u(c_t)+E_t\beta u(c_{t+1}) \quad \text{s.t} \\ c_t=e_t-p_t\xi \\ c_{t+1}=e_{t+1}+x_{t+1}\xi \end{gathered} \tag{2}$$

where ξ represents the amount of the asset investors would choose to buy and e represents the income level without consumption.

In Equation (2), to find the optimal consumption level, substitute the constraints into the objective and set the first order derivative with respect to ξ equals to 0, the first-order condition for the optimal consumption level would be:

$$p_t u'(c_t) = E_t\left[\beta u'(c_{t+1}) x_{t+1}\right] \tag{3}$$

where $p_t u'(c_t)$ represents the loss in utility if the investor buys another unit of the asset, and $E_t[\beta u'(c_{t+1}) x_{t+1}]$ represents the increase in utility the investor generates from the additional payoff at time t+1. The investor will keep buying or selling the asset until the current marginal utility loss equals the future marginal utility gain and the level of consumption at the equilibrium is the desired amount for this investor.

Equation (3) can be rewritten as:

$$p_t = E_t\left[\beta \frac{u'(c_{t+1})}{u'(c_t)} x_{t+1}\right] \tag{4}$$

Equation (4) denotes the asset price's relationship with consumption. As we can see, investors can calculate the asset price p_t if they know other variables, for example, expected asset payoff x_{t+1}, investor's desired amount in current and future consumption, denote by c_t and c_{t+1}. Recall that assets perform well (bad) in the good (bad) economy state, thus while assets perform well in good economy, it would offer a higher payoff and higher price and vice versa. This is the basic consumption-based model. However this model does not perform well in empirical tests.

2.1.2 The CAPM

Equation (4) suggests that if investors' assets perform poorly, consumption will be lower and marginal utility will be higher. Therefore prices should be lower for the assets that have a positive relationship with large indices, these large indices can be regarded as market portfolios in the actual market. This reflects the CAPM, which is developed by Treynor (1961, 1962), Sharpe (1964), Lintner (1965a,b) and Mossin (1966). The CAPM is used to determine a theoretically expected required rate of return of an asset. This model expresses the expected required return of asset as the sum of risk free element plus a risk premium variable.

The CAPM takes the form of:

$$E(r_i)=r_f+\beta_i[E(r_m-r_f)]$$

where $$\beta_i=\frac{\sigma_{i,M}}{\sigma_M^2}\;; \tag{5}$$

where r_i represents the individual stock return; r_f represents the risk free rate; r_m represents market return and β is a coefficient that represents risk; $\sigma_{i,M}$ represents the covariance between the stock and market and σ_M^2 represses the market variance.

Equation (5) shows that the expected return of a typical security depends on the market premium, and the risk coefficient, beta. If beta increases, the expected return will also increase. The stock's risk, which is denoted by beta, depends on the covariance between this stock and market portfolio. This theory can be extended: according to the CAPM, stocks are correctly priced based on their returns. However it is possible that a security is sold at a fairly low price yet yields more than it should yield. Since the high-yield-low-price stock attracts more investors, as more investors start to invest in this stock, it bids up the price and thus lowers its return. The stock return will keep decreasing until it equals its fair yield. This fair yield is the expected return explained by the left-hand side of Equation 5. Similarly, for low-yield-high-price stock, investors would start to sell it off, until the return is pushed up to the fair level.

The CAPM fails in the empirical field. It is restricted to several assumptions. Fama and French (2004) argue that some of the assumptions are unrealistic. For example, the CAPM assumes that investors can freely short sell assets. It also assumes that investors can borrow or lend at the risk free rate. These assumptions are not realistic in the actual market. Furthermore, Fama and French (2004) point out that the CAPM fails to capture portfolio returns sorted based on book-to-market ratio.

2.1.3 The Arbitrage Pricing Theory (APT)

Ross (1976) develops the APT and argues that the APT is superior to the CAPM because it captures multi-factor rather than the market. In this model, each factor has its own exposure to risk and therefore exhibits different risk coefficients (beta). The model is expressed as:

$$E(r) = r_f + \beta_1 * [E(r_{M1} - r_f)] + \beta_2 [E(R_{M2} - R_f)] + \cdots + \beta_n [E(R_{Mn} - R_f)] \tag{6}$$

where $\beta_{1,\,2\ldots n}$ are different risk coefficients on different elements E ($r_{M1,\,2\ldots n} - r_{f1,\,2\ldots n}$).

Looking at the relationship between individual stock and the market, investors can easily observe that when the market goes up, most of the individual stocks will follow the market and increase as well. Also stocks that fall in the same category in the market show similar movement when the market changes. However in contrast to these similar movements, individual stock still contains unique movement, which is known as firm-specific movement. Theoretically, the risks that are associated with these firm-specific movements should be priced. Yet, APT suggests that these firm-specific risks are avoidable. These risks can be eliminated through diversification by investing in portfolios. However the risk associated with the market cannot be eliminated. $\beta_{1,\,2\ldots n}$ in Equation 6 shows that the risks in the model are only associated with factors

In short, the CAPM can be considered a single factor model according to the APT. Although the development of CAPM is a big progress in the literature, the CAPM fails in the actual market. APT suggests that in contrast to the single factor model, the multifactor model should be applied. However the APT does not tell investors what these factors are. Section 2.2 describes the multifactor investigations in asset pricing. The most prominent development is the Fama and French three-factor model.

2.2 Multifactor model

The previous discussion suggests that there may be more factors other than the market that help to price assets. This section reviews the literatures on multifactor model, the most remarkable achievement is the Fama and French three-factor model.

2.2.1 Previous works

Prior research has identified the explanatory power of different variables. For example: market equity, earnings-to-price ratio, leverage and book-to-market ratio. Banz (1981) argues that small stocks with lower market equity exhibit extremely high average returns given their beta estimates, while the large stocks' average returns are found to be "too low". Hence, the market equity (ME), which is measured by the product of stock price and total shares, increases the explanatory power in capturing cross-sectional average asset returns. Basu (1983) jointly tests the earnings-to-price ratio (E/P), market beta and size and comments on the earnings-to-price ratio (E/P) about the explanatory power on the cross-section of average U.S. stock returns. Ball (1978) also documents that earnings-to-price ratio is a comprehensive measurement of those unnamed factors in analyzing expected stock returns. Regarding the explanatory power of the earnings-to-price ratio, Jaffee and Westerfield (1989) have also confirmed it. Bhandari (1988) finds that firm's leverage contains information about the cross-sectional average stock return as well as the market beta. Barbee, Mukherji and Raines (1996) support Bhandari (1988), in that leverage, which is measured by the ratio of debt to equity (D/E), helps to explain stock returns. However, Barbee, Mukherji and Raines (1996) suggest that the role of D/E is captured by the sales-to-price ratio (S/P) because a company's earnings are not that stable due to lots of temporary issues. Ball (1978), Stattman (1980), Rosenberg, Reid and Lanstein (1985), Chan, Hamao, and Lakonishok (1991) and Berk (1995) document the importance of book-to-market ratio in explaining the average returns in the U.S market.

2.2.2 Fama French three-factor model

Fama and French (1992) jointly test market beta (β), size (ME), E/P, leverage, and book-to-market ratio in explaining the cross-sectional variation in stock returns. They suggest that if size (ME), leverage, E/P and book-to-market ratio are used alone in regression, the resulting coefficient shows some information. Among these combinations, size (ME) and book-to-market ratio perform better than E/P and leverage in capturing average stock returns. Overall, by investigating the average returns on NYSE, Amex, and NASDAQ stocks from 1963 to 1990, Fama and French (1992) document that size and book to market factors perform best in explaining the cross section of average stock returns.

On the basis of Fama and French (1992), Fama and French (1993) construct the Fama and French three-factor model. The three-factor model includes the market, SMB and HML factor. The SMB factor (small minus big) is calculated as the difference between the portfolio returns on small and big companies and the HML factor (high minus low) is calculated as the difference between the portfolio returns on the high book-to-market ratio and low book-to-market ratio companies. The three-factor model exhibits extremely high R^2 in the U.S market. Hence Fama and French argue that this model is an excellent fit for the U.S market.

2.2.2 Further investigations on explanatory factors

In the spirit of Fama and French, Lakonishok, Shleifer, and Vishny (1994) document the explanatory power of earnings-to-price ratio, cash flow-to-price ratio, and sales growth. Kothari et al. (1995) argue that the strong explanatory power of book-to-market ratio may subject it to some bias, and it may be data and/or period specific. Barbee, Mukherji and Raines (1996) support Kothari et al. (1995) for the findings on the book-to-market ratio. In addition, they find the strong explanatory power of sale-to-price ratio and debt-to-equity ratio in capturing average stock returns. Fama and French (1996) reinvestigate their model with some previously identified explanatory variables, for example, earnings-to-price ratio, cash flow-to-price ratio, sales growth. Their results show that these variables cannot take the place of book-to-market ratio in explaining the cross-section of stock returns. Fama and French (1995) find that when they form portfolios based on book-to-equity ratio, firms with lower book-to-market ratio remain more profitable than the firms with higher book-to-equity ratio for at least five years. This finding is a reinforcement of the findings of Penman (1991). Lakonishok, Shleifer, and Vishny (1994) suggest that on average, value stocks with low book-to-market ratios are overpriced, while growth stocks with higher book-to-market ratios are underpriced, thus buying these value stocks and selling growth stocks brings considerable benefits.

2.3 The profitability factor

2.3.1 Background

Fama and French (2006) use current earning as the measure of profitability and do not find the prediction power of profitability. Fama and French (2008) argue that they cannot clearly show the positive relationship between profitability and average stock returns if they control size and book-to-market ratio.

2.3.2 Novy-Marx (2013) profitability factor

In support of Titman, Wei, and Xie (2004), Novy-Marx (2013) comments that the three-factor still fails in explaining the U.S market and points out the importance of the profitability factor. In Novy-Marx (2013), the profitability is measured by the ratio of gross profit to asset. Novy-Marx comments that, in contrast to Fama and French (2006), which use the current earning as a measurement, his definition of profitability factor should be applied instead because it has "roughly the same power as book-to-market in predicting the cross-section of average returns".

2.3.3 Fama French (2015) Five-factor Model

Fama and French (2015) produce a latest five-factor model, which combines the original three-factor model with two additional factors: profitability and investment. In their paper there is another way of defining the profitability, which is measured as revenue minus the cost of goods sold, the interest and the selling, general and administration cost in time t, divided by the book value of equity in the previous time period, t-1. Their results show that new Fama French five-factor model provides a better measurement than the Fama French three-factor model in terms of the U.S stock market. However, the Fama French sample results suggest that with profitability and investment factors, the HML factor seems to be redundant. Fama and French point out that much evidence exists which proves the power of the HML factor therefore their results might be sample or region specific. Therefore it is important to have out of sample evidence to support the five-factor model.

In short, Section 2.3 discusses the prior research on the multifactor model in the U.S. The big success of the three-factor model has enabled it to become widely used in the U.S market. However Novy-Marx (2013) and Fama and French (2015) argue that the three-factor model still fails. The profitability factor, in contrast, has strong explanatory power. A five-factor model, which includes the market, size, book-to-market, profitability and investment, outperforms the three-factor model in the U.S. market. The next section reviews the international literature on the multifactor model.

2.4 International Evidence of the multifactor model

This section reviews the international literature on the multifactor model. Capaul, Rowley, and Sharpe (1993) capture the value premium across international stocks within ten years. This value premium is confirmed in Cai (1997). Chan et al. (1991) find a strong value premium in Japan and suggests that book-to-market ratio (B/M) and cash-to-price ratio (C/P) have strong explanatory power in capturing stock returns. Fama and French (1998) investigate the U.S and 12 other major countries from Europe, Australia, and the Far East and document the existence of value premium across the world. They also suggest that the multifactor model helps to capture the worldwide value premium. Maroney and Protopapadakis (2002) examine stock returns for Australia, Canada, Germany, France, Japan, the U.K., and the U.S. market and emphasize the explanatory power of the Fama French three-factor model and the book-to-market factor. Leledakis and Davidson (2001) document the value premium in the United Kingdom and point out the explanatory power of the sales-to-price ratio (S/P). They also comment on the importance of the size and book-to-market factors in capturing cross-sectional stock returns. Wolmarans (2000) documents the value premium in South Africa and compares the dividend yield with earnings yield in terms of a ranking method and the results show the earnings yield helps to explain the stock returns better than the dividend yield in South Africa. Hou, Karolyi and Kho (2011) comprehensively examine size, book-to-market, dividend, earnings yield, cash flow-to price leverage and momentum factor across 49 countries for 3 decades and documents the existence of the global cash flow-to-price factor. Fama and French (2012) document a global four-factor model. Moreover, they find the HML factor is important in the Asia-Pacific region.

In sum, various variables are found to have explanatory power worldwide. Although there are lots of examinations across the world, literature on the Australian market is relatively limited. The next section reviews the literature in Australia.

2.5 Australian evidence of the alternative pricing models

The Australian market is a good candidate for the out of sample test. It is the second largest market in the Asia-Pacific region and the eighth largest market in the world, with a total market capitalization close to \$1.5 trillion (ASX website, 2015). Thus the Australian market is small enough to present an out of sample evidence to the findings in the U.S. while at the same time large enough to be of interest to academia and practice. Moreover, Fama and French (1998) document the highest value premium exists in Australia.

2.5.1 The CAPM in Australia

Findings on whether the CAPM fails on the Australian market are relatively mixed. Durack et al. (2004) find that the CAPM has low explanatory power in the Australian stock market with an R^2 of only 7.25%. Gaunt (2004) suggests that the Fama and French model works better than the CAPM in Australia. Brailsford et al. (2012b) suggest the weakness of CAPM with detailed hand-collected data over a 25 year period. Toms (2014) finds that the discount rate used by the CAPM overestimates the risk which suggests the weakness of the CAPM. The accounting-based risk measurement, on the other hand, offers reasonably better explanatory power in empirical tests than the CAPM in Australia. Liu and Di Iorio (2015) find strong evidence that firm-specific volatility risk has positive relationship with stock returns in Australian, which is not captured by the CAPM. Mazzola and Gerace (2015) suggest the weakness of the CAPM in the empirical field when rebalancing frequency and transaction costs are taken into account. Contrarily, Walsh (2014) argues the CAPM is still useful in pricing assets because in reality different investors would exhibit different investment horizons rather than the homogenous investment horizon, which is suggested by the CAPM assumptions.

2.5.2 Size and Book-to-market factor in Australia

The size effect, which means that smaller firms tend to have higher expected returns than larger firms, has been documented in Australia, however, with mixed outcomes. Brown, Keim, Kleidon, and Marsh (1983), Gaunt, Gray, McIvor (2000), Durack et al. (2004), Kassimatis(2008), Bettman, Ng, and Sault (2011), Brailsford et al. (2012b), Beedles, Dodd, and Officer (1988) suggest that the size effect is extremely large in Australian stock market. However the findings from the research by Faff (2001, 2004) show that the size effect in Australian stock market is negative.

Prior studies have confirmed the importance of the book-to-market ratio in Australia. Gaunt (2004), Gharghori et al. (2006, 2007, 2009, 2013) document the significant book-to-market effect on the Australian stock market. Kassimatis (2008) documents the book-to-market effect in Australia. Furthermore, Gaunt (2004) documents the important role of the book-to-market factor in Australia. Faff (2001) examines the Fama and French three-factor model in Australia from 1991 to 1999 and comments on the strong explanatory power of the Fama French book-to-market factor. Nguyen and Gharghori (2007) document the value premiums brought by the Fama French factors and argue that the book-to-market factor is the main factor in explaining the average stock returns. Fama and French (2012) find the HML factor is important in the Asia-Pacific region including Australia.

2.5.3 Australian Extension of Fama and French three-factor model

Similar to Fama and French (1998), Halliwell et al. (1999) also find the value premium in

Australia by studying the Fama and French model using Australian data from 1981 to 1991. Anderson, Lynch and Mathiou (1990) test the price-to-earnings ratio in the Australian stock market and document that the pricing-to-earning factor has explanatory power except for small firms. Gharghori and Faff (2007) examine the Fama French model in terms of default risk and they find that although the Fama French factor cannot explain the default risk, the premium on the Fama French factors is still significantly strong, even stronger than in the U.S market. This finding is also confirmed in Nguyen and Gharghori (2009). Gharghori and Veeraraghavan (2009) investigate size, book-to-market, earnings-to-price, cash flow-to-price, leverage and the liquidity factor in Australian market. They are first to document that size, book-to-market, earnings-to-price and cash flow-to-price factors have explanatory power across average stock returns. Brailsford et al. (2012b) test the Fama and French three-factor model in Australia with detailed hand-collected data, which includes about 98% of the listed stocks from 1982 to 2006 in order to resolve the data limitation issue. Their results reinforce the value premium and book-to-market effect in Australia. Gharghori, Stryjkowski and Veeraraghavan (2013) also reinforce the existence of the value premium in the Australian market and by comparing four variables, including book-to-market, sales-to-price, earnings-to-price and cash-flow-to-price ratio. Besides these, they suggest that the best variable to capture cross-sectional stock return in Australia is the book-to-market ratio. Faff, Gharghori and Nguyen (2014) are the first to compare the conditional Fama and French three-factor model with the GDP-augmented Fama and French pricing model in Australia. They find that macroeconomic variables have power in pricing stocks.

2.5.4 Profitability and Investment factors

Findings on the profitability factor and investment factor in Australia are relatively limited. Dou et al. (2012) confirm the profitability premium in the Australian stock market by using the return-on-asset as the measurement of profitability. Zhong et al. (2014) suggest the explanatory power of gross profitability on Australian asset returns. Gray and Johnson (2011) confirm that if size is controlled, asset growth can be used to explain the cross-sectional stock returns.

2.5.5 Alternative pricing models in Australia

The Fama French three-factor model is widely used in the Australian market. However the debate whether the three-factor model fails in the Australian market is intense. Faff (2001), Gaunt (2004) and Gharghori et al. (2007) find the R^2 in Australia is only about 50% to 60% in capturing cross-sectional asset returns, while it is much higher in U.S. market, around 90%. Gharghori and Veeraraghavan (2009) suggest that the performance of the three-factor model is not very satisfactory in Australia. Brailsford et al. (2012b) analyze the Australian market with hand-collected data and comment that the Fama French three-factor model is not a complete model in capturing stock returns. There are still lots of mispricing. Vu, Chai and Do (2014) examine the liquidity risk in Australia and confirm the important role of the liquidity risk regardless the measurement used in the pricing model. Durand, Limkriangkrai and Chai (2015) suggest that neither the four- nor the five-factor model can offer a relatively comprehensive explanation of returns on the Australian market by using comprehensive hand-collected data by Brailsford et al. (2012b). Hence, it is worthwhile to investigate whether adding more factors is beneficial and helps to improve the asset pricing model in the Australian market.

2.6 Research Gap

Prior investigations leave a research gap for this thesis: First, recall that the Novy-Marx profitability is calculated as the gross profit divided by the total asset. Fama and French profitability is calculated as revenue minus the cost of goods sold, minus the interest and the selling, general and administration costs in time t, divided by the book value of equity in the previous time period, t-1. These different definitions may lead to different outcomes. Thus it is necessary to test both definitions in the Australian market in order to check whether the five-factor model is definition sensitive. Second, in the spirit of Fama and French (2012, 2015), in terms of testing whether the HML factor is useful in the Australian market will be a good out of sample evidence to the finding in the U.S. market. If there is evidence to support the HML factor, then this out of sample evidence will support the five-factor model.

Chapter 3

Data and Methodology

The data used in this study are mainly collected from the Share Price and Price Relative (SPPR) obtained from SIRCA and Thomson Reuters DataStream. My sample covers the ordinary stocks traded on the Australian Securities Exchange (ASX) from January 2001 to December 2013. To perform the analysis, I require two types of data: market data and accounting data. The Share Price and Price Relative Database (SPPR) includes the monthly market data I need to conduct the tests, for example: closing stock price, net stock return, market return, the government bond risk free rate and market capitalization. The accounting information used in the factor construction, is obtained from DataStream, on a yearly basis. The main software packages involved in this study include Excel, Ox Metrics and Eviews.

Australian companies have the financial year end date on the last day of June. This means that I collect the accounting information commencing on 30th June each year. Also, in the spirit of Fama and French (1993, 2015), I form the portfolio at the end of the December each year. The time between the accounting information and the portfolio formation produces a minimum of a six-month lag. The lag is necessary to prevent the look-ahead bias. This bias can be the result of using the data that would not have been available at the specific time period and it causes the result to be inaccurate.

The data from SPPR needs to be cleaned. First, the SPPR does not directly provide the net returns, so I need to transfer the SPPR gross return into net returns. Second, for certain time periods, the missing data needs to be deleted before conducting the analysis. Third, in order to construct portfolios, I need the market capitalization in the previous period MV_{t-1}.

According to Fama and French (2015), the five-factor model includes the size, book to market, profitability and investment factor. Size is represented by the market value of equity for each firm, which is the market capitalization in SPPR. The book-to-market ratio is collected from DataStream.

The Fama and French's definition of operating profitability is denoted as FFOP, and is calculated as follows:

$$FFOP_t = \frac{Rev_t - COGS_t - Interest_t - SGAC_t}{\text{Book value of Equity}_{t-1}}$$

where Rev_t is firm's revenue in time t, $COGS_t$ represents Cost of Goods Sold in time t, $interest_t$ is the interest expense in time t and $SGAC_t$ is Selling, General and administration cost in time t.

The Novy-Marx operating profitability is represented by NMOP and it is measured in a different way:

$$NMOP = \frac{Rev_t - COGS_t}{Asset_t}$$

Both definitions of the profitability factor are applied in this thesis.

The investment, is measured by asset growth according to Fama and French (2015), and is expressed as:

$$\text{Investment}_t = \frac{\text{Asset Growth at the end of t-1}}{\text{Total Asset}_{t-1}}$$

3.1.1 Factor construction

To construct the mimicking factor portfolios, I follow the procedures in Novy-Marx (2013) and Fama and French (2015). In this thesis, the factors involved include: the market factor, the size factor (SMB), the book to market factor (HML), the profitability factor computed based on Novy-Marx's definition of profitability (i.e., the NMOP formula above) (henceforth denoted as NMPMU), the profitability factor computed based on the Fama and French's definition of profitability (i.e., the Investment formula above) (henceforth denoted as FFPMU), and the investment factor (INV). I calculate the profitability factor in two ways. Since the Australian stock market has different characteristics compared to the U.S. market, in this study, the breakpoints I use are slightly different. According to Brailsford et al (2012), the size cut off point is obtained by sorting stocks based on their market capitalization, MV, at the end of December each year. The largest 200 companies, after sorting, are marked as large companies and the remaining companies are all classified as small companies.

In order to create the two mimicking factors comprising the small-minus-big (SMB) factor and the high-minus-low (HML) factor, I perform a 2 by 3 sort based on size and book-to-market ratio. This sort produces six portfolios in the end. Starting from 2001, at the end of December each year, stocks are sorted based on their market capitalizations. The 200 companies with the largest market value are classified as large companies and the remaining companies are classified as small companies. To obtain the breakpoint for the book-to-market ratio, I take the 30^{th} and 70^{th} percentile of the book-to-market ratio for the largest 200 companies and these two numbers are employed as the breakpoints for the whole sample each year. Stocks with book-to-market ratios less than the 30^{th} percentile belong to the group of growth companies. Stocks with book-to-market ratios between the 30^{th} and 70^{th} percentile belong to the medium company and stocks with book-to-market ratios larger than 70^{th} percentile belong to the group of value companies. The breakpoints for the book-to-market ratio are similar to those used in the U.S. studies.

The intersections provide six size and book-to-market sorted portfolios: small-growth, small-medium, small-value, big-growth, big-medium and big-value. Then I calculate the monthly returns from 2001 to 2013 for these six portfolios. Consistent with Fama and French (2015), the portfolio returns are value weighted. It is worth noting that, the sorting is completed in June in year t, while 12 monthly returns are calculated for year t+1 and these portfolios are reformed at the end of each year.

SMB is then calculated as the average return on the small portfolios minus the average return on the big portfolios as follows:

$$SMB = \frac{1}{3} * \left(r_{small\text{-}growth} + r_{small\text{-}medium} + r_{small\text{-}value}\right) - \frac{1}{3} * \left(r_{big\text{-}growth} + r_{big\text{-}medium} + r_{big\text{-}value}\right)$$

where r represents monthly value weighted returns.

HML is calculated as the average return on the portfolios with high book to market ratio minus the average return on the low book to market ratio portfolios.

$$HML = \frac{1}{2} * \left(r_{small\text{-}value} + r_{big\text{-}value}\right) - \frac{1}{2} * \left(r_{small\text{-}growth} + r_{big\text{-}growth}\right)$$

To create the other three mimicking factors, I follow the same procedure in creating SMB and HML. Recall that there are two definitions of profitability factors, the Novy-Marx profitable minus unprofitable factor is denoted as NMPMU and Fama and the French profitable minus unprofitable factor is denoted as FFPMU.

To create NMPMU and FFPMU, I create a 2 by 3 sort based on size and Novy-Marx operating profit (NMOP) and Fama and French operating profit (FFOP), respectively. Calculations for

NMPMU and FFPMU are the same, as expressed below:

$$\text{NMPMU}=\frac{1}{2}*\left(r_{\text{small-profitable}}+r_{\text{big-profitable}}\right)-\frac{1}{2}*\left(r_{\text{small-unprofitable}}+r_{\text{big-unprofitable}}\right)$$

$$\text{FFPMU}=\frac{1}{2}*\left(r_{\text{small-profitable}}+r_{\text{big-profitable}}\right)-\frac{1}{2}*\left(r_{\text{small-unprofitable}}+r_{\text{big-unprofitable}}\right)$$

The investment factor is called INV in this thesis. It is the average return on low investment stock minus the average return on high investment stock.

$$\text{INV}=\frac{1}{2}*\left(r_{\text{small-low}}+r_{\text{big-low}}\right)-\frac{1}{2}*\left(r_{\text{small-high}}+r_{\text{big-high}}\right)$$

Monthly value weighted portfolio returns used to construct mimicking factors are computed using Ox Metrics. Sample code used for creating SMB and HML is provided in the Appendix 1. For other mimicking factors, the code is almost the same except for a little modification.

Table 3.1 reports the summary statistics for the factor portfolios. Panel A shows the average number of firms in each group in forming the mimicking factors. As can be seen, most of the companies are classified as small companies. This is not surprising, because the Australian market is small compared to a developed market like the U.S.

Panel B reports the descriptive statistics for the MKT, SMB, HML, FFPMU, NMPMU and INV factors. Where market return is the excess return, which is calculated as the market return minus the risk free rate. From Panel B we can see that the mean returns for all these factors are positive. This means on average, these factors offer a premium to investors. Fama and French's profitability factor, denoted by FFPMU, exhibits the highest average return, at about 1%. This factor also has the highest median (2%), standard error (0.5%) and standard deviation (6%). These results imply that the Fama and French profitability factor comprises the highest risk and offers the highest return. All factors exhibit negative skewness, which means they are "skewed to the left". Looking at the kurtosis, the HML factor has the highest value at about 2.8, which means it has the most peak data distribution. The highest risk and return offer the FFPMU the highest

Sharpe Ratio, at about 23%, which means this factor has the highest risk-adjusted return. The SMB, on the other hand, has the lowest risk-adjust return at about 2%.

Panel C reports the correlations between these factors. As can be seen, the HML, profitability and investment factors are negatively related to the market. This is consistent with Fama and French (2015), where they also document the negative relationship.

Figure 1 displays the returns we would generate if we invested one dollar in each of these factors from year 2002 to 2013. To calculate this, I use monthly compounded return:

$$P_t=1*(1+r_{t-1})^t$$

where P_t denotes the total amount investor would generate at time t, r_{t-1} represents the portfolio monthly realized return in the previous time, t-1.

From the graph we can see that all the returns show increasing trends and the FFPMU factor outperforms all of the other factors in generating the highest returns. The NMPMU factor, on the other hand, has the lowest return. These factors might be sensitive to the method of calculation since calculating the FFPMU factor requires more accounting information than calculating the NMPMU factor. The SMB, HML and Investment factor appear as a similar trend on this graph and the HML factor shows the best performance among these three factors. This is a sign that the HML factor brings value.

Table 3.1 Summary Statistics for the mimicking factors

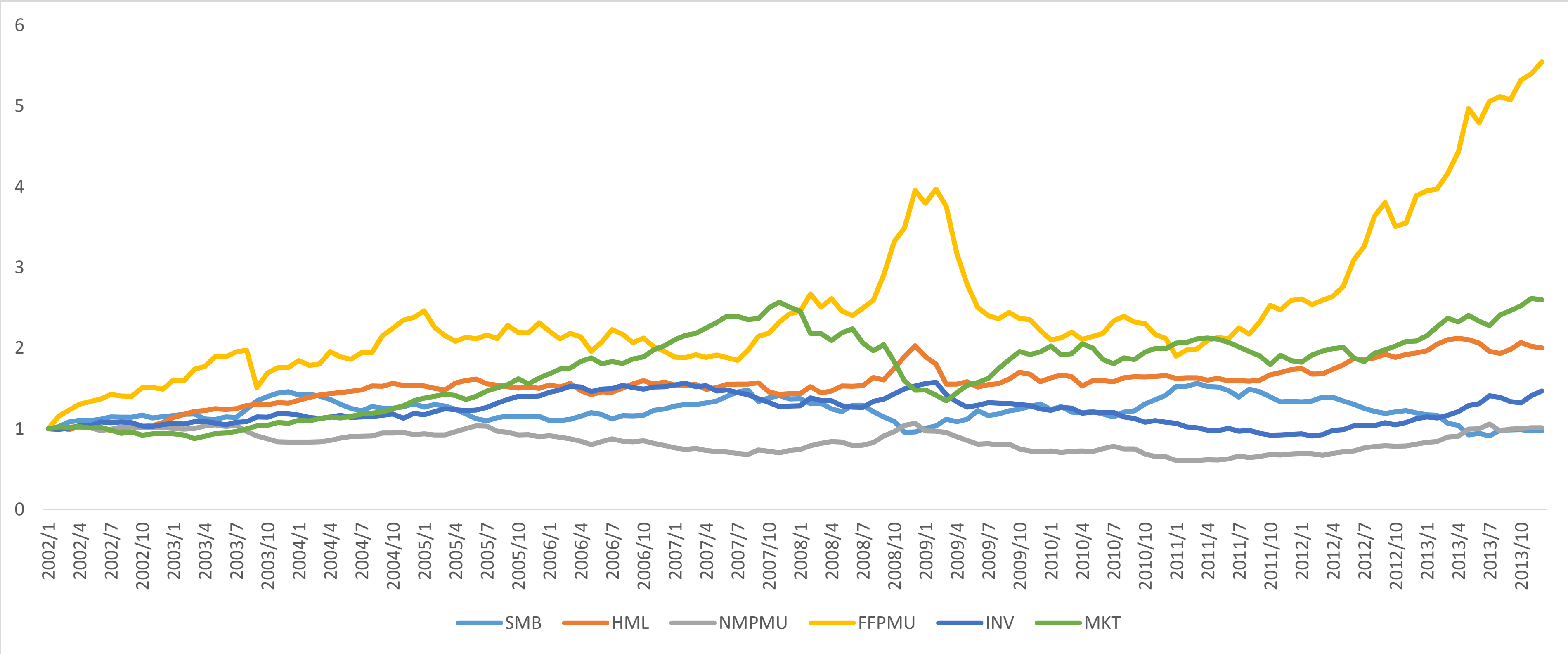
Panel A : Average Number of Firms in each factor							
	Low	Medium	High		Low	Medium	High
	Size-BM				Size-NMOP		
Small	117	177	162	Small	152	161	105
Large	59	73	21	Large	8	60	61
	Size-FFOP				Size-Investment		
Small	73	102	32	Small	130	148	127
Large	8	12	52	Large	25	86	45

Panel B : Descriptive Statistics of the Factors						
	SMB	HML	NMPMU	FFPMU	INV	MKT
Mean	0.0006	0.0053	0.0008	0.0133	0.0030	0.0035
Standard Error	0.0032	0.0026	0.0029	0.0048	0.0024	0.0031
Median	0.0023	0.0076	0.0027	0.0158	0.0039	0.0115
Standard Deviation	0.0386	0.0312	0.0350	0.0581	0.0294	0.0374
Kurtosis	0.6425	2.8041	0.3737	1.8649	0.2981	1.3374
Skewness	-0.2092	-0.7089	-0.0153	-0.5090	-0.0645	-0.9712
Range	0.2184	0.2272	0.1856	0.3870	0.1738	0.2090
Minimum	-0.1226	-0.1372	-0.0884	-0.2333	-0.0971	-0.1354
Maximum	0.0958	0.0900	0.0971	0.1537	0.0767	0.0736
Sharpe Ratio	0.0154	0.1711	0.0242	0.2296	0.1006	0.0945

Panel C : Correlations						
	SMB	HML	NMPMU	FFPMU	INV	MKT
SMB	1.00					
HML	-0.33	1.00				
NMPMU	-0.81	0.26	1.00			
FFPMU	-0.40	0.27	0.53	1.00		
INV	-0.20	0.25	0.20	0.21	1.00	
MKT	0.23	-0.23	-0.43	-0.36	-0.20	1.00

NOTE: Stocks are sorted based on their market capitalization once per year at December. Once the stocks are sorted, the largest 200 companies are marked and noted as large companies and the remaining companies are all classified as small companies. The cutoff points for book-to-market ratio is obtained from the 30th and 70th percentile among these 200 largest companies and then applied to the entire sample. Breakpoints for other factors: Novy-Marx profitability, Fama and French profitability and asset growth are calculated using a same way as book-to- market ratio. Once the stocks are sorted based on size and other characteristics accordingly, the intersections produce six portfolios for each factors. Returns are monthly, value-weighted and calculated from year t+1. SMB is calculated as the average return on the small portfolios minus the average return on big portfolios based on the sort on size and book-to-market ratio. HML is calculated as the average return on the portfolios with high book to market ratio minus the average return on the low book to market ratio portfolios based on the sort on size and book-to-market ratio. NMPMU is calculated as the difference between average returns on the portfolios with high Novy-Marx's profitability and portfolios with low Novy-Marx's profitability based on size and Novy-Marx's profitability sorted portfolios. FFPMU is calculated using a same way as NMPMU using the portfolios sorted by size and Fama and French's profitability. INV is calculated as the difference between average returns on the low asset growth portfolio and high asset growth portfolio. MKT is the excess return for the markets, which is calculated as the market return minus the risk free rate. Panel A of the Table 3.1 shows the average number of firms in each group during year 2002 to year 2013. Panel B shows the means, standard deviation and other descriptive statistics for the factors and Panel C reports the correlations between factors.

Figure 3.1: $1 Investing in Factors



NOTE:
This figure displays the return generated from $1 investment in each factor from 2002 to 2013. Returns are monthly compounded. It is calculated as:

$$P_t=1^*(1+r_{t-1})^t$$

where P_t denotes the total amount investor would generate at time t, r_{t-1} is the portfolio monthly realized return in previous time, t-1.

3.1.2 Portfolio construction

In forming the test portfolios, I follow Fama and French (1993, 2015) and Novy-Marx (2013). These test portfolios are formed based on size and book-to-market ratio, size and Novy-Marx operating profit, NMOP, size and Fama and French operating profit, FFOP and size and investment, respectively.

Under each sort, I form 3 by 3 portfolios[1] based on different cut off points. To obtain the size and book-to-market sorted portfolios, starting from the December in year 2001, stocks are sorted based on their market capitalizations. The smallest companies represent 5% of the total market capitalizations. The Medium sized companies represent the next 15% of market capitalizations and the rest of the companies are classified as large companies. After sorting by size, stocks are then independently sorted based on their book-to-market ratio. The 30^{th} and 70^{th} percentile of the largest 200 companies' book-to-market ratios are calculated and stored, and then are applied to the entire sample. Stocks with book-to-market ratios less than the 30th percentile belong to the group of growth companies. Stocks with book-to-market ratios between the 30th and 70th percentile belong to the group of medium companies and stocks with book-to-market ratios larger than the 70th percentile belong to the group of value companies. Portfolios are reformed once per year from 2001 to 2012, leading to portfolio returns from January 2002 to December 2013. The intersections produce nine portfolios that are sorted on size and book-to-market ratio. The procedures are the same to construct the size and NMOP, the size and FFOP and size and investment sorted portfolios. In sum, these independent double sorts lead to four sets of 3 by 3 portfolio returns. Returns are calculated on a monthly basis and are value weighted, which means in total there are 144 monthly value weighted portfolio returns.

[1] In Fama and French (1993,2014) and Novy-marx (2013), they perform a 5 by 5 sort on the portfolios, while in this study the market is not big enough to produce 5 by 5 sort portfolios

Table 3.2 shows the summary statistics for the 3 by 3 sorted test portfolios and Panel A shows the average excess returns and average number of firms in each group. Using the first part in Panel A as an example: the top left belongs to the group with the smallest size and book-to-market ratio. Size increases vertically and book-to-market ratio increases horizontally. The bottom right belongs to the group with the largest size and book-to-market ratio.

For portfolios sorted in terms of size and book-to-market ratio, the returns are significant for the small-medium BM group (0.84%), medium-high BM group (0.89%) and large-high BM group (0.69%). For portfolios sorted based on size and two operating profits (FFOP and NMOP), the returns are significant for the group of small-medium BM and the medium-high BM group, with returns of 1.59%, 2.27%, 1.04% and 1.22% respectively. The returns are not significant for stocks sorted based on size and investment. Looking horizontally through Panel A, for portfolios sorted by size-FFOP and size-NMOP, returns for small groups increase from 0.21% to 2.27% and from 0.22% to 1.22 as we increase FFOP and NMOP from the lowest to the highest. However, in other groups, we cannot observe a clear pattern. In the category of size-FFOP sorted portfolios, profitable firms tend to have higher return than the unprofitable firms for all-sized companies, while in the size-NMOP sorted portfolios, we can only observe this pattern in the small group. For size-Investment group, the low investment group exhibits higher returns than the group with high investment. Furthermore, by looking through Panel A vertically, in the category of size and two operating profits sorted portfolios, small companies generate higher returns than large companies. This is evidence of the size effect. If we refer to the size-investment sorted portfolio, we can again observe the size effect.

Panel B reports average number of firms, average firm market capitalizations and percentage of average market capitalizations within each of the sorts. Recall that in the Australian stock market most companies are classified as small companies. And consistent with this, the results show the large number falling in the small group. In contrast, there are few observations falling in the big group. The large value companies make up the largest market capitalizations. As can be seen, if size is increasing, the corresponding market capitalization increases as well. This means size is successfully controlled in this test. The percentage of market capitalization reflects the break points, which have been described above in the information on the portfolio construction, where most companies are allocated to the medium group in each sort.

Sample of the Ox Metrics code used to create the 3 by 3 portfolio based on the size and book-to-market is provided in Appendix 1. For other portfolios the code is almost the same except for a little modification.

Table 3.2 Summary Statistics for Testing Portfolios

Panel A: Average Firm Excess Return							
		Average Return (%)			t(return)		
		Low 1	2	High 3	Low 1	2	High 3
Size and Book-to-Market							
	Small 1	-0.08	0.84	0.66	-0.13	1.81*	1.47
SIZE	2	0.47	0.51	0.89	1.26	1.48	2.61**
	Big 3	0.47	0.46	0.69	1.25	1.33	1.90*
Size and FFOP							
	Small 1	0.21	1.59	2.27	0.39	3.16**	2.80**
SIZE	2	-0.02	0.5	0.39	-0.03	1.56	1.18
	Big 3	0.07	0.52	0.41	0.10	1.65	1.25
Size and NMOP							
	Small 1	0.22	1.04	1.22	0.36	2.47**	2.95**
SIZE	2	0.63	0.48	0.55	1.44	1.39	1.59
	Big 3	0.63	0.44	0.53	1.46	1.29	1.52
Size and Investment							
	Small 1	0.52	0.68	0.49	1.11	1.40	0.88
SIZE	2	0.47	0.47	0.27	1.30	1.39	0.68
	Big 3	0.4	0.45	0.22	1.03	1.34	0.55

Table 3.2 Continued

Panel B: Number of Firms, Average Firms Capitalization and Percentage of Firms Capitalization									
	Number of Firms			MV ($millions)			Percentage		
				Size and Book-to-Market					
	Low 1	2	High 3	Low 1	2	High 3	Low 1	2	High 3
Small 1	103	402	253	77	66	54	0.0063	0.0210	0.0108
2	32	68	25	5943	5793	2577	0.1502	0.3112	0.0509
Big 3	13	25	6	13262	14027	7657	0.1362	0.2771	0.0363
				Size and FFOP					
Small 1	185	35	9	55	157	195	0.0189	0.0101	0.0032
2	9	39	19	1411	3978	5950	0.0235	0.2865	0.2088
Big 3	1	16	11	6387	8236	9532	0.0118	0.2434	0.1937
				Size and NMOP					
Small 1	285	163	71	52	94	96	0.0193	0.0200	0.0089
Medium 2	21	63	25	2307	4036	3933	0.0630	0.3306	0.1279
Big 3	5	24	9	6848	8918	9184	0.0445	0.2783	0.1075
				Size and Investment					
Small 1	192	247	142	54	87	86	0.0076	0.0158	0.0089
2	32	73	28	4291	6274	3778	0.1007	0.3357	0.0775
Big 3	13	28	8	9014	14791	10964	0.0859	0.3036	0.0643

NOTE: This table shows the summary statistics for 3*3 sorted test portfolios. Panel A shows the average excess return and average number of firms in each group. Panel B reports average number of firms, average firm market capitalizations and percentage of market capitalizations under each sorting method, and starting from December in year 2001, stocks are sorted based on their market capitalizations. The smallest companies represent 5% of total market capitalizations, and similar to the way in forming the mimicking factors, these stocks are labelled numerically as 1. The Medium sized companies represent the next 15% of market capitalizations and then labelled as 2. The rest companies are classified as large companies and labelled as 3. After size sorting, companies are then independently sorted based on their book-to-market ratio. The 30th and 70th percentile of the largest 200 companies' book-to-market ratios are calculated and stored, and then are used as breakpoint and applied to the entire sample. Stocks with book-to-market ratio Stock with a book to market ratio less than the 30th percentile belongs to group 1, stock with a book to market ratio between the 30th and 70th percentile belongs to the group 2 and stock with a book to market ratio larger than 70th percentile belongs to group 3. Portfolios are reformed at the end of each year from 2001 to 2012, leading to a portfolio return from January 2002 to December 2013. The intersection produces nine size and book-to-market sorted portfolio. The procedures are the same referring to the size and NMOP, size and FFOP and size and investment sorted portfolios. In Panel A, average excess return and t-statistics on average returns are reported. Panel B reports the average number of firms in each portfolio, average market capitalizations (in millions) and percentage of the market capitalization for each group. * and ** denote the significance on 5% and 1% level, respectively. Average excess return is reported under percentage value.

3.2 Methodology

3.2.1 Asset Pricing Tests

In this study, I evaluate alternative multifactor asset pricing models. In addition to these multifactor models, the performance of the CAPM is also evaluated. According to Fama and French (2015) and Novy-Marx (2013), there are two definitions of the operating profit and both of these two definitions are applied in this thesis. The models are shown as follows:

The CAPM:

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ e_{it} \tag{7}$$

The three-factor-model:

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_i + e_{it} \tag{8}$$

The five-factor-model with Fama French Profitability:

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_t +p_i FFPMU_t + l_i INV_t+ e_{it} \tag{9}$$

The five-factor-model with Novy-Marx Profitability:

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_t +p_i NMPMU_t + l_i INV_t+ e_{it} \tag{10}$$

The four-factor-model with Fama French Profitability:

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+p_i FFPMU_t + l_i INV_t+ e_{it} \tag{11}$$

The four-factor-model with Novy-Marx Profitability:

$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+p_i NMPMU_t+l_i INV_t+e_{it} \tag{12}$$

where r_{it} is the return for portfolio I, within different sorts, at time t. r_{ft} is corresponding risk-free rate at time t. MKT represents the market factor, which is calculated as market excess return. SMB, HML, FFPMU, NMPMU and INV are the mimicking factors constructed from the test portfolios formed by size and book-to-market ratio, size and Fama and French operating profit, size and Novy-Marx operating profit and size and investment, respectively and e_{it} represents the regression residual. Two main tasks for this thesis include: First, evaluating the performance of the new five-factor model on the Australian market, with both Novy-Marx and Fama and French's definitions on profitability. Second, testing whether the HML factor is redundant in the Australian market by addressing the performance of the four-factor model.

3.2.2 The Wald test

In order to check the usefulness of the factors I perform Wald tests for both three- and five-factor models. The null hypothesis for the Wald test is that the testing coefficients are jointly equal to zero. If the test statistics can successfully reject this null hypothesis, then it is evidence that the factors are useful explanatory factors. For the three-factor model, the Wald test is conducted on the coefficient for the SMB and HML factors. For the five-factor models, the Wald test is conducted on the coefficients for the profitability (FFPMU, NMPMU) and the investment factors (INV).

3.2.3 The GRS test

In this thesis, the GRS test is conducted for all models. Sometimes, while investors may see a model with high goodness of fit, yet in fact it does not perform well as an explanatory model. Hence, the Gibbons, Ross, and Shanken's (GRS 1989) F-statistic is computed as a supportive approach in determining the power of the asset pricing model. The GRS test is conducted on the regression intercepts. The regression intercept is a measure of the model's magnitude with respect to mispricing. If the assets are correctly priced, if there is no mispricing, the intercepts should be zero. Therefore, the GRS tests on the intercepts enable investors to judge the power of these asset-pricing models.

The GRS test takes a form of:

$$\left(\frac{T}{N}\right)*\left(\frac{T\text{-}N\text{-}L}{T\text{-}L\text{-}1}\right)*\left[\frac{\hat{\alpha}'*\hat{\Sigma}^{-1}*\hat{\alpha}}{1+\overline{\mu}'*\hat{\Omega}^{-1}*\overline{\mu}}\right]\sim F(N,\ T\text{-}N\text{-}L)$$

where T represents total number of observations; N represents the number of estimated regressions; L is the number of factors used in regression models; $\hat{\alpha}$ is the vector of estimated intercepts (alphas), it takes the form of N*1; Σ is the covariance matrix computed from residuals; $\overline{\mu}$ represents the vector for means of factors which has a form of L*1 and Ω represents the covariance matrix for factors.

3.2.4 The Information Ratio

In this thesis, I calculate the information ratios for all models. The information ratio IR (α) is a ratio that measures the risk-adjusted reward on a certain investment, which tells investors how much excess returns could be generated by taking an extra risk. In contrast to the Sharpe ratio, which is also a measurement of risk-adjusted reward. The information ratio is a calculation using alphas and residuals. In other words, it is a measure of tracking errors. Therefore, the model with low information ratios is better than the model with a high information ratio. The information ratio IR (α) is calculated as:

$$IR(\alpha)=\sqrt{\hat{\alpha}'*\hat{\Sigma}^{-1}*\hat{\alpha}}$$

where $\hat{\alpha}$ is the N*1 vector of estimated intercepts (alphas) and Σ is the covariance matrix for residuals.

The next chapter presents and discusses the empirical results.

Chapter 4

Results

The previous chapter discusses the data and methodology involved in this thesis. This chapter presents and discusses the results from the empirical analysis. Section 4.1 compares the performance of the CAPM and the three-factor model in Australia. Section 4.2 discusses the performance of the three and five-factor models under different sorting methods and Section 4.3 compares the differences between the models.

4.1. The CAPM versus Three Factor Model

4.1.1 The CAPM in the Australian market

This section evaluates the performance of the CAPM in the Australian market, by regressing different test portfolio returns (size-BM, size-Fama and French operating profit, size-Novy-Marx operating profit and size-investment portfolios) on the market factor.

Recall that the CAPM is expressed as:

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ e_{it} \tag{7}$$

where r_{it} represents the different portfolio returns in time t, r_{ft} is the corresponding risk free rate at time t, α_i is the intercept from the regression, β_i is the risk coefficient on market, MKT represent the market factor, and e_{it} is the regression residuals.

Table 4.1 regresses the nine test portfolios against the market factor utilizing different sorts. In Panel A, size increases vertically and the book-to-market ratio increases horizontally. The top left belongs to the group with the smallest size and book-to-market ratio while the bottom right belongs to the group with the largest size and book-to-market ratio. The same table outline applies to other sorting methods. Panel A shows that most alphas are positive except the one for small-low BM companies. These non-zero alphas imply the mispricing of the CAPM. The t-statistics suggest the mispricing is only significant at 1% level for medium-high BM companies. Looking at the betas on market, all betas are highly statistically significant with high t-statistics, which address the core position of the market in the model. Smaller (growth) companies exhibit higher betas than the large (value) companies. This is consistent with the theory, since the small (growth) companies are more vulnerable than the large (value) companies hence the higher investment risk offers higher returns.

Similarly, the CAPM shows mispricing for size-FFOP, size-NMOP and size-investment portfolios. In both size-FFOP and size-NMOP portfolios, alphas are significant for small-medium profitable and small-highly profitable groups. Loadings on the market decrease with size, and profitability. This implies that larger-profitable firms are less risky than smaller-unprofitable firms. In regard to the size and investment sorted portfolios, the mispricings (alphas) are not significant.

Table 4.1 Performance of the CAPM in the Australian stock market

Panel A : Size - Book to market							
		Low 1	2	High	Low 1	2	High
		Alpha			t(Alpha)		
SIZE	Small 1	-0.59	0.40	0.23	-1.56	1.54	0.95
	2	0.10	0.16	0.57	0.54	1.05	3.01**
	Big 3	0.11	0.12	0.38	0.54	0.69	1.56
		β_i(MKT)			$t(\beta_i)$		
	Small 1	1.44	1.23	1.20	14.31**	17.80**	18.37**
	2	1.04	0.99	0.92	21.15**	24.84**	18.19**
	Big 3	1.02	0.96	0.86	19.51**	21.10**	13.17**
Panel B : Size - FFOP							
		Alpha			t(Alpha)		
SIZE	Small 1	-0.27	1.17	1.73	-0.80	3.41**	2.62**
	2	-0.48	0.19	0.09	-1.09	1.14	0.45
	Big 3	-0.38	0.23	0.12	-0.66	1.24	0.59
		β_i(MKT)			$t(\beta_i)$		
	Small 1	1.37	1.20	1.54	15.04**	13.03**	8.76**
	2	1.30	0.88	0.84	11.06**	20.12**	16.00**
	Big 3	1.26	0.82	0.81	8.30**	16.61**	14.55**
Panel C : Size - NMOP							
		Alpha			t(Alpha)		
SIZE	Small 1	-0.30	0.64	0.85	-0.73	2.76**	3.31**
	2	0.25	0.12	0.23	0.88	0.85	1.15
	Big 3	0.30	0.10	0.23	0.93	0.61	1.01
		β_i(MKT)			$t(\beta_i)$		
	Small 1	1.47	1.13	1.04	13.41**	18.17**	15.15**
	2	1.08	1.01	0.89	14.47**	26.30**	16.71**
	Big 3	0.95	0.98	0.86	11.09**	22.67**	14.20**
Panel D : Size - Investment							
		Alpha			t(Alpha)		
SIZE	Small 1	0.10	0.23	-0.01	0.34	0.81	-0.02
	2	0.12	0.11	-0.10	0.64	0.89	-0.45
	Big 3	0.04	0.10	-0.11	0.19	0.73	-0.41
		β_i(MKT)			$t(\beta_i)$		
	Small 1	1.18	1.27	1.41	15.12**	17.01**	15.09**
	2	1.00	1.01	1.05	19.67**	30.32**	17.22**
	Big 3	1.00	0.98	0.95	16.16**	26.07**	12.94**

NOTE:
This table reports the CAPM regression results. Portfolio (size-BM, size-FFOP,size-NMOP and size-investment) returns are regressed on the market factor:

$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+e_{it}$$

where r_{it} is monthly stock return and r_{ft} is the monthly risk free rate. MKT represents the market factor, which is the monthly market excess return. ** and * represent the significance at level 1% and level 5% respectively. Alpha is reported under percentage value.

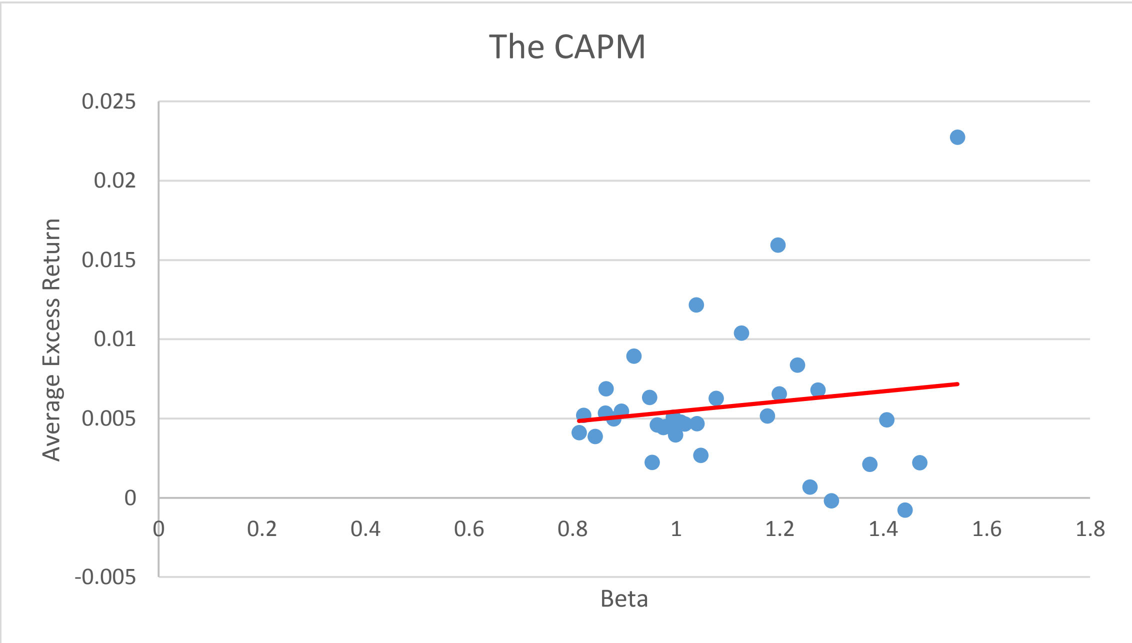
4.1.2 CAPM versus the Three-factor model

This section compares the performance between the CAPM and the three-factor model in the Australian market. Figure 4.1 presents the performance of CAPM graphically. The x-axes represent the risk coefficient, which is the beta, and the y-axes represent the average portfolio returns for nine portfolios under different sorts. Overall, the results for the 36 portfolios are presented on the graph. Recall that the CAPM assigns each stock a "fair" value, as is explained by the Equation 7

$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+e_{it} \tag{7}$$

The r_{it} should be the theoretical "fair" value for the portfolio. This fair return is represented by the red line shown in Figure 4.1 and as can be seen that most of the blue scatter plots do not line on, or even close to the red line. This means the CAPM is not strong enough to capture the portfolio returns here. Hence it is a sign of the CAPM's poor performance.

Figure 4.1: Performance of the CAPM



NOTE:
This graph shows the performance of the CAPM on all the portfolios under size-book to market, FFPMU, NMPMU and investment sorted, with a total of 36 portfolios. The red line represents the "fair" value suggest by the CAPM.

Table 4.2 compares performance between the CAPM and the three-factor model. Panel A of Table 4.2 shows the R^2 for each of the portfolios between the CAPM and the three-factor model. In addition, I report the Wald test statistics in Panel A. ** and * denote the Wald test significance at 1% and 5% level, respectively. Recall that if the Wald test statistic is significant, it means the SMB and HML factor add value in explaining stock returns.

From Panel A we can see that for size-BM portfolios, the CAPM produces an average R^2 around 69.71%, while the three factor model offers higher average R^2 at about 80.94%. This higher R^2 persists in other sorts. The higher R^2's imply that the three-factor model fits the data better than the CAPM. It is evidence that the three-factor model works as a better explanatory model compared to the CAPM. In addition to this, overall, the Wald test statistics on the coefficients of SMB and HML suggest that both factors are useful in explaining stock returns. This reinforces the power of the three-factor model.

Panel B compares the GRS statistics and information ratios between the CAPM and the three-factor model. The GRS test rejects both models with low p-values for size-BM, size-FFOP and size-NMOP portfolios. However, for size-investment portfolios, the p-value is 0.29 for the CAPM and 0.4 for the three-factor model. The high p-value implies that the GRS test cannot reject the CAPM or the three-factor model for size-investment portfolios. In terms of the information ratios, overall, the three-factor model exhibits a lower information ratio compared to the CAPM. The lower information ratios suggest that the thee-factor model is less involved in the tracking error hence it works better than the CAPM in the Australian market.

My findings here are consistent with Fama and French (1993), in that the three-factor model offers a better description of the stock returns. In addition, my findings reinforce the literature in the Australian market. Consistent with Durack et al. (2004), Gaunt (2004) and Brailsford et al. (2012b) my findings suggest the weakness of the CAPM in Australia. Furthermore, my results confirm the power of the three-factor model in Australia.

Table 4.2 The CAPM versus The Three factor model

Panel A: R^2 for CAPM and Three Factor model						
	CAPM			3 Factor Model		
	Low 1	2	3	Low 1	2	High
			Size – Book to market			
Small 1	58.77	68.83	70.18	85.72**	92.12**	91.97**
2	75.74	81.16	69.75	82.17**	83.57**	74.34**
Big 3	72.63	75.65	54.68	79.82**	79.18**	59.54**
			Size - FFOP			
Small 1	61.16	54.14	34.60	87.42**	67.32**	46.89**
2	45.88	73.85	64.08	51.93**	73.83	64.34
Big 3	32.22	65.78	59.55	36.89**	65.76	59.6
			Size - NMOP			
Small 1	55.58	69.72	61.49	85.87**	84.69**	76.85**
2	59.32	82.85	66.06	65.05**	84.29**	66.41
Big 3	46.01	78.20	58.38	48.65**	80.23**	59.17
			Size - Investment			
Small 1	61.40	66.86	61.33	87.67**	89.50**	82.40**
2	72.96	86.52	67.38	72.77	87.98**	68.34*
Big 3	64.54	82.60	53.77	64.63	85.09**	53.78

Panel B : GRS statistics and Information ratios on CAPM and Three factor model			
	GRS	P-Value	IR(α)
		Size - Book to market	
CAPM	3.40	0.00	0.48
3 Factor Model	2.81	0.00	0.45
		Size - FFOP	
CAPM	3.09	0.00	0.46
3 Factor Model	3.13	0.00	0.48
		Size - NMOP	
CAPM	2.26	0.02	0.39
3 Factor Model	2.03	0.04	0.38
		Size - Investment	
CAPM	1.21	0.29	0.29
3 Factor Model	1.06	0.40	0.28

NOTE:
This table shows the R^2, GRS and information ratio statistics for all 9 portfolios for both the CAPM and three factor model under different sorting methods. Panel A reports the R^2 and Wald test statistics for the CAPM and the three-factor model. Panel B reports the GRS statistics and information ratios on the CAPM and the three-factor model.

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ e_{it}$$

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_i + e_{it}$$

r_{it} is monthly portfolio return and r_{ft} is the monthly risk free rate. MKT represents the market factor, which is the monthly market excess return. SMB, HML are the mimicking factors and e_{it} represents the residuals. ** and * represents the significance of the Wald test on SMB and HML at level 1% and level 5% respectively. R^2 is reported under percentage value.

4.2 Performance between the three- and five-factor models

This section discusses the performance of the three- and five-factor models by regressing size-BM (section 4.2.1), size-Fama and French operating profit (section 4.2.2), size-Novy-Marx operating profit (section 4.2.3) and size-investment (section 4.2.4) portfolio returns on three (MKT, SMB and HML) and five factors (MKT, SMB, HML, profitability and investment), respectively. The three-factor model is expressed in Equation 8 and the five-factor models with different profitability factors are expressed in Equation 9 and 10.

$$r_{it}\text{-}r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+h_i HML_i+e_{it} \tag{8}$$

$$r_{it}\text{-}r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+h_i HML_t+p_i FFPMU_t+l_i INV_t+e_{it} \tag{9}$$

$$r_{it}\text{-}r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+h_i HML_t+p_i NMPMU_t+l_i INV_t+e_{it} \tag{10}$$

4.2.1 Performance of nine size and book-to-market (BM) sorted portfolios

Panel A of Table 4.3 regresses the size-BM portfolio returns on the MKT, SMB and HML factors. Looking at Panel A, overall alphas are positive except for small-low BM companies, which is -0.38%. Alphas are significant at 5% level for all low BM companies. These significant alpha for the top left group implies that the three-factor model has a problem explaining returns for small-low BM companies. This finding is consistent with Fama and French (1993, 2015). They suggest that the three-factor model has a problem in explaining returns for the growth companies in U.S, especially for small-low BM companies. My Australian evidence confirms this problem.

Loadings on the market factor decrease with size for all BM groups, for example, for the low BM groups, market risk decreases from 1.18 to 0.97. Small companies have positive loadings on SMB while big companies have negative loadings on SMB. For the HML factor, the low BM (growth) group has negative loading on the HML factor while the high BM (value) group loads positively on HML. Furthermore, the HML factor is statistically significant for all companies with high t-statistics. The high t-statistics suggest the importance of the HML factor.

Panel B and Panel C regress the size-BM portfolio returns on five factors. As expressed in Equation 9 and 10, the five factors are: the MKT, SMB, HML, profitability (Fama and French profitability and Novy-Marx profitability) and INV.

In both Panel B and C, alphas become significant only for the medium-low BM and large-low BM groups. This implies that adding extra factors helps to ease the three-factor's problem on explaining returns for small-low BM (growth) companies. The Australian evidence support Fama and French (2015), where they also suggest that adding extra factors slightly improves the problem with three-factor model in the U.S market.

In the five-factor models, loadings on MKT decrease with size. Small companies load positively, while big companies load negatively on SMB. Low BM (growth) group has negative, while high BM (value) group has positive loadings on the HML. The t-statistic on the HML factor suggests that this factor is significant for size-BM portfolios. All companies have negative exposure to the investment factor (INV) and there is no clear pattern in terms of the two profitability factors.

In short, for size and book-to-market sorted portfolios, consistent with Fama and French (1993, 2015), the Australian evidence shows that the three-factor model has a problem explaining returns for the small-low BM (growth) companies. Alternatively, adding extra two factors helps reducing this problem. The HML factor is significant in both five-factor models for size-BM portfolios.

Table 4.3 Performance of nine Size and Book-to-market sorted portfolios

		Panel A : Three Factor Model					
		Low 1	2	High	Low 1	2	High
		Alpha			t(Alpha)		
	Small 1	-0.38	0.28	0.03	-1.69*	2.12*	0.20
	2	0.34	0.08	0.38	2.09*	0.59	2.16*
	Big 3	0.35	0.05	0.20	2.06*	0.29	0.83
		MKT(β_i)			t(β_i)		
	Small 1	1.18	1.10	1.11	19.08**	30.38**	31.43**
	2	0.99	1.05	0.97	22.43**	26.86**	20.04**
	Big 3	0.97	1.03	0.94	20.77**	23.29**	14.50**
SIZE		SMB(s_i)			t(s_i)		
	Small 1	0.87	0.74	0.69	14.04**	20.51**	19.49**
	2	-0.10	-0.13	0.03	-2.28*	-3.22**	0.65
	Big 3	-0.14	-0.17	-0.05	-3.08**	-3.86**	-0.82
		HML(h_i)			t(h_i)		
	Small 1	-0.30	0.22	0.37	-3.97**	4.99**	8.37**
	2	-0.40	0.12	0.31	-7.29**	2.41*	5.15**
	Big 3	-0.42	0.11	0.31	-7.19**	2.05*	3.85**

		Panel B : Five Factor model with FFPMU					
		Low 1	2	High	Low 1	2	High
		Alpha			t(Alpha)		
	Small 1	-0.20	0.34	0.01	-0.89	2.53*	0.09
	2	0.37	0.01	0.40	2.18*	0.10	2.15*
	Big 3	0.36	-0.03	0.29	2.03*	-0.17	1.20
		MKT(β_i)			t(β_i)		
	Small 1	1.12	1.08	1.11	17.89**	28.87**	30.05**
	2	0.98	1.06	0.97	21.15**	26.42**	18.92**
	Big 3	0.96	1.04	0.91	19.65**	22.94**	13.41**
		SMB(s_i)			t(s_i)		
	Small 1	0.81	0.72	0.69	12.79**	19.16**	18.57**
	2	-0.11	-0.10	0.03	-2.35*	-2.52*	0.52
	Big 3	-0.15	-0.14	-0.09	-2.96**	-3.15**	-1.26
SIZE		HML(h_i)			t(h_i)		
	Small 1	-0.25	0.25	0.37	-3.37**	5.47**	8.34**
	2	-0.38	0.12	0.32	-6.90**	2.38**	5.18**
	Big 3	-0.41	0.11	0.33	-6.87**	2.03**	4.08**
		FFPMU(f_i)			t(f_i)		
	Small 1	-0.10	-0.03	0.02	-2.27*	-1.05	0.77
	2	-0.01	0.06	0.00	-0.27	2.16*	-0.04
	Big 3	0.00	0.07	-0.06	0.06	2.11*	-1.21
		INV(I_i)			t(I_i)		
	Small 1	-0.18	-0.10	-0.06	-2.34*	-2.20*	-1.25
	2	-0.07	-0.06	-0.05	-1.18	-1.20	-0.86
	Big 3	-0.05	-0.07	-0.08	-0.79	-1.25	-0.98

Table 4.3 Continued

		Panel C : Five Factor model with NMPMU					
		Low 1	2	High	Low 1	2	High
		Alpha				t(Alpha)	
	Small 1	-0.24	0.31	0.01	-1.12	2.32*	0.09
	2	0.30	0.11	0.44	1.87*	0.79	2.45*
	Big 3	0.30	0.08	0.25	1.80*	0.51	1.02
		MKT(β_i)				t(β_i)	
	Small 1	1.07	1.09	1.13	16.11**	27.00**	28.66**
	2	1.03	1.02	0.92	21.36**	23.32**	17.05**
	Big 3	1.02	1.00	0.90	19.91**	20.13**	12.36**
		SMB(s_i)				t(s_i)	
	Small 1	0.60	0.73	0.76	6.11**	12.18**	12.88**
	2	0.04	-0.18	-0.08	0.61	-2.73**	-1.05
	Big 3	0.02	-0.23	-0.14	0.21	-3.17**	-1.26
SIZE		HML(h_i)				t(h_i)	
	Small 1	-0.30	0.24	0.38	-3.98**	5.33**	8.63**
	2	-0.37	0.12	0.31	-6.79**	2.44*	5.04**
	Big 3	-0.39	0.12	0.32	-6.74**	2.08*	3.86**
		NMPMU(n_i)				t(n_i)	
	Small 1	-0.36	0.00	0.11	-3.16**	-0.06	1.57
	2	0.22	-0.07	-0.16	2.59**	-0.93	-1.73*
	Big 3	0.24	-0.09	-0.11	2.66**	-1.00	-0.87
		INV(l_i)				t(l_i)	
	Small 1	-0.19	-0.11	-0.05	-2.57*	-2.29*	-1.21
	2	-0.07	-0.05	-0.05	-1.25	-1.00	-0.87
	Big 3	-0.05	-0.06	-0.09	-0.82	-1.04	-1.08

NOTE:

This table shows three-factor and five-factor regression results for all nine portfolios under size and book-to-market sorted. For the three-factor model, size-BM portfolio returns are regressed on the market, SMB and HML factors. For the five factors, size-BM portfolio returns are regressed on the market, SMB, HML, profitability (FFPMU, NMPMU) and investment factors. Panel A shows the regression results for three-factor model, Panel B shows the results statistics for five factor model with FFPMU and Panel C shows the regression results for five factor model with NMPMU.

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_i + e_{it}$$

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_t +f_i FFPMU_t + l_i INV_t+ e_{it}$$

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_t +n_i NMPMU_t + l_i INV_t+ e_{it}$$

r_{it} is monthly size-BM portfolio return and r_{ft} is the monthly risk free rate. MKT represents the market factor, which is the monthly market excess return. SMB, HML, FFPMU, NMPMU and INV are the mimicking factors and e_{it} is the regression residual. ** and * represent the significance at level 1% and level 5% respectively. Alpha is reported under percentage value.

4.2.2 Performance of nine Size and Fama and French operating profit (FFOP) sorted portfolios

Panel A of Table 4.4 regresses the size-FFOP portfolio returns on the MKT, SMB and HML factors. Looking at the alphas in Panel A, consistent with Fama and French (2015), sorting stocks based on the profitability ratio reduced the three-factor's problem on the extremely small-unprofitable companies. Only two out of all nine alphas are significant, which belong to small-medium profitable and small- highly profitable groups. All portfolios are positively related to the market. For small and medium sized companies, loadings on the market decrease with profitability. Loadings on the market and the SMB factor decrease with size. For medium and profitable firms, small (large) companies load positively (negatively) on SMB. Loadings on the HML also decrease with size, small (large) companies load positively (negatively) on the HML factor. However, for size-FFOP portfolios, only one HML factor is significant at the 5% level.

Panel B and Panel C regress the size-Fama and French operating profit (FFOP) portfolio returns on the MKT, SMB, HML, profitability (Fama and French profitability and Novy-Marx profitability) and INV factors.

Looking at the alphas, only two alphas are significant regardless the usage of the profitability factor. The significant alphas all belong to small groups. Portfolio returns are positively related to market and loadings on the market factor decrease with size. For the loadings on the profitability factors, in Panel B of Table 4.4, while unprofitable companies load negatively, profitable firms load positively on the Fama and French Profitable minus unprofitable factor (FFPMU). The results match the way in building the profitability factor. In Panel C, if the Novy-Marx profitable minus unprofitable factor (NMPMU) is used in the model, the pattern that unprofitable companies load negatively, profitable firms load positively on the NMPMU factor can only be observed for small companies.

For size-FFOP portfolios, if the FFPMU factor is used in the five-factor model, t-statistics suggest that only three out of nine HML factors are statistically significant at the 5% level. On the other hand, if the NMPMU factor is used in the five-factor model, the HML factor becomes not significant.

In sum, for portfolios that are sorted by size and Fama and French operating profit (FFOP), alphas for extremely small-unprofitable companies are no longer significant. This implies that sorting stocks based on size and Fama and French operating profit helps to ease the problem associated with the three-factor model in regard to explaining the returns for these extremely small-unprofitable companies. However, for the size-FFOP portfolios, the HML factor seems not to be significant. This problem somehow reflects Fama and French (2015), where they argue that the HML factor might be redundant. The Australian evidence shows that this problem appears if stocks are sorted by size and FFOP. However, using this evidence alone is not strong enough to determine if the HML factor is redundant in the Australian market. The next section examines the model performance for portfolios that are sorted by size and Novy-Marx operating profit.

Table 4.4 Performance of nine Size and Fama and French profitability (FFOP) sorted portfolios

Panel A : Three-factor Model							
		Low 1	2	High	Low 1	2	High
		Alpha				t(Alpha)	
	Small 1	-0.32	1.19	1.98	-1.60	4.01**	3.27**
	2	-0.44	0.23	0.15	-1.03	1.37	0.76
	Big 3	-0.21	0.28	0.19	-0.38	1.48	0.87
		MKT(β_i)				t(β_i)	
	Small 1	1.18	1.06	1.28	21.79 **	13.08**	7.74**
	2	1.18	0.86	0.82	10.20**	18.95**	14.97**
	Big 3	1.11	0.81	0.80	7.29**	15.78**	13.68**
SIZE		SMB(s_i)				t(s_i)	
	Small 1	0.91	0.59	0.79	16.90**	7.32**	4.75**
	2	0.48	0.01	0.01	4.13**	0.20	0.26
	Big 3	0.41	-0.04	-0.02	2.72**	-0.75	-0.32
		HML(h_i)				t(h_i)	
	Small 1	0.11	-0.01	-0.40	1.62	-0.08	-1.93*
	2	-0.05	-0.07	-0.11	-0.36	-1.22	-1.57
	Big 3	-0.25	-0.09	-0.11	-1.35	-1.34	-1.47

Panel B : Five-factor model with FFPMU							
		Alpha				t(Alpha)	
	Small 1	-0.05	1.02	1.78	-0.29	3.36**	2.86**
	2	0.28	0.08	0.01	0.74	0.50	0.06
	Big 3	0.54	0.11	0.04	1.02	0.60	0.18
		MKT(β_i)				t(β_i)	
	Small 1	1.10	1.10	1.33	21.03**	13.23**	7.77**
	2	0.97	0.90	0.86	9.25**	19.58**	15.30**
	Big 3	0.89	0.86	0.84	6.09**	16.53**	14.04**
		SMB(s_i)				t(s_i)	
	Small 1	0.83	0.65	0.85	15.67**	7.71**	4.96**
	2	0.24	0.06	0.06	2.27*	1.23	1.08
	Big 3	0.16	0.02	0.03	1.11	0.32	0.50
SIZE		HML(h_i)				t(h_i)	
	Small 1	0.16	-0.02	-0.37	2.46*	-0.17	-1.79*
	2	0.06	-0.09	-0.12	0.47	-1.54	-1.77*
	Big 3	-0.15	-0.10	-0.12	-0.83	-1.63	-1.62
		FFPMU(f_i)				t(f_i)	
	Small 1	-0.17	0.14	0.21	-4.86**	2.41*	1.83*
	2	-0.49	0.11	0.11	-6.91**	3.36**	2.82**
	Big 3	-0.53	0.13	0.12	-5.33**	3.55**	2.85**
		INV(I_i)				t(I_i)	
	Small 1	-0.08	-0.09	-0.38	-1.24	-0.90	-1.82*
	2	-0.11	-0.02	-0.04	-0.83	-0.31	-0.61
	Big 3	-0.04	-0.04	-0.06	-0.21	-0.64	-0.87

Table 4.4 Continued

		Panel C : Five-factor model with NMPMU					
		Low 1	2	High	Low 1	2	High
			Alpha			t(Alpha)	
	Small 1	-0.23	1.12	1.91	-1.17	3.78**	3.16**
	2	-0.41	0.16	0.07	-0.95	0.97	0.38
	Big 3	-0.25	0.21	0.11	-0.43	1.11	0.50
			MKT(β_i)			t(β_i)	
	Small 1	1.11	1.14	1.41	18.55**	12.64**	7.68**
	2	1.17	0.93	0.90	9.02**	18.72**	15.08**
	Big 3	1.16	0.89	0.88	6.75**	15.82**	13.96**
			SMB(s_i)			t(s_i)	
	Small 1	0.74	0.82	1.20	8.34**	6.13**	4.38**
	2	0.50	0.20	0.24	2.61*	2.66*	2.72**
	Big 3	0.57	0.18	0.23	2.24*	2.09*	2.43*
SIZE			HML(h_i)			t(h_i)	
	Small 1	0.11	0.03	-0.29	1.64	0.28	-1.40
	2	-0.01	-0.05	-0.08	-0.10	-0.88	-1.17
	Big 3	-0.22	-0.06	-0.07	-1.11	-0.94	-1.01
			NMPMU(n_i)			t(n_i)	
	Small 1	-0.24	0.34	0.63	-2.31*	2.19*	2.00*
	2	0.06	0.27	0.33	0.28	3.17**	3.23**
	Big 3	0.24	0.31	0.36	0.83	3.21**	3.34**
			INV(l_i)			t(l_i)	
	Small 1	-0.11	-0.07	-0.35	-1.57	-0.69	-1.69*
	2	-0.19	0.00	-0.03	-1.25	-0.03	-0.39
	Big 3	-0.12	-0.02	-0.05	-0.63	-0.34	-0.65

NOTE:

This table shows three-factor and five-factor regression results for all nine portfolios under size and Fama and French operating profit (FFOP) sorted. For the three-factor model, size-FFOP portfolio returns are regressed on the market, SMB and HML factors. For the five factors, size-FFOP portfolio returns are regressed on the market, SMB, HML, profitability (FFPMU, NMPMU) and investment factors. Panel A shows the regression results for three factor model, Panel B shows the regression results for five factor model with FFPMU and Panel C shows the regression results for five factor model with NMPMU.

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_i + e_{it}$$

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_t +f_i FFPMU_t + l_i INV_t+ e_{it}$$

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_t +n_i NMPMU_t + l_i INV_t+ e_{it}$$

r_{it} is the monthly size-FFOP portfolio return and r_{ft} is the monthly risk free rate. MKT represents the market factor, which is the monthly market excess return. e_{it} is the residual. SMB, HML, FFPMU, NMPMU and INV are the mimicking factors. ** and * represent the significance at level 1% and level 5% respectively. Alpha is reported under percentage value.

4.2.3 Performance of nine Size and Novy-Marx operating profit (NMOP) sorted portfolios

Panel A of Table 4.5 regresses the size-NMOP portfolio returns on the MKT, SMB and HML factors. Similar to our observations for size-Fama and French operating profit portfolios, sorting stocks based on size and Novy-Marx operating profit can also help easing the three-factor's problem in regard to explaining the returns for extremely small companies.In Panel A of Table 4.5, alpha for extremely small-unprofitable companies are not significant. Portfolio returns are positively related to the market and loadings on the market factor decrease with size and Novy-Marx profitability factor. Small companies load positively, while large companies load negatively on the SMB factor. But this pattern cannot be observed for the unprofitable companies. For the unprofitable companies, both small and large companies are positively related to the SMB, with coefficients of 1.08 and 0.21, which are statistically significant. Although this relationship does not apply to every company, we can still observe the deceasing loadings on SMB as we increase size in each profitability group. In terms of the HML factor, small (large) companies load positively (negatively) on the HML factor. Overall, t-statistics on the HML factors suggest that this factor is still significant in the three-factor model for size-NMOP portfolios.

Panel B and C of Table 4.5 regress the size and Novy-Marx operating profit portfolio returns against the MKT, SMB, HML, profitability (FFPMU and NMPMU) and INV factors. Looking through Panel B, for medium and profitable groups, small (large) companies are positively (negatively) loaded on the SMB. However, for the unprofitable group, both small and large companies load positively on the SMB, with corresponding coefficients of 0.97 and 0.16 respectively. The t-statistics suggest these coefficients are significant. Small (large) companies are positively (negatively) loaded on the HML factor. The t-statistics on the HML factor suggest the significance of this factor. Profitable (unprofitable) firms are positively (negatively) loaded on the Fama and French profitability factor (FFPMU). Most companies are negatively loaded on the INV factor with the exception of the medium-unprofitable and large-unprofitable companies.

In Panel C, all portfolios are positively related to SMB, which seems to be unusual. However we can still observe the decreasing loadings on the SMB factor as we move from small to large companies. Small (large) companies load positively (negatively) on HML and profitable (unprofitable) firms load positively (negatively) on NMPMU. The t-statistics suggest the significance of the HML factor for the portfolios, which are sorted on size and Novy-Marx operating profit. There is no clear pattern in terms of the INV factor.

To summarize, for size-Novy-Marx operating profit portfolios, alphas is not significant for the extremely small-unprofitable companies. This suggests that using a size-NMOP sort eases the three-factor model's mispricing problem. The t-statistics on the HML factor suggest the importance of the HML factor for size-NMOP portfolios. This is in contradiction to the findings on the HML factor for size-Fama and French operating profit portfolios, where the HML factor seems to be less significant. The findings from size-Novy-Marx operating profit portfolios suggest that the HML might be definition sensitive. Further investigations on the HML factor are necessary.

Table 4.5 Performance of nine Size and Novy-Marx Profitability (NMOP) sorted portfolios

Panel A : Three-factor Model							
		Low 1	2	High	Low 1	2	High
		Alpha			t(Alpha)		
	Small 1	-0.29	0.56	0.73	-1.23	3.30**	3.61**
	2	0.31	0.23	0.27	1.17	1.62	1.32
	Big 3	0.37	0.23	0.28	1.15	1.45	1.20
		MKT(β_i)			t(β_i)		
	Small 1	1.22	1.03	0.95	18.97**	22.43**	17.19**
	2	0.99	0.97	0.90	13.71**	25.47**	16.30**
	Big 3	0.88	0.94	0.88	10.09**	22.05**	13.98**
SIZE		SMB(s_i)			t(s_i)		
	Small 1	1.08	0.54	0.54	16.82**	11.84**	9.81**
	2	0.32	0.00	-0.10	4.40**	0.00	-1.79*
	Big 3	0.21	-0.04	-0.13	2.47*	-0.86	-2.13*
		HML(h_i)			t(h_i)		
	Small 1	0.03	0.16	0.21	0.37	2.84**	3.06**
	2	-0.09	-0.18	-0.07	-1.01	-3.70**	-0.99
	Big 3	-0.10	-0.21	-0.09	-0.97	-4.06**	-1.10

Panel B : Five-factor model with FFPMU							
		Low 1	2	High	Low 1	2	High
		Alpha			t(Alpha)		
	Small 1	0.06	0.40	0.57	0.29	2.42*	2.76**
	2	0.55	0.21	0.09	2.09*	1.43	0.46
	Big 3	0.54	0.21	0.06	1.65	1.29	0.28
		MKT(β_i)			t(β_i)		
	Small 1	1.11	1.07	1.00	18.49**	23.27**	17.70**
	2	0.92	0.98	0.95	12.67**	24.42**	16.93**
	Big 3	0.83	0.94	0.94	9.35**	21.15**	14.82**
		SMB(s_i)			t(s_i)		
	Small 1	0.97	0.59	0.60	15.92**	12.79**	10.50**
	2	0.24	0.01	-0.04	3.23**	0.17	-0.73
	Big 3	0.16	-0.03	-0.06	1.76*	-0.69	-0.98
SIZE		HML(h_i)			t(h_i)		
	Small 1	0.11	0.15	0.19	1.46	2.70**	2.77**
	2	-0.06	-0.17	-0.09	-0.74	-3.50**	-1.32
	Big 3	-0.11	-0.21	-0.11	-0.98	-3.82**	-1.46
		FFPMU(f_i)			t(f_i)		
	Small 1	-0.22	0.12	0.12	-5.25**	3.76**	3.10**
	2	-0.18	0.02	0.13	-3.67**	0.91	3.28**
	Big 3	-0.15	0.03	0.15	-2.45*	0.85	3.57**
		INV(I_i)			t(I_i)		
	Small 1	-0.21	-0.06	-0.01	-2.77**	-1.09	-0.10
	2	0.05	-0.06	-0.01	0.54	-1.24	-0.16
	Big 3	0.17	-0.08	-0.01	1.53	-1.43	-0.18

Table 4.5 Continued

		Panel C: Five-factor model with NMPMU					
		Low 1	2	High	Low 1	2	High
		Alpha				t(Alpha)	
	Small 1	-0.06	0.46	0.62	-0.30	2.92**	3.18**
	2	0.36	0.17	0.14	1.37	1.28	0.75
	Big 3	0.38	0.17	0.14	1.19	1.13	0.63
		MKT(β_i)				t(β_i)	
	Small 1	1.02	1.14	1.07	16.38**	23.95**	18.28**
	2	0.93	1.04	1.03	11.49**	25.22**	17.68**
	Big 3	0.84	1.01	1.02	8.64**	22.01**	15.47**
		SMB(s_i)				t(s_i)	
	Small 1	0.60	0.84	0.86	6.43**	11.85**	9.86**
	2	0.15	0.18	0.24	1.26	2.94**	2.71**
	Big 3	0.09	0.16	0.24	0.61	2.35*	2.49*
SIZE		HML(h_i)				t(h_i)	
	Small 1	0.02	0.20	0.24	0.33	3.74**	3.65**
	2	-0.11	-0.15	-0.04	-1.22	-3.16**	-0.54
	Big 3	-0.14	-0.18	-0.05	-1.31	-3.50**	-0.65
		NMPMU(n_i)				t(n_i)	
	Small 1	-0.67	0.43	0.46	-6.23**	5.26**	4.53**
	2	-0.24	0.27	0.48	-1.73*	3.76**	4.81**
	Big 3	-0.20	0.29	0.54	-1.18	3.72**	4.80**
		INV(l_i)				t(l_i)	
	Small 1	-0.24	-0.04	0.01	-3.32**	-0.82	0.15
	2	0.02	-0.06	0.01	0.22	-1.24	0.11
	Big 3	0.14	-0.08	0.01	1.30	-1.44	0.12

NOTE:

This table shows three-factor and five-factor regression results for all nine portfolios under size and Novy-Marx operating profit (NMOP) sorted. For the three-factor model, size-NMOP portfolio returns are regressed on the market, SMB and HML factors. For the five factors, size-NMOP portfolio returns are regressed on the market, SMB, HML, profitability (FFPMU, NMPMU) and investment factors. Panel A shows the regression results for three factor model, Panel B shows the regression results for five factor model with FFPMU and Panel C shows the regression results for five factor model with NMPMU.

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_i + e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_t +f_i FFPMU_t + l_i INV_t+ e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_t +n_i NMPMU_t + l_i INV_t+ e_{it}$$

r_{it} is monthly size-NMOP portfolio return and r_f is the monthly risk free rate. MKT represents the market factor, which is the monthly market excess return. SMB, HML, FFPMU, NMPMU and INV are the mimicking factors. ** and * represents the significance at level 1% and level 5% respectively. Alpha is reported under percentage value.

4.2.4 Performance of nine size and Investment sorted portfolios

Panel A of Table 4.6 regresses the size-investment portfolio returns on the MKT, SMB and HML factor. As expressed in in Equation 8:

$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+h_i HML_i+e_{it} \tag{8}$$

where r_{it} is the size-investment portfolio return, r_{ft} is the risk free rate of return and e_{it} represents the regression residual.

Panel A of Table 4.6 shows the alphas are not significant for any groups. This suggests that allocating portfolios based on size and investment might be a good choice in terms of avoiding mispricing. Loadings on the market decrease with size. For low and medium investment groups, small (large) companies have positive (negative) loadings on SMB. Small companies are positively, while large companies are loaded on HML. However, for size-investment portfolios, only one HML factor is statistically significant in the three-factor model.

Panel B and Panel C regress the size and investment portfolio returns on five factors. As expressed in Equation 9 and 10, the five factors include the MKT, SMB, HML, profitability (FFPMU, NMPMU) and INV.

$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+h_i HML_t+f_i FFPMU_t+l_i INV_t+e_{it} \tag{9}$$

$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+h_i HML_t+n_i NMPMU_t+l_i INV_t+e_{it} \tag{10}$$

where r_{it} is the size-investment portfolio return, r_{ft} is the risk free rate of return and e_{it} represents the regression residual.

In Panel B, small (large) companies load positively (negatively) on the HML factor for companies with low and medium investment. For companies with high investment, both small and large companies load positively on the HML. The t-statistics on the HML factor suggest that the HML factor is still reasonable significant in the five-factor model for size-investment portfolios. Looking at the INV factor, the high t-statistics suggest that the INV factor becomes significant for every group for size-investment portfolios. We can observe a similar pattern for the HML factor in Panel C. This suggests that, for size-investment portfolios, regardless of the definitions of the profitability factor, the HML factor is still useful in the five-factor model.

In short, forming portfolios based on size and investment produces smallest number of significant alpha. This suggests that in terms of pricing errors, sorting stocks based on size and investment might be a good choice.

To summarize this section, the five-factor model helps to ease the problem associated with the three-factor model's problem in regard to explaining the returns on extremely small-low BM or small-unprofitable companies. This is evidence that the five-factor model works better than the three-factor model in the Australian market. The Australian evidence on the HML factor suggests that overall the HML factor is significant with additional profitability and investment factors. However the five-factor model might be definition sensitive.

Table 4.6 Performance of nine Size and Investment sorted portfolios

Panel A : Three Factor Model

		Low 1	2	High	Low 1	2	High
		Alpha			t(alpha)		
	Small 1	-0.03	0.19	0.01	-0.17	1.21	0.03
	2	0.14	0.14	-0.03	0.73	1.18	-0.13
	Big 3	0.07	0.14	-0.06	0.30	1.06	-0.21
		MKT(β_i)			t(β_i)		
	Small 1	1.04	1.11	1.22	22.63**	25.36**	18.55**
	2	1.00	1.03	1.00	18.89**	31.48**	16.06**
	Big 3	1.01	1.01	0.92	15.74**	27.83**	12.01**
SIZE		SMB(s_i)			t(s_i)		
	Small 1	0.80	0.75	0.82	17.43**	17.16**	12.55**
	2	-0.05	-0.14	0.09	-0.95	-4.38**	1.48
	Big 3	-0.10	-0.18	0.06	-1.53	-5.07**	0.73
		HML(h_i)			t(h_i)		
	Small 1	0.25	0.08	0.01	4.33**	1.56	0.11
	2	-0.04	-0.06	-0.12	-0.57	-1.39	-1.49
	Big 3	-0.05	-0.07	-0.09	-0.60	-1.53	-0.95

Panel B : Five Factor model with FFPMU

		Alpha			t(Alpha)		
	Small 1	0.02	0.30	0.32	0.12	1.94*	1.46
	2	0.07	0.12	0.20	0.35	1.00	1.02
	Big 3	0.02	0.10	0.18	0.09	0.74	0.71
		MKT(β_i)			t(β_i)		
	Small 1	1.03	1.07	1.11	22.05**	25.39**	18.66**
	2	1.03	1.03	0.92	20.13**	32.15**	16.72**
	Big 3	1.04	1.02	0.83	16.40**	28.46**	11.73**
		SMB(s_i)			t(s_i)		
	Small 1	0.78	0.72	0.72	16.62**	16.86**	11.99**
	2	-0.02	-0.13	0.02	-0.48	-4.16**	0.28
	Big 3	-0.08	-0.17	-0.02	-1.29	-4.69**	-0.34
SIZE		HML(h_i)			t(h_i)		
	Small 1	0.23	0.14	0.11	4.10**	2.66*	1.49
	2	-0.09	-0.04	-0.01	-1.48	-0.93	-0.22
	Big 3	-0.10	-0.05	0.02	-1.36	-1.17	0.20
		FFPMU(f_i)			t(f_i)		
	Small 1	-0.06	-0.03	-0.15	-1.97	-0.96	-3.66**
	2	0.00	0.05	-0.08	-0.01	2.19*	-2.12*
	Big 3	-0.03	0.06	-0.08	-0.59	2.54*	-1.64*
		INV(I_i)			t(I_i)		
	Small 1	0.15	-0.26	-0.41	2.70**	-5.05**	-5.52**
	2	0.32	-0.17	-0.49	5.00**	-4.31**	-7.31**
	Big 3	0.35	-0.17	-0.53	4.48**	-3.96**	-6.10**

Table 4.6 Continued

		Panel C : Five Factor model with NMPMU					
		Low 1	2	High	Low 1	2	High
		Alpha				t(Alpha)	
	Small 1	-0.03	0.27	0.15	-0.18	1.79*	0.70
	2	0.04	0.18	0.13	0.20	1.59	0.67
	Big 3	-0.04	0.18	0.13	-0.18	1.42	0.52
		MKT(β_i)				t(β_i)	
	Small 1	1.02	1.08	1.13	20.20**	23.62**	16.96**
	2	1.06	1.01	0.91	19.38**	28.83**	15.32**
	Big 3	1.08	0.99	0.81	15.81**	25.20**	10.59**
		SMB(s_i)				t(s_i)	
	Small 1	0.71	0.71	0.68	9.51**	10.44**	6.84**
	2	0.05	-0.16	-0.05	0.67	-3.10**	-0.58
	Big 3	0.00	-0.20	-0.14	-0.01	-3.50**	-1.25
SIZE		HML(h_i)				t(h_i)	
	Small 1	0.21	0.13	0.07	3.72**	2.51*	0.96
	2	-0.08	-0.03	-0.04	-1.36	-0.73	-0.57
	Big 3	-0.10	-0.04	-0.01	-1.32	-0.93	-0.13
		NMPMU(n_i)				t(n_i)	
	Small 1	-0.14	-0.03	-0.16	-1.61	-0.43	-1.38
	2	0.12	-0.01	-0.15	1.22	-0.13	-1.45
	Big 3	0.10	-0.01	-0.22	0.86	-0.17	-1.70*
		INV(l_i)				t(l_i)	
	Small 1	0.15	-0.27	-0.43	2.53*	-5.14**	-5.63**
	2	0.32	-0.16	-0.51	5.04**	-4.06**	-7.46**
	Big 3	0.35	-0.16	-0.54	4.45**	-3.66**	-6.26**

NOTE:
This table shows three-factor and five-factor regression results for all nine portfolios under size and investment sorted. For the three-factor model, size- investment portfolio returns are regressed on the market, SMB and HML factors. For the five factors, size- investment portfolio returns are regressed on the market, SMB, HML, profitability (FFPMU, NMPMU) and investment factors. Panel A shows the regression results for three factor model, Panel B shows the regression results for five factor model with FFPMU and Panel C shows the regression results for five factor model with NMPMU.

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_i + e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_t +f_i FFPMU_t + l_i INV_t+ e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_t +n_i NMPMU_t + l_i INV_t+ e_{it}$$

r_{it} is monthly size-investment portfolio return and r_f is the monthly risk free rate. MKT represents the market factor, which is the monthly market excess return. SMB, HML, FFPMU, NMPMU and INV are the mimicking factors. ** and * represent the significance at level 1% and level 5% respectively. Alpha is reported under percentage value.

4.3 Three-factor model versus Five-factor model

4.3.1 Goodness of fit between models

To assess the goodness of fit of the three- and five-factor models, I compute the R^2 for each model from the regressions. Table 4.7 reports the R^2 statistics for the three-and five-factor models. In addition, the Wald test statistics on the five-factor models are also reported. ** and * denote the Wald test significance at 1% and 5% level, respectively. Recall that the null hypothesis for the Wald test is that the testing coefficients are jointly equal to zero. If the test statistics can successfully reject this null hypothesis, it is evidence that the factors are useful explanatory factors. In this section, the Wald test is conducted for the coefficients on profitability and investment factors.

As can be seen, in Table 4.7, for small companies, R^2's range from 85% to 90% and for large companies, R^2's range from 53% to 65%. These results suggest that all of the models fit better in the small groups than the large groups. Next, for size-BM portfolios, the three-factor model produces an average R^2 of 80.94%. If the Fama and French profitable minus unprofitable (FFPMU) factor is used, the five-factor model produces an average R^2 of 81.14%. If the Novy-Marx profitable minus unprofitable (NMPMU) factor is employed, the five-factor model produces an average R^2 of 81.33%. The higher average R^2's imply that the five-factor model has better goodness of fit than the three-factor model for size-BM portfolios. The Wald test statistics suggest that overall, profitability and investment factors are useful in the five-factor model.

Looking though Table 4.7, for size-Fama and French operating profit (FFOP) portfolios, using the FFPMU factor in the five-factor model produces highest average R^2 of 65.35%. For size-Novy-Marx operating profit portfolios, using the FFPMU factor in the five-factor model still produces highest average R^2, at 81.07%. The highest R^2 from using the FFPMU factor persists in the size-investment portfolios. Overall, the three-factor model produces an average R^2 of 72.94% across sorts, while the five-factor models produce average R^2's of 75.39% and 74.93% with FFPMU and NMPMU, respectively.

These results suggest that the five-factor model is superior to the three-factor model in terms of goodness of fit. In addition, the Wald test on the coefficients of the profitability and investment factor reinforces the power of the five-factor model by suggesting the usefulness of the profitability and investment factors. In support of Fama and French (2015), the Australian evidence also suggests that adding factors produces higher goodness of fit.

4.3.2 GRS Statistics and Information ratios

Recall that the GRS test statistic is conducted on the intercepts from test portfolios. The intercepts measure the magnitude in terms of mispricing for different models. The GRS test thus enables investors to judge the power of the asset pricing models. Information ratio is calculated based on the alphas and residuals, the lower the information ratio, the better the model.

Table 4.8 reports the GRS statistics and the information ratios for the three- and five-factor models. For size-BM portfolios, all models are rejected by the GRS test with extremely low p-values (0 for the three-factor model and 0.01 for the five-factor model). However the information ratios still provide some judging powers between models. The three-factor model produces the lowest information ratio at 0.451. This means that for size-BM portfolios, the three-factor model performs the best. For size-Fama and French operating profit (FFOP) portfolios, again, all models are rejected by the GRS test. The five-factor model with Fama and French profitable minus unprofitable (FFPMU) factor performs the best with the lowest information ratio of 0.397. For size and Novy-Marx operating profit (NMOP) portfolios, the three-factor model is rejected by the GRS test. Even so, the GRS test cannot reject the five-factor models with high p-values at 0.19 and 0.08, respectively. Using the FFPMU factor produces lowest information ratio of 0.334, suggesting that the five-factor model is superior to and surpasses the three-factor model.

The GRS test cannot reject any model for size-investment portfolios. The three-factor model exhibits a p-value of 0.4. The five-factor model exhibits a p-value of 0.66 with the Fama and French profitable minus unprofitable (FFPMU) factor and exhibits a p-value of 0.46 with the

Novy-Marx profitable minus unprofitable (NMPMU) factor. These p-values show weak evidence to reject these models. In addition, the five-factor model with the FFPMU factor performs the best by producing the lowest information ratio, at 0.244.

Table 4.7 The Three- versus the Five-factor model (1)

	Three-Factor Model				Five-Factor Model FFPMU				Five-Factor Model NMPMU		
	Low 1	2	High		Low 1	2	High		Low 1	2	High
					Size - Book to market						
Small 1	85.72	92.12	91.97	Small 1	86.64**	92.36**	91.97	Small 1	87.08**	92.30	92.07
2	82.17	83.57	74.34	2	82.10	83.99	74.11	2	82.92**	83.56	74.66
Big 3	79.82	79.18	59.54	Big 3	79.62	79.70	59.73	Big 3	80.62**	79.20	59.52
					Size - FFOP						
Small 1	87.42	67.32	46.89	Small 1	89.29**	68.29**	48.41**	Small 1	87.92**	68.06	48.65**
2	51.93	73.83	64.34	2	64.17**	75.46**	65.83**	2	51.80	75.25**	66.40**
Big 3	36.89	65.76	59.60	Big 3	47.07**	68.19**	61.41**	Big 3	36.47	67.71**	62.18**
					Size - NMOP						
Small 1	85.87	84.69	76.85	Small 1	88.76**	85.96**	78.04**	Small 1	89.48**	87.1**	79.56**
2	65.05	84.29	66.41	2	67.71**	84.31	68.39**	2	65.31	85.68**	70.82**
Big 3	48.65	80.23	59.17	Big 3	50.67**	80.31	62.09**	Big 3	49.04	82.01**	64.51**
					Size - Investment						
Small 1	87.67	89.50	82.40	Small 1	88.36**	91.12**	86.74**	Small 1	88.25**	91.07**	85.65**
2	72.77	87.98	68.34	2	76.64**	89.47**	77.74**	2	76.89**	89.11**	77.36**
Big 3	64.63	85.09	53.78	Big 3	68.68**	86.83**	64.05**	Big 3	68.77**	86.21**	64.09**

NOTE:
This table shows R^2 statistics for all models and it also reports the Wald test statistics on the two five factor models.

$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+h_i HML_i+e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+h_i HML_t+f_i FFPMU_t+l_i INV_t+e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+h_i HML_t+n_i NMPMU_t+l_i INV_t+e_{it}$$

r_{it} is monthly portfolio (size-BM, size-FFOP, size-NMOP and size-investment) return and r_f is the monthly risk free rate. MKT represents the market factor, which is the monthly market excess return. SMB, HML, FFPMU, NMPMU and INV are the mimicking factors. The stars are generated from the Wald test on profitability and investment coefficients. ** and * represent whether the extra profitability and investment factors are useful at 1% and 5% level of significance respectively. R^2 is reported under percentage value.

Table 4.8 The Three- versus the Five-factor model (2)

	GRS	P VALUE	IR(α)
Size - Book to market			
3 Factor Model	2.81	0.00**	0.451
5 Factor Model FFPMU	2.61	0.01**	0.455
5 Factor Model NMPMU	2.76	0.01**	0.457
Size - FFOP			
3 Factor Model	3.13	0.00**	0.476
5 Factor Model FFPMU	1.99	0.05*	0.397
5 Factor Model NMPMU	2.76	0.01**	0.457
Size - NMOP			
3 Factor Model	2.03	0.04*	0.383
5 Factor Model FFPMU	1.41	0.19	0.334
5 Factor Model NMPMU	1.77	0.08	0.366
Size - Investment			
3 Factor Model	1.06	0.40	0.276
5 Factor Model FFPMU	0.75	0.66	0.244
5 Factor Model NMPMU	0.99	0.46	0.273

NOTE:
This table shows the GRS results and information ratios on all models under different sorting methods (size-BM, size-FFOP, size-NMOP and size-investment).

$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+h_i HML_i+e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+h_i HML_t+f_i FFPMU_t+l_i INV_t+e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+h_i HML_t+n_i NMPMU_t+l_i INV_t+e_{it}$$

r_{it} is monthly stock return and r_f is the monthly risk free rate. MKT represents the market factor, which is the monthly market excess return. SMB, HML, FFPMU, NMPMU and INV are the mimicking factors. ** and * represent the significance at level 1% and level 5% respectively.

To summarize: First, consistent with Faff (2001), Gaunt (2004), Gharghori et al. (2007), Gharghori and Veeraraghavan (2009) and Brailsford et al. (2012b), although the three-factor model works better on Australian market than the CAPM, the three-factor model still fails in the Australian market. Second, similar to Gray and Johnson (2011), Novy-Marx (2013), Dou et al. (2012), Zhong et al. (2014) and Fama and French (2015), the Australian evidence supports the power of the five-factor model. Third, the five-factor model with the Fama and French profitable minus unprofitable (FFPMU) factor does the best job in Australia.

Chapter 5

Is HML factor redundant?

Fama and French (2015) argue that the HML factor seems to be redundant if the profitability and investment factors are added into the model. However this problem might be sample and/or region specific. In this chapter, I apply the four-factor model (without HML) to the Australian stock market as an out of sample test. Both the Fama and French profitable minus unprofitable (FFPMU) factor and the Novy-Marx profitable minus unprofitable (NMPMU) factor are included in the analysis.

Table 5.1 regresses the size-BM, size-FFOP, size-NMOP and size-investment portfolio returns on the market, SMB, profitability (FFPMU, NMPMU) and INV factors. In terms of the model's mispricing, for simplicity, I only report the alphas and the t-statistics on alphas from the regressions in Table 5.1. Recall that by producing significant alphas, the three-factor model presents a particular problem explaining returns for companies of extremely small size and low BM. Looking at the t-statistics for alphas in Table 5.1, regardless of the usage of the profitability factor, the four-factor model improves the explanatory power of the returns on small-low BM companies, as the alphas for these companies are no longer significant. This finding suggests that, consistent with Fama and French (2015), the Australian evidence reveals that adding factors improves the three-factor model.

To assess the performance comparing the different models, I report the R^2, GRS statistics and information ratios for the three-, four- and five-factor models in Table 5.2. Panel A of Table 5.2 reports the goodness of fit between the four- and five-factor models with different definitions of the profitability factors. As can be seen, using the Novy-Marx profitable minus unprofitable (NMPMU) factor produces higher average goodness of fit for size-BM (average R^2 of 78.17%) and size and Novy-Marx operating profit (NMOP) portfolios (average R^2 of 74.23%). On the other hand, using the Fama and French profitable minus unprofitable (FFPMU) factor produces higher goodness of fit for size-Fama and French operating profit (FFOP, average R^2 of 74.32%) and size-investment portfolios (average R^2 of 73.95). Next, comparing the goodness of fits between the four- and five-factor models. Overall the five-factor model produces average R^2 of 75.39% if the FFPMU factor is used and 74.93% if the NMPMU factor is employed. The four-factor model exhibits average R^2 of 74.32% if the FFPMU factor is used and 73.95% if the NMPMU factor is applied. These results suggest that by capturing more variables, the five-factor model is still preferable to the four-factor model.

Table 5.1 Performance of the Four-factor models

		Four Factor Model with FFPMU						Four Factor Model with NMPMU					
		Alpha			t(alpha)			Alpha			t(alpha)		
		Low 1	2	High	Low 1	2	High	Low 1	2	High	Low 1	2	High
		size-BM											
	Small 1	-0.32	0.46	0.18	-1.37	3.10**	1.13	-0.41	0.45	0.23	-1.83*	3.12**	1.46
	2	0.19	0.07	0.55	0.99	0.46	2.73**	0.09	0.18	0.61	0.49	1.26	3.22**
	Big 3	0.17	0.02	0.45	0.86	0.14	1.75*	0.08	0.15	0.43	0.43	0.92	1.72
		size-FFOP											
	Small 1	0.02	1.01	1.61	0.09	3.39**	2.60*	-0.17	1.14	1.75	-0.86	3.92**	2.93**
	2	0.31	0.04	-0.04	0.82	0.27	-0.21	-0.42	0.13	0.03	-0.99	0.82	0.15
	Big 3	0.47	0.07	-0.01	0.9	0.35	-0.07	-0.37	0.17	0.06	-0.66	0.94	0.31
SIZE		size-NMOP											
	Small 1	0.11	0.47	0.66	0.51	2.80**	3.15**	-0.05	0.57	0.75	-0.24	3.56**	3.80**
	2	0.52	0.13	0.05	2.00	0.87	0.26	0.3	0.09	0.12	1.15	0.66	0.66
	Big 3	0.49	0.12	0.01	1.52	0.69	0.05	0.3	0.07	0.11	0.95	0.44	0.51
		size-Investment											
	Small 1	0.13	0.36	0.37	0.72	2.32*	1.70*	0.09	0.34	0.19	0.53	2.28*	0.9
	2	0.02	0.1	0.2	0.12	0.87	1	-0.01	0.17	0.11	-0.07	1.48	0.57
	Big 3	-0.03	0.07	0.19	-0.12	0.57	0.75	-0.1	0.16	0.13	-0.44	1.26	0.51

NOTE:
This table shows the results for alphas from the two four factor models

$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+f_i FFPMU_t+l_i INV_t+e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+\beta_i MKT_t+s_i SMB_t+n_i NMPMU_t+l_i INV_t+e_{it}$$

r_{it} is monthly portfolio(size-BM, size-FFOP, size-NMOP and size-investment) return and r_f is the monthly risk free rate. MKT represents the market factor, which is the monthly market excess return. SMB, FFPMU, NMPMU and INV are the mimicking factors. This table shows regression statistics for the four factor models on 9 portfolios. ** and * represent the significance at level 1% and level 5% respectively. Alpha is reported under percentage value.

In terms of comparison, Panel B of Table 5.2 reports the GRS statistics and information ratios generated from the three-, four- and five-factor model. Recall that the GRS test is conducted on the intercepts from regressions. The intercepts measure the magnitude in terms of mispricing for different models. The GRS test thus enables investors to judge the power of the asset pricing model. Information ratio is calculated based on the alphas and residuals. The lower the information ratio, the better the model. For size-BM portfolios, the GRS tests reject all models. The three-factor model produces a lowest information ratio at 0.451 and this suggests that the three-factor model performs the best for size-BM portfolios. For portfolios sorted on size and Fama and French operating profit (FFOP), the GRS test cannot reject the four-factor model with Fama and French profitable minus unprofitable (FFPMU) factor. This model exhibits a p-value of 0.06, however the p-value is close to the point of rejection.

The GRS test cannot reject either the four- or the five-factor models for portfolios that are sorted on size and Novy-Marx operating profit (NMOP). Furthermore, using the FFPMU factor in the five-factor model produces the lowest information ratio at 0.334. This supports the power of the five-factor model. Finally, for size-investment portfolios, the GRS test cannot reject any of the models. The best model suggested by the lowest information ratio (0.244) for size-investment portfolios is the five-factor model with Fama and French profitable minus unprofitable (FFPMU) factor.

Overall, the Australian evidence suggests that the five-factor model is superior to the four-factor model. The outperformance of the five-factor model implies the usefulness of the HML factor in the Australian market. Contrary to Fama and French (2015), Australian out of sample test results suggest that Fama and French's findings on the HML factor could be restricted to sample and/or region.

Table 5.2 Performance of the alternative asset pricing models

Panel A: R^2 for the four-factor models and the five-factor models												
	5 Factor Model FFPMU			5 Factor Model NMPMU			4 Factor Model - FFPMU			4 Factor Model - NMPMU		
	Low 1	2	High	Low 1	2	High	Low 1	2	High	Low 1	2	High
Size - Book-to-market												
Small 1	86.64	92.36	91.97	87.08	92.30	92.07	85.64	90.78	88.00	85.70	90.78	87.88
2	82.10	83.99	74.11	82.92	83.56	74.66	76.11	83.46	69.29	77.38	82.97	70.22
Big 3	79.62	79.70	59.73	80.62	79.20	59.52	72.84	79.25	55.19	74.43	78.70	55.48
Size - FFOP												
Small 1	89.29	68.29	48.41	87.92	68.06	48.65	88.90	68.51	47.59	87.77	68.27	48.29
2	64.17	75.46	65.83	51.80	75.25	66.40	64.37	75.22	65.30	52.14	75.29	66.31
Big 3	47.07	68.19	61.41	36.47	67.71	62.18	47.18	67.81	60.95	36.36	67.73	62.17
Size - NMOP												
Small 1	88.76	85.96	78.04	89.48	87.1	79.56	88.99	85.33	76.99	89.55	85.90	77.75
2	67.71	84.31	68.39	65.31	85.68	70.82	67.81	83.04	68.22	65.19	84.76	70.97
Big 3	50.67	80.31	62.09	49.04	82.01	64.51	50.68	78.38	61.78	48.77	80.55	64.66
Size - Investment												
Small 1	88.36	91.12	86.74	88.25	91.07	85.65	87.04	90.73	86.62	87.17	90.73	85.66
2	76.64	89.47	77.74	76.89	89.11	77.36	76.44	89.48	77.90	76.75	89.14	77.47
Big 3	68.68	86.83	64.05	68.77	86.21	64.09	68.49	86.79	64.29	68.61	86.23	64.35

Table 5.2 Continued

Panel B: GRS and information ratios			
	GRS	P VALUE	IR (α)
	Size - Book to market		
3 Factor Model	2.81	0.00**	0.451
5 Factor Model FFPMU	2.61	0.01**	0.455
5 Factor Model NMPMU	2.76	0.01**	0.457
4 Factor Model FFPMU	2.81	0.00**	0.466
4 Factor Model NMPMU	3.25	0.00**	0.485
	Size - FFOP		
3 Factor Model	3.13	0.00**	0.476
5 Factor Model FFPMU	1.99	0.05*	0.397
5 Factor Model NMPMU	2.76	0.01**	0.457
4 Factor Model FFPMU	1.89	0.06	0.382
4 Factor Model NMPMU	2.82	0.00**	0.452
	Size - NMOP		
3 Factor Model	2.03	0.04*	0.383
5 Factor Model FFPMU	1.41	0.19	0.334
5 Factor Model NMPMU	1.77	0.08	0.366
4 Factor Model FFPMU	1.57	0.13	0.348
4 Factor Model NMPMU	2.18	0.03*	0.397
	Size - Investment		
3 Factor Model	1.06	0.40	0.276
5 Factor Model FFPMU	0.75	0.66	0.244
5 Factor Model NMPMU	0.99	0.46	0.273
4 Factor Model FFPMU	0.88	0.54	0.261
4 Factor Model NMPMU	1.21	0.29	0.296

NOTE:
Panel A of Table 5.2 shows the R^2 for the four-factor models and the five factor models. Panel B shows GRS statistics and information ratio for the four factor model, together with the three-and five-factor models, in order to make comparison between models.

$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_i + e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_t +f_i FFPMU_t + l_i INV_t+ e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ h_i HML_t +n_i NMPMU_t + l_i INV_t+ e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+f_i FFPMU_t + l_i INV_t+ e_{it}$$
$$r_{it}-r_{ft}=\alpha_i+ \beta_i MKT_t+ s_i SMB_t+ n_i NMPMU_t + l_i INV_t+ e_{it}$$

r_{it} is monthly portfolio (size-BM, size-FFOP, size-NMOP and size-investment) return and r_{ft} is the monthly risk free rate. MKT represents the market factor, which is the monthly market excess return. SMB, HML, FFPMU, NMPMU and INV are the mimicking factors. ** and * represent the significance at level 1% and level 5% respectively. R^2 is reported under percentage value.

Chapter 6

Conclusion

In this thesis, I evaluate the performance of various asset pricing models, namely the CAPM, the three-, four- and five-factor models, in the Australian market. The evaluation of the asset pricing model is important in finance because it will help finance manager to determine the appropriate discount rate to be used in capital budgeting. Furthermore, in mutual funds, asset pricing model helps to evaluate the performance of mutual funds by correctly addressing the pricing risks. In the spirit of Novy-Marx (2013) and Fama and French (2015), I apply both definitions of the profitability factors in the Australian market to test whether the five-factor model is definition sensitive. Additionally, Fama and French (2015) suggest that their sample results show that the HML factor is redundant if the profitability and investment factors are added into the model. However their findings could be sample and/or region specific. Given that Fama and French (2012) document the importance of the HML factor in capturing international returns. It is necessary to study whether the HML factor is redundant in the international market if profitability and investment are controlled. By employing the out of sample test in the Australian market. The Australian market is small enough to present an out of sample evidence to the findings in the U.S. while at the same time large enough to be of interest to academia and practice.

The analysis sample in Australia involves the ordinary stocks traded on the Australian market from 2001 to 2012. Stocks are sorted based on size-BM, size-Fama and French operating profit (FFOP), size and Novy-Marx operating profit (NMOP) and size-investment at mid of each year. Based on the sorts I assign these stocks into different groups. First I form 2 by 3 sorts to build factor portfolios and based on the portfolio returns, I construct the mimicking factors. In addition, I form 3 by 3 sorts on test portfolios to regress against these mimicking factors. To evaluate the goodness of fit for each model, I compute R^2 for each regression. Furthermore, in order to compare the models, I conduct the Wald test, the GRS test and calculate the information ratio.

The results suggest that overall, the GRS test cannot reject the four or five-factor models for portfolios which are sorted by size and Novy-Marx operating profit (NMOP) and size-investment. Using Fama and French profitable minus unprofitable (FFPMU) as the profitability factor, the five-factor model produces higher average R^2 of 75.39%, where using the Novy-Marx profitable minus unprofitable (NMPMU) factor produces lower average R^2 of 74.93%. This suggests that the five-factor model could be definition sensitive. The t-statistics on the HML factors imply that the HML factor is still significant with extra factors added into the model. Looking at the goodness of fit between the five-factor model and four-factor model, the five-factor model outperforms the four-factor model regardless of the definitions of the profitability. Furthermore, using the FFPMU as the profitability factor produces lower information ratio for portfolios that are sorted according to size and Novy-Marx operating profit and size-investment, with information ratios of 0.334 and 0.244, respectively. These results suggest that the five-factor model provides a better measurement in the Australian market. Contrary to Fama and French (2015), the HML factor is still meaningful. Their findings could be sample and/or region specific. The findings of my study support the superiority of the five-factor model.

Last, my study findings may provide insight for for academia and practice. First, in particular, by confirming the explanatory power of the five-factor model and the HML factor. This thesis adds to the debate whether the three-factor model is no longer powerful. Second, my study findings suggest that fund managers in Australia should apply the five-factor model to price risk because the five-factor model carries better risk characteristics in the Australian market. In particular, forming portfolios based on the profitability and investment could bring values in the Australian market.

Limitations and suggestions for future research

In this thesis I follow Fama and French (2015) to evaluate the performance of the asset pricing models in explaining returns on size-BM, size-Fama and French operating profit, size-Novy-Marx operating profit and size-investment portfolios. As acknowledged in Fama and French (2014), portfolios are sorted on the same variables used to construct the factors. Therefore the tests are in effect “home games”. Future research can therefore extend the model by examining the performance of the five-factor model on anomalies that are not directly associated with the five risk factors. For example: the momentum, which is recommended by Jegadeesh and Titman (1993) and accruals, which is suggested by Sloan (1996).

Reference List

Anderson, D., A. Lynch, and N. Mathiou. (1990). Behavior of CAPM anomalies in smaller firms: Australian evidence. *Australian Journal of Management* 15:1–38.

Ball, R. (1978). Anomalies in relationships between securities' yields and yield-surrogates. *Journal of Financial Economics*, *6*(2), 103-126.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3-18.

Barbee Jr, W. C., Mukherji, S., & Raines, G. A. (1996). Do sales-price and debt-equity explain stock returns better than book-market and firm size?. *Financial Analysts Journal*, *52*(2), 56-60.

Basu, S. (1983). The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. *Journal of financial economics*, *12*(1), 129-156.

Beedles, W. L., P. Dodd, and R. R. Officer. (1988). Regularities in Australian share returns. *Australian Journal of Management* 13:1–29.

Berk, J. B. (1995). A critique of size-related anomalies. *Review of Financial Studies*, *8*(2), 275-286.

Bettman, J. L., Ng, W. S. K., & Sault, S. J. (2011). The economic significance of trading based on the size effect in Australia. *Australian Journal of Management*, *36*(1), 59-73.

Bhandari, L. C. (1988). Debt/equity ratio and expected common stock returns: Empirical evidence. *The Journal of Finance*, *43*(2), 507-528.

Brailsford, T., C. Gaunt, and M. A. O'Brien. 2012(b). Size and book-to-market factors in Australia. *Australian Journal of Management* 37:261–281.

Brown, P., D. B. Keim, A. W. Kleidon, and T. A. Marsh. (1983). Stock return seasonalities and tax-loss selling hypothesis: Analysis of the arguments and Australian evidence. *Journal of Financial Economics* 12:105–128.

Cai, J. (1997). Glamour and value strategies on the Tokyo Stock Exchange.*Journal of Business Finance & Accounting*, *24*(9‐10), 1291-1310.

Capaul, Carlo, Ian Rowley, and William F. Sharpe, (1993). International value and growth stock returns, *Financial Analysts Journal*, January-February, 27–36.

Chan, Louis K. C., Yasushi Hamao, and Josef Lakonishok, (1991). Fundamentals and stock returns in Japan, *Journal of Finance*, *46*, 1739–1789.

Cochrane, J. H. (2005). *Asset pricing* (Vol. 1). Princeton, NJ: Princeton university press.

Corporate overview. Retrieved from http://www.asx.com.au/about/corporate-overview.htm

Dou, P. Y., D. R. Gallagher, and D. H. Schneider. (2012). Dissecting anomalies in the Australian stock market. *Australian Journal of Management* 38:353–373.

Durack, N., Durand, R. B., & Maller, R. A. (2004). A best choice among asset pricing models? The conditional capital asset pricing model in Australia. *Accounting & Finance*, *44*(2), 139-162.

Durand, R. B., Limkriangkrai, M., & Chai, D. (2015). The Australian asset-pricing debate. *Accounting & Finance*.

Faff, R. (2001). An examination of the Fama and French three-factor model using commercially available factors. *Australian Journal of Management*,*26*(1), 1-17.

Faff, R. (2004). A simple test of the Fama and French model using daily data: Australian evidence. *Applied Financial Economics*, *14*(2), 83-92.

Faff, R., Gharghori, P., & Nguyen, A. (2014). Non-nested tests of a GDP-augmented Fama–French model versus a conditional Fama–French model in the Australian stock market. *International Review of Economics & Finance*, *29*, 627-638.

Fama, E. F., & French, K. R. (1992). The cross - section of expected stock returns. *The Journal of Finance*, *47*(2), 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56.

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance*, *51*(1), 55-84.

Fama, E. F., & French, K. R. (1998). Value versus growth: The international evidence. *The Journal of Finance*, *53*(6), 1975-1999.

Fama, E. F., & French, K. R. (2004). The capital asset pricing model: Theory and evidence. *Journal of Economic Perspectives*, *18*, 25-46.

Fama, E. F., & French, K. R. (2006). Profitability, investment and average returns. *Journal of Financial Economics*, *82*(3), 491-518.

Fama, E. F., & French, K. R. (2008). Dissecting anomalies. *The Journal of Finance*, *63*(4), 1653-1678.

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, *105*(3), 457-472.

Fama, E. F., & French, K. R. (2014). Dissecting anomalies with a five-factor model. *Fama-Miller Working Paper*.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model.*Journal of Financial Economics*, *116*(1), 1-22.

Gaunt, C., P. Gray, ad J. McIvor. (2000). The impact of share price on seasonality and size anomalies in Australian equity returns. *Accounting & Finance* 40:33–50.

Gaunt, C. (2004). Size and book to market effects and the Fama French three factor asset pricing model: evidence from the Australian stockmarket. *Accounting & Finance*, *44*(1), 27-44.

Gharghori, P., Chan, H., & Faff, R. (2007). Are the Fama-French factors proxying default risk?. *Australian Journal of Management*, *32*(2), 223-249.

Gharghori, P., Lee, R., & Veeraraghavan, M. (2009). Anomalies and stock returns: Australian evidence. *Accounting & Finance*, *49*(3), 555-576.

Gharghori, P., Stryjkowski, S., & Veeraraghavan, M. (2013). Value versus growth: Australian evidence. *Accounting & Finance*, *53*(2), 393-417.

Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica: Journal of the Econometric Society*, 1121-1152.

Gray, P., and J. Johnson. (2011). The relationship between asset growth and the cross- section of stock returns. *Journal of Banking and Finance* 35:670–680.

Hou, K., Karolyi, G. A., & Kho, B. C. (2011). What factors drive global stock returns?. *Review of Financial Studies*, *24*(8), 2527-2574.

Jaffe, J., Keim, D. B., & Westerfield, R. (1989). Earnings yields, market values, and stock returns. *The Journal of Finance*, *44*(1), 135-148.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*,*48*(1), 65-91.

Kassimatis, K. (2008). Size, book to market and momentum effects in the Australian stock market. *Australian Journal of Management*, *33*(1), 145-168.

Kothari, S. P., Shanken, J., & Sloan, R. G. (1995). Another look at the cross‐section of expected stock returns. *The Journal of Finance*, *50*(1), 185-224.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, (1994). Contrarian investment, extrap-olation, and risk, *Journal of Finance 49*, 1541-1578.

Leledakis, G., & Davidson, I. (2001). Are two factors enough? The UK evidence. *Financial Analysts Journal*, 96-105.

Liu, B., & Di Iorio, A. (2015). The pricing of idiosyncratic volatility: An Australian study. *Australian Journal of Management*, 0312896214541554.

Maroney, N., & Protopapadakis, A. (2002). The book-to-market and size effects in a general asset pricing model: Evidence from seven national markets. *European Finance Review*, *6*(2), 189-221.

Mazzola, P., & Gerace, D. (2015). A Comparison Between a Dynamic and Static Approach to Asset Management Using CAPM Models on the Australian Securities Market. *Australasian Accounting, Business and Finance Journal*,*9*(2), 43-58.

Nguyen, A., Faff, R., & Gharghori, P. (2007). An examination of conditional asset pricing models in the Australian equities market. *Applied Financial Economics Letters*, *3*(5), 307-312.

Nguyen, A., Faff, R., & Gharghori, P. (2009). Are the Fama–French factors proxying news related to GDP growth? The Australian evidence. *Review of Quantitative Finance and Accounting*, *33*(2), 141-158.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics, 108*(1), 1-28.

Penman, Stephen H., (1991). An evaluation of accounting rate of return, *Journal of Accounting, Auditing, and Finance 6*, 233-255.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, *13*(3), 341-360.

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management*, *11*(3), 9-16.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk*. *Journal of Finance, 19*(3), 425-442.

Sloan, R. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings?(Digest summary). *Accounting review*,*71*(3), 289-315.

Stattman, D. (1980). Book values and stock returns. *The Chicago MBA: A Journal of Selected Papers*, *4*(1), 25-45.

Titman, S., Wei, K. C., & Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis*, *39*(04), 677-700.

Toms, S. (2014). Accounting-based Risk Management and the Capital Asset Pricing Model: An Empirical Comparison. *Australian Accounting Review*, *24*(2), 127-133.

Treynor, J. L. (1961). *Toward a theory of market value of risky assets*.

Vu, V., Chai, D., & Do, V. (2014). Empirical tests on the liquidity-adjusted capital asset pricing model. *Pacific-Basin Finance Journal*.

Walsh, K. (2014). The investment horizon and asset pricing models. *Australian Journal of Management*, 0312896214521439.

Wolmarans, H. P. (2000). Does "dividend investing" have value for the South African investor?. *Meditari Accountancy Research*, *8*(1), 229-247.

Zhong, A., M. Limkriangkrai, and P. Gray. (2014). Anomalies, risk adjustment and seasonality: Australian evidence. *International Review of Financial Analysis* 35:207–218.

Appendix 1 Ox Code For Factor construction

Below is the ox sample used to construct returns for SMB and HML factors. For other factors the code is the same expect a little modification on the column selection. Brief explanations are described in the brackets.

```
#include <oxstd.oxh>
#include <oxfloat.h>
main()
{
```

(Declaring variables, bp stands for the cutoff points, which is entered manually each year)

```
    decl mData, mYear, mYear1; decl selection_month=6;
    decl sy=2012; decl pm; decl bp1=0.512820512820513; decl bp2=1.35135135135135;
    decl mBig, mSmall, mGrowth, mMedium, mValue mPortfolio, mS,mB,s,b,rs,rb;
    decl wS,wB, mP1, mP2,+mWS,mWB;  decl mR1,mR2;
    decl mG,mM,mV,g,m,v,rg,rm,rv; decl wG,wM,wV, mP3, mP4,mP5;
    decl mWG,mWM,mWV;  decl mR3,mR4,mR5; decl growth,medium,value, mB1, mB2,mB3; mPS, mPB;
    decl ASG,RSG,ASM,RSM,ASV,RSV,ABG,RBG,ABM,RBM,ABV,RBV;  decl x=<>; decl mPBA;
    decl SG,SM,SV,BG,BM,BV;
    mData = loadmat("D:/ox/SPPRox.xlsx");
```

(Sort on size)

```
    mYear = selectifr(mData, mData[][1] .== sy);
    mYear = selectifr(mYear, mYear[][2] .== selection_month);
    mYear = sortbyc(mYear, 7);
    mYear = deleteifr(mYear, mYear[][7] .== 0);
    mSmall = mYear[0:rows(mYear)-201][];
    mBig = mYear[rows(mYear)-200:][];
    mSmall ~= 1;
    mBig ~= 2;
    mYear = mSmall | mBig;
```

(Second sort on Book-to-Market ratio)

```
    mYear1 = selectifr(mData, mData[][1] .== sy);
    mYear1 = selectifr(mYear1, mYear1[][2] .== selection_month);
    mYear1 = deleteifr(mYear1, mYear1[][9] .== 0);
    mYear1 = deleteifr(mYear1, mYear1[][9] .== M_NAN);
    mYear1 = sortbyc(mYear1, 9);
    mGrowth = selectifr(mYear1, mYear1[][9] .< bp1);
    mGrowth ~= 1;
    mMedium = selectifr(mYear1, mYear1[][9] .< bp2);
    mMedium = selectifr(mMedium, mMedium[][9] .>= bp1);
    mMedium ~= 2;
    mValue = selectifr(mYear1, mYear1[][9] .>= bp2);
    mValue  ~= 3;
    mYear1 = mGrowth | mMedium | mValue;
```

(Form portfolios)

```
    mPortfolio = selectifr(mData, mData[][1] .== sy + 1);
```

(Choosing in monthly data and give them different size labels (1,2,3))

```
    rs=rows(mSmall);
    rb=rows(mBig);
    mP1 = mP2 = <>;
    for (s=0; s<rs; ++s)
    {
        mS = selectifr(mPortfolio,mPortfolio[][0].== mSmall[s][0]);
        if(mS == <>) continue;
        mS ~= 1;
        mP1 |= mS;
    }
    for (b=0; b<rb; ++b)
    {
        mB = selectifr(mPortfolio,mPortfolio[][0].== mBig[b][0]);
        if(mB == <>) continue;
        mB ~= 2;
        mP2 |= mB;
    }
    mPS= mP1|mP2;
```

(Choosing in monthly data and give them different book-to-market labels (1,2,3))

```
rg=rows(mGrowth);
rm=rows(mMedium);
rv=rows(mValue);
mP3 = mP4 = mP5= <>;
for (g=0; g<rg; ++g)
{
    mG = selectifr(mPS,mPS[][0].== mGrowth[g][0]);
    if(mG == <>) continue;
    mG ~= 1;
    mP3 |= mG;
}
for (m=0; m<rm; ++m)
{
    mM = selectifr(mPS,mPS[][0].== mMedium[m][0]);
    if(mM == <>) continue;
    mM ~= 2;
    mP4 |= mM;
}
for (v=0; v<rv; ++v)
{
    mV = selectifr(mPS,mPS[][0].== mValue[v][0]);
    if(mV == <>) continue;
    mV ~= 3;
    mP5 |= mV;
}
mPB=mP3|mP4|mP5;
```

(Return calculation)

```
SG = SM = SV = BG = BM = BV = <>;

for (pm=1; pm<=12; ++pm)
{
    x = selectifr(mPB,mPB[][2].==pm);
```

(Small – Growth group)

```
    ASG = selectifr(x, x[][14].== 1);
    ASG = selectifr(ASG, ASG[][15].==1);
    ASG = deleteifr(ASG, ASG[][4] .== M_NAN);
    ASG ~= ASG[][8]./sumc(ASG[][8]);
    RSG = ASG[][4].*ASG[][16];
    RSG = sumc(RSG);
```

(Small – Medium group)

```
    ASM=selectifr(x,x[][14].==1);
    ASM=selectifr(ASM,ASM[][15].==2);
    ASM ~= ASM[][8]./sumc(ASM[][8]);
    RSM = ASM[][4].*ASM[][16];
    RSM = deleter(RSM);
    RSM = sumc(RSM);
```

(Small – Value group)

```
    ASV=selectifr(x,x[][14].==1);
    ASV=selectifr(ASV,ASV[][15].==3);
    ASV ~= ASV[][8]./sumc(ASV[][8]);
    RSV = ASV[][4].*ASV[][16];
    RSV = deleter(RSV);
    RSV = sumc(RSV);
```

(Big – Growth group)

```
    ABG=selectifr(x,x[][14].==2);
    ABG=selectifr(ABG,ABG[][15].==1);
    ABG ~= ABG[][8]./sumc(ABG[][8]);
    RBG = ABG[][4].*ABG[][16];
    RBG = deleter(RBG);
    RBG = sumc(RBG);
```

(Big – Medium group)

```
    ABM=selectifr(x,x[][14].==2);
    ABM=selectifr(ABM,ABM[][15].==2);
    ABM ~= ABM[][8]./sumc(ABM[][8]);
    RBM = ABM[][4].*ABM[][16];
    RBM = deleter(RBM);
    RBM = sumc(RBM);
```

(Big – Value group)

```
    ABV=selectifr(x,x[][14].==2);
    ABV=selectifr(ABV,ABV[][15].==3);
```

```
        ABV ~= ABV[][8]./sumc(ABV[][8]);
        RBV = ABV[][4].*ABV[][16];
        RBV = deleter(RBV);
        RBV = sumc(RBV);

        SG |= RSG;
        SM |= RSM;
        SV |= RSV;
        BG |= RBG;
        BM |= RBM;
        BV |= RBV;
    }
    println("SG",SG);
    println("SM",SM);
    println("SV",SV);
    println("BG",BG);
    println("BM",BM);
    println("BV",BV);
}
```

Appendix 2 Ox Code For portfolio construction

Below is the ox sample code used to construct returns for portfolios that are sorted by size and book-to-market ratio. For portfolios under other sorts, the code is the same expect a little modification on the column selection. Brief explanations are described in the brackets.

```
#include <oxstd.oxh>
#include <oxfloat.h>
main()
{
    decl mData, mYear, mYear1; decl selection_month=6;
    decl sy=2001;decl bBP1=0.386100386100386;  decl bBP2=0.813008130081301;
    decl sBP1=0.05; decl sBP2=0.15; decl mS1,mS2,mS3;    decl mB1,mB2,mB3;
    decl mPortfolio,s1,s2,s3,rs1,rs2,rs3, S1,S2,S3,size1,size2,size3,mSize,mBM;
    decl b1,b2,b3,rb1,rb2,rb3,B1,B2,B3, BM1,BM2,BM3;decl pm; decl mBMA;
    decl x1,x2,x3,x4,x5,x6,x7,x8,x9;
    decl ASS,RSS,SS,ASS1,ASS2,ASM,RSM,SM,ASM1,ASM2,ASB,RSB,SB,ASB1,ASB2;
    decl AMS,RMS,MS,AMS1,AMS2,AMM,RMM,MM,AMM1,AMM2,AMB,RMB,MB,AMB1,AMB2;
    decl ABS,RBS,BS,ABS1,ABS2,ABM,RBM,BM,ABM1,ABM2,ABB,RBB,BB,ABB1,ABB2;
    decl n1,n2,n3,n4,n5,n6,n7,n8,n9,m1,m2,m3,m4,m5,m6,m7,m8,m9;
    mData = loadmat("D:/ox/SPPRox.xlsx");
```

(Sort on size)

```
    mYear = selectifr(mData, mData[][1] .== sy);
    mYear = selectifr(mYear, mYear[][2] .== selection_month);
    mYear = sortbyc(mYear, 7);
    mYear = deleteifr(mYear, mYear[][7] .== 0);
    mYear ~=mYear[][7]./sumc(mYear[][7]);
    mYear ~=cumulate(mYear[][14]);
    mS1 = selectifr(mYear, mYear[][15] .< sBP1);
    mS1 ~= 1;
    mS2 = selectifr(mYear, mYear[][15] .< sBP2);
    mS2 = selectifr(mYear, mYear[][15] .>= sBP1);
    mS2 ~= 2;
    mS3 = selectifr(mYear, mYear[][15] .>= sBP2);
    mS3 ~= 3;
    mYear = mS1 | mS2 | mS3;
```

(Sort on book-to-market ratio)

```
    mYear1 = selectifr(mData, mData[][1] .== sy);
    mYear1 = selectifr(mYear1, mYear1[][2] .== selection_month);
    mYear1 = deleteifr(mYear1, mYear1[][9] .== M_NAN);
    mB1 = selectifr(mYear1, mYear1[][9] .< bBP1);
    mB1 ~= 1;
    mB2 = selectifr(mYear1, mYear1[][9] .< bBP2);
    mB2 = selectifr(mYear1, mYear1[][9] .>= bBP1);
    mB2 ~= 2;
    mB3 = selectifr(mYear1, mYear1[][9] .>= bBP2);
    mB3 ~= 3;
   mYear1 = mB1 | mB2 | mB3;
```

(Form portfolios)

```
    mPortfolio = selectifr(mData, mData[][1] .== sy + 1);
    size1 = size2 = size3= <>;
    rs1=rows(mS1);
    rs2=rows(mS2);
    rs3=rows(mS3);
```

(Choosing from monthly data and label 3 different size groups)

```
    for (s1=0; s1<rs1; ++s1)    //to select the monthly small companies
    {
        S1 = selectifr(mPortfolio,mPortfolio[][0].== mS1[s1][0]);
        if(S1 == <>) continue;
        S1 ~= 1;
        size1 |= S1;
    }
    for (s2=0; s2<rs2; ++s2)
    {
        S2 = selectifr(mPortfolio,mPortfolio[][0].== mS2[s2][0]);
        if(S2 == <>) continue;
        S2 ~= 2;
```

```
        size2 |= S2;
    }
    for (s3=0; s3<rs3; ++s3)
    {
        S3 = selectifr(mPortfolio,mPortfolio[][0].== mS3[s3][0]);
        if(S3 == <>) continue;
        S3 ~= 3;
        size3 |= S3;
    }
    mSize= size1 | size2 | size3 ;
```

(Choosing from monthly data and label 3 different book-to-market groups)

```
    BM1 = BM2 = BM3  = <>;
    rb1=rows(mB1);
    rb2=rows(mB2);
    rb3=rows(mB3);
    for (b1=0; b1<rb1; ++b1)
    {
        B1 = selectifr(mSize,mSize[][0].== mB1[b1][0]);
        if(B1 == <>) continue;
        B1 ~= 1;
        BM1 |= B1;
    }
    for (b2=0; b2<rb2; ++b2)
    {
        B2 = selectifr(mSize,mSize[][0].== mB2[b2][0]);
        if(B2 == <>) continue;
        B2 ~= 2;
        BM2 |= B2;
    }
    for (b3=0; b3<rb3; ++b3)
    {
        B3 = selectifr(mSize,mSize[][0].== mB3[b3][0]);
        if(B3 == <>) continue;
        B3 ~= 3;
        BM3 |= B3;
    }
    mBM= BM1 | BM2 | BM3;
```

(Calculating Returns)

```
    x1=x2=x3=x4=x5=x6=x7=x8=x9=<>;
    n1=n2=n3=n4=n5=n6=n7=n8=n9=<>;
    m1=m2=m3=m4=m5=m6=m7=m8=m9=<>;
    SS=SM=SB=MS=MM=MB=BS=BM=BB=<>;
```

(Size 1 BM1)

```
for (pm=1;pm<=12;++pm)
{
    x1=selectifr(mBM,mBM[][2].==pm);

    ASS=selectifr(x1,x1[][14].==1);
    ASS=selectifr(ASS,ASS[][15].==1);
    ASS = deleteifr(ASS, ASS[][4] .== M_NAN);
    ASS1 = ASS[][8]./sumc(ASS[][8]);
    RSS = ASS[][4].*ASS1;
    ASS2 = sumc(RSS);
    SS |= ASS2;
    n1 |= rows(ASS);
    m1 |= sumc(ASS[][8]);
}
```

(Size1 BM2)

```
for (pm=1;pm<=12;++pm)
{
    x2=selectifr(mBM,mBM[][2].==pm);

    ASM=selectifr(x2,x2[][14].==1);
    ASM=selectifr(ASM,ASM[][15].==2);
    ASM = deleteifr(ASM, ASM[][4] .== M_NAN);
    ASM1 = ASM[][8]./sumc(ASM[][8]);
    RSM = ASM[][4].*ASM1;
    ASM2 = sumc(RSM);
    SM |= ASM2;
    n2 |= rows(ASM);
    m2 |= sumc(ASM[][8]);

}
```

(Size1 BM3)

```
for (pm=1;pm<=12;++pm)
{
    x3=selectifr(mBM,mBM[][2].==pm);

    ASB=selectifr(x3,x3[][14].==1);
    ASB=selectifr(ASB,ASB[][15].==3);
    ASB = deleteifr(ASB, ASB[][4] .== M_NAN);
    ASB1 = ASB[][8]./sumc(ASB[][8]);
    RSB = ASB[][4].*ASB1;
    ASB2 = sumc(RSB);
    SB |= ASB2;
    n3 |= rows(ASB);
    m3 |= sumc(ASB[][8]);
}
```

(Size2 BM1)

```
for (pm=1;pm<=12;++pm)
{
    x4=selectifr(mBM,mBM[][2].==pm);
    AMS=selectifr(x4,x4[][14].==2);
    AMS=selectifr(AMS,AMS[][15].==1);
    AMS = deleteifr(AMS, AMS[][4] .== M_NAN);
    AMS1 = AMS[][8]./sumc(AMS[][8]);
    RMS = AMS[][4].*AMS1;
    AMS2 = sumc(RMS);
    MS |= AMS2;
    n4 |= rows(AMS);
    m4 |= sumc(AMS[][8]);
}
```

(Size2 BM2)

```
for (pm=1;pm<=12;++pm)
{
    x5=selectifr(mBM,mBM[][2].==pm);

    AMM=selectifr(x5,x5[][14].==2);
    AMM=selectifr(AMM,AMM[][15].==2);
    AMM = deleteifr(AMM, AMM[][4] .== M_NAN);
    AMM1 = AMM[][8]./sumc(AMM[][8]);
    RMM = AMM[][4].*AMM1;
    AMM2 = sumc(RMM);
    MM |= AMM2;
    n5 |= rows(AMM);
    m5 |= sumc(AMM[][8]);
}
```

(Size2 BM3)

```
for (pm=1;pm<=12;++pm)
{
    x6=selectifr(mBM,mBM[][2].==pm);
    AMB=selectifr(x6,x6[][14].==2);
    AMB=selectifr(AMB,AMB[][15].==3);
    AMB = deleteifr(AMB, AMB[][4] .== M_NAN);
    AMB1 = AMB[][8]./sumc(AMB[][8]);
    RMB = AMB[][4].*AMB1;
    AMB2 = sumc(RMB);
    MB |= AMB2;
    n6 |= rows(AMB);
    m6 |= sumc(AMB[][8]);
}
```

(Size3 BM1)

```
for (pm=1;pm<=12;++pm)
{
    x7= selectifr(mBM,mBM[][2].==pm);
    ABS=selectifr(x7,x7[][14].==3);
    ABS=selectifr(ABS,ABS[][15].==1);
    ABS = deleteifr(ABS, ABS[][4] .== M_NAN);
    ABS1 = ABS[][8]./sumc(ABS[][8]);
    RBS = ABS[][4].*ABS1;
    ABS2 = sumc(RBS);
    BS |= ABS2;
    n7 |= rows(ABS);
    m7 |= sumc(ABS[][8]);
}
```

(Size3 BM2)

```
for (pm=1;pm<=12;++pm)
{
```

```
    x8= selectifr(mBM,mBM[][2].==pm);

    ABM=selectifr(x8,x8[][14].==3);
    ABM=selectifr(ABM,ABM[][15].==2);
    ABM = deleteifr(ABM, ABM[][4] .== M_NAN);
    ABM1 = ABM[][8]./sumc(ABM[][8]);
    RBM = ABM[][4].*ABM1;
    ABM2 = sumc(RBM);
    BM |= ABM2;
    n8 |= rows(ABM);
    m8 |= sumc(ABM[][8]);
}
```

(Size3 BM3)

```
for (pm=1;pm<=12;++pm)
{
    x9= selectifr(mBM,mBM[][2].==pm);
    ABB=selectifr(x9,x9[][14].==3);
    ABB=selectifr(ABB,ABB[][15].==3);
    ABB = deleteifr(ABB, ABB[][4] .== M_NAN);
    ABB1 = ABB[][8]./sumc(ABB[][8]);
    RBB = ABB[][4].*ABB1;
    ABB2 = sumc(RBB);
    BB |= ABB2;
    n9 |= rows(ABB);
    m9 |= sumc(ABB[][8]);
}

println(SS~SM~SB~MS~MM~MB~BS~BM~BB);
println(n1~n2~n3~n4~n5~n6~n7~n8~n9);
println(m1~m2~m3~m4~m5~m6~m7~m8~m9);
}
```