**Risk Analysis of Pension Funds Investment choices**

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*This version: 9th November 2018*

**Abstract**

Using a sample from January 1990 to December 2016 of monthly asset classes, we provide a comprehensive and more consistent approach to analyse and compare the risk-return relationships of Australian superannuation investment options. In estimating the risk profile of the investment options, we allow for the movement of the asset classes over time by employing a varying coefficient panel estimation technique. We find that while risk increases across different investment options from moderate to aggressive options, using different percentages of identifying a balance fund does not impact on risk measure over the longer term. We equally find that risk-return relationships of investment options are not sensitive to the modelling framework except in the crisis analysis, where the Fama French five factor model provides greater sensitivity.

**Keywords:** Risk**,** Fama French Five factor model, Australian superannuation funds, investment options, varying coefficient panel data.

1. **Introduction**

The objective and the key research question of this study is to assess the risk associated with the investment options of superannuation’s funds in Australia (referred to as pension funds in the international pension market). Given a shift from defined benefit (DB) to defined contribution (DC) (e.g., Clare and Connor, 1999) and a wide variety of choice available to investors (e.g., Gerrans, 2006), individuals are faced with the challenge of making the right investment choice for their circumstances. In addition, with longevity risk, the choice of right asset allocation becomes an important decision not just for the younger working investors but is equally an issue for those who are older and closer to retirement. It is important to assess what is the appropriate mix of asset allocation that will maximise the return so that the individual’s retirement nest egg will be increased eventually. It is essential to realise that most probably having a risky investment strategy may pay off and maximise the investment nest egg rather than faced with the possibility of running out of money at a later stage of retirement and needing to live another 10-15 years on the public pension system.

One of the key factors of an individual’s focus choosing investment options among superannuation funds is the return figure that is being reported by the fund. While return is a key factor, our study’s focus is to assess whether the risk associated with the investment options are properly reported or are they being underreported. One of the challenges that the superannuation fund industry in Australia is coping with is the variability in the definitions that is being used by superannuation to define the composition of the portfolios they hold. Australian superannuation tend to use their own judgement when it comes to classifying their investments as "growth", or riskier, or "defensive", or more stable. The standard definition of growth assets in finance and as per Australian Securities and Investment Commission (ASIC)[[2]](#footnote-2) is that growth investment includes asset classes like equity and property, while the defensive assets tend to be bonds and cash. An article which appeared in the Australian Financial Review[[3]](#footnote-3) in January 2018, highlights that in a submission made by the National Australian Bank (NAB) wealth division it is clear that many funds with unlisted assets were “effectively ‘under-reporting’ the true extent of growth asset exposure in their portfolios. This impacts on the ability to appropriately compare like-for-like superannuation products.” Some superannuation funds in Australia are heavily investing in infrastructure and property and yet these are classified in different ways by funds. Hence, while some superannuation fund managers seem to provide very good results in terms of returns, they may be possibly mis-specifying risk to the members. The industry clearly recognises the fact that there are discrepancies in the disclosure statement and a clear definition of what is growth and defensive is hard to assess. Hence the key contribution of this study is to assess the risk of investment options using a standard approach. In particular, by using beta as a key risk measure, we assess the long term riskiness of the investment options by classifying asset classes using the standard definition of growth and defensive assets across monthly assets classes of 1,213 investment options for a period of January 1990 to December 2016.

Risk assessment of the stock market is largely researched in the finance literature, hence it is important to provide a comprehensive risk analysis to superannuation funds. There is a wide literature in the risk-return trade-off with mixed views as to what will be the best investment options as investors are at different stages of life. Davis (2001) outlines that investment funds should be looking at the most efficient portfolio that is by considering the Markowitz’s modern portfolio theory. He argues that once the efficient frontier is set, then the fund should identify the level of risk that it is willing to take to achieve the desired rate of return. There are numerous papers which examine the idea of de-risking and its relationship to the age of the investors. Samuelson (1989) suggests that investors should be more risk tolerant when they are young and decrease exposure to relatively risky equities in favour of lower risk cash and fixed interest securities as they age. Samuelson (1969) however highlights that a greater aggressive allocation is irrational with a constant investment opportunity set. Samuelson (1991) further showed that that the young investors should be more risk tolerant if the assumption of a random walk for securities is replaced with mean reversion, that is, a loss will ultimately be corrected to a profit over the long term. He further shows in his 1994 study that a desired minimum level of retirement wealth, imply an optimal investment strategy of declining equity allocation with age. However, a different view is from McNaughton, Piggott, and Purcal (1999), who suggest that an increasing equity allocation with age is more likely. Recently, Estrada (2016) looks into an aggressive asset allocation suggested by Warren Buffet of the 90/10 investment option that is 90 percent being in growth strategy. Using the historical returns, he considers how a hypothetical investment portfolio performs over a long time period over 30 year’s period starting from 1900 to 1930 and his final years include 1985 to 2014. His findings suggest that retirees might be able to lean heavily on stocks without putting their nest egg in grave danger. Given the mixed literature and the volatile state of the market over the past few decades, the focus of our focus is to assess how the associated risk, as measured by beta, varies in each of the investment options for a period of 27 years from January 1990 to December 2016.

Our second contribution, is to assess the risk of the investment options by considering two different methods of classification for the investment options, that is, we establish the extent to which beta, our measure of risk, varies as the definition of investment options changes, in particular a balanced option. In this regard, we aim to answer the question “does the definition of 41-60% of growth assets in the fund as compared to 31-70% of growth assets really matter?” In addition to the variability in the definition of which asset class is a growth or a defensive asset, another unresolved definition in the superannuation (pension) system is “what is a balanced option?” We have a large number of individual fund members who fall in the default category in the investment options. Gerrans et al. (2010) highlights that the total growth assets in the default option of funds across the superannuation industry vary from 40 percent for retail funds to 70 percent for industry funds. The default option is very important to consider given that we now have the legislated MySuper options in place. Most funds implemented the MySuper options by either (1) by changing the existing default option (balanced option) to MySuper option or (2) considered a Lifecycle Investment strategy. However, there is no clear definition of what a balanced option is. There is no clear distinction of what a growth versus a balanced fund is. It is suggested that a growth fund should have a 55% to 80% allocation to growth assets, yet we do have a number of funds with the same percentage allocation and yet the label is a balanced fund. For example, superannuation ratings agency, SuperRatings, categorises a balanced option as 60% to 76% allocation to growth assets, while superannuation ratings agency Chant West’s description of ‘balanced’ however is 41% to 60% in growth assets[[4]](#footnote-4). In comparison, a growth option under the SuperRatings categories, is 77% to 90% allocation to growth assets, while Chant West’s description is of growth is 61% to 80% allocation to growth assets. Hence in our study, we use two methods of classification, in particular the classification by Canstar rating (which is similar to Chantwest) and the standard definition provided by ASIC to assess to what extent beta varies as we vary the percentage of growth and defensive.

Our third contribution is the methodological approach to estimate the risk coefficients (i.e., betas). Given the sample period of 27 years of asset classes, it is expected that superannuation funds managers will switch between asset classes over time. Hence, at a specific time, a fund is classified in one category depending on the proportion of its growth assets and the classification of a fund can be time-dependent since the proportion of its growth assets can change over time. This characteristic represents the dynamic switching behaviour among investment options of a fund. Hence, rather than considering a traditional risk modelling framework with an assumption of constant risk profile, we estimate the risk coefficients using a dynamic approach which will accommodate both mentioned characteristics by employing the panel data model developed by Feng et al. (2017). We include variants to estimate the betas and hence our study will consider the CAPM (Capital Asset Pricing Model) as well as Fama French (FF) three factor model, FF four factor model and FF five factor model. This varying coefficient model allows the relationship between risk and return to be different based on the time-varying categories. We further consider a sub-sample analysis of the effect of the 2007 Global Financial Crisis (GFC)

Hence, we assess risk across investment options and our key research questions can be summarised as follows; (1) Do betas as risk measures vary by investment type, that is from a moderate option to an aggressive option?; (2) Are betas sensitive to model specifications?; (3) How much does beta vary as the definition of investment options changes in particular for a balanced fund/growth fund?; and (4) Does the GFC matter for the estimates of betas? The key results of our analysis can be summarised as follows: (1) The results show that the level of risk increases from moderate to aggressive options as expected given the aggressive options include equity and property as asset classes; (2) risk does not vary across the different definitions of the investment options used, that is varying definitions of a balanced option of 41-60% or 31-70% does not impact on the risk level. These results are for a period of 27 years of study, that is over the long term the riskiness of balanced funds does not vary; (3) the results show no obvious sensitivity of estimated betas to the modelling specifications used in the non-crisis period, that is, the risk estimations are consistent across the modelling techniques including CAPM, FF three factor, FF four factor and FF five factor model; (4) However, the beta estimates in the GFC seem to be sensitive to the models. In the GFC, crisis period betas are lower than the non-crisis period for CAPM, FF three factor and FF four factor model, and this holds for both method of classifications. Only the five factor model captures the higher risk in the GFC shown by a higher beta in both classifications used.

The remainder of the paper is organized as follows. Section 2 details the data, section 3 presents the modelling framework. The results are discussed in section 4 and section 5 concludes the paper.

1. **Data**

The data in this paper is sourced from the Morningstar Direct database. The sample is 27 years starting January 1990 to December 2016 and the original sample from Morningstar consists of 1213 investment options from various Australian superannuation funds. A brief explanation of the data is as follows: the data provides details of the investment options held by superannuation funds for example, Care Super. Hence, we have data on Care Super Capital Guaranteed, Care Super Capital Secured, Care Super Balanced among others. We have the historical asset allocation of each of these investment options over 27 years on a monthly basis. The asset classes available include cash, domestic and international shares, domestic and international fixed income securities as well as listed (domestic and international) and unlisted property. Morningstar Direct equally provides access to the monthly historical price index from which we can derive the historical returns. The choice of the data period captures a few key dates, including 1992 the year the Superannuation guarantee was introduced, and periods of high volatility including the South East Asian crisis in 1997 to 1998, the 2001 Dot com crisis and the GFC from mid-2007 to 2009, all of which had significant impact on the Australian stock market. Australian superannuation funds were faced with significant losses in the crisis period, in particular the GFC. Many retirees in Australia have been heavily affected due to the relatively large investment losses in Australia because of the large share of equities which at the time of the GFC was around 57 percent before the crisis hit, compared with an average of 36 percent in the 20 OECD countries. Australian superannuation funds accounted for -26.3 percent loss, which was the second largest in the world after Ireland[[5]](#footnote-5).

We classify the asset classes into growth and defensive assets. The defensive assets include cash, fixed income securities (domestic and international). The growth assets that we consider include, shares (domestic and international) and property (both listed and unlisted) and these usually aim for higher average returns over the long term. However, this equally implies higher volatility corresponding to higher risk, which may result in higher losses in bad years as compared to the return obtained from lower risk options. Australian superannuation funds provide investors with a variety of investment options that can suit the investment profile of the investors including a mixture of growth assets up to a ‘high growth option’ where investors can have the option of investing up to 100 percent in growth assets like shares and property. The objective of this study is to have some uniformity in the definition of asset classes included in the growth options, hence enabling a better comparison of the riskiness of investment options provided by superannuation funds. Using the historical asset allocation, we consider two methods of classification to redefine the investment options[[6]](#footnote-6). Table 1 provides a summary of the two classification methods and the percentage of growth assets to define the four broad categories of investment options, that is, multi-sector moderate, multi-sector balanced, multi-sector growth and multi-sector aggressive. In the first option, we consider the definition provided by Canstar[[7]](#footnote-7), that is, we will consider a multi-sector aggressive (where the growth assets[[8]](#footnote-8) are between 81 percent-100percent), multi-sector growth (growth assets are in between 61-80 percent), multi-sector balanced (growth assets are in between 41-60 percent), and multi-sector moderate (growth assets are in between 21-40 percent). In our second method of classification we consider the guidelines provided by ASIC[[9]](#footnote-9) and define the investment options as follows. An aggressive investment option will have 85-100 percent in growth assets, a growth investment option will be in between 71 to 84 percent; a balanced option will be between 31 to 70 percent; moderate option will be in between 1 to 30 percent. Considering the two methods of defining investment options, will enable to assess if the risk level varies as the percentage of growth assets varies and equally shed some light if the varying definitions of investment options across superannuation funds impact on the risk level faced by members over the longer term.

Following our first method of classification, Canstar, we have 862 investment options which include 116 investment options from the moderate category, 87 investment options from the balanced category, 184 investment options from the growth category and 475 investment options from the aggressive category (this is referred as Option 1-Canstar classification). Using the definition by AISC of how to classify investment options, our final sample includes 995[[10]](#footnote-10) investment options distributed as 109 in the moderate investment option, 261 in balanced option, 128 investment options in growth category and 428 investment options in the aggressive category.

1. **Modelling Framework**

As highlighted in the previous section, at a specific time, a superannuation fund investment option is classified in one investment category depending on proportion of its growth assets. In addition, the classification of a superannuation fund can be time-dependent since the proportion of its growth assets can change over time. Therefore, it is essential that estimations of the risk-return relationship in superannuation funds accommodate differences in risk profiles of investment options as well as time varying classification of the funds. In this study, we utilise a varying coefficient panel framework to analyse the risk behaviour of Australian superannuation fund investment options. Specifically, we apply a general estimation framework developed by Feng et al. (2017) in different model specifications, which allow the relationship between risk and return to be different across different defined time-varying categories, representing investment options and crisis periods. We ensure robustness of results using four models in our investigation, which are widely used in the literature, including the CAPM, the FF three factor model, the FF four factor model and the FF five factor model.

One of the most widely used models to estimate risk in the finance literature has been the CAPM of Sharpe (1964) due to its simplicity and ease to implement. The CAPM assumes the expected return on a portfolio can be explained by the return on the market portfolio, and in our analysis, it can be defined as follows:

 (1)

where is a random error term; is the return on a superannuation fund *i* at time *t*; is the risk-free return; is the return on the market portfolio. is a vector of time-varying category variables which captures the information of economic regimes (crisis and non-crisis) and the categories of investment options defined in previous section. denotes unobservable fixed effects of superannuation fund *i* that can be arbitrarily correlated with any other variables. In this modelling setup, , which represents the sensitivity (or riskiness) of investment options to performance of market portfolio, is a function of , that is, the risk-return relationship is allowed to be different across each investment option and crisis/non-crisis period.

According to the CAPM, investors only price market risk. Fama and French (1993, 1996) find that the non-market risk factors including the size factor, *SMB* (the return on a portfolio of small stocks less the return on a portfolio of large stocks) and the value factor, *HML* (the return on a portfolio of high book-to-market-value stocks less the return on a portfolio of low book-to-market-value stocks) are statistically important in explaining the cross-section of equity returns. We therefore estimate the riskiness of investment options, as measured by beta, using the FF three factor model which is specified as follows:

 (2)

This model specification aims to capture a varying relationship between portfolio returns and market portfolio return (or risk level of each investment option), a varying relationship between portfolio returns and *SMB* factor, and a varying relationship between portfolio returns and *HML* factor by measuring the coefficients , and respectively in equation (2).

Carhart (1997) extended the FF three factor model to include the momentum factor. This aims to further improve the model’s ability to capture the cross-sectional variation of stock returns, which is referred as the FF Four factor model. To serve our purpose, the model is specified as follow:

 (3)

where is the momentum factor measured as the difference between the returns of diversified portfolios.

Another improved version of FF three factor model, that includes two additional factors, was introduced by Fama and French (2015), as they believe the returns of a portfolio are also closely related to investment profitability and investment patterns. In our study, we use the Fama French five factors which have been calculated in similar method as Fama and French (2015), but using Australian stock market data. The monthly asset-pricing factors are constructed in the spirit of Fama and French (1993) with minor modifications tailored to the Australian equity market. In brief, each December, stocks are independently double sorted into 2x3 size/book-to-market-value portfolios. Stocks within the S&P/ASX200 index are classified as Big, with the remainder classified Small. Portfolio cut-offs for book-to-market-value (BM) are based on the 30th and 70th percentiles of BM for the S&P/ASX200. Stocks are value weighted into portfolios with annual rebalancing. In a similar fashion, the momentum factor is formed to be size neutral and utilises momentum cut-offs drawn from the 30th and 70th percentiles of the S&P/ASX200 constituents[[11]](#footnote-11). The *RMW* factor portfolio and the *CMA* factor portfolio were constructed in the same way as the *HML* factor portfolios using the 30th and 70th percentiles. To fit our analysis, we specify the FF five factor model as follows:

 (4)

where is the difference between the returns on diversified portfolios of robust stocks and weak profitable stocks, and is the difference between the returns on diversified portfolios of stocks with low and high investment.

It should be noted that, given a superannuation fund *i* , the estimated risk coefficients (i.e., ) as well as other factor coefficients (including , , , , ) from the above models in ([1](#_bookmark0)), ([2](#_bookmark1)), ([3](#_bookmark2)) and ([4](#_bookmark3)) are dependent on each category defined in vector of time varying categorical variables, . We include different categories of investment options and economic regimes (crisis and non-crisis periods) in so that the risk coefficients are varying across different investment categories, and at the same time, across crisis and non-crisis periods. This requires advanced estimation techniques, rather than the traditional Ordinary Least Square (OLS), which can effectively capture the dependent structure of risk coefficients on investment options and crises as well as the characteristics of panel data. We, therefore, employ the Feng et al. (2017) method to solve this problem. To adapt the estimation framework of Feng et al. (2017), we can rewrite all models (1), (2), (3), (4) in a general form as follows,

 (5)

where . Besides, elements of vector of explanatory variables, , and elements of vector of risk coefficients and factor coefficients, , depend on the specification in each of four models employed. For example, in equation (1), and = ; whereas, in equation (4),

and
and other employed models, (2) and (3), can be rewritten in a similar fashion.

Given *z* denotes an individual categorical element of , Feng et al. (2017) show that the risk and factor coefficients in each category *z*, , can be estimated as follows,

where and are transformed and after removing the fixed effects ; is a multivariate kernel function of Aitchison and Aitken (1976) with its optimal bandwidths selected through a cross validation criterion function (see Feng et al., 2017).

1. **Empirical Results**

***4.1 Initial Return Analysis***

Using the monthly price data, we compute the continuously compound returns and present the summary statistics in table 2. Table 2 summarises the average long term return of the four investment options calculated using the Canstar classification in panel A and panel B summarises the returns using the ASIC classification. Consistent in both panels, the highest monthly average return for the sample period is for the multi-sector growth options and across the two methods of classification used. As expected, the higher the percentage of growth assets the higher is the expected return over each of the categories. The growth and aggressive options outperform the moderate and balanced options, and the two different methods of classification do not provide different average returns; the mean across the two methods are quite similar. Hence, defining a balanced fund using 41-60 % or a balanced fund as 31-70% does not indicate a large difference in the monthly average return over the longer term. The monthly maximum average return is 1.5497% in the panel A and 2.0357%, in panel B, both from the aggressive investment option. The definition of an aggressive investment options in panel A includes growth assets of 81-100 % and the variability of the return as shown by the range and the standard deviation are 1.6976% and 0.2445%, respectively. Panel B defines an aggressive option with growth assets in the range of 85-100 % and the range which the return varies is 3.1457% and the standard deviation is 0.2919%. Similarly, the minimum monthly average returns observed in aggressive categories from two classification methodologies are -0.1479% (panel A) and -1.1100% (panel B) respectively. Hence, while defining investment options using different definitions highlight that the monthly average return in the long term does not vary, there is quite a large variation in the returns, which is the risk associated with the investment option. As such we focus our results now on the risk assessment for each of the categories by considering the beta estimates across the models explained in the previous section.

* 1. ***Risk Analysis- Full sample***

Our sample period is over a 27 years period and hence the market has had significant periods of stock market volatility with some significant crisis including the 1997 Asian Crisis, the 2001 Dot Com Crisis and the 2007 GFC. Hence, we estimate the risk associated with the investment options using our models defined in the previous section considering possibly different impacts of crisis and non-crisis periods. We define three crisis periods as follows: 1997 Asian financial crisis from January 1997 to June 1999; the 2000 dot com crisis from September 1999 to April 2003 and 2007 GFC from January 2007- September 2009. Vector of categorical variables *Zit* = (*Z1it* , *Z2it*) in equations (1), (2), (3) and (4), comprises of *Z1it* and *Z2it*, in which *Z1it* capture the investment option information of superannuation fund *i* across time *t* including moderate option, balanced options, growth option and aggressive option. We consider two approaches to classify investment options, the Canstar and ASIC method. Across both methods of classification, *Z2it* is defined as crisis =1 and non-crisis =0 periods. As we expect the superannuation fund managers may actively change their investment strategy during non-crisis and crisis period, *Z* should vary in both cross sectional and time series dimensions. In order to implement the models, we use balanced data which removes those investment options with incomplete data during these three crisis periods. We first estimate the varying coefficient CAPM in (1), FF three factor model in (2), FF four factor model in (3) and FF five factor model in (4) based on full sample data for the period January 1990 to December 2016. The estimation for the non-crisis period is the full sample excluding the three crisis periods as defined above and the crisis period is the combination of the 1997 Asian crisis, the 2000 Dot Com crisis and the 2007 GFC. The results in table 3 reports the risk measures using the Canstar method of classifying the investment options and the results in table 4 reports the risk estimation using the ASIC method of classifying the investment options.

Analysis of table 3 and table 4 shows that the level of risk as measured by beta, increases as the investment type varies from being moderate to aggressive options[[12]](#footnote-12). Similar to the trend that we have reported in the returns statistics observed in table 2, the beta coefficient increases across both table 3 and table 4. For the non-crisis period, the moderate investment option has a beta of 0.1620 and the coefficient increases gradually to 0.6399 for the aggressive option under the CAPM model with the Canstar classification method. The coefficients are very similar in table 4 using the ASIC classification, that is a beta of 0.1210 for the moderate option increasing to 0.6437 for the aggressive option. The beta estimate, , in the FF three factor, FF four factor and FF five factor estimation shows similar trend for both table 3 and table 4, that is, lower for the moderate option and higher for the aggressive options. As expected, the level of risk in the market during the crisis period is higher with market returns being more volatile. As can be seen from table 3 for CAPM estimations, the moderate option in the crisis period has a beta of 0.1652 and the aggressive option has a beta of 0.7340. While the gap between CAPM betas of the moderate option in the crisis and the non-crisis is slight (0.1652 versus 0.1620), the difference is more pronounced as we move to a more aggressive investment option with non-crisis aggressive beta of 0.6399 and an aggressive crisis beta of 0.7340. This risk trend is consistent across different models and methods of classification under consideration as shown in table 3 and table 4. This leads to our first key conclusion. The results observed in table 3 and 4 clearly highlight that as the percentage of growth assets increases, the level of risk that superannuation fund managers are undertaking is higher. While the returns may be higher overall, it is significantly associated with more volatility, particularly in a crisis period where the aggressive investment options can have larger variability of return given they have a higher beta than a moderate option. Our definition of growth assets includes both equity and property market and our results have important implication that it provides a consistent method of classifying the assets and provides the market with a more unbiased estimate of risk.

 We report the coefficients of the FF three factor, FF four factor and FF five factor model. The FF three factor models capture the size and value variable through SMB and HML. Carhart (1997) further extended the FF three factor model to include the momentum factor measured by UMD. The momentum factor is used to show the tendency for the stock price to continue rising if it is going up and to continue declining if it is going down. While both the FF three factor and four factor model are known to have significant improvement over the CAPM given it adjusted for these anomalies, it is argued that it does not capture the profitability and the investment factor, which is captured by FF five factor model. We run our analysis using the two definitions to classify the investment options using equations (2), (3) and (4). The coefficients of SMB (size), HML (value), UMD (momentum), RMW (profitability) and CMA (investment) are reported across table 3 and table 4 for the two classifications used. Chen and Bassett (2014) highlight that the FF regression coefficients are often interpreted in absolute terms. A positive SMB coefficient implies that a portfolio has higher expected returns if small cap stocks outperform large cap stocks, that is the portfolio is predominantly small cap stocks, while a negative SMB shows that the portfolio is predominantly large cap stocks. Elton, Grubber and Blake (2011) argue that the average SMB coefficient is positive demonstrating that a general tendency for US mutual funds to hold small stocks, but they equally find that over 25% of the sample has a negative coefficient which indicates tendency of larger stock holding. In the Australian context, Chan, Faff, Gallagher and Looi (2009) study 34 Australian funds and find no significant impact of size on trading cost. They find that market impact is larger for larger funds. However, the larger funds trade in securities with lower bid ask spreads negating the higher impact. Hence, as evidence, it is quite inconclusive in terms of the coefficient of the SMB variable. Our results indicate a negative SMB coefficient across all the modelling of the FF three factor, FF four factor and FF five factor estimations, except for the crisis analysis under the five factor model where we have a positive coefficient for the moderate, balanced and aggressive investment option under the ASIC classification, which indicates that in the crisis period the investment options reflect more of a small cap preference.

Similarly, a positive HML coefficient implies that high book to value stock (value stock) outperform low book to value stock (growth stock), that is they are predominantly value stocks. A negative HML coefficient indicates that the portfolio has mostly growth stocks. Our results show that across both table 3 and table 4, for the non-crisis analysis, HML has a negative coefficient which is consistent across all investment options which reflects that the portfolio consists of mostly growth stocks. The crisis analysis in table 3 however has mixed signs of HML coefficients for the FF four factor and FF five factor models while in table 4 the growth investment options under the crisis analysis has mostly a negative coefficient for the FF three, FF four and FF five factor models, highlighting investment in growth stocks. For the momentum factor UMD, a positive UMD coefficient indicates a bullish market in general and a negative UMD coefficient is typical of bearish market. The non-crisis coefficient for the FF four factor model shows a positive UMD coefficient across tables 3 and 4 which is reflecting more of a stable economy and high investor confidence in a bullish market. The crisis analysis for the UMD coefficient across both tables 3 and 4 are mainly negative (except for the moderate option under the ASIC classification). This shows the volatility in the market in the crisis period reflecting the falling prices and pessimism in the market. Fama and French (2015) introduced the five-factor model to capture the return premiums associated with profitability (RMW) and investment (CMA). The starting point of the five factor model is the dividend discount model and they find that based on the new factors the following is expected: (i) a higher book-to-market ratio implies a higher expected return (i.e., positive HML coefficient); (ii) firms with higher profitability relative to current book equity have higher expected returns (i.e., positive RMW coefficient); and (iii) a higher expected growth in book equity due to reinvestment and earnings means lower expected returns (i.e., negative CMA coefficient). Since the introduction of these factors, there are numerous papers which have provided empirical evidence for the profitability and investment effects (see for example, Novy-Marx, 2013; Titman, Wei and Xie, 2004). Fama and French (2015) further show that the HML factor is redundant when profitability and investment has been included in the model. While this test is in the US context, in the Australia context, Chiah, Chai and Zhong (2016) show that the HML is not redundant and hence in our study we use the five factor model including HML to apply to the investment options of superannuation funds. The results of the FF five factor models across tables 3 and tables 4 are consistent for both non-crisis and crisis period. For the non- crisis period, the coefficient of HML is negative as highlighted previously, that is the investment held by Australian superannuation fund reflects more of the growth stocks. This is quite in line with the OECD figures which highlight that Australian superannuation funds are one of the highest investors in the equity market and hence we expect this negative coefficient. The profitability as measured by RMW coefficient, is positive under both classification method in the non-crisis period, which implies that higher profitability in the non-crisis period will lead to a higher expected return. The investment coefficient (CMA coefficient) is negative, which is consistent with expectations as per the Fama French (2015) findings, that is, the growth due to re-investment of earnings will lead to lower expected returns. The crisis results in both tables are different to the non-crisis period. While the profitability coefficient does not change, the investment coefficient and HML coefficients do change signs. The CMA coefficient for both classification methods change to positive across all the investment categories moderate, balanced, growth and aggressive. Further, in the crisis period, the moderate, balanced and aggressive option has a positive HML coefficient which shows that in a crisis period, the portfolio is dominated by value stock.

Based on the above discussion and the results in table 3 and table 4, we therefore establish these conclusions to our research questions; (1) as the percentage of growth assets increases the level of risk goes up as measured by beta, that is the moderate option is a safer bet in terms of riskiness as compared to an aggressive option; (2) risk does not vary as we change the method of classification – hence as a fund change the composition of the balanced funds, that is, a change from 41-60 % to a 31-70 % option, the risk level to members over the longer term does not vary; (3) the estimations of risk, that is the beta coefficient, *βM*, is not model sensitive, that is it does not matter whether we use CAPM, FF three, four or five factor for both non-crisis and crisis period, however the HML (value proxy) and CMA (investment proxy) coefficients seem to be different in between the non-crisis and crisis period.

* 1. ***Crisis Analysis: The Global Financial Crisis (GFC)***

In the previous analysis, we consider three volatile periods in our sample, the 1997 Asian crisis, the 2001 Dot.com crisis and the 2007 GFC. Out of the three crises, we now focus the risk analysis on the most significant crisis that the industry was faced with, that is the 2007 GFC. Because Australian superannuation funds tend to invest in growth assets as compared to the rest of the world, it has been clearly established that when the GFC hit in 2007, the Australian superannuation industry suffered huge losses as compared to the rest of the world. From the end of 2007 to mid-2012, Australia's superannuation funds lost an average of 4.5 per cent a year, much worse than the advanced countries average of 1.6 per cent[[13]](#footnote-13). Gerrans, Faff, and Hartnett (2015) tested the individual financial risk tolerance during the crisis using a risk tolerance survey. The results show that the crisis had an impact on the investors, however, the results are inconclusive in terms of how the crisis had an impact on asset allocation decisions. As such, in our study, we focus on how the risk varies across the investment options as defined using the two methods of classification and report the results in table 5 (classification as per Canstar) and table 6 (classification as per ASIC). Similar to the previous analysis, we have a non-crisis analysis and a crisis analysis, however the definition of non-crisis and crisis here is different. The non-crisis period in table 5 and table 6 is the 6-month period prior to GFC and 6-month period post GFC. The crisis analysis for both tables here is the period of the GFC only which is January 2007-September 2009. Analysis of table 3 confirms our initial observation that beta increases as the investment changes from moderate to aggressive options. For both non-crisis periods, holding investment in the higher risk (CAPM beta of 0.9143 for aggressive option) will lead to a higher expected return (CAPM beta of 0.3562 for moderate option). The CAPM model in table 6 which classifies the investment options slightly differently using the ASIC definitions of investment options shows similar results with the moderate option in table 6 non-crisis analysis, has a beta of 0.3143 and the aggressive option a beta of 0.9249. However, a significant observation is the difference we obtain in the results when we compare the non-crisis and crisis period, in contrast to the results in table 3 and table 4, is that, in the GFC analysis, risk estimates seem to be model sensitive for this sample. It seems that only the FF five factor model favours the higher risk higher return theory that is the beta of the GFC period is higher than non-crisis period only in the FF five factor estimate. The estimation using CAPM, FF three factors and FF four factors shows the contrary, that is a higher beta for non-crisis period than crisis period irrespective of the method to classify investment options. The non-crisis beta estimate using the FF five factor for moderate in the non–crisis period is 0.3064 (crisis beta is 0.3940) and for the aggressive option under the non-crisis period the beta estimate is 0.7580 (versus the crisis period beta of 0.9485). We have similar results in table 6, the non-crisis beta for moderate option is 0.2701 and aggressive is 0.7751 and the crisis beta for moderate option is 0.3661 and for the aggressive option it is 0.9612. Further, the SMB coefficient is different as compared to table 3 and table 4. We have a positive SMB coefficient that is, the portfolio of equity investment is predominantly small cap stock. The HML coefficient is mostly positive for the non-crisis analysis that is value stocks are dominant and the crisis period we have a shift to negative HML coefficient in a crisis period that is predominantly growth stock. The profitability coefficient (RMW coefficient) is similar to the previous analysis that is the higher the profitability the higher the expected return. However, the CMA coefficient is all positive across both table 5 and table 6 (except for the aggressive option in the non-crisis analysis for table 5), that is, the higher the amount reinvested, the higher the expected return. Hence, by applying the FF five factor model to the Australian investment options, we show support for the FF five factors in the risk estimation of Australian superannuation funds. Our results on the empirical modelling using FF five factors support the results the of Chiah, Chia and Zhong (2016), highlighting in the Australian market, that the FF five-factor model is able to explain more asset-pricing anomalies than the three-factor model and in our study the five factor model is better than the CAPM and the FF four factor model as well and this is irrespective of the method we use to classify investment options.

1. **Conclusion**

We provide a comprehensive and more consistent method of analysing the risk of investment options of Australian superannuation funds which allows a better comparison of the risk profile. Our research has implications from both a practical and empirical perspective. We address some key challenges that the Australian superannuation fund industry is faced with, in particular: (1) is there a consistent method of classifying the growth assets which allows comparison of the risk associated with the portfolios of the superfunds and (2) does the varying percentages that Australian superannuation funds use to define the investment option for example, does a 41-60 % in growth assets definition for a balanced fund as compared to a 31-70% impact on the risk assessment over the long term. From an empirical perspective, our modelling captures the movement in the asset classes over time as the superannuation fund change their asset allocations. We equally use alternative methods of estimation including the CAPM, FF three factor, FF four factor and FF five factor model.

In summary, the key research questions that we consider are as follows: (1) does the level of risk, as measured by beta, vary by investment types that is from moderate to aggressive options; (2) does the varying percentages used to define an investment option, in particular, we consider for instance a balanced option of 41-60 or 31-70 in growth assets have different level of risk over the longer term; (3) is beta sensitive across different risk model specifications; and lastly, (4) we assess if the GFC, in particular, has an impact on the risk level of investment options. The key results of our analysis can be summarised as follows: (1) risk increases from moderate to aggressive options as expected given the aggressive options include a higher percentage of growth assets; (2) risk does not vary across the different definitions of the investment options used, that is a definition of a balanced option of 41-60% or 31-70% in growth assets does not impact on the risk level over the longer term; (3) the results do not seem to support the sensitivity of beta across modelling frameworks used in the non-crisis period, that is, the beta coefficients are consistent across the estimation techniques including CAPM, FF three factor, FF four factor and FF five factor model. However, the beta estimates in the GFC seem to be sensitive to the model specifications.

**References**

Aitchison, J. and Aitken, C.G.G.,1976. Multivariate binary discrimination by the kernel method. *Biometrika*, 63, pp. 413-420.

ASIC- Super investment Options; <https://www.moneysmart.gov.au/superannuation-and-retirement/how-super-works/super-investment-options>

Banz, R.W., 1981. The Relationship between Return and Market Value of Common Stocks, *Journal of Financial Economics*.9, pp. 3-18.

Cai, Z and Li, Q, 2008. Non-parametric estimation of varying coefficient panel data models. *Econometric Theory*, 24, pp. 1321-1342.

Carhart, M., 1997. On persistence of mutual fund performance. *Journal of Finance*, 52, pp. 57-82.

Fama, E.F. and French K.R., 1992. The Cross-Section of Expected Stock Returns. *Journal of Finance*, 47, pp. 27–65.

Chan, H., Faff; R., Gallagher, D.R. and Looi, A., 2009. Fund size, transaction costs and performance: size matters. *Australian Journal of Management*, 34, pp.73-96.

Chen, H. and Bassett. G., 2014. What does βSMB >0 really mean?, *Journal of Financial Research*, 34, pp. 543-551.

Chiah, M., Chai, D., Zhong, A., 2016. A Better Model? An Empirical Investigation of the Fama–French Five‐factor Model in Australia. *International Review of Finance*, 16, pp. 595-638.

Clare, R., and Connor, D. 1999. The Superannuation Industry in Australia. Sydney: ASFA Research Centre.

Elton, E.J. Grubber, M.J., and Blake, C.R. 2011. Holdings data, security returns and the selection of superior mutual funds. *Journal of Financial and Quantitative Analysis*, 46, pp.341-367.

Estrada, J. 2016. Buffett’s Asset Allocation Advice: Take it with a Twist. *The Journal of Wealth Management*, 18, pp. 59-64.

Fama, E.F. and French, K.R., 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33, pp.3–56.

Fama, E.F. and French, K.R, 1996, Multifactor Explanations of Asset Pricing Anomalies. *Journal of Finance*, 51, pp.55–84.

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

Feng, G., Gao, J., Peng, B., and Zhang, X., 2017. A varying-coefficient panel data model with fixed effects: theory and an application to US commercial banks. *Journal of Econometrics*, 196, pp. 68-82.

Gerrans, P., Clark-Murphy, M. and Speelman, C.2010. Asset allocation and age effects in retirement savings choices. *Accounting and Finance*, 50, pp. 301-19.

Gerrans, P., Gardner, D., Clark-Murphy, M. and Speelman, C. 2006. An investigation of home bias in superannuation investment choices. *Economic Papers*, 25, pp.17-31.

Gerrans, P., Faff, R., and Hartnett, N., 2015. Individual financial risk tolerance and the global financial crisis. Accounting and Finance, 55, pp. 165-185.

McNaughton, T., Piggot, J., and Purcal, S. 1999. Growing Old Gracefully: Age Phasing, Targets and Saving Rules. [www.actuary.web.unsw.edu.au/files/Growoldjppm.pdf](http://www.actuary.web.unsw.edu.au/files/Growoldjppm.pdf)

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

Rosenberg, B., Kenneth R., and Lanstein,R., 1985. Pervasive Evidence of Market Inefficiency. *Journal of Portfolio Management*, 9, pp.18-28.

Samuelson, P.A. 1969. Lifetime Portfolio Selection by Dynamic Stochastic Programming. *Review of Economic Statistics*, 51, pp.239-246.

Samuelson, P.A.1989. A case at last for age-phased reduction in equity. *Proceedings of the National Academy of Sciences* 86, pp. 9048-9051.

Samuelson, P.A. 1991. Long-run risk tolerance when equity returns are mean regressing pseudoparadoxes and vindication of businessman’s risk. *Money, Macroeconomics and Economic Policy*, Editors Brainard, W., Nordhaus, W. and Watts, H, MIT Press.

Samuelson, P.A. 1994. The long-term case for equities and how it can be oversold. *Journal of Portfolio Management*, 21, pp.15-24.

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

Stattman, D., 1980. Book Values and Stock Returns. *The Chicago MBA: A Journal of Selected Papers*, 4, pp. 25-45.

Sun, Y., Carroll, R. J., Li, D. 2009. Semiparametric estimation of fixed effects panel data varying coefficient models. *Advances in Econometrics*, 25, pp. 101-129.

Titman, S., K. C. J. Wei, and F. Xie. 2004. Capital investments and stock returns. *Journal of Financial and Quantitative Analysis,* 39, pp. 677–700.

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

**Appendix**

**Table 1: Classification of Investment Options.**

This table details the percentage of growth assets that we use to define the four broad investment options. Our first method is similar to what Canstar provides as definition and method 2 is what ASIC provides as definition.

|  |  |  |  |
| --- | --- | --- | --- |
| **Classification of Investment Options**  |  |  |  |
|  | **Method 1: Canstar** | **Method 2: ASIC** |
| **Investment Options** | **% Growth Assets**  | **No of observations** | **% Growth Assets**  | **No of Observations** |
| Multi- Sector Moderate  | 21-40% | 116 | 1-30 % | 109 |
| Multi-Sector Balanced |  41-60% | 87 | 31-70% | 261 |
| Multi-sector Growth  | 61-80% | 184 | 71-84% | 128 |
| Multi-Sector Aggressive | 81-100% | 475 | 85-100% | 428 |

|  |  |
| --- | --- |
| **Classification of Investment Options**  |  |
|  | **Option 1 : Canstar** |
| **Investment Options** | **% Growth Assets**  | **No of Options** |
| Multi- Sector Moderate  | 21-40% | 116 |
| Multi-Sectir Balanced |  41-60% | 87 |
| Multi-sector Growth  | 61-80% | 184 |
| Multi-Sector Aggressive | 81-100% | 475 |

**Table 2: Summary Statistics of Returns**

This table summarises the return statistics of the investment options as defined using Canstar method in panel A and Panel B using the definition by ASIC.

|  |
| --- |
| **Panel A: Summary statistics of monthly returns of super funds during whole sample**  |
| **period based on Canstar classifications** |  |  |
|   | **Moderate (21-40)** | **Balanced (41-60 %)** | **Growth (61-80 %)** | **Aggressive (81-100 %)** |
| Mean | 0.3997% | 0.4807% | 0.5352% | 0.5247% |
| Maximum | 0.6719% | 0.7158% | 0.9354% | 1.5497% |
| Minimum | 0.1511% | 0.2315% | 0.1879% | -0.1479% |
| Range  | 0.5208% | 0.4843% | 0.7475% | 1.6976% |
| Std. Dev | 0.0905% | 0.1128% | 0.1332% | 0.2445% |
| Count | 116 | 87 | 184 | 475 |
| **Panel B : Summary statistics of monthly returns of super funds during whole sample**  |
| **period based on ASIC classifications** |  |  |
|   | **Moderate (1-30 %)** | **Balanced (31-70% )** | **Growth (71-84%%)** | **Aggressive (85-100%)** |
| Mean | 0.3907% | 0.4726% | 0.5795% | 0.5207% |
| Maximum | 0.5680% | 0.8457% | 1.5067% | 2.0357% |
| Minimum | 0.1229% | 0.0258% | 0.0346% | -1.1100% |
| Range | 0.4451% | 0.8199% | 1.4721% | 3.1457% |
| Std Ev | 0.0816% | 0.1326% | 0.1902% | 0.2919% |
| Count | 109 | 261 | 128 | 428 |

**Table 3: Estimates using the full sample and Canstar Classification**

This table provides the beta estimates using the varying coefficient models estimate using four estimation techniques, the CAPM, FF three factor model, FF four factor model and FF five factor model. The non-crisis period is the full sample January 1990 to December 2006 minus Dot Com, Asian and GFC and Crisis is a combination of the three crises. The three crisis periods including 1997 Asian financial crisis (January 1997-June 1999), 2001 dot com crisis (September 1999-April 2003) and 2007 subprime financial crisis (January 2007-September 2009). The model is estimated using a non-crisis and crisis sample and by using the **Canstar** method of classifying investment options. Standard errors are presented in parenthesis and \*, \*\*, \*\*\* indicate estimates are statistically significant at 10%, 5% and 1% level of significance.

|  |  |  |
| --- | --- | --- |
|   | **Non-crisis period** | **Crisis period** |
|   | Rm-Rf | SMB | HML | UMD | RMW | CMA | Rm-Rf | SMB | HML | UMD | RMW | CMA |
| **CAPM model** |
| Moderate (21-40%) | 0.162\*\*\* |  |  |  |  |  | 0.1652\*\*\* |  |  |  |  |  |
|  | (0.006) |  |  |  |  |  | (0.0048) |  |  |  |  |  |
| Balanced (41-60%) | 0.3898\*\*\* |  |  |  |  |  | 0.4467\*\*\* |  |  |  |  |  |
|  | (0.0108) |  |  |  |  |  | (0.0073) |  |  |  |  |  |
| Growth (61-80%) | 0.496\*\*\* |  |  |  |  |  | 0.5163\*\*\* |  |  |  |  |  |
|  | (0.0053) |  |  |  |  |  | (0.0084) |  |  |  |  |  |
| Aggressive (81-100%) | 0.6399\*\*\* |  |  |  |  |  | 0.734\*\*\* |  |  |  |  |  |
|  | (0.01) |  |  |  |  |  | (0.0185) |  |  |  |  |  |
| **Three factor model** |
| Moderate (21-40%) | 0.1567\*\*\* | -0.015\*\*\* | -0.007 |  |  |  | 0.1683\*\*\* | -0.004 | 0.0249\*\*\* |  |  |  |
|  | (0.0061) | (0.005) | (0.0071) |  |  |  | (0.0105) | (0.0081) | (0.0083) |  |  |  |
| Balanced (41-60%) | 0.3868\*\*\* | -0.015\*\*\* | -0.019\*\*\* |  |  |  | 0.4557\*\*\* | -0.022\*\*\* | 0.0169\*\* |  |  |  |
|  | (0.0053) | (0.0044) | (0.006) |  |  |  | (0.0098) | (0.0076) | (0.0077) |  |  |  |
| Growth (61-80%) | 0.4927\*\*\* | -0.034\*\*\* | -0.017\*\*\* |  |  |  | 0.5305\*\*\* | -0.056\*\*\* | 0.0078 |  |  |  |
|  | (0.0049) | (0.0039) | (0.0054) |  |  |  | (0.0076) | (0.0077) | (0.0082) |  |  |  |
| Aggressive (81-100%) | 0.6368\*\*\* | -0.046\*\*\* | -0.008 |  |  |  | 0.7503\*\*\* | -0.04\*\* | 0.0226 |  |  |  |
|  | (0.0088) | (0.0063) | (0.0103) |  |  |  | (0.0186) | (0.017) | (0.018) |  |  |  |
| **Four factor model** |
| Moderate (21-40%) | 0.1581\*\*\* | -0.014\*\*\* | -0.004 | 0.0092 |  |  | 0.1673\*\*\* | -0.005 | 0.0192\*\* | -0.006 |  |  |
|  | (0.0062) | (0.0051) | (0.0077) | (0.006) |  |  | (0.0105) | (0.0081) | (0.009) | (0.0059) |  |  |
| Balanced (41-60%) | 0.3884\*\*\* | -0.014\*\*\* | -0.016\*\* | 0.01\* |  |  | 0.4524\*\*\* | -0.022\*\*\* | 0.0026 | -0.016\*\*\* |  |  |
|  | (0.0052) | (0.0044) | (0.0064) | (0.0052) |  |  | (0.0097) | (0.0074) | (0.0089) | (0.006) |  |  |
| Growth (61-80%) | 0.4953\*\*\* | -0.032\*\*\* | -0.012\*\* | 0.0182\*\*\* |  |  | 0.526\*\*\* | -0.058\*\*\* | -0.015 | -0.029\*\*\* |  |  |
|  | (0.0048) | (0.0039) | (0.0057) | (0.0049) |  |  | (0.0077) | (0.0076) | (0.0093) | (0.0055) |  |  |
| Aggressive (81-100%) | 0.6397\*\*\* | -0.045\*\*\* | -0.003 | 0.0191\*\* |  |  | 0.7451\*\*\* | -0.042\*\* | -0.002 | -0.03\*\* |  |  |
|  | (0.0089) | (0.0064) | (0.011) | (0.009) |  |  | (0.0186) | (0.0168) | (0.0209) | (0.0122) |  |  |
| **Five factor model** |
| Moderate (21-40%) | 0.1805\*\*\* | -0.013\*\*\* | -0.01 |  | 0.0168\*\*\* | -0.008 | 0.1946\*\*\* | 0.0044 | 0.0216\*\* |  | 0.0063 | 0.0329\*\*\* |
|  | (0.006) | (0.0049) | (0.0082) |  | (0.0058) | (0.0071) | (0.0098) | (0.0073) | (0.0088) |  | (0.0053) | (0.0099) |
| Balanced (41-60%) | 0.4057\*\*\* | -0.009\*\* | -0.009\*\* |  | 0.0267\*\*\* | -0.008 | 0.4725\*\*\* | 0.0103 | 0.0089 |  | 0.0435\*\*\* | 0.0575\*\*\* |
|  | (0.0087) | (0.0042) | (0.0041) |  | (0.0066) | (0.006) | (0.0099) | (0.0068) | (0.008) |  | (0.0086) | (0.0088) |
| Growth (61-80%) | 0.499\*\*\* | -0.032\*\*\* | -0.019\*\*\* |  | 0.0167\* | -0.004 | 0.557\*\*\* | -0.015\*\*\* | -0.001 |  | 0.0436\*\*\* | 0.1061\*\*\* |
|  | (0.1) | (0.0038) | (0.0063) |  | (0.0088) | (0.0043) | (0.0076) | (0.0042) | (0.006) |  | (0.0098) | (0.0078) |
| Aggressive (81-100%) | 0.6552\*\*\* | -0.036\*\*\* | -0.008 |  | 0.037\*\*\* | 0 | 0.7842\*\*\* | 0.0261\*\* | 0.0005 |  | 0.0983\*\*\* | 0.1276\*\*\* |
|   | (0.0098) | (0.006) | (0.0132) |   | (0.0078) | (0.0055) | (0.0188) | (0.0102) | (0.0021) |   | (0.01) | (0.0045) |

**Table 4: Estimates using the full sample and ASIC Classification**

This table provides the beta estimates using the varying coefficient models estimate using four estimation techniques, the CAPM, FF three factor model, FF four factor model and FF five actor model. The non-crisis period is the full sample January 1990 to December 2006 minus Dot Com, Asian and GFC and Crisis is a combination of the three crises. The three crisis periods including 1997 Asian financial crisis (January 1997-June 1999), 2001 dot com crisis (September 1999-April 2003) and 2007 subprime financial crisis (January 2007-September 2009). The model is estimated using a non-crisis and crisis sample and by using the **ASIC** method of classifying investment options. Standard errors are presented in parenthesis and \*, \*\*, \*\*\* indicate estimates are statistically significant at 10%, 5% and 1% level of significance.

|  |  |  |
| --- | --- | --- |
|   | **Non-crisis period** | **Crisis period** |
|   | Rm-Rf | SMB | HML | UMD | RMW | CMA | Rm-Rf | SMB | HML | UMD | RMW | CMA |
| **CAPM model** |  |  |  |  |  |  |  |  |  |  |  |  |
| Moderate (21-40%) | 0.121\*\*\* |  |  |  |  |  | 0.1076\*\*\* |  |  |  |  |  |
|  | (0.0018) |  |  |  |  |  | (0.0076) |  |  |  |  |  |
| Balanced (41-60%) | 0.4107\*\*\* |  |  |  |  |  | 0.449\*\*\* |  |  |  |  |  |
|  | (0.006) |  |  |  |  |  | (0.0126) |  |  |  |  |  |
| Growth (61-80%) | 0.5252\*\*\* |  |  |  |  |  | 0.5482\*\*\* |  |  |  |  |  |
|  | (0.0122) |  |  |  |  |  | (0.0093) |  |  |  |  |  |
| Aggressive (81-100%) | 0.6437\*\*\* |  |  |  |  |  | 0.7399\*\*\* |  |  |  |  |  |
|  | (0.004) |  |  |  |  |  | (0.0199) |  |  |  |  |  |
| **Three factor model** |  |  |  |  |  |  |  |  |  |  |  |  |
| Moderate (21-40%) | 0.1163\*\*\* | -0.016\*\*\* | -0.004 |  |  |  | 0.1079\*\*\* | 0.0122 | 0.0316\*\*\* |  |  |  |
|  | (0.006) | (0.0051) | (0.0064) |  |  |  | (0.0111) | (0.0093) | (0.0089) |  |  |  |
| Balanced (41-60%) | 0.4081\*\*\* | -0.018\*\*\* | -0.016\*\*\* |  |  |  | 0.4597\*\*\* | -0.029\*\*\* | 0.0194\*\*\* |  |  |  |
|  | (0.0039) | (0.0035) | (0.0048) |  |  |  | (0.0067) | (0.0059) | (0.0063) |  |  |  |
| Growth (61-80%) | 0.5218\*\*\* | -0.039\*\*\* | -0.023\*\* |  |  |  | 0.5642\*\*\* | -0.064\*\*\* | 0 |  |  |  |
|  | (0.0072) | (0.0063) | (0.0094) |  |  |  | (0.0129) | (0.0108) | (0.0133) |  |  |  |
| Aggressive (81-100%) | 0.6448\*\*\* | -0.045\*\*\* | -0.009 |  |  |  | 0.7557\*\*\* | -0.038\*\* | 0.023 |  |  |  |
|  | (0.0093) | (0.0073) | (0.0113) |  |  |  | (0.0191) | (0.0177) | (0.0183) |  |  |  |
| **Four factor model** |  |  |  |  |  |  |  |  |  |  |  |  |
| Moderate (21-40%) | 0.1181\*\*\* | -0.015\*\*\* | -0.001 | 0.0116\* |  |  | 0.1089\*\*\* | 0.0121 | 0.0356\*\*\* | 0.005 |  |  |
|  | (0.0059) | (0.0048) | (0.007) | (0.0062) |  |  | (0.0108) | (0.0097) | (0.0099) | (0.0055) |  |  |
| Balanced (41-60%) | 0.4102\*\*\* | -0.017\*\*\* | -0.012\*\*\* | 0.0145\*\*\* |  |  | 0.4565\*\*\* | -0.03\*\*\* | 0.0047 | -0.017\*\*\* |  |  |
|  | (0.004) | (0.0033) | (0.0046) | (0.0045) |  |  | (0.0073) | (0.0057) | (0.007) | (0.0043) |  |  |
| Growth (61-80%) | 0.5235\*\*\* | -0.038\*\*\* | -0.02\*\* | 0.0103 |  |  | 0.5581\*\*\* | -0.064\*\*\* | -0.034\*\* | -0.041\*\*\* |  |  |
|  | (0.0074) | (0.0063) | (0.0097) | (0.0086) |  |  | (0.013) | (0.0113) | (0.0168) | (0.0085) |  |  |
| Aggressive (81-100%) | 0.6481\*\*\* | -0.044\*\*\* | -0.002 | 0.0213\*\* |  |  | 0.7508\*\*\* | -0.039\*\* | 0 | -0.028\*\* |  |  |
|  | (0.0096) | (0.0068) | (0.0115) | (0.01) |  |  | (0.0192) | (0.0172) | (0.0206) | (0.0123) |  |  |
| **Five factor model** |  |  |  |  |  |  |  |  |  |  |  |  |
| Moderate (21-40%) | 0.1442\*\*\* | -0.007 | -0.006 |  | 0.0248\*\*\* | -0.005 | 0.1586\*\*\* | 0.0052 | 0.0249\*\* |  | 0.001 | 0.0319\*\*\* |
|  | (0.0058) | (0.0044) | (0.0065) |  | (0.008) | (0.006) | (0.0098) | (0.0089) | (0.0098) |  | (0.0098) | (0.0074) |
| Balanced (41-60%) | 0.4239\*\*\* | -0.014\*\*\* | -0.013\*\*\* |  | 0.0254\*\*\* | -0.006 | 0.482\*\*\* | 0 | 0.0069 |  | 0.0384\*\*\* | 0.0796\*\*\* |
|  | (0.0041) | (0.0035) | (0.005) |  | (0.0068) | (0.0053) | (0.0074) | (0.0058) | (0.0068) |  | (0.0066) | (0.01) |
| Growth (61-80%) | 0.5201\*\*\* | -0.044\*\*\* | -0.015\* |  | 0.006 | -0.017\*\* | 0.5953\*\*\* | -0.007 | -0.008 |  | 0.0504\*\*\* | 0.116\*\*\* |
|  | (0.007) | (0.0066) | (0.0083) |  | (0.0054) | (0.0066) | (0.0105) | (0.0099) | (0.0103) |  | (0.0058) | (0.0088) |
| Aggressive (81-100%) | 0.6669\*\*\* | -0.034\*\*\* | -0.01 |  | 0.0393\*\*\* | 0.0053 | 0.7937\*\*\* | 0.0324\*\* | 0.0066 |  | 0.1047\*\*\* | 0.1197\*\*\* |
|   | (0.0098) | (0.007) | (0.0102) |   | (0.0078) | (0.0053) | (0.0188) | (0.0138) | (0.0112) |   | (0.0112) | (0.0099) |

**Table 5: Estimates of 2007 GFC- Crisis Analysis: Canstar Classification**

This table provides the beta estimates using the varying coefficient models estimate using four estimation techniques, the CAPM, FF three factor model, FF four factor model and FF five factor model for the 2007 GFC analysis. The definition of non-crisis is the 6-month period prior to GFC and 6-month period post GFC and the crisis period is the 2007 GFC period that is January 2007 to Sept 2009. The classification of investment options is done as per the Canstar option. Standard errors are presented in parenthesis and \*, \*\*, \*\*\* indicate estimates are statistically significant at 10%, 5% and 1% level of significance.

|  |  |  |
| --- | --- | --- |
|   | **Non-crisis period** | **Crisis period** |
|   | Rm-Rf | SMB | HML | UMD | RMW | CMA | Rm-Rf | SMB | HML | UMD | RMW | CMA |
| **CAPM model** |  |  |  |  |  |  |  |  |  |  |  |  |
| Moderate (21-40%) | 0.3562\*\*\* |  |  |  |  |  | 0.2115\*\*\* |  |  |  |  |  |
|  | (0.0074) |  |  |  |  |  | (0.0102) |  |  |  |  |  |
| Balanced (41-60%) | 0.5357\*\*\* |  |  |  |  |  | 0.4218\*\*\* |  |  |  |  |  |
|  | (0.0044) |  |  |  |  |  | (0.0066) |  |  |  |  |  |
| Growth (61-80%) | 0.6556\*\*\* |  |  |  |  |  | 0.5233\*\*\* |  |  |  |  |  |
|  | (0.0162) |  |  |  |  |  | (0.0168) |  |  |  |  |  |
| Aggressive (81-100%) | 0.9143\*\*\* |  |  |  |  |  | 0.8083\*\*\* |  |  |  |  |  |
|  | (0.011) |  |  |  |  |  | (0.0127) |  |  |  |  |  |
| **Three factor model** |  |  |  |  |  |  |  |  |  |  |  |
| Moderate (21-40%) | 0.362\*\*\* | 0.0402\*\*\* | -0.039\*\*\* |  |  |  | 0.2449\*\*\* | -0.064\*\*\* | 0.0313\*\*\* |  |  |  |
|  | (0.008) | (0.0064) | (0.0056) |  |  |  | (0.0053) | (0.0071) | (0.0059) |  |  |  |
| Balanced (41-60%) | 0.5188\*\*\* | 0.0731\*\*\* | -0.022 |  |  |  | 0.4455\*\*\* | -0.042\*\*\* | 0.0284\*\* |  |  |  |
|  | (0.0231) | (0.019) | (0.0138) |  |  |  | (0.0106) | (0.0146) | (0.0116) |  |  |  |
| Growth (61-80%) | 0.6365\*\*\* | 0.0784\*\*\* | -0.023\*\*\* |  |  |  | 0.5737\*\*\* | -0.116\*\*\* | 0.0313\*\*\* |  |  |  |
|  | (0.0106) | (0.0081) | (0.0071) |  |  |  | (0.0067) | (0.0104) | (0.0083) |  |  |  |
| Aggressive (81-100%) | 0.8979\*\*\* | 0.1147\*\*\* | -0.059\*\*\* |  |  |  | 0.8508\*\*\* | -0.074\*\*\* | 0.052\*\*\* |  |  |  |
|  | (0.0168) | (0.0137) | (0.0129) |  |  |  | (0.0112) | (0.0158) | (0.0131) |  |  |  |
| **Four factor model** |  |  |  |  |  |  |  |  |  |  |  |  |
| Moderate (21-40%) | 0.3607\*\*\* | 0.0401\*\*\* | -0.039\*\*\* | -0.001 |  |  | 0.2406\*\*\* | -0.088\*\*\* | -0.038\*\*\* | -0.068\*\*\* |  |  |
|  | (0.0077) | (0.0063) | (0.0055) | (0.0043) |  |  | (0.0047) | (0.0067) | (0.0069) | (0.004) |  |  |
| Balanced (41-60%) | 0.5036\*\*\* | 0.071\*\*\* | -0.024\* | -0.021\*\* |  |  | 0.4362\*\*\* | -0.079\*\*\* | -0.084\*\*\* | -0.109\*\*\* |  |  |
|  | (0.0201) | (0.0185) | (0.014) | (0.0093) |  |  | (0.0106) | (0.0129) | (0.0158) | (0.0106) |  |  |
| Growth (61-80%) | 0.6296\*\*\* | 0.0777\*\*\* | -0.024\*\*\* | -0.009 |  |  | 0.567\*\*\* | -0.153\*\*\* | -0.085\*\*\* | -0.116\*\*\* |  |  |
|  | (0.01) | (0.0079) | (0.0073) | (0.0073) |  |  | (0.0068) | (0.0087) | (0.0108) | (0.0072) |  |  |
| Aggressive (81-100%) | 0.8662\*\*\* | 0.1107\*\*\* | -0.065\*\*\* | -0.044\*\*\* |  |  | 0.8417\*\*\* | -0.131\*\*\* | -0.119\*\*\* | -0.171\*\*\* |  |  |
|  | (0.0171) | (0.0134) | (0.0129) | (0.0113) |  |  | (0.0111) | (0.0148) | (0.016) | (0.0106) |  |  |
| **Five factor model** |  |  |  |  |  |  |  |  |  |  |  |  |
| Moderate (21-40%) | 0.3064\*\*\* | 0.0544\*\*\* | -0.004 |  | 0.0726\*\*\* | 0.044\*\*\* | 0.394\*\*\* | 0.0535\*\*\* | -0.01\* |  | 0.0428\*\*\* | 0.1588\*\*\* |
|  | (0.0097) | (0.0064) | (0.0052) |  | (0.0098) | (0.0065) | (0.0045) | (0.0074) | (0.006) |  | (0.0058) | (0.0078) |
| Balanced (41-60%) | 0.4533\*\*\* | 0.1002\*\*\* | 0.0136 |  | 0.1108\*\*\* | 0.1108\*\*\* | 0.5067\*\*\* | 0.1096\*\*\* | -0.017 |  | 0.0447\*\*\* | 0.2019\*\*\* |
|  | (0.0233) | (0.0193) | (0.0138) |  | (0.0204) | (0.014) | (0.0092) | (0.0225) | (0.0137) |  | (0.0135) | (0.0215) |
| Growth (61-80%) | 0.5732\*\*\* | 0.0966\*\*\* | 0.0187\*\* |  | 0.1014\*\*\* | 0.0428\*\*\* | 0.6595\*\*\* | 0.0738\*\*\* | -0.026\*\*\* |  | 0.0451\*\*\* | 0.2709\*\*\* |
|  | (0.0134) | (0.0086) | (0.0081) |  | (0.0162) | (0.0102) | (0.0072) | (0.0113) | (0.0088) |  | (0.0091) | (0.0126) |
| Aggressive (81-100%) | 0.758\*\*\* | 0.1686\*\*\* | 0.0107 |  | 0.2553\*\*\* | -0.016 | 0.9485\*\*\* | 0.1677\*\*\* | -0.035\*\* |  | 0.0993\*\*\* | 0.3185\*\*\* |
|   | (0.0181) | (0.0144) | (0.0125) |   | (0.0226) | (0.0175) | (0.0137) | (0.0239) | (0.016) |   | (0.0161) | (0.0226) |

**Table 6: Estimates of 2007 GFC- Crisis Analysis: ASIC Classification**

This table provides the beta estimates using the varying coefficient models estimate using four estimation techniques, the CAPM, FF three factor model, FF four factor model and FF five factor model for the 2007 GFC analysis. The definition of non-crisis is the 6-month period prior to GFC and 6-month period post GFC and the crisis period is the 2007 GFC period that is January 2007 to Sept 2009. The classification of investment options is done as per the ASIC option. Standard errors are presented in parenthesis and \*, \*\*, \*\*\* indicate estimates are statistically significant at 10%, 5% and 1% level of significance.

|  |  |  |
| --- | --- | --- |
|   | **Non-crisis period** | **Crisis period** |
|   | Rm-Rf | SMB | HML | UMD | RMW | CMA | Rm-Rf | SMB | HML | UMD | RMW | CMA |
| **CAPM model** |  |  |  |  |  |  |  |  |  |  |  |  |
| Moderate (21-40%) | 0.3143\*\*\* |  |  |  |  |  | 0.1893\*\*\* |  |  |  |  |  |
|  | (0.0012) |  |  |  |  |  | (0.021) |  |  |  |  |  |
| Balanced (41-60%) | 0.5654\*\*\* |  |  |  |  |  | 0.4393\*\*\* |  |  |  |  |  |
|  | (0.0098) |  |  |  |  |  | (0.0154) |  |  |  |  |  |
| Growth (61-80%) | 0.6651\*\*\* |  |  |  |  |  | 0.574\*\*\* |  |  |  |  |  |
|  | (0.0054) |  |  |  |  |  | (0.0174) |  |  |  |  |  |
| Aggressive (81-100%) | 0.9249\*\*\* |  |  |  |  |  | 0.8196\*\*\* |  |  |  |  |  |
|  | (0.0093) |  |  |  |  |  | (0.0129) |  |  |  |  |  |
| **Three factor model** |  |  |  |  |  |  |  |  |  |  |  |
| Moderate (21-40%) | 0.3208\*\*\* | 0.0368\*\*\* | -0.039\*\*\* |  |  |  | 0.2189\*\*\* | -0.057\*\*\* | 0.0273\*\*\* |  |  |  |
|  | (0.01) | (0.0075) | (0.0064) |  |  |  | (0.0057) | (0.0086) | (0.0065) |  |  |  |
| Balanced (41-60%) | 0.5532\*\*\* | 0.0693\*\*\* | -0.028\*\*\* |  |  |  | 0.4788\*\*\* | -0.086\*\*\* | 0.0269\*\*\* |  |  |  |
|  | (0.0115) | (0.0091) | (0.0073) |  |  |  | (0.0064) | (0.0086) | (0.0066) |  |  |  |
| Growth (61-80%) | 0.5974\*\*\* | 0.123\*\*\* | 0.0455\*\* |  |  |  | 0.6196\*\*\* | -0.096\*\*\* | 0.0405\*\* |  |  |  |
|  | (0.0274) | (0.0206) | (0.0199) |  |  |  | (0.0164) | (0.0226) | (0.0198) |  |  |  |
| Aggressive (81-100%) | 0.918\*\*\* | 0.1043\*\*\* | -0.069\*\*\* |  |  |  | 0.8627\*\*\* | -0.072\*\*\* | 0.0558 |  |  |  |
|  | (0.0177) | (0.0135) | (0.014) |  |  |  | (0.0119) | (0.0179) |  |  |  |  |
| **Four factor model** |  |  |  |  |  |  |  |  |  |  |  |  |
| Moderate (21-40%) | 0.3181\*\*\* | 0.0364\*\*\* | -0.039\*\*\* | -0.003 |  |  | 0.2157\*\*\* | -0.08\*\*\* | -0.035\*\*\* | -0.061\*\*\* |  |  |
|  | (0.0104) | (0.0074) | (0.0071) | (0.0053) |  |  | (0.0053) | (0.0077) | (0.0078) | (0.0049) |  |  |
| Balanced (41-60%) | 0.5463\*\*\* | 0.0684\*\*\* | -0.029\*\*\* | -0.009\* |  |  | 0.4723\*\*\* | -0.121\*\*\* | -0.076\*\*\* | -0.103\*\*\* |  |  |
|  | (0.0108) | (0.009) | (0.0072) | (0.0053) |  |  | (0.0059) | (0.0078) | (0.009) | (0.0063) |  |  |
| Growth (61-80%) | 0.5894\*\*\* | 0.1227\*\*\* | 0.0452\*\* | -0.012 |  |  | 0.6065\*\*\* | -0.135\*\*\* | -0.093\*\*\* | -0.132\*\*\* |  |  |
|  | (0.0246) | (0.019) | (0.0186) | (0.0129) |  |  | (0.0146) | (0.0194) | (0.0251) | (0.0132) |  |  |
| Aggressive (81-100%) | 0.8855\*\*\* | 0.1003\*\*\* | -0.075\*\*\* | -0.045\*\*\* |  |  | 0.8539\*\*\* | -0.131\*\*\* | -0.12\*\*\* | -0.176\*\*\* |  |  |
|  | (0.0176) | (0.0128) | (0.0139) | (0.0114) |  |  | (0.0125) | (0.0164) | (0.018) | (0.0118) |  |  |
| **Five factor model** |  |  |  |  |  |  |  |  |  |  |  |  |
| Moderate (21-40%) | 0.2701\*\*\* | 0.0503\*\*\* | -0.005 |  | 0.0663\*\*\* | 0.0429\*\*\* | 0.3661\*\*\* | 0.0521\*\*\* | -0.01 |  | 0.0327\*\*\* | 0.1537\*\*\* |
|  | (0.0111) | (0.008) | (0.0065) |  | (0.0116) | (0.0081) | (0.0053) | (0.0092) | (0.0072) |  | (0.0071) | (0.009) |
| Balanced (41-60%) | 0.4881\*\*\* | 0.0911\*\*\* | 0.0109 |  | 0.0964\*\*\* | 0.0302\*\*\* | 0.5518\*\*\* | 0.0761\*\*\* | -0.018\*\* |  | 0.0372\*\*\* | 0.2273\*\*\* |
|  | (0.012) | (0.0094) | (0.0071) |  | (0.0127) | (0.0084) | (0.0059) | (0.0113) | (0.0083) |  | (0.008) | (0.0118) |
| Growth (61-80%) | 0.54\*\*\* | 0.1447\*\*\* | 0.0863\*\*\* |  | 0.1049\*\*\* | 0.0288 | 0.7151\*\*\* | 0.1103\*\*\* | -0.025 |  | 0.0487\*\* | 0.3011\*\*\* |
|  | (0.0247) | (0.022) | (0.0182) |  | (0.028) | (0.0205) | (0.0202) | (0.0318) | (0.0239) |  | (0.0231) | (0.0345) |
| Aggressive (81-100%) | 0.7751\*\*\* | 0.1589\*\*\* | 0.0039 |  | 0.2638\*\*\* | -0.01 | 0.9612\*\*\* | 0.1705\*\*\* | -0.033\* |  | 0.1\*\*\* | 0.3213\*\*\* |
|   | (0.0194) | (0.0154) | (0.0134) |   | (0.0236) | (0.0175) | (0.0135) | (0.0259) | (0.017) |   | (0.0166) | (0.0233) |

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The authors wish to thank Dr Haotian Chan for research assistance in this project and this project was funded by the Australian Centre of Financial Studies, Monash Business School. The authors also wish to thank Prof Phil Gray for providing the Fama French factors for the Australian market. We would like to thank Dr Bin Peng for kindly sharing the Matlab code to estimating the varying-coefficient panel model.

 [↑](#footnote-ref-1)
2. See: https://www.moneysmart.gov.au/superannuation-and-retirement/how-super-works/super-investment-options [↑](#footnote-ref-2)
3. <http://www.afr.com/personal-finance/superannuation-and-smsfs/super-funds-accused-of-masking-portfolio-risks-20180105-h0dyxp> [↑](#footnote-ref-3)
4. <https://www.superguide.com.au/comparing-super-funds/superannuation-investment-difference-balanced-growth-option> [↑](#footnote-ref-4)
5. See: OECD (2009), Pensions at a Glance: Retirement-Income Systems in OECD Countries, Figure 1.3 [↑](#footnote-ref-5)
6. As of Sept 2017, for instance, CareSuper had 13 investment options, while Cbus had only 6 investment options. Source: AIST PD Programs [↑](#footnote-ref-6)
7. See <https://www.canstar.com.au/managed-funds/types-of-managed-funds-and-how-they-perform-long-term/> [↑](#footnote-ref-7)
8. Growth assets are includes domestic and international shares, listed and unlisted property. [↑](#footnote-ref-8)
9. <https://www.moneysmart.gov.au/superannuation-and-retirement/how-super-works/super-investment-options> [↑](#footnote-ref-9)
10. The initial sample from Morningstar include 1,213 options. Given we use the two methods of classification, the final numbers dropped to 862 options for the Canstar classification and ASIC classification drops to 995 options. Regarding the Canstar classification, we exclude options which have less than 20% growth assets as per the definition (note moderate is 21-40%). For the ASIC classification, the initial sample of 1,213 options includes a small number of 100% cash investment options, which is not included as per the ASIC defined ranges. [↑](#footnote-ref-10)
11. Monthly asset-pricing factors were kindly provided by Professor Philip Gray. Further details of their construction can be found in Zhong et al. (2014). [↑](#footnote-ref-11)
12. Across four model specifications employed, we consider six factors in total, including performance of market portfolio (associated with systematic risk estimate $β\_{M}$), SMB (associated with $β\_{SMB}$), HML (associated with $β\_{HML}$), UMD (associated with $β\_{UMD}$), RMW (associated with $β\_{RMW}$), and CMA (associated with $β\_{CMA}$). We focus our discussion of risk profile of investment options on $β\_{M}$ since it represents the systematic risk of investment options. Other betas can be considered as impacts of control factors on performance of investment options. Henceforth, when we mention about beta, we refer to $β\_{M}$. [↑](#footnote-ref-12)
13. <http://www.theaustralian.com.au/business/financial-services/super-funds-losses-among-worst-in-world/news-story/6a151a41e76c7c97f6c91f179b7e60d6> [↑](#footnote-ref-13)