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Risk Analysis of Pension Fund Investment Choices

We provide a comprehensive and more consistent approach to analyse and compare the risk-return relationships of Australian superannuation investment options for the period January 1990 to December 2016. In estimating the risk profiles 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 balanced fund does not impact the long-term risk measurement. We equally find that the risk-return relationships of investment options are not sensitive to the modelling framework, except for the crisis analysis, in which the Fama-French five-factor model provides greater sensitivity.

Key words: Australian superannuation funds; Fama-French; Five-factor model; Investment options; Risk; Varying coefficient panel data.

In this study, the objective and key research questions are to assess the risk associated with the investment options of superannuation 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., Langford *et al*., 2006; Gerrans *et al*., 2006), individuals are faced with the challenge of making the right investment choice for their circumstances. In addition, with longevity risk, the right asset allocation choice becomes an important decision, not

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only for younger working investors but also for those who are older and closer to retirement. It is important to assess the appropriate mix of asset allocation that will maximize the return to ensure that an individual's retirement nest egg will eventually increase. It is essential to realize that, most likely, having a risky investment strategy may pay off and maximize the investment nest egg rather than face 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 being reported by the fund. The pensions literature mostly focuses on return analysis. Sawicki (2000) analyses Australian wholesale balanced funds and find that returns are associated with assets under management. Del Guerico and Tkac (2002) compare the performance of various mutual funds, while Parwada and Faff (2005) assess the factors that are important to award investment management mandates and conclude that returns do not affect the probability of having investment mandates. While return is a key factor, our study's focus is to assess whether the risk associated with the investment options are being properly reported or being under-reported. One of the challenges facing the Australian superannuation fund industry is the variability in definitions used by superannuation funds to define the composition of portfolios. Australian superannuation funds tend to use their own judgement to classify investments as 'growth' (i.e., riskier) or 'defensive' (i.e., more stable). The standard definition of growth assets in finance and as per the Australian Securities and Investment Commission (ASIC)[1] is that growth investment includes asset classes such as equity and property, while defensive assets tend to be bonds and cash. An article in the *Australian Financial Review*[2] in January 2018 highlights that, according to a submission made by the National Australian Bank (NAB) wealth division, many funds with unlisted assets are '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 heavily invest in infrastructure and property, however, they are subject to different classifications by funds. Hence, while some superannuation fund managers seem to provide very good results, in terms of returns, they may be mis-specifying the risk to their members. The industry clearly recognizes that there are discrepancies in the disclosure statement, and that a clear definition of what is growth and defensive is difficult to assess. Hence, the key contribution of this study is to assess the risk of investment options using a standard approach. In particular, using beta as a key risk measure, we assess the long-term riskiness of investment options by classifying asset classes using the standard definition of growth and defensive

[1] See https://www.moneysmart.gov.au/superannuation-and-retirement/how-super-works/super-investment-options.

[2] http://www.afr.com/personal-finance/superannuation-and-smsfs/super-funds-accused-of-masking-portfolio-risks-20180105-h0dyxp

assets across monthly assets classes of 1,213 investment options for the period January 1990 to December 2016.

Risk assessment of the stock market has been largely researched in the finance literature; it is also important to provide a comprehensive risk analysis of superannuation funds. Many studies have investigated the risk-return trade-off, with mixed views as to what the best investment options are at different stages of an investor's life. Davis (2001) states that investment funds should seek the most efficient portfolio (i.e., by considering 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. Numerous studies have examined the idea of de-risking and its relationship to investor's age. Samuelson (1989) suggests that investors should be more risk tolerant when they are young and decrease their exposure to relatively risky equities, in favour of lower risk cash and fixed interest securities as they age. Samuelson (1969), however, maintains that a more aggressive allocation is irrational with a constant investment opportunity set. Samuelson (1991) further shows that 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. In his 1994 study, he further shows that a desired minimum level of retirement wealth implies an optimal investment strategy of declining equity allocation with age. However, McNaughton *et al.* (1999) have a different view. They suggest that as investors age, an increasing equity allocation is more likely. Recently, Estrada (2016) reviewed an aggressive asset allocation suggested by Warren Buffet, the 90/10 investment option, with 90% invested according to a growth strategy. Using historical returns, he considers how a hypothetical investment portfolio performs over a long-term period (over 30 years), from 1900 to 1930; his final years include 1985 to 2014. His findings suggest that retirees might be able to lean heavily on stocks without placing their nest eggs in grave danger. Given the mixed literature and the volatile state of the market over the past few decades, our research focuses on how to assess the associated risk, as measured by beta, in each of the investment options for a 27-year period, from January 1990 to December 2016.

Our second contribution is to assess the risk of the investment options by considering two different classification methods; we establish the extent to which beta, our measure of risk, varies as the definition of investment options changes, particularly a balanced option. In this regard, we aim to answer the following question. Does the definition of 41–60% of growth assets in the fund compared to 31–70% of growth assets truly 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 many individual fund members who fall into the default category in their investment options. Gerrans *et al.* (2010) writes that the total growth assets in the default option of funds across the superannuation industry varies from 40% for retail funds to 70% for industry funds. The default option is important to consider given that Australia now has legislated MySuper options in place. Most funds implement the MySuper options by either (i) changing the existing default option (balanced option) to the MySuper option or (ii) considering a Lifecycle Investment strategy. However, there is no clear definition of a balanced option. There is no clear distinction between a growth fund and a balanced fund. It is suggested that a growth fund should have a 55% to 80% allocation to growth assets, however, some funds with the same percentage allocation are labelled as balanced funds. For example, one superannuation ratings agency, SuperRatings, categorizes a balanced option as 60% to 76% allocation to growth assets, while another superannuation ratings agency, Chant West, describes 'balanced' as having 41% to 60% invested in growth assets.[3] In comparison, the growth option under the SuperRatings categories is a 77% to 90% allocation to growth assets, while Chant West's description of growth is a 61% to 80% allocation to growth assets. Hence, in our study, to assess to what extent beta varies as we vary the percentages of growth and defensive investments, we use two classification methods: the classification used by Canstar's[4] rating system (similar to that of Chant West) and the standard definition provided by ASIC.

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 fund managers will switch between asset classes over time. Thus, 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, as the proportion of its growth assets can change over time. This characteristic represents dynamic switching behaviour among the investment options of a fund. Rather than considering a traditional risk modelling framework, with an assumption of a constant risk profile, we estimate the risk coefficients using a dynamic approach that will accommodate both mentioned characteristics by employing the panel data model developed by Feng *et al.* (2017). We include variants to estimate the betas, therefore, our study will consider the Capital Asset Pricing Model (CAPM), as well as the 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 differ, based on the time-varying categories. We further consider a sub-sample analysis of the effect of the 2007 global financial crisis (GFC).

We assess risk across investment options, and our key research questions can be summarized as follows. (1) Do betas, as risk measurements, vary by investment type (i.e., 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, particularly for a balanced fund/growth fund? (4) Does the GFC matter for the estimates of betas? The key results of our analysis can be summarized as follows. First, the results show that the level of risk increases from moderate to aggressive options, as expected, given that the

3 https://www.superguide.com.au/comparing-super-funds/superannuation-investment-difference-balanced-growth-option

4 https://www.canstar.com.au/

aggressive options include equity and property as asset classes. Second, risk does not vary across the different definitions of the investment options used, thus, varying the definitions of a balanced option of 41–60% or 31–70% does not impact the risk level. These results are for a 27-year study period; over the long term, the riskiness of balanced funds does not vary. Third, the results show no obvious sensitivity of the estimated betas to the modelling specifications used in the non-crisis period; the risk estimations are consistent across the modelling techniques, including CAPM and the FF three-factor, four-factor, and five-factor models. Fourth, however, the beta estimates in the GFC seem to be sensitive to the models. In the GFC, the crisis period betas are lower than those of the non-crisis period for CAPM, and the FF three-factor and four-factor models, and this result remains true for both classification methods. Only the five-factor model captures the higher risk in the GFC, as shown by a higher beta in both classifications used.

DATA

The data in this paper are sourced from the Morningstar Direct database. The sample consists of 1,213 investment options from various Australian superannuation funds over a 27-year period, ranging from January 1990 to December 2016. A brief explanation of the data is as follows: the data provide details of the investment options held by the superannuation funds (e.g., Care Super). We collected data from Care Super Capital Guaranteed, Care Super Capital Secured, and Care Super Balanced, among others. We also identified 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 from 1997 to 1998, the 2001 dotcom crisis and the GFC, from mid-2007 to 2009, all of which had a significant impact on the Australian stock market. Australian superannuation funds were faced with significant losses during the crisis periods, particularly the GFC. Many retirees in Australia have been heavily affected by the relatively large investment losses in Australia because of the large share of equities, which at the time of the GFC, was approximately 57% before the crisis hit, compared with an average of 36% in the 20 OECD countries. Australian superannuation funds accounted for a –26.3% loss, which was the second largest worldwide, after Ireland[5].

[5] See: OECD (2009), *Pensions at a Glance: Retirement-Income Systems in OECD Countries*, Figure 1.3

TABLE 1

CLASSIFICATION OF INVESTMENT OPTIONS

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

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

We classify the asset classes into growth and defensive assets. The defensive assets include cash and 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 assets usually aim for higher average returns over the long term. However, this reality equally implies that higher volatility corresponds to higher risk, which may result in higher losses in bad years, 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 profiles of investors, including a mixture of growth assets up to a 'high growth option', where investors have the option of investing up to 100% in growth assets, such as shares and property. The objective of this study is to provide some uniformity in the definition of the asset classes included in the growth options, thereby enabling a better comparison of the riskiness of investment options provided by superannuation funds. Using the historical asset allocation, we consider two classification methods to redefine the investment options.[6] Table 1 summarizes the two classification methods and the percentage of growth assets to define the four broad categories of investment options: 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] we will consider multi-sector aggressive (in which the growth assets[8] range from 81–100%), multi-sector growth (growth assets range from 61–80%), multi-sector balanced (growth assets range from 41–60%), and multi-sector moderate (growth assets range from 21–40%). In our second classification method, we consider the

[6] As of September 2017, for instance, CareSuper had 13 investment options, while Cbus had only six investment options. Source: AIST PD Programs

[7] See https://www.canstar.com.au/managed-funds/types-of-managed-funds-and-how-they-perform-long-term/

[8] Growth assets include domestic and international shares, listed and unlisted property.

guidelines provided by ASIC[9] and define the investment options as follows. An aggressive investment option will have 85 to 100% in growth assets; a growth investment option will have 71 to 84%; a balanced option will have 31 to 70%, and a moderate option will have 1 to 30%. Considering the two methods of defining investment options will enable the assessment of whether the risk level varies as the percentage of growth assets varies and will also help to determine if the varying definitions of investment options across superannuation funds impact the risk level faced by members over the longer term.

Following our first method of classification, Canstar, we have 862 investment options, including 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 (which is referred as Option 1-Canstar classification). Using the ASIC definition of how to classify investment options, our final sample includes 926[10] investment options distributed as follows: 109 in the moderate investment option, 261 in the balanced option, 128 investment options in the growth category, and 428 investment options in the aggressive category.

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 the proportion of its growth assets. In addition, the classification of a superannuation fund can be time-dependent because 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 the risk profiles of investment options, as well as time varying classifications of the funds. In this study, we utilize 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) to different model specifications, which allow the relationship between risk and return to vary across different defined time-varying categories, representing investment options and crisis periods. In our investigation, we ensure the robustness of our results by using four models, which are widely used in the literature, including the CAPM and the FF three-factor, four-factor, and five-factor models.

One of the most widely used models to estimate risk in the finance literature has been Sharpe's (1964) CAPM, due to its simplicity and ease to implement. The

9 https://www.moneysmart.gov.au/superannuation-and-retirement/how-super-works/super-investment-options

10 The initial sample from Morningstar includes 1,213 options. Given that we use the two classification methods, the final numbers decreased to 862 options for the Canstar classification, and the ASIC classification drops to 926 options. Regarding the Canstar classification, we exclude options with less than 20% growth assets, as per the definition (note that 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.

CAPM assumes that 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:

$$R_{it} - R_{Ft} = \beta_M(Z_{it})(R_{Mt} - R_{Ft}) + \omega_i + e_{it}, \tag{1}$$

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

According to the CAPM, investors only price market risk. Fama and French (1993, 1996) report that 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:

$$R_{it} - R_{Ft} = \beta_M(Z_{it})(R_{Mt} - R_{Ft}) + \beta_{SMB}(Z_{it})SMB_t + \beta_{HML}(Z_{it})HML_t + \omega_i + e_{it}. \tag{2}$$

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 $\beta_M(Z_{it})$, $\beta_{SMB}(Z_{it})$ and $\beta_{HML}(Z_{it})$, respectively, in equation (2).

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

$$\begin{aligned} R_{it} - R_{Ft} = {} & \beta_M(Z_{it})(R_{Mt} - R_{Ft}) + \beta_{SMB}(Z_{it})SMB_t + \beta_{HML}(Z_{it})HML_t \\ & + \beta_{UMD}(Z_{it})UMD_t + \omega_i + e_{it}, \end{aligned} \tag{3}$$

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

Another improved version of the FF three-factor model, which includes two additional factors, was introduced by Fama and French (2015); they believe that the returns of a portfolio are also closely related to investment profitability and investment patterns. In our study, we use the Fama-French five-factor model, which is calculated in a manner similar to that of 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 as 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 utilizes momentum cut-offs drawn from the 30th and 70th percentiles of the S&P/ASX200 constituents.[11] The *RMW* factor portfolio and the *CMA* factor portfolio were constructed in the same manner as the *HML* factor portfolios, using the 30th and 70th percentiles. To fit our analysis, we specify the FF five-factor model as follows:

$$\begin{aligned} R_{it} - R_{Ft} = {} & \beta_M(Z_{it})(R_{Mt} - R_{Ft}) + \beta_{SMB}(Z_{it})SMB_t + \beta_{HML}(Z_{it})HML_t \\ & + \beta_{RMW}(Z_{it})RMW_t + \beta_{CMA}(Z_{it})CMA_t + \omega_i + e_{it}, \end{aligned} \tag{4}$$

where RMW_t is the difference between the returns on diversified portfolios of robust stocks and weak profitable stocks, and CMA_t is the difference between the returns on diversified portfolios of stocks with low and high investment.[12]

Note that given a superannuation fund *i*, the estimated risk coefficients (i.e., β_M), as well as other factor coefficients (including $\beta_{SMB}, \beta_{HML}, \beta_{UMD}, \beta_{RMW}, \beta_{CMA}$) from the above models in (1), (2), (3), and (4), are dependent on each category defined in the vector of time varying categorical variables, Z_{it}. We include different categories of investment options and economic regimes (crisis and non-crisis periods) in Z_{it} so that the risk coefficients vary across different investment categories and, at the same time, across crisis and non-crisis periods. This process 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

[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).

[12] Using the standard OLS estimation for the Fama-French family models can have some limitations especially when the factors are strongly correlated, as this may raise a concern of multicollinearity (see Allen and McAleer, 2018). For panel data, if Fama and MacBeth (1973) based approaches are employed for the estimation, the classic errors-in-variables (EIV) problem can be a concern because the betas are the covariates in each cross-section equation. Since it is unavoidable that the estimated betas contain measurement errors, the estimated coefficient in cross-sectional regressions can be biased (see Pukthuanthong *et al.*, 2019). We ensure that our estimation does not suffer the EIV by employing the estimation method proposed by Feng *et al.* (2017), which obtains the estimates of model parameters via optimizing the kernel function of Aitchison and Aitken (1976). We also analyse the overall and rolling window correlations among the factors and find that these correlations are relatively low for the Australian market. Besides, the estimated standard errors are low indicating that our estimation does not suffer from multicollinearity.

data. Therefore, we use 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), and (4) in a general form, as follows,

$$Y_{it} = X'_{it}\beta(Z_{it}) + \omega_i + e_{it}, \tag{5}$$

where $Y_{it} = R_{it} - R_{Ft}$. In addition, elements of vector of explanatory variables, X_{it}, and elements of vector of risk coefficients and factor coefficients, $\beta(Z_{it})$, depend on the specifications in each of four models employed. For example, in equation (1), $X_{it} = (R_{Mt} - R_{Ft})$ and $\beta(Z_{it}) = \beta_M(Z_{it})$, whereas in equation (4),

$$X_{it} = [(R_{Mt} - R_{Ft}), SMB_t, HML_t, RMW_t, CMA_t]'$$

and

$$\beta(Z_{it}) = [\beta_M(Z_{it}), \beta_{SMB}(Z_{it}), \beta_{HML}(Z_{it}), \beta_{RMW}(Z_{it}), \beta_{CMA}(Z_{it})]'$$

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

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

$$\widehat{\beta}(z) = \left(\sum_{i=1}^{N}\sum_{t=1}^{T} \underset{it}{\tilde{X}}\underset{it}{\tilde{X}}{}' L\left(Z_{it}, z, \widehat{\lambda}\right)\right)^{-1} \left(\sum_{i=1}^{N}\sum_{t=1}^{T} \underset{it}{\tilde{X}}\underset{it}{\tilde{Y}} L\left(Z_{it}, z, \widehat{\lambda}\right)\right), \tag{6}$$

where $\underset{it}{\tilde{X}}$ and $\underset{it}{\tilde{Y}}$ are transformed X_{it} and Y_{it} after removing the fixed effects ω_i; $L(.)$ is a multivariate kernel function of Aitchison and Aitken (1976), with its optimal bandwidths $\widehat{\lambda}$ selected through a cross validation criterion function (see Feng *et al.*, 2017).

EMPIRICAL RESULTS

Initial Return Analysis

Using the monthly price data, we compute the continuously compound returns and present the summary statistics in Table 2. Table 2 summarizes the average long-term return of the four investment options calculated using the Canstar classification in panel A, and panel B summarizes 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 the expected return over each of the categories. The growth and

TABLE 2

SUMMARY STATISTICS OF RETURNS

Panel A: Summary statistics of the monthly returns of super funds for the whole sample period, based on the 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 the monthly returns of super funds for the whole sample period, based on the 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

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

aggressive options outperform the moderate and balanced options, and the two different methods of classification do not provide different average returns; the means across the two methods are quite similar. Hence, defining a balanced fund using 41–60%, or a balanced fund using 31–70%, does not indicate a great difference in the monthly average return over the longer term. The monthly maximum average return is 1.5497% in panel A and 2.0357%, in panel B, both from the aggressive investment option. In panel A, the definition of an aggressive investment option includes growth assets of 81–100%, and the variability of the return is 1.6976%, as indicated by the range, with a standard deviation of 0.2445%. Panel B defines an aggressive option with growth assets in the range of 85–100%, and the range in which the return varies is 3.1457%, with a standard deviation of 0.2919%. Similarly, the minimum monthly average returns observed in aggressive categories from the two classification methodologies are –0.1479% (panel A) and –1.1100% (panel B), respectively. While defining investment options using different definitions highlights 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. Thus, 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.

TABLE 3

ESTIMATES USING THE FULL SAMPLE AND CANSTAR CLASSIFICATION

	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)

(Continues)

TABLE 3

CONTINUED

	Non-crisis period						Crisis period					
	Rm-Rf	SMB	HML	UMD	RMW	CMA	Rm-Rf	SMB	HML	UMD	RMW	CMA
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)

This table provides the beta estimates using the varying coefficient models estimate, applying four estimation techniques: the CAPM and the FF three-factor, four-factor, and five-factor models. The non-crisis period is the full sample (January 1990 to December 2006) minus the dotcom, Asian and GFC crises, and Crisis is a combination of the three crises. The three crisis periods include the 1997 Asian financial crisis (January 1997 to June 1999), 2001 dotcom crisis (September 1999 to April 2003) and 2007 subprime financial crisis (January 2007 to September 2009). The model is estimated using non-crisis and crisis samples, as well as the **Canstar** method of classifying investment options. Standard errors are presented in parentheses, and *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% levels of significance, respectively.

TABLE 4

ESTIMATES USING THE FULL SAMPLE AND ASIC CLASSIFICATION

	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)

(Continues)

Table 4

CONTINUED

	Non-crisis period						Crisis period					
	Rm-Rf	SMB	HML	UMD	RMW	CMA	Rm-Rf	SMB	HML	UMD	RMW	CMA
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)

This table provides the beta estimates using the varying coefficient models estimate, by applying four estimation techniques: the CAPM and the FF three-factor, four-factor, and five-factor models. The non-crisis period is the full sample (January 1990 to December 2006), minus the dotcom, Asian and GFC crises, and Crisis is a combination of the three crises. The three crisis periods include the 1997 Asian financial crisis (January 1997 to June 1999), 2001 dotcom crisis (September 1999 to April 2003) and 2007 subprime financial crisis (January 2007 to 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 parentheses, and *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% levels of significance, respectively.

Risk Analysis—Full Sample

Our sample period is over 27 years, therefore, the market has demonstrated significant periods of stock market volatility, with some significant crises, including the 1997 Asian crisis, the 2001 dotcom crisis and the 2007 GFC. We estimate the risk associated with the investment options using our models, which are defined in the previous section and consider the possible different impacts of crisis and non-crisis periods. We define three crisis periods as follows: the 1997 Asian financial crisis from January 1997 to June 1999; the 2000 dotcom crisis from September 1999 to April 2003 and the 2007 GFC from January 2007 to September 2009. The vector of categorical variables $Z_{it} = (Z_{1it}, Z_{2it})$ in equations (1), (2), (3), and (4) is composed of Z_{1it} and Z_{2it}, in which Z_{1it} capture the investment option information of superannuation fund i across time t, including moderate options, balanced options, growth options, and aggressive options. We consider two approaches to classify the investment options: the Canstar and ASIC methods. Across both classification methods, Z_{2it} is defined as the crisis =1 and non-crisis =0 periods. As we expect, the superannuation fund managers may actively change their investment strategies during non-crisis and crisis periods; Z should vary in both cross-sectional and time-series dimensions. To implement the models, we use balanced data, which removes the investment options with incomplete data during the 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 dotcom crisis and the 2007 GFC. The results in Table 3 report the risk measures using the Canstar method of classifying the investment options, and the results in Table 4 show the risk estimation using the ASIC method of classifying the investment options.

Analysis of Tables 3 and 4 shows that the level of risk, as measured by beta, increases as the investment type varies from moderate to aggressive.[13] Similar to the trend we have reported in the returns statistics observed in Table 2, the beta coefficient increases across both Tables 3 and 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 using the Canstar classification method. The coefficients are similar in Table 4, using the ASIC classification (i.e., a beta of 0.1210 for the moderate option, increasing to 0.6437 for the aggressive option). The beta estimate, $\beta_{M,}$ in the FF three-factor, four-factor, and five-factor estimations shows a similar trend for both Tables 3 and

[13] Across the four model specifications employed, we consider six factors in total, including the 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 because it represents the systematic risk of investment options. Other betas can be considered as the impacts of control factors on the performance of investment options. Henceforth, when we reference beta, we refer to β_M.

4 (i.e., 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 shown in Table 3, for the 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 a non-crisis aggressive beta of 0.6399 and an aggressive crisis beta of 0.7340. This risk trend is consistent across the different models and methods of classification under consideration, as shown in Tables 3 and 4.

Our result that the betas of investment options are consistently less than one is consistent with the literature on the pension fund beta (see for example, Jin *et al.*, 2006; An *et al.*, 2013; Mohan and Zhang, 2014). We note that under the asset pricing model we employ, beta is estimated using the S&P/ASX200 market returns. As a result, a beta of 1 indicates that the investment portfolio has the same movement as the S&P/ASX 200 stock market index. In other words, this investment portfolio is equivalent with a well-diversified *stock* portfolio in the Australian *stock* market. As assets other than Australian stocks, which are less exposed to the Australian stock market movements (e.g., Australian bonds, international stocks and bonds), are included in this portfolio, the beta can be substantially less than 1. Different from index funds, which try to replicate the movements of market index, superannuation funds can include domestic stocks and bonds, international stocks and bonds, and property in their investment options. Therefore, it is intuitively and economically meaningful to obtain beta estimates being less than one.

Overall, the results observed in Tables 3 and 4 clearly demonstrate that as the percentage of growth assets increases, the level of risk that the superannuation fund managers are undertaking increases. While the returns may be higher overall, they are significantly associated with more volatility, particularly in a crisis period in which the aggressive investment options can have a greater variability of returns, given that they have a higher beta than a moderate option. Our definition of growth assets includes both equity and property markets, and our results have important implications, in that this definition 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, four-factor, and five-factor models. 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 models are known to have significant improvements over the CAPM, given that it is adjusted for these anomalies, it is argued that it does not capture the profitability and the investment factor, which is captured by the FF five-factor model. We perform 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 Tables 3 and 4 for the two classifications used. Chen and Bassett (2014) report 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 *et al*. (2011) argue that the average SMB coefficient is positive, demonstrating a general tendency for US mutual funds to hold small stocks, however, they also find that over 25% of the sample has a negative coefficient, which indicates a tendency of larger stock holdings. In an Australian context, Chan *et al*. (2009) studied 34 Australian funds and reported no significant impact of size on trading cost. They report that the 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 evidenced, the results are inconclusive, in terms of the coefficient of the SMB variable. Our results indicate a negative SMB coefficient across all models of the FF three-factor, four-factor, and five-factor estimations, except for the crisis analysis under the five-factor model, for which we have a positive coefficient for the moderate, balanced, and aggressive investment options under the ASIC classification, indicating 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 stocks (value stock) outperform low book to value stocks (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 Tables 3 and 4, for the non-crisis analysis, HML has a negative coefficient that 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 five-factor models, while in Table 4, the growth investment options under the crisis analysis have a mostly negative coefficient for the FF three-, four-, and five-factor models, highlighting investments in growth stocks. For the momentum factor UMD, a positive UMD coefficient indicates a generally bullish market, and a negative UMD coefficient is typical of a bearish market. The non-crisis coefficient for the FF four-factor model shows a positive UMD coefficient across Tables 3 and 4, which reflects 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 is primarily negative (except for the moderate option under the ASIC classification), which 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 results are expected: (1) a higher book-to-market ratio implies a higher expected return

TABLE 5

ESTIMATES OF THE 2007 GFC CRISIS ANALYSIS: CANSTAR CLASSIFICATION

	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)

(Continues)

TABLE 5

CONTINUED

	Non-crisis period						Crisis period					
	Rm-Rf	SMB	HML	UMD	RMW	CMA	Rm-Rf	SMB	HML	UMD	RMW	CMA
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)

This table provides the beta estimates using the varying coefficient models estimate by applying four estimation techniques: the CAPM and the FF three-factor, four-factor, and five-factor models for the 2007 GFC analysis. The definition of non-crisis is the 6-month period prior to the GFC and the 6-month period post-GFC; the crisis period is the 2007 GFC period (January 2007 to September 2009). The classification of investment options is performed as per the Canstar option. Standard errors are presented in parentheses, and *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% levels of significance, respectively.

Table 6

ESTIMATES OF THE 2007 GFC CRISIS ANALYSIS: ASIC CLASSIFICATION

	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)

(Continues)

TABLE 6

CONTINUED

	Non-crisis period						Crisis period					
	Rm-Rf	SMB	HML	UMD	RMW	CMA	Rm-Rf	SMB	HML	UMD	RMW	CMA
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)

This table provides the beta estimates using the varying coefficient models estimate, by applying four estimation techniques: the CAPM and the FF three-factor, four-factor, and five-factor models for the 2007 GFC analysis. The definition of non-crisis is the 6-month period prior to the GFC and the 6-month period post-GFC; the crisis period is the 2007 GFC period (January 2007 to September 2009). The classification of investment options is performed as per the ASIC option. Standard errors are presented in parentheses, and *, **, and *** indicate that the estimates are statistically significant at the 10%, 5%, and 1% levels of significance, respectively.

(i.e., positive HML coefficient); (2) firms with higher profitability relative to current book equity have higher expected returns (i.e., positive RMW coefficient); and (3) 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 have been numerous studies providing empirical evidence for the profitability and investment effects (e.g., Novy-Marx, 2013; Titman *et al.*, 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 *et al.* (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 4 are consistent for both non-crisis and crisis periods. For the non-crisis period, the coefficient of HML is negative, as previously highlighted, meaning that the investment held by Australian superannuation funds reflects more of the growth stocks. This finding aligns with the OECD figures indicating that Australian superannuation funds are some of the highest investors in the equity market, therefore, we expect this negative coefficient. Profitability, as measured by the RMW coefficient, is positive under both classification methods 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 and French (2015) findings (i.e., the growth due to re-investment of earnings will lead to lower expected returns). The crisis results in both tables are different from 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 changes to positive across all investment categories (i.e., moderate, balanced, growth, and aggressive). Furthermore, in the crisis period, the moderate, balanced, and aggressive options have 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 Tables 3 and 4, we make the following conclusions regarding our research questions: (1) as the percentage of growth assets increases, the level of risk increases, as measured by beta, indicating that the moderate option is a safer bet, in terms of risk, compared to the aggressive option; (2) risk does not vary as we change the method of classification, hence, as a fund changes the composition of the balanced funds (e.g., a change from a 41–60% option to a 31–70% option), the risk level to members over the longer term does not vary; (3) the estimations of risk (i.e., the beta coefficient, β_M) is not model sensitive, thus, it does not matter whether we use CAPM or the FF three-, four- or five-factor model for non-crisis and crisis periods; however, the HML (value proxy) and CMA (investment proxy) coefficients seem to differ in between the non-crisis and crisis periods.

Crisis Analysis: The Global Financial Crisis (GFC)

In the previous analysis, we considered three volatile periods in our sample, the 1997 Asian crisis, the 2001 dotcom crisis and the 2007 GFC. Of the three crises, we now focus the risk analysis on the most significant crisis the industry faced, the 2007 GFC. Because Australian superannuation funds tend to invest in growth assets 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 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% a year, much worse than the advanced countries average of 1.6%.[14] Gerrans *et al.* (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 investors, however, the results are inconclusive in terms of how the crisis had an impact on asset allocation decisions. 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 the GFC and the 6-month period post-GFC. The crisis analysis for both tables here is the period of the GFC only, which is January 2007 to 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) 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 as the moderate option in Table 6 non-crisis analysis and has a beta of 0.3143, and the aggressive option has 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 periods, in contrast to the results in Tables 3 and 4; in the GFC analysis, the 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; the beta of the GFC period is higher than that of the non-crisis period only for the FF five-factor estimate. The estimation using CAPM, FF three factors, and FF four factors shows the contrary, a higher beta for the non-crisis period than crisis period, regardless of the method used to classify investment options. The non-crisis beta estimate using the FF five-factor for moderate risk 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 show similar results in Table 6, indicating the non-crisis beta for the moderate option is 0.2701, and for the aggressive option, 0.7751; the crisis beta for the moderate option is 0.3661, and for the aggressive option, 0.9612. Furthermore, the SMB coefficient is different compared to Tables 3 and 4. We have a positive SMB coefficient; the portfolio of equity investment is predominantly small cap stock. The HML coefficient is mostly

[14] http://www.theaustralian.com.au/business/financial-services/super-funds-losses-among-worst-in-world/news-story/6a151a41e76c7c97f6c91f179b7e60d6

positive for the non-crisis analysis; value stocks are dominant, and for the crisis period, we have a shift to a negative HML coefficient in a crisis period (i.e., predominantly growth stock). The profitability coefficient (RMW coefficient) is similar to the previous analysis: the higher the profitability, the higher the expected return. However, the CMA coefficient is all positive in Tables 5 and 6 (except for the aggressive option in the non-crisis analysis for Table 5): the higher the amount reinvested, the higher the expected return. Thus, by applying the FF five-factor model to the Australian investment options, we demonstrate 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 of Chiah *et al.* (2016), indicating that in the Australian market, 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, regardless of the method we use to classify investment options.

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 practical and empirical perspectives. We address some key challenges facing the Australian superannuation fund industry, in particular: (1) is there a consistent method of classifying growth assets that allows comparison of the risk associated with the portfolios of the superfunds? and (2) do the varying percentages that Australian superannuation funds use to define investment options (e.g., a 41–60% growth assets definition for a balanced fund compared to a 31–70% definition) impact 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 funds change their asset allocations. We equally use alternative estimation methods, including the CAPM and three-factor, four-factor, and five-factor models.

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

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