An Analysis of the Sensitivity of Australian Superannuation Funds to Market Movements: A Markov Regime Switching Approach

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Abstract

This paper investigates the sensitivity of Australian superannuation funds in relation to equity and bond markets. In particular, it examines the extent, speed and duration of response of the Australian superannuation funds' returns to movements in the US and Australian equity and bond markets under down, normal and up market conditions through the application of Markov regime switching analysis. The results reveal that Australian superannuation funds' returns are most affected by movements in the US equity markets, then by the Australian equity market and lastly, by the US bond markets. Funds' returns are not influenced at all by movements in the Australian bond market. They respond quickly and briefly to movements in markets in all market regimes. Funds' returns move positively with US equity markets under all market conditions but most especially during down markets. They are influenced by the Australian equity market only during normal market conditions and by the US bond markets only during up markets. In line with those of previous studies, these results imply that Australian superannuation funds are not able to time their exposure to markets and that their performance is indicative of an efficient market.

Keywords**:** Superannuation funds, Markov switching, Sensitivity of Funds

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I. INTRODUCTION

The Australian retirement, pension or superannuation fund is the largest in Asia and the fourth largest in the world after that of the US, Luxembourg and France. In 2000, Australian superannuation fund assets totalled US$342 billion and by 2004, this has doubled to US$635 billion. This figure is expected to increase further to US$1,081 billion by 2010 and US$1,743 billion by 2015 (Axiss, 2005). Given the crucial role that superannuation plays in providing for the retirement needs of Australians, it is imperative that superannuation funds should at the very least be safe. Thus, it is important that the risks associated with superannuation funds be understood fully so these risks could be managed carefully. One of these risks is systematic risk or market risk.

There is a significant body of literature which investigates different aspects of superannuation such as taxation (Bateman *et al*, 1993; Knox, 1993), annuities (Piggot *et al*, 2005), retirement timing (Kingston, 2000), disclosure (Gallery and Gallery, 2003), safety (Valentine, 2003), performance (Bird *et al*, 1983; Robson, 1986; Sinclair, 1990; Hallahan, 1999; Sawicki and Ong, 2000; Gallagher, 2001; Prather *et al*, 2001; Drew and Stanford, 2003; Hallahan and Faff, 2004), returns, volatility and expenses (Coleman *et al*, 2004), but none has focused primarily on the sensitivity of superannuation funds to market movements. Hence, this paper addresses this gap in the superannuation literature. It investigates the sensitivity of Australian superannuation funds with respect to the Australian and US equity and bond markets.

It is quite well established in the literature that financial markets are characterised by cycles or regimes such as down, normal and up market conditions and that the relationship between risks and returns can differ under these different market conditions (Fabozzi and Francis, 1977, 1979; Chen, 1982; Bhardwaj and Brooks, 1993; Wiggins, 1993; Granger and Silvapulle, 2002; Tu, 2004). In spite of this, most of the existing literature on superannuation funds does not take this important factor into account systematically. Therefore, this paper also addresses this knowledge gap in the superannuation literature.

As stated earlier, this paper analyses the sensitivity of Australian superannuation funds in relation to the equity and bond markets. In particular, it examines the extent, speed and duration of response of the Australian superannuation funds' returns to movements in the US and Australian equity and bond markets under down, normal and up market conditions through the application of Markov regime switching analysis (Hamilton, 1989). One of the major advantages of this approach is that it does not require prior specifications or dating of market conditions. Instead, market conditions and their corresponding probabilities of occurrence are endogenously determined rather than pre-determined. Thus, the use of the Markov switching model allows a more robust and informative analysis on the sensitivity of Australian superannuation funds. To the knowledge of the authors, no study on the Australian superannuation fund has yet utilised the Markov switching approach. In order to measure the extent of the response of Australian superannuation funds to movements in the equity and bond markets, a Markov Switching Vector Autoregression Model (VAR) is estimated. With this model, an impulse response analysis is then conducted afterwards to determine the speed and duration of the response.

The remaining parts of this paper are organised as follows. Section two provides a brief discussion of funds sensitivity and market timing. Section three presents a review of the literature on sensitivity and Australia superannuation funds. Section four discusses the methodology and data used in the study. Section five presents the empirical results of the study while Section six embodies the conclusion and suggestions for further research.

II. FUNDS' SENSITIVITY TO MARKET MOVEMENTS AND MARKET TIMING

This paper analyses the sensitivity of Australian superannuation funds to market movements. The funds analysed in this study, called "multi-sector funds", are those with portfolios that consist of investments in different asset classes such as equities, bonds, and properties in domestic as well as foreign markets, with the bulk of their investments being in equities and bonds. Hence, their portfolios can be therefore exposed to the movements of domestic and international equity and bond markets. During up market conditions, exposure would be desirable but not during down market conditions. Funds may therefore want to manage their exposure or practice market timing. They may attempt to anticipate market movements and then correspondingly re-balance or change the composition of their portfolio ahead of this anticipated market movement in order to improve their performance. For instance, if they anticipate a down equity market, funds may re-balance their portfolio in such a way that they will be holding less equities and/or holding equities which are less sensitive to the market, such as the so-called defensive stocks. Thus, if during a down equity market, it is found that the fund is not sensitive to the market, then this could be a confirmation that the fund has been successful in its market timing. However, if the fund is sensitive to the equity market, then this could indicate lack of success in their market timing. Thus, knowing the sensitivity of the fund in each market regime would provide an indication of the market timing ability of funds.

The decision of asset allocation would depend on the fund's aims in returns and risk tolerance in selecting an appropriate investment strategy. Different investment strategies varies in its level of risk and return and the key in choosing an investment option is deciding the rate of return investors want, relative to the amount of risk that they are prepared to accept. Funds could allocate their assets into the equity market if they are prepared to accept high risk with high returns, or they could allocate their assets into the bond market with a lower risk and lower returns. Generally, funds would allocate assets into the equity market during bullish market conditions and shift their assets into the bond market during bearish market conditions, depending on their investment strategy and the level of exposure they are willing to accept.

The funds which are the subjects of this study are allowed by the government regulatory body, Australian Prudential Regulation Authority (APRA), to vary the weights of the asset classes in their portfolio within certain ranges, as shown in the table below.

[INSERT TABLE 1 HERE]

If it is shown that funds are able to time the market successfully, then this could also be an indication that the market is inefficient. The speed and duration by which funds are impacted by the market, which can be gleaned through the so-called impulse response analysis could further provide evidence of the efficiency of the funds in processing market information. Thus, the analysis of the sensitivity of funds could also provide information with regards to the efficiency of markets.

III. REVIEW OF THE LITERATURE

The evidence from studies on the performance of managed funs is that only a limited number of fund managers possess market timing skills (see, for example, Treynor and Mazuy, 1966; Jensen, 1968; Kon and Jen, 1978; Henriksson and Merton, 1981; Kon, 1983; Henriksson, 1984; Admati *et al*, 1986; Lehmann and Modest, 1987; Lee and Rahman, 1990; Daniel *et al*, 1996; Kao *et al*, 1998; Blake *et al*, 1999; Dellva *et al*, 2001). In the case of Australian superannuation funds, the few studies conducted on this issue have found that these funds do not possess any market timing skills at all (see Prather *et al*, 2001; Drew *et al*, 2005; and Faff *et al*, 2005). These studies, however, do not allow for changing probability distributions between regimes and for the endogenous determination of structural breaks. The present study addresses this concern through the application of the Markov regime switching approach. As far as the authors know, this study is the first of its kind in the area of superannuation research.

As stated earlier, the speed and duration of response of Australian fund returns to movements in the Australian and US equity and bond markets would provide an indication of the efficiency of funds. Studies have found the performance of superannuation funds to be indicative of market efficiency (see, for instance Beechey *et al*, 2000; Gallagher and Jarnecic, 2002; and Drew and Stanford, 2003). Again, these studies, however, do not allow for switching probability distributions associated with differing market conditions. Thus, this paper can provide further robust evidence with regards to the market timing ability and efficiency in the response to market movements of Australian superannuation funds.

IV. METHODOLOGY AND DATA

Methodology

We make use of a multi-index model in which returns are a function of the Australian equity market, US equity market, Australian bond market and US bond market. In its simplest form, this could be represented as follows:

$$R_S = \beta_0 + \beta_{E.Aus} F_{E.Aus} + \beta_{E.US} F_{E.US} + \beta_{B.Aus} F_{B.Aus} + \beta_{B.US} F_{B.US} + e \qquad (1)$$

where R_S is the returns of superannuation funds';
$F_{E.Aus}$ is the returns on Australian equity market;
$F_{E.US}$ is the returns on US equity market;
$F_{B.Aus}$ is the returns on Australian bond market;
$F_{B.US}$ is the returns on US bond market; and
e is the error terms.

$\beta_{E.AUS}$ $\beta_{E.US}$ $\beta_{B.Aus}$ $\beta_{B.US}$ represent the sensitivity of funds returns to the movement of the Australian equity market, US equity market, Australian bond market, US bond market, respectively.

In this paper, we allow each beta to vary or switch across different market conditions. Each beta therefore will have a value for each market condition such as an up market, a normal market and a down market. We do this through the use of the Markov regime switching model based on the work of Hamilton (1989) and Krolzig (1997) which provide for procedures to estimate these switching values of betas. The different market regimes are endogenously identified by the model. The probability of occurrence (called regime probability) as well the duration of each regime is also determined. In addition, the probability of switching to another regime when one is in a certain regime is identified as well. This so called "transition probability" therefore provides another indication of the volatility of a certain regime.

We also decompose each beta to trace the co-movement of fund returns with each of the four systematic risk factors. We do this by performing an impulse response analysis (see Ehrmann *et al*, 2001, pp. 10-11). All this analysis is performed within the context of a Vector Autoregression (VAR), which involves multivariate and simultaneous system of equations (see Sims, 1980).

In this study, we consider VAR models with changes in regime (Markov switching-VAR). In the most general specification of an MS-VAR model, all parameters of the VAR are conditioned on the state s_t of the Markov chain. Denoting the number of regimes by m and the number of lags by p and the observed time series vector y_t is given by:

$$y_t = \begin{cases} v_1 + B_{11} y_{t-1} + \ldots + B_{p1} y_{t-p} + A_1 u_t & \text{if } s_t = 1 \\ \vdots & \\ v_m + B_{1m} y_{t-1} + \ldots + B_{pm} y_{t-p} + A_m u_t & \text{if } s_t = m \end{cases} \qquad (1)$$

where $y = [y_1, y_2, y_3, y_4]$;

y_1 is the returns on Australian equity market;

y_2 is the returns on US equity market;

y_3 is the returns on Australian bond market;

y_4 is the returns on US bond market;

v represent the regime-dependent intercept term;

B is the parameters shift functions;

s_t is assumed to follow the discrete time and discrete state stochastic process of a hidden Markov chain;

u_t is the vector of fundamental disturbances, is assumed to be uncorrelated at all leads and lags:- $u_t \sim \text{NID}(0, I_K)$;

K is the dimension of the coefficient matrix A (i.e. it describes the number of endogenous variable).

A more detailed discussion of the estimation of the Markov switching model is provided in the Appendix.

In order to determine the appropriate MS model to use (see Figure 1), we conduct a number of diagnostic tests. We test the data for unit roots (using the Augmented Dickey Fuller and Phillips-Perron tests) and hetersoskedasticity (based on the White Test). We also test for the optimal number of regimes and number of lags for the model based on the Akaike Information Criterion. After we have determined the specific form of the MS model, we then estimate the model on the procedures developed by Hamilton (1989) and Krolzig (1997) (see Appendix for the technical details) and derive the following based on the Markov switching model: (a) regime probabilities; (b) transition probabilities; and (c) parameters or coefficients. We then conduct an impulse response analysis using the Choleski decomposition method (see Appendix for further explanation).

[INSERT FIGURE 1 HERE]

Data

This study covers the period January 1997 to September 2005. We chose this period due to the completeness of data and its richness with financial market events such as, for example the Asian crisis in 1997, Russian crisis in late 1998, Dotcom collapse in 2000, September 11 attacks in 2001, Enron bankruptcy in late 2002, Worldcom and Delphia bankruptcy in 2003. This study utilises weekly data in order to avoid noise, non-synchronous trading and the day of the week effects associated with daily data. There are 457 weeks during the study period. Data is collected every Thursday of the week. In the case when Thursday data is not available, Friday data is used.

The Australian superannuation funds data used in this study are supplied by Morningstar Research Pty Ltd (Morningstar), an independent measurement service and research house which monitor the managed funds industry in Australia.

Table 2 shows the different groups of superannuation funds according to type of investment in the Morningstar database. It can be seen that the biggest number of superannuation funds are those with multi-sector investments, which represents 38.0% of the total number of funds. This paper focuses on multi-sector superannuation funds, which is most suitable for the purposes of this paper because these funds generally invest across two or more asset classes, such as equity markets, bond markets, property and/or cash reserves.

[INSERT TABLE 2 HERE]

All funds included in this analysis are present in the database during the whole period of study, thereby, avoiding the survivorship bias problem created when funds, which do not survive for the full sample period, are absent from the database. "Dead" funds and funds that do not have sufficient data for two or more missing weeks are removed from the analysis.[1] The missing data are mostly due to non-working days such as holidays. When data for a certain week is not available, the previous week data is substituted for the missing data in that particular week. After the process of filtering, 313 funds are left in the Multi-sector funds category and these funds are then used in this study[2]. This sample represents about 19.5% of the total number of Multi-sector superannuation funds.

The weekly returns from superannuation funds are calculated based on the exit price of the fund (which is net of management fees, excluding entry and exit loads) using the discrete returns formula of $R_t = \ln(\text{price}_t/\text{price}_{t-1}) \times 100$[3]. Then, the funds' returns were combined or pooled by taking the weighted average of all the funds' returns. The weight of each fund is based on its net asset value.

This paper also utilises the Morgan Stanley Capital Indices (MSCI) data for equity and bond indices in Australia and the US. For consistency, the returns for Australian and the US equity and bond markets are also calculated based on the same discrete returns formula. The MSCI datasets are obtained from *DataStream*.

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[1] These include funds that are no longer traded, have only monthly data and with missing data for more than two weeks in the Morningstar database.

[2] The recommended sample size is 311 funds (i.e. calculated at 95% confidence level and 5% confidence limits of the total funds' in Multi-sector funds).

[3] The continuous return formula is used as it is well-known to provide more accurate measure of return compared to the discrete formula (Brailsford *et al*, 2004: pp.9). Other studies evaluating funds performance have used the same way of measuring returns (see, Sawicki and Ong, 2000; Benson and Faff, 2003; and Bohl *et al*, 2005)

V. EMPIRICAL RESULTS

Diagnostic Test Results

To test for unit roots in each of the returns time series, the study performed the Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) tests, as discussed previously. The null hypothesis of non-stationarity (unit root) and alternative hypothesis of stationarity (no unit root) are tested for each data series, in original form. The calculated *t*-statistics are presented in Table 3. The ADF and PP tests reject the null hypothesis of a unit root at 5% level of significance. Both unit root tests suggest the funds' returns and MSCI indices (Australian Equities, US Equities, Australian Bonds and US Bonds) are stationary. Additionally, Krolzig (1997) noted that there would not be substantial change in the results when differenced data set are employed, since the Markov switching smoothed regime probabilities are similar whether the estimation is carried out using level or differenced data set. Consequently, the returns time series will be used in the subsequent analysis without further differencing or testing for cointegration. Hence, this study will utilise the MS(m)-VAR(p) model (see Figure 1).

[INSERT TABLE 3 HERE]

The White's (1980) test of the null hypothesis of no heteroskedasticity against heteroskedasticity of some unknown general form is conducted. The results show a Chi-square of 427.1949 corresponding to a 300 degrees of freedom with a p-value of 0.0000. Thus, the null hypothesis, is rejected which suggests that the data contain heteroskedasticity. Consequently, the study applies the Markov switching MSIAH(m)-VAR(p) model.

The Akaike Information Criterion (AIC) values for 2 to 4 regimes and 1 to 4 lags are shown in Table 4. The results show that the lowest AIC value corresponds to the Markov regime switching model with 3 regimes and 1 lag. Hence, this study adopts the Markov switching MSIAH(3)-VAR(1) model. Several other studies have used the three-regime model and have found it to perform well in capturing market cycles and forecasting future market conditions (see, for instance, Hamilton and Susmel, 1994; Krolzig and Toro, 2000; Granger and Silvapulle, 2002; Krolzig *et al*, 2002).

[INSERT TABLE 4 HERE]

Regime and Transition Probabilities

Table 5 presents the corresponding probabilities and characteristics of each regime. As can be seen in this table, more than half of the time (53.3%), fund returns stayed in regime 2, about a quarter of the time (25.9%) in regime 1 and the rest (20.8%) in regime 3. Regime 2 has the longest duration (26 weeks) while the other two regimes lasted very shortly (around 2 weeks on the average, only). Regime 3 has the highest return while regime 1 has the lowest, as shown in column 4 of the table. Our three regimes correspond roughly to down (regime 1), normal (regime 2) and up (regime 3) states of the funds' performance as far as the average returns are concerned.

[INSERT TABLE 5 HERE]

As can be seen in the last column of this table, regimes 1 and 3 are characterised by high volatility while regime 2, by low volatility (less than half of the other two regimes). Regimes 1 and 3 are therefore highly unstable while regime 2 is stable.

This is further confirmed by the results shown in Table 6. In this table, the three numbers in a particular row show the probability of a regime shifting into regimes 1, 2 and 3, respectively. For example, in row 1, the first number, 0.5534, indicates the probability of regime 1 shifting into regime 1, which means staying in regime 1; the second number, 0.0447, shows the probability of regime 1 switching to regime 2, while the last number, 0.4019 shows the probability of regime 1 switching to regime 3.

There is only a 55.34% probability (see the intersection of row 1 and column 1) that regime 1 will stay in itself and a 40.19% (see row 1 and column 3) probability that it will switch to regime 3. For regime 3, the probability of remaining in itself is only 49.62% (intersection of row 3 and column 3) and the probability of switching to regime 1 is 46.13% (row 3 and column 1). Thus, these figures show that there is a high probability of switching between regimes, 1 and 3, which further confirm that these regimes are unstable or highly volatile.

[INSERT TABLE 6 HERE]

As shown by the number in the intersection between row 2 and column 2 in Table 6, there is a 96.17% probability that regime 2 will remain in itself; thus, further confirming that regime 2 is stable.

Our findings are consistent with those of other studies that have employed a Markov switching three-regime model. For example, Hamilton and Susmel (1994) analysed the stock market returns and found that 99.14% observations remained in the normal regime. Krolzig and Toro (2000) studied the U.S. business cycle and found 94.87% of observations remained in the normal regime. Krolzig *et al* (2002) found 93.98% of UK labour market staying in the normal regime.

Figure 2 provides a graphical representation of the regime probabilities. By simple inspection, we can clearly see a rapid switching between the down regimes and the up regimes during the period 1997-2001. It is evident from this Figure that there is switching between regimes 1 and 3, which support the results presented earlier in Table 5 which point to a high volatility of each of these two regimes – 14.35% for the up market and 11.26% for the down market. Additionally, it is obvious from this diagram that the largest probability corresponds to regime 2, which is supported by the long duration (26 weeks) and lower volatility presented in Table 5.

[INSERT FIGURE 2 HERE]

As can be seen further from Figure 2, the down market conditions or regime 1 captured the periods where financial distress events occurred, such as the Asian crisis in 1997, Russian crisis in late 1998, Dotcom collapse in 2000, September 11 attacks in 2001, Enron bankruptcy in late 2002 and bankruptcies of Worldcom and Delphia in 2003. The events captured are mostly events occurring in the US, implying that the US market could have a major impact on Australian superannuation funds' returns. It is noticeable that most observations remained in regime 2 after the year 2000. This regime has captured recovery from the Asian crisis in 1997 and the Russian crisis of 1998 although there are a couple of switches between regimes 1 and 3 due to the financial distress events that had happened in the US. The results have shown that the funds' returns are low and more volatile during periods of financial distress, and higher and less volatile when markets are back to normal conditions.

Other studies that have employed the Markov switching model have shown that this model is able to capture the periods containing market crashes. For instance, Tu (2004) analysed the investment decisions of 25 portfolios under up and down market conditions during 1963-2002 and their model is able to capture events such as the oil price shocks in 1970s, the recession in the early 1980s, the October 1987 stock market crash, the 1997 Asian crisis and the recession in 2000. Humala (2005) applied the MSIAH-VAR model and their model had also identified the period of financial distress correctly.

Regime Coefficients

The estimated parameters of the Markov switching MSIAH(3)-VAR(1) model are presented in Table 7, which provide information on the sensitivity of funds' returns to the movement in Australian equity, US equity, Australian bond and US bond markets in each regime. The only coefficients that are statistically significant are those corresponding to the US equity market in regimes 1, 2 and 3; Australian equity market in regime 2; and US bond market in regime 3. These coefficients are all positive indicating that funds' returns would move in the same direction with these markets. The Australian equity market only affects the funds' returns during normal market condition, indicating that funds' returns are not sensitive to the Australian equity market movements during the down and up market conditions.

[INSERT TABLE 7 HERE]

The overall results in Table 7 show that during down conditions, the only market that influences superannuation funds' returns are the US equity market. However, in normal market conditions, both Australian and US equity markets affect funds' returns. Finally, funds' returns are more sensitive to the US equity market and US bond market during the up market condition.

The Australian superannuation funds' returns are exposed highest to US equity market during down market conditions rather than during up market conditions. This may imply that fund managers do not have market timing skills. A successful timing strategy would be to reduce exposure during down market condition and increase exposure during up market condition. This result is in line with Prather *et al* (2001) that found no significant timing performance of 148 multi-sectors funds. The results of this study are consistent with those of Treynor and Mazuy (1966) and Fabozzi and Francis (1979) who found that fund managers did not reduce (increase) the funds' beta in down (up) market conditions to earn higher returns. This is also confirmed by the study of Drew *et al* (2005) who found that superannuation fund managers do not have market timing ability or do not time the market at all because the costs of such timing are prohibitive.

The Australian bond market, on the contrary, does not significantly affect the returns of superannuation funds in any market regime. The US bond market, however, does but only during up market condition. This provides opportunity for Australian superannuation funds to benefit from up condition of US bond markets. The funds' returns are not affected during down condition of US bond market.

Overall, the model coefficients estimated by Markov switching model indicate that funds' do not rebalance their portfolio according to what is desirable for each market condition. A possible reason could be their inability to predict the market correctly. On the other hand, if fund managers are able to predict the market markets and do not shift their portfolio composition, this may imply that the cost of switching is high and this prohibits portfolio rebalancing; or it could be that funds' objectives are fixed and government regulations put restrictions on their ability to rebalance their portfolio.

Our results revealed that US equity market is the dominant market affecting funds' returns during all market conditions. It is well established in the literature that the US stock market drives equity markets worldwide including Australia. Several other studies have found that the US market have a significant influence towards the Australian market. For example, Roca (1999) found that the Australian equity market is linked with the US in the short run. Sheng and Tu (2000) supported this claim by stating that US market have strong relationship (both in short and long-term) with most of the Asian markets. Eun and Shin (1989) found that the US market is rapidly transmitting shocks to other markets in a clearly recognisable manner, whereas no single foreign market can significantly explain the US market movements. They also found dynamic response patterns to be generally consistent with the notion of informationally efficient international stock market.

Impulse Response Analysis

Further investigation to analyse the speed and duration of the superannuation funds' returns response to equity and bond markets movements is performed by decomposing the coefficients in each regime through the use of impulse response analysis based on the Markov switching model. The impulse response analysis shows the expected change in the funds' returns after a one standard deviation shock to the Australian and US equity and bond markets under the down, normal and up market conditions. Figure 3 presents the impulse response of funds' returns to those markets which have significant coefficients in the Markov switching model, namely the Australian equity market in regime 2; the US equity market in regime 1, 2 and 3; and US bond market in regime 3 (refer to Table 7).

[INSERT FIGURE 3 HERE]

The results of the impulse response analysis show that funds' react to movements in the Australian and US equity and bond markets immediately, within week 1, and complete their response by week 2. During normal market conditions, funds' returns respond positively to the Australian equity market immediately and this response fades out after the first week. The response to US equity market took a week longer to complete, indicating that funds' returns are more efficient in responding to the Australian equity market than to the US equity market during normal market times.

Furthermore, the impulse responses have confirmed results shown in Figure 2 and Table 7, where the US equity market is the main influence of the Australian superannuation funds' returns under all market conditions. The results may be due to the market dynamics, in particular the regulation of the Australian Stock Exchange (ASX) to halt trading for 10 minutes on price-sensitive announcements, allowing fund managers to make informed decision by carefully interpreting the meaning of the announcements before rebalancing their portfolio.

As can be seen further in Figure 3, the superannuation funds' returns responds the most to US equity market movements in regime 1, then in regime 2, while the response is smallest in regime 3. This implies that funds' returns are most sensitive to the US equity market during down market conditions and least sensitive during up market conditions. Fund managers therefore are most exposed to down market conditions (regime 1), in which returns are lowest but least exposed during up markets (regime 3) when returns are highest. This therefore provides further evidence that fund managers may not have the market-timing ability; as such they do not rebalance their portfolio to take advantage of the period of high returns.

During up market conditions, funds' returns respond positively to the US bond market, which is also completed by week 2. This suggests that US bond market would have an impact on funds' returns during up market conditions and fund managers could take advantage of this opportunity. It is noticeable, however, that Australian superannuation funds' are influenced more by the equity market than to the bond market movements. This may be due to the heavier weighting of equities in their portfolios in line with the Australian Prudential Regulation Authority (APRA) suggested asset allocation benchmark of about 50% into equities and 25% in bonds (see Table 1).

As the study have used weekly data and the responses of funds' returns to the Australian equity market, US equity market and US bond market completed within two weeks time, this study therefore considers the responses to be efficient. This result supports Beechey *et al* (2000) who found efficiency in the price reaction of managed funds and Bracker et al (1999) and Roca (1999) who found the same with regards to stock market price response.

IV. CONCLUSION

This paper investigates the sensitivity of Australian superannuation funds in relation to equity and bond markets. In particular, it examines the extent, speed and duration of response of the Australian superannuation funds' returns to movements in the US and Australian equity markets under down, normal and up market conditions. The investigation is carried out through the application of the Markov regime switching model in which an impulse response analysis was also conducted. The study utilises weekly returns of 313 superannuation funds from the Morningstar database and the Australian equity market, US equity market, Australian bond markets and US bond market based on the Morgan Stanley Capital International (MSCI) indices during the period January 1997 to September 2005.

The overall results show that Australian superannuation funds are exposed most to the movements in the US equity market, then to the Australian equity market and lastly, to the US bond market. They are not affected at all by movements in the Australian bond market. With regards to the US equity market, their exposure is higher during down markets and lower during up markets. They are therefore exposed most to the US equity market during periods of low returns and are not able to take most advantage of periods of high returns. With regards to the Australian equity market, the funds are not exposed during down and up markets and hence are not subject to the prospects of high returns as well as low returns. The exposure of these funds to the US bond market is more favourable as this is during up market conditions. These results demonstrate that Australian superannuation funds are not able or do not manage their portfolio exposure to take advantage of market conditions. Hence, this could be an evidence of their lack of market-timing skills. These results confirm those of previous studies.

The results also reveal that superannuation funds immediately and quickly (within two weeks) respond to movements in markets. Their response to the Australian equity market movement was quicker (one week) as compared to their response to the US equity and bond markets. Given that the study is based on weekly data, this response may be considered as efficient. Again, these results support those of previous studies.

Further studies could also extend the Markov switching model to allow for time-varying transition probabilities (Diebold *et al*, 1992), where transition probabilities are allowed to vary with such information variables as the strength of the economy, deviations of fundamentals from actual values, and other leading indicators of change. Variables such as interest rate, inflation rate, economic growth rate and business cycles could be examined as to how they affect the sensitivity of superannuation funds.

REFERENCES

Admati, A. R., Bhattacharya, S., Pfleiderer, P. and Ross, S. A. (1986) On Timing and Selectivity, *Journal of Finance*, **41**, 715-730.

APRA (1999) Superannuation Circular No. II.D.1: Managing Investments and Investment Choice, *Australia Prudential Regulation Authority*, April 1999.

Axiss (2005) The Global Significance of Australia's Investment Fund Assets Pool. Available from: http://www.axiss.gov.au/index.cfm?event=object.showContent&objectID=B3D85CF6-D9D9-4294-5B430285B9E1CF92.

Bateman, H., Kingston, G. and Piggott, J. (1993) *Taxes, Retirement Transfers, and Annuities*. Working Paper 92-18, University of New South Wales.

Beechey, M., Gruen, D. and Vickery, J. (2000) *The Efficient Market Hypothesis: A Survey*. Research Discussion Paper 2000-01, Reserve Bank of Australia.

Benson, K. L. and Faff, R. W. (2003) A Performance Analysis of Australian International Equity Trusts, *Journal of International Financial Markets, Institutions and Money*, **13**, 69-84.

Bhardwaj, R. K. and Brooks, L. D. (1993) Dual Betas from Up and Down Markets: Reversal of the Size Effect, *Journal of Financial Research*, **16**, 269-283.

Bird, R., Chin, H. and McCrae, M. (1983) The Performance of Australian Superannuation Funds, *Australian Journal of Management*, **8**, 49-69.

Blake, D., Lehmann, B. N. and Timmermann, A. (1999) Asset Allocation Dynamics and Pension Fund Performance, *Journal of Business*, **72**, 429-461.

Bohl, M. T., Brzeszczynski, J. and Wilfing, B. (2005) *Institutional Investors and Stock Returns Volatility: Empirical Evidence from a Natural Experiment*. Working Paper, European University Viadrina.

Bracker, K., Docking, D. S. and Koch, P. D. (1999) Economic Determinants of Evolution in International Stock Market Integration, *Journal of Empirical Finance*, **6**, 1-27.

Brailsford, T., Heaney, R. and Bilson, C. (2004) *Investments: Concepts and Applications*, 2nd ed, Thomson, South Melbourne.

Chan, K., Chan, K. C. and Karolyi, G. A. (1991) Intraday Volatility in the Stock Index and Stock Index Futures Markets, *Review of Financial Studies*, **4**, 657-684.

Chen, S. (1982) An Examination of Risk Return Relationship In Up and Down Markets Using Time Varying Betas, *Journal of Financial and Quantitative Analysis*, **17**, 265-285.

Christiano, L., Eichenbaum, M. and Evans, C. (1999) *Monetary Policy Shocks: What Have We Learned and to What End?*, Elsevier Science, Amsterdam.

Chu, C.-S. J., Santoni, G. J. and Tung, L. (1996) Stock Market Volatility and Regime Shifts in Returns, *Information Sciences*, **94**, 179-190.

Coleman, A. D. F., Esho, N. and Wong, M. (2004) *The Investment Performance of Australian Superannuation Funds*. Working Papers wp-0010, Australian Prudential Regulation Authority.

Dellva, W. L., DeMaskey, A. L. and Smith, C. Y. (2001) Selectivity and Market Timing Performance of Fidelity Sector Mutual Funds, *Financial Review*, **36**, 39-54.

Diebold, F. X., Lee, J.-H. and Weinbach, G. C. (1992) *Regime Switching with Time-Varying Transition Probabilities.* Working Paper 93-12, Federal Reserve Bank of Philadelphia.

Drew, M. E. and Stanford, J. D. (2003) Returns from Investing in Australian Equity Superannuation

Funds, 1991-1999, *Service Industries Journal*, **23**, 12-24.

Drew, M. E., Veeraraghavan, M. and Wilson, V. (2005) Market Timing, Selectivity and Alpha Generation: Evidence from Australian Equity Superannuation Funds, *Investment Management and Financial Innovations*, **2**, 111-127.

Ehrmann, M., Ellison, M. and Valla, N. (2003) Regime-Dependent Impulse Response Functions in a Markov-Switching Autoregression Model, *Economics Letters*, **78**, 295-299.

Eun, C. S. and Shim, S. (1989) International Transmission of Stock Market Movements, *Journal of Financial and Quantitative Analysis*, **24**, 241-256.

Fabozzi, F. J. and Francis, J. C. (1977) Stability Tests for Alphas and Betas Over Up and Down Market Conditions, *Journal of Finance*, **32**, 1093-1099.

Fabozzi, F. J. and Francis, J. C. (1979) Mutual Fund Systematic Risk for Up and Down Markets: An Empirical Examination, *Journal of Finance*, **34**, 1243-1250.

Faff, R., Gallagher, D. R. and Wu, E. (2005) Tactical Asset Allocation: Australian Evidence, *Australian Graduate School of Management*, **30**, 261-282.

Gallagher, D. R. and Jarnecic, E. (2002) The Performance of Australian Bond Funds, *Journal of Management*, **27**, 163-185.

Gallery, G. and Gallery, N. (2003) Inadequacies and Inconsistencies in Superannuation Fund Financial Disclosure: The Need for a Principles-Based Approach, *Australian Economic Review*, **36**, 89-97.

Gelos, R. G. and Ratna, S. (2001) Financial Market Spillovers in Transition Economies, *Economics of Transition*, **9**, 53-86.

Granger, C. W. J. and Silvapulle, P. (2002) *Capital Asset Pricing Model, Down, Usual and Up Market Conditions and Beta Instability: A Value-At-Risk Approach*. Working Paper, University of California.

Hallahan, T. (1999) The Information Content of Portfolio Performance History and Persistence in Fund Performance: An Examination of Rollover Funds, *Accounting and Finance*, **39**, 255-274.

Hamilton, J. D. (1989) A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle, *Econometrica*, **57**, 357-384.

Hamilton, J. D. and Susmel, R. (1994) Autoregressive Conditional Heteroskedasticity and Changes in Regime, *Journal of Econometrics*, **64**, 307-333.

Henriksson, R. D. (1984) Market Timing and Mutual Fund Performance: An Empirical Investigation, *Journal of Business*, **57**, 73-96.

Henriksson, R. D. and Merton, R. C. (1981) On the Market Timing and Investment Performance II: Statistical Procedures for Evaluating Forecasting Skills, *Journal of Business*, **54**, 513-533.

Humala, A. (2005) Interest Rate Pass-Through and Financial Crises: Do Switching Regimes Matters? The Case of Argentina, *Applied Financial Economics*, **15**, 77-94.

Jensen, M. C. (1968) The Performance of Mutual Funds in the Period 1945-1964, *Journal of Finance*, **23**, 389-416.

Kao, G. W., Cheng, L. T. W. and Chan, K. C. (1998) International Mutual Fund Selectivity and Market Timing During Up and Down Market Conditions, *Financial Review*, **33**, 127-144.

Kingston, G. H. (2000) Efficient Timing of Retirement, *Review of Economic Dynamics*, **3**, 831-840.

Knox, D. M. (1993) Taxing Superannuation in Australia: The Costs and Benefits of the Alternatives, *Australian Tax Forum*, **10**, 39-74.

Kon, S. J. (1983) The Market-Timing Performance of Mutual Fund Managers, *Journal of Business*, **56**, 323-347.

Kon, S. J. and Jen, F. C. (1978) Estimation of Time-Varying Systematic Risk and Performance for Mutual Fund Portfolios: An Application of Switching Regression, *Journal of Finance*, **33**, 457-475.

Krolzig, H.-M. (1997) *Markov-Switching Vector Autoregressions: Modelling, Statistical Inference and Application to Business Cycle Analysis*, Springer, Berlin.

Krolzig, H.-M., Marcelline, M. and Mizon, G. E. (2002) A Markov-switching Vector Equilibrium Correction Model of the UK Labour Market, *Empirical Economics*, **27**, 233-254.

Krolzig, H.-M. and Toro, J. (2000) *A New Approach to the Analysis of Shocks and the Cycle in a Model of Output and Employment*. Working Paper ECO 99/30, European University Institute.

Lee, C. F. and Rahman, S. (1990) Market Timing, Selectivity, and Mutual Fund Performance: An Empirical Investigation, *Journal of Business*, **63**, 261-278.

Lehmann, B. and Modest, D. (1987) Mutual Fund Performance Evaluation: A Comparison of Benchmarks and Benchmark Comparisons, *Journal of Finance*, **42**, 233-265.

Piggot, J., Emiliano, A. V. and Detzel, B. (2005) The Simple Analytics of a Pooled Annuity Fund, *Journal of Risk and Insurance*, **72**, 497-520.

Prather, L. J., Middleton, K. L. and Cusack, A. J. (2001) Are N+1 Heads Better Than One? The Timing and Selectivity of Australian-Managed Investment Funds, *Pacific-Basin Finance Journal*, **9**, 379-400.

Robson, G. (1986) The Investment Performance of Unit Trusts and Mutual Funds in Australia for the Period 1969 to 1978, *Accounting & Finance*, **26**, 55-79.

Roca, E. D. (1999) Short-term and Long-term Price Linkages between the Equity Markets of Australia and its Major Trading Partners, *Applied Financial Economics*, **9**, 501-511.

Sarno, L. and Valente, G. (2005) Modelling and Forecasting Stock Returns: Exploiting the Futures Market, Regime Shifts and International Spillovers, *Journal of Applied Econometrics*, **20**, 345-376.

Sawicki, J. and Ong, F. (2000) Evaluating Managed Fund Performance Using Conditional Measures: Australian Evidence, *Pacific-Basin Finance Journal*, **8**, 505-528.

Sclove, S. L. (1983) Time-Series Segmentation: A Model and A Method, *Information Sciences*, **29**, 7-25.

Sheng, H. C. and Tu, A. H. (2000) A Study of Cointegration and Variance Decomposition among National Equity Indices Before and During the Period of the Asian Financial Crisis, *Journal of Multinational Financial Management*, **10**, 345-365.

Sims, C. A. (1980) Macroeconomics and Reality, *Econometrica*, **48**, 1-48.

Sinclair, N. (1990) Market Timing Ability of Pooled Superannuation Funds: January 1981 to December 1987, *Accounting & Finance*, **30**, 511-565.

Treynor, J. and Mazuy, K. (1966) Can Mutual Funds Outguess the Market?, *Harvard Business Review*, **44**, 131-136.

Tu, J. (2004) *Are Up and Down Markets Economically Important?* Working Paper, Singapore Management University.

Valentine, T. (2003) Is Superannuation Safe?, *Australian Economic Review*, **36**, 108-117.

White, H. (1980) A Heteroskedasticity Consistent Matrix Estimator and a Direct Test for Heteroskedasticity, *Econometrica*, **48**, 817-838.

Wiggins, J. B. (1993) Betas In Up and Down Markets, *Financial Review*, **27**, 107-123.

APPENDIX

SPECIFICATION AND ESTIMATION OF THE MARKOV REGIME-SWITCHING MODEL[4]

This appendix provides a more detailed technical discussion of the Markov regime switching model. The diagnostic tests results are discussed in Section five and the test results have suggested the use of Markov switching-Vector Autoregression (MS-VAR) model. Hence, the discussion focuses on the MS-VAR model.

Denoting the number of regimes by m and the number of lags p respectively, the equation to be estimated is expressed as follows.

$$y_t = v(s_t) + A_1 (s_t)\, y_{t-1} + \ldots + A_p (s_t)\, y_{t-p} + A(s_t)u_t \qquad (2)$$

Transition Probabilities

The regime generating process in Markov switching model is an ergodic Markov chain with a finite number of states, $s_t = 1, \ldots, m$ which is defined by the transition probabilities.

$$p_{i,j} = \Pr(s_{t+1} = j \mid s_t = i), \sum_{j=1}^{m} p_{ij} = 1 \quad \forall i, j \in \{1, \ldots, m\} \qquad (3)$$

The probability of regime i occurring next period given that the current regime is j is fixed. This stochastic process is defined by the transition matrix P as follows.

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix}, \qquad (4)$$

where $p_{iM} = 1 - p_{i1} - \ldots - p_{i,M-1}$ for $i = 1, \ldots, M$.

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[4] This section relies heavily on Krolzig (1997).

As the Markov switching model requires the number of regimes to be specified before running the model, this study uses the AIC criterion in selecting the optimal number of regimes and lags. Several studies have supported the use of AIC to choose the appropriate Markov switching model (see, for instance, Sclove, 1983 and Chu, Santoni and Liu, 1996).

Regime Probabilities

This procedure estimates the coefficient matrix, the variance-covariance matrix for each regime, the transition matrix, and the optimal inference for the regimes throughout the sample period. The latter are referred to as the regime probabilities $\hat{\xi}_t^i$ defined below, where T denotes the end period for the estimation.

$$\hat{\xi}_t^i = \Pr(s_t = i) \quad \text{for } i = 1, \ldots, m \text{ and } t = 1, \ldots, T \qquad (5)$$

Regime Coefficients

The MS-VAR model coefficients can be estimated using a two-stage maximum likelihood procedure. The estimation of the Markov switching model is conducted by applying the EM (Expectation-Maximisation) algorithm (see Hamilton, 1989 and Krolzig, 1997). The first *expectations* step optimally infers the hidden Markov chain for a given set of parameters. The second *maximisation* step then re-estimates for parameters for the inferred hidden Markov chain.

Impulse Response Analysis[5]

The second stage in estimating the Markov switching model is the identification of the contemporaneous relationships between variables. Like Christiano *et al* (1999), this paper uses the

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[5] This section borrows heavily from Ehrmann *et al* (2001: pp.10-11)

Choleski decomposition, which assumes that the system is recursive and hence allows the process of identification. The identification problem arises because the EM algorithm gives only estimates of the variance-covariance matrices $\Sigma^i, \ldots, \Sigma^m$ and not the matrices $A_i, \ldots, A_m$. To identify these matrices the model has to impose restrictions on the parameter estimates from the unrestricted model. Matrix A_i is computed from the regime dependent variance covariance matrix from the reduced form VAR, Σ^i.

$$\Sigma^i = E\,(A^i U_t U_t' A^{i\prime}) = A^i\, I\, A^{i\prime} = A^i A^{i\prime} \tag{6}$$

Matrix A_i has K^2 elements and Σ^i has only $\frac{K(K+1)}{2}$ elements. In order for A_i to be defined from Equation 7, there must exist $\frac{K(K+1)}{2}$ missing restrictions. Sims (1980) derives the additional restrictions by imposing a recursive structure on the model. The endogenous variables are ordered and it is assumed that the fundamental disturbance to a variable has only contemporaneous effects on the variable itself and on variables ordered below it. For example, in a four-variable system, the third disturbance has only contemporaneous effects on the third and fourth endogenous variables. Under this identification procedure, the matrix A_i is lower triangular and is exactly identified. It can be easily recovered from a Choleski decomposition of the matrix Σ^i.

The impulse response functions summarise expected changes in the endogenous variables after a one standard deviation shock to one of the fundamental disturbances. This provides a useful analytical tool to investigate the dynamics of the changes in variables' responses from down to up market condition or vice versa. Based on a Markov switching model, this study estimates a regime-dependent impulse response function analogous to the concept introduced by Ehrmann *et al* (2001). This function describes the relationship between endogenous variables and fundamental disturbances *within* a regime. Regime-dependent impulse response functions are conditional on a given regime prevailing at the time of the disturbance and throughout the duration of the response.

The validity of regime conditioning depends on the time horizon of the impulse response and the expected duration of the regime. As long as the time horizon is not excessive and the transition matrix predicts regimes, which are highly persistent, then the conditioning is valid and regime-dependent impulse response functions are a useful analytical tool. For a longer time horizon or frequently switching regimes, it would be more attractive to condition on the expected path of the regime throughout the response.

Mathematically, the regime-dependent impulse response function at time $t + h$, when a one standard error shock to the k^{th} fundamental disturbance occurs at time t and the prevailing regime is i is expressed as follows.

$$\frac{\partial E_t Y_{t+h}}{\partial U_{k,t}} \mid s_t = \ldots = s_{t+h} = \theta^i_{k,h}, \text{ for } h \geq 0 \tag{7}$$

A series of K-dimensional response vectors $\theta^i_{k,1}, \ldots, \theta^i_{k,h}$ show the responses of the endogenous variables to a shock to the k^{th} fundamental disturbance. In this study, the duration for the impulse response is set at 5 weeks, in which the Australian market is said to be efficient and portfolio rebalancing period would be quicker, hence 5 weeks is the optimal period (see, Chan *et al*, 1991; Beechey *et al*, 2000; Gelos and Ratna, 2001). These response vectors are computed by combining unrestricted parameter estimates of the reduced-form Markov switching vector auto-regression model, B, and the identified matrix, A in Equations 2 and 3.

The first response vector measures the effect on endogenous variables of the k^{th} fundamental disturbance. A one standard deviation shock to the k^{th} fundamental disturbance implies that the initial disturbance vector is $U_0 = (0, \ldots, 1, \ldots, 0)$ i.e. a vector of zeros apart from the k^{th} element that is one. Pre-multiplying this vector by the estimate of the regime-dependent matrix $\hat{A}_i$ as in Equation 2 gives the impulse responses.

The remaining response vectors are calculated by solving the endogenous variables in Equation 2. Equations 8 and 9 show the solution linking the estimated response vectors with estimated parameters. The faster the response of shocks to equality, the more sensitive the endogenous variables are to the fundamental disturbances.

$$\hat{\theta}^{i}_{k,0} = \hat{A}_i U_0 \tag{8}$$

and

$$\hat{\theta}^{i}_{k,h} = \sum_{j=i}^{\min(h,p)} \left(\hat{B}^{i}_{j}\right)^{h-j-1} \hat{A}_i U_0, \text{ for } h > 0 \tag{9}$$

This study uses the Markov switching model that allows all parameters including intercepts, coefficients and variance covariance matrices for the reduced-form VAR to switch according to a hidden Markov chain. According to Krolzig's (1997) notation, this specification may be referred as: MSIAH(*m*)-VAR(*p*)[6]. The MSIAH model has been supported by several studies to be a superior model when evaluating out-of-sample performance on the basis of the ability of the model to match the full out-of-sample predictive density of stock returns (Sarno and Valente, 2005). Additionally, MSIAH model is able to capture the market conditions without prior specifications and it provides better analysis of the data over linear models (Humala, 2005).

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[6] This study has also considered the specifications of Markov switching models with Autoregressive Conditional Heteroskedasticity (ARCH). However, the MSIAH model used in this study is able to capture ARCH effect (Krolzig, 1997: pp.24-25).

Figure 1

Econometric Techniques and Data Used

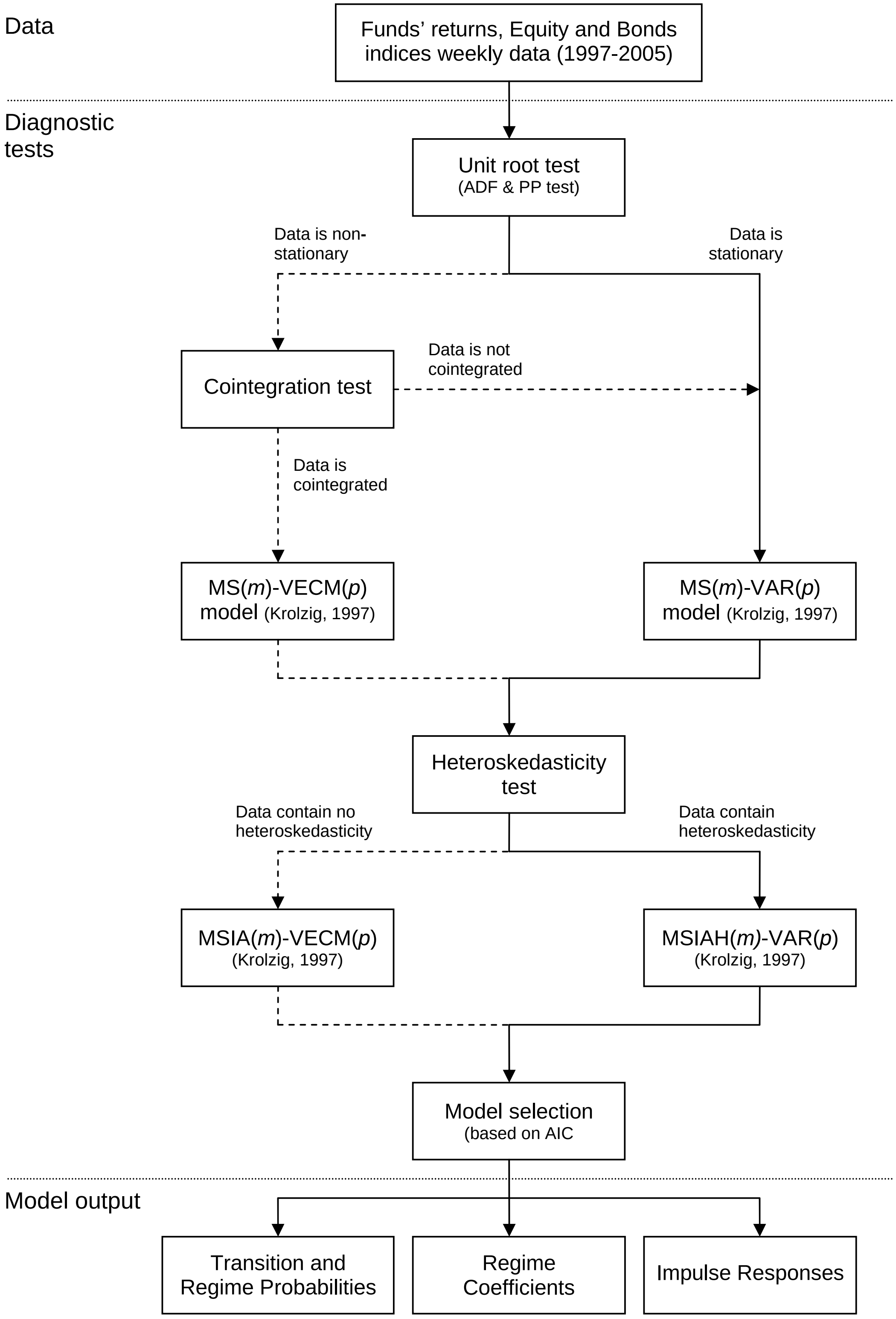

Figure 2

Markov Switching Regime Probabilities

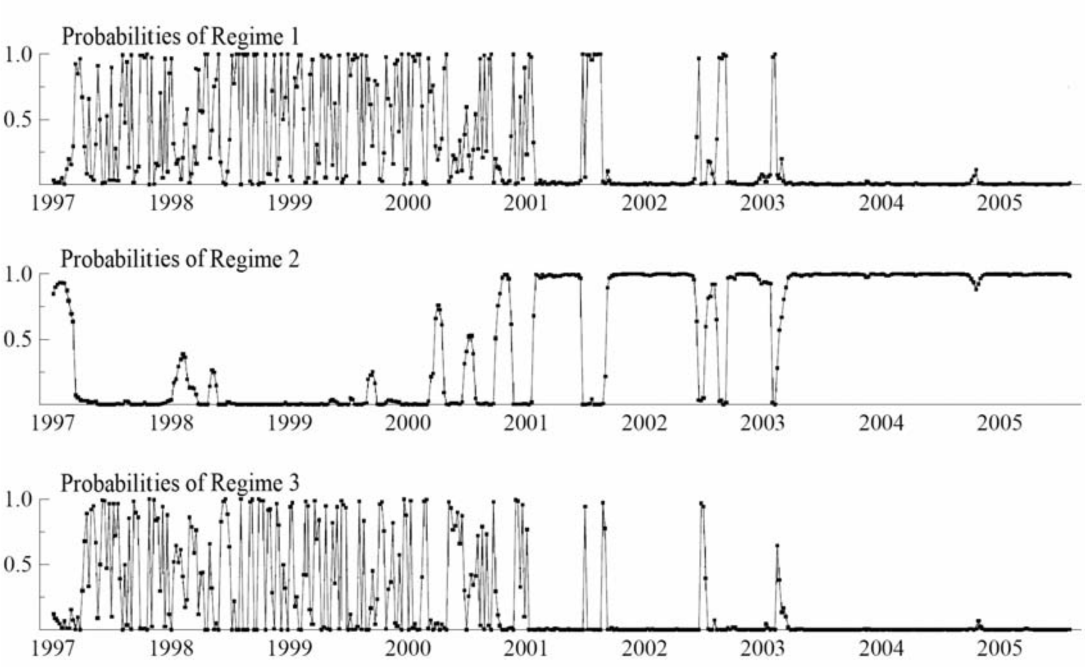

Figure 3

Impulse Response of Funds' Returns to a Shock in the Australian Equity, US Equity and US Bond Markets

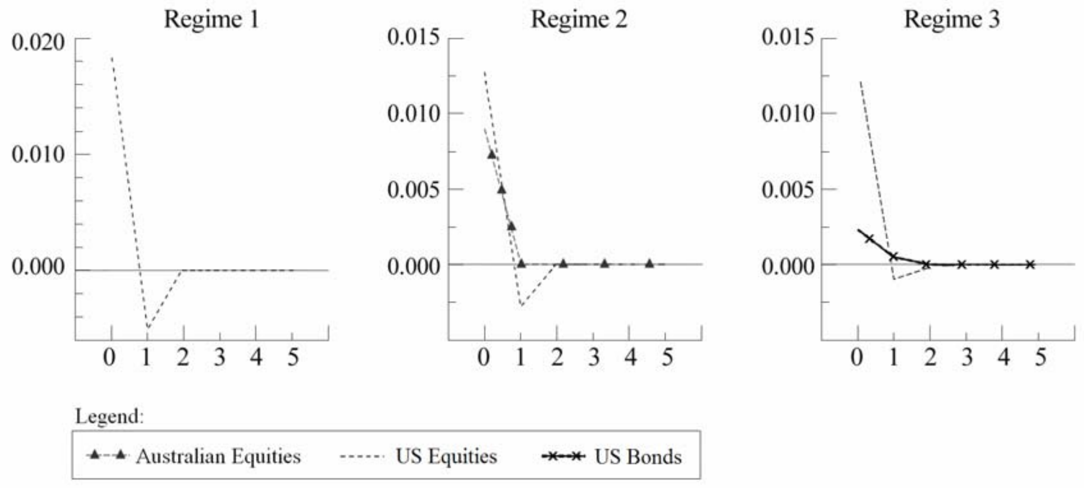

Table 1

Asset Allocation Benchmark

Asset Classes	Range	Benchmark
Cash	0% – 20%	10%
Bond	20% – 40%	25%
Equity	50% – 70%	50%
Property	10% – 30%	15%

Source: APRA (1999)

Table 2

List of Superannuation Funds in Morningstar Database

	Number of Funds	Proportion
Australian Equity	944	22.3%
Australian Fixed Interest	403	9.5%
Cash	261	6.2%
International and Australian Equity	107	2.5%
International Equity	629	14.9%
International Fixed Interest	76	1.8%
Multi-sector	1,608	38.0%
Property	60	1.4%
Reserve Back	141	3.3%
Total	4,229	100%

Table 3

Unit Root Tests Results

	Augmented Dickey-Fuller	Philips-Perron
Funds' Returns	-20.52	-20.52
Australian Equity	-22.04	-22.07
US Equity	-9.33	-22.26
Australian Bond	-22.55	-22.55
US Bond	-21.31	-21.31

Note: Unit root tests based on model with constant and trend
Critical value at 5% level of significance: -3.45

Table 4

Akaike Information Criterion Values for Markov Switching Models

	2 regimes	3 regimes	4 regimes
Lag 1	-38.1504	-38.3206 *	-38.2672
Lag 2	-38.1328	-38.2516	-38.2371
Lag 3	-38.0482	-38.1257	-38.1660
Lag 4	-38.0718	-38.0456	-38.1326

Note: * Lowest AIC value.

Table 5

Probabilities and Characteristics of Each Regime

	Probability	Average Duration (in weeks)	Number of Observations	Average Returns	Average Volatility*
Regime 1	0.2589	2.24	119.1	0.0090	0.1126
Regime 2	0.5331	26.12	241.7	0.0152	0.0604
Regime 3	0.2080	1.99	95.2	0.0370	0.1435

Note: * Average volatility is the average variance of funds' returns

Table 6

Probabilities of Switching between Regimes

To: From:	Regime 1	Regime 2	Regime 3
Regime 1	0.5534	0.0447	0.4019
Regime 2	0.0370	0.9617	0.0013
Regime 3	0.4613	0.0425	0.4962

Table 7

Estimated Coefficients for Markov Switching Model:
Funds' Returns vs. Australian Equity, US Equity,
Australian Bond and US Bond Markets

Independent variables	Regime 1	Regime 2	Regime 3
Australian Equity	–0.0021	0.0132 *	0.0031
US Equity	0.0189 *	0.0071 *	0.0096 *
Australian Bond	0.0235	0.0034	0.0142
US Bond	–0.0241	0.0150	0.0342 *

Note: The autoregressive coefficients values are shown in lag 1
* 5% significance level