AN ANALYSIS ON AUSTRALIAN SUPERANNUATION FUNDS VOLATILITY USING EGARCH APPROACH

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Abstract. This paper analyses the volatility of Australian superannuation funds in relation to share and bond markets in the US and Australia using EGARCH model for the period 1997-2005. Volatility within markets clearly influences investor profits from investments. If investors are able to foresee the future volatility, they could mitigate their losses and hedge against risks. The preliminary findings analysis suggest that EGARCH (2,1) model fits best to our data. The findings further reveal that the volatility from the Australian share market affects performance of Australian superannuation funds more than US share market. However, the superannuation funds are not highly correlated with the bond markets, which may provide a possible opportunity for portfolio diversification.

Keywords: Superannuation funds; Volatility; Performance; EGARCH
JEL Classifications: G23, C30, C52
1. INTRODUCTION

The Australian retirement, pension or superannuation fund is the largest in Asia and the fourth largest in the world subsequent to the US, Luxembourg and France. In 2000, Australian superannuation fund assets totalled US$342 billion and by 2004, this had doubled to US$635 billion. The investments are expected to increase 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. This study attempts to investigate the volatility of Australia superannuation funds in relation to the assets invested to uncover how these assets are affecting returns of the superannuation funds. By doing so, this study provides useful information for understanding the extent of international market co-movements and investors would be able to predict volatility and manage their investment portfolio according to the market movements.

From an asset management point of view, it is important to assess the risk-return characteristics of a portfolio and evaluate its implications for efficient portfolio management strategies. The advocates of the Capital Asset Pricing Model (CAPM) maintain that (assuming market efficiency) asset allocation to the invested assets may lead to lower returns in the long-run due to diversification costs, as the assets are only part of the market portfolio (Markowitz approach). The opponents to the latter approach underlie that the portfolio could attain higher return relative to the market because it integrates information not directly conceived or evaluated accordingly by the markets (Kurtz, 1999). The key issues for asset valuation and portfolio management remain whether the investments can potentially result in boosting investors’ profit by generating higher returns relative to the market portfolio, hence by understanding the risk profile of superannuation investments and the mechanism of volatility dynamics in the assets invested have important implications for portfolio management decisions and identifying investment opportunities.

Despite extensive past research in volatility dynamics, there is no general agreement as to how the predictability of volatility be modelled more efficiently; and how to condition such models for the asymmetric nature of asset return volatility (Henry,
1998). Empirical evidence has indicated that a negative shock to assets' returns can potentially generate more volatility than a positive shock of equal magnitude (Pagan and Schwert, 1990; Nelson, 1991; Engle and Ng, 1993). In the case, that stock prices fall due to some bad news, the weight attached to debt in the capital structure increases as the equity value of the firm decreases, resulting to higher debt-to-equity-ratio and making the firm riskier. Generally, such increases in leverage makes the equity holders who bear the residual risk of the firm anticipate higher expected future return volatility (Black, 1976; Christie, 1982). In order to examine these issues, this study employs the asymmetric EGARCH models to model the assets' returns volatility. The paper also attempts to fill some of the gaps in the literature of superannuation.

The remaining parts of this paper are organised as follows: in section two, a review of the literature on ARCH effects is presented; in section three, the methodology and the data used in the study are described; in section four, the empirical results is presented which is followed finally by the conclusion and suggestions for further research in section five.

2. LITERATURE REVIEW

Early studies by Lee and Ohk (1991) examined the conditional heteroskedasticity of stock return series of Hong Kong, Japan, Korea, Singapore, Taiwan and the US using ARCH model and daily data from 1981-1988. They found strong ARCH effects in all six countries. Chan and Karolyi (1991) used the daily Nikkei Stock Average data from 1986 to 1990 and found that a GARCH model characterises the Japanese stock market.

Bae and Karolyi (1994) investigated the volatility spillovers between Japan and the US stock markets using intraday open and closing prices of the Nikkei Stock Average and Standard and Poor’s 500. The study applied two asymmetric GARCH models to allow for the differing impacts of 'bad' news and 'good' news. They found that 'bad' news from domestic and foreign markets appear to have a much larger impact on subsequent return volatility than 'good' news. The magnitude and persistence of
shocks originating in New York or Tokyo that transmit to the other markets around the world appear to be significantly understated when asymmetric effects are ignored.

Hamao et al (1990) examined the transmission of the first and second moments in common stock prices across Tokyo, London and New York with the use of daily opening and closing prices of the Nikkei 225 Stock Index, Financial Times Stock Exchange 100 Share index and the Standard and Poor’s 500 Composite Index from 1985 to 1988. The analysis was based on a GARCH(1,1)-M model. They found evidence of price volatility spillovers from New York to Tokyo, London to Tokyo, and New York to London are observed, but no price volatility spillover effects in other directions are found for the October 1987 period.

Engle and Ng (1993) examined the impact of news on volatility in the Japanese stock market using daily stock market data from 1980 to 1987. Three asymmetric versions of the GARCH(1,1) model were fitted. The best model turned out to be the EGARCH as it is able to capture most of the asymmetry. Nicholls and Tonuri (1995) sought to explain the volatility of the Australian stock market by fitting several asymmetric GARCH models on the returns of Australian Fifty Leaders Statex - Actuaries Accumulation Index from 1988 to 1991. The EGARCH(1,1) model was found to best fit the data. Kearns and Pagan (1991) also investigated the monthly volatility of the Australian stock market over the period 1875-1987, and fitted ARCH, GARCH and EGARCH models to the data. It was found that the asymmetric EGARCH(1,2) model was the best representation of the volatility of returns.

Theodossiou and Lee (1995) studied the nature of stock market volatility and its relation to expected returns for ten industrialised countries – Australia, Belgium, Canada, France, Italy, Japan, Switzerland, the UK, the US and West Germany using weekly aggregate weekly stock market returns during the period 1976 to 1991. Significant conditional heteroskedasticity was present in the return series of all ten markets, indicating the presence of volatility clustering; that is, the tendency of large stock price changes followed by large stock price changes, but with unpredictable sign.
Koutmos (1996) studied lead/lag and volatility interactions among the stock markets of the UK, France, Germany and Italy with the use of a VAR-EGARCH model. The study found significant lead/lag relationships and asymmetric volatility interactions among the markets. Poon and Taylor (1992) examined the relationship between returns and volatility in the UK stock market during the period 1965 to 1989. GARCH(1,1) and EGARCH models were fitted with the use of daily, weekly, fortnightly and monthly data. While the GARCH(1,1) model was the best fit, the results however did not establish any clear relationship between returns and volatility.

Gallo and Pacini (2000) applied EGARCH(1,1) model to examine the effects of trading activity on market volatility and found ARCH effects in the stock market and persistence of volatility that are due to the opening and closing price of the market during the period 1985 to 1995. Chen and Kuan (2000) investigated time irreversibility of the US stock index returns using EGARCH models on the DJIA, NYSE, S&P500, NASDAQ, Russell 2000 (RS2000) and Pacific Exchange Technology (PETECH) index from the period 1991 to 2000 and found asymmetric volatility in these indexes that was captured by the EGARCH model. Karanasos and Kim (2003) found that EGARCH model provides more accurate reproduce nature of the sample autocorrelation of squared returns than the GARCH model in examining the Korean KOSPI, Japanese Nikkei, Taiwanese Stock Exchange and Singapore Straits Times Index.

Brandt and Jones (2006) tested numerous specifications of the EGARCH models on the S&P500 index during 1962 to 2004 and found that the EGARCH models significantly improves the in-sample fit and the accuracy of out-of-sample forecasts. Beach and Orlov (2007) have used EGARCH-M(1,1) to find the optimal portfolio for international diversification during 1988 to 2002, the study concluded that the returns on portfolio surpass those of portfolios that rely on market equilibrium weights.

As the literature review shows, financial time series data often contain heteroskedasticity effect, i.e. an unequal variance in the regression errors. If the analysis does not account for this effect, the result would lead to a bias estimator due to large volatility clustering within the dataset. For a certain time, the volatility can be successively large and in another time, the values can be successively low. This type
of volatility clustering may be due to the sensitivity of financial markets: for example, to rumours, political upheavals, changes in government monetary and fiscal policies, and the like (Gujarati, 1995). This observation suggests that there is some kind of autocorrelation in the variance of the error terms as volatility is not constant but varies from period to period (Davidson and Mackinnon, 1993). This autocorrelation may be due to an autoregressive conditional heteroskedasticity (ARCH) effect. However, even if the error terms are not actually correlated the variance calculation depends on past squared errors and as such often gives the impression is that they are (Maddala, 1992).

Clearly, the markets investigated above are characterised by the presence of ARCH effects. The presence of ARCH characteristics affects the correlation structure among the time series. Often the calculations of pairwise correlations is based upon assumptions that suggest that the time series involved are mean and variance stationary; in which the conditional and unconditional estimates are the same. If, however, this assumption is not true as in the case where ARCH effects are present, the computed correlations will be greater than what they should actually be. In the area of finance, important decisions regarding hedging and diversification strategies are based on the nature of the correlations between different markets and assets; and if correlations are overestimated then this would lead to underestimation of diversification benefits and will in turn lead to erroneous portfolio construction strategies.

In the context of analysing the volatility of Australian superannuation funds, none of the studies reviewed have focused on applying EGARCH model. Hence, this study will address the gap in the literature by analysing the volatility of the Australian superannuation funds with respect to the assets invested within the portfolio using EGARCH model, which provides more flexible parameters than other ARCH models.

3. DATA AND METHODOLOGY

A simple regression model usually used in such studies is often in the following form:
\[ R_{SF} = \alpha + \beta \cdot R_s - \epsilon_i \]  

where, \( R_{SF} \) is the return on Australian superannuation funds; \( \alpha \) is the intercept term; \( \beta \) is the beta parameter; \( R_s \) is the returns on assets invested in portfolio; and \( \epsilon_i \) is the residual component.

The regression above is also known as the CAPM model, however it does not include autoregressive conditional heteroskedasticity (ARCH) effect, which could have underestimation or overestimation impact on the result especially in analysing financial time series data as discussed previously.

The ARCH concept originally proposed by Engle (1982) with the idea that the variance of the error term at time \( t \) depends on the size of the squared error terms in previous periods. Engle suggests that the conditional variance or predictable volatility depends on past news: the older the news, the less effect it has on current volatility. In an ARCH(q) model, old news which arrived at the market more than \( q \) periods ago has no effect at all on current volatility. Engle (1982) therefore suggests that the conditional variance \( h_t \) can be modelled as a function of the lagged \( \epsilon \)’s; in the form of a \( q \)-th order autoregressive conditional heteroskedasticity model. ARCH (q) given below (Engle and Ng, 1993).

\[ h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 \]  

(2)

where, \( \alpha_0, \alpha_1, \ldots, \alpha_q \) are constant parameters. The effect of a shock \( i \) periods ago \((i \leq q)\) on current volatility is governed by the parameters \( \alpha_i \). Normally, it would be expected that \( \alpha_i < \alpha_j \) for \( i > j \).

Bollerslev (1986) generalises the ARCH (q) model to the GARCH (p,q) model. The GARCH model allows for both autoregressive and moving average components in the heteroskedastic variance (Enders, 1995). The GARCH is an infinite order ARCH model (Engle and Ng, 1993). The GARCH (p,q) model can be expressed as follows:

\[ h_t = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-i} \]  

(3)
where, $a_1, \ldots, a_p, \beta_1, \ldots, \beta_p$ are constant parameters.

The GARCH process assumes constant unconditional mean and variance, but the conditional mean and variance are time-dependent. The time dependency of the conditional variance tends to capture the clumping of volatility within time-periods.

Within the finance literature, $\varepsilon_t$ is a collective measure of news at time $t$. A positive $\varepsilon_t$ (an unexpected increase in price) suggests the arrival of good news, while a negative $\varepsilon_t$ (an unexpected decrease in price) suggests the arrival of bad news. Further, a large value of $|\varepsilon_t|$ implies that the news is 'significant' or 'big' in the sense that it produces a large unexpected change in price. This can be seen in the following: Let $y_t$ be the rate of return of a particular stock or the market portfolio from $t - 1$ to $t$. Also, let $F_{t-1}$ be the past information set containing the realised values of all relevant variables up to time $t - 1$. Since investors know the information in $F_{t-1}$ when they make their investment decision at $t - 1$, the relevant expected return and volatility to the investors are the conditional expected value of $y_t$ given $F_{t-1}$, and the conditional variance of $y_t$ given $F_{t-1}$. Denote those by $m_t$ and $h_t$, respectively, that is $m_t = E(y_t|F_{t-1})$ and $h_t = \text{Var}(y_t|F_{t-1})$. Given these definitions, the unexpected return at time $t$ is $\varepsilon_t = y_t - m_t$ and $\varepsilon_t$ is a collective measure of news at time $t$ (Engle and Ng, 1993).

In the standard ARCH ($q$) and GARCH ($p,q$) model, the conditional variance depends only on the magnitude and not on the sign of the past news – that is, good news and bad news have the same impact on volatility. These models therefore assume a symmetrical news impact on volatility. These models, therefore, would not be able to deal with a situation where an unexpected drop in price (bad news) increases predictable volatility more than an unexpected increase in price (good news) of similar magnitude. This asymmetry has been noted in a number of studies in the past (Black, 1976; Christie, 1982; French et al, 1987; Nelson, 1991 and Schwert, 1990).

The phenomenon may be explained in terms of the so-called "leverage effect". An unexpected decrease in share price decreases the value of equity relative to debt, and thus increases corporate leverage that in turn increases the risk of holding shares. This increase in risk translates into a rise in expected returns, which further decreases the price of the share. Because of the leverage effect, bad news (a sudden decrease in
share price) leads to a more magnified impact on volatility (a further decline in share price). Some researchers, however, believe that the leverage effect may not be the only explanation for the asymmetric impact of news on volatility (French et al., 1987). For example, Campbell and Hentschel (1992) claimed that the mere arrival of information itself could cause this asymmetry. News, per se, because of its being unexpected, will increase volatility. When news is bad, volatility increases more because it reinforces the initial increase in volatility arising from the surprise; however, when news is good, this tends to offset the initial impact of news on volatility, which therefore leads to lower volatility.

In finance, the use of a symmetric model when in fact an asymmetric model is called for creates serious consequences. In the symmetric situation, the model underestimates the impact of negative news and overestimates that of positive news. Thus, predictable volatility, which is an important input into the calculation of option prices and market risk premium is either overestimated or underestimated; thus leading to serious errors in portfolio selection and hedging strategies.

One of the earlier models that attempt to capture the asymmetry phenomenon is the EGARCH model proposed by Nelson (1991). The conditional variance equation of this model is

\[
\log(h_t) = \omega + \sum_{i=1}^{d} \alpha_i \epsilon_{t-i} + \gamma (|z_{t-i} + E[z_{t-i}]|) + \sum_{i=1}^{q} \beta_i \log(h_{t-i}).
\]

(4)

The EGARCH model has some distinct advantages over the GARCH model. The logarithmic form ensures that the estimated conditional variance is strictly positive, thus the non-negativity constraints used in the estimation of the GARCH models are not necessary. It has also been argued that a negative shock may cause volatility to rise more than a positive shock of the same magnitude, which is taken into consideration with the parameter \( \gamma \) ensuring the EGARCH model with a negative sign and indicating that bad news generate more volatility than good news. This study employs such an EGARCH model to analyse the superannuation funds volatility in relation to the assets invested in the portfolio.
Sources of Data

The analysis in this study covers the period January 1997 to September 2003. The period studied is due to the completeness of data and this period is rich with events, 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 Delphi 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 and 313 funds in the study period. 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 \( R_t = \ln(\text{price}_{t}/\text{price}_{t-1}) \times 100 \). Then the funds’ returns are analysed and combined or pooled by taking the weighted average of all the funds’ returns. The weight used in each fund based on its net asset value. 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.

The Australian superannuation funds data used in this study is provided by the Morningstar Research Pty Ltd (Morningstar), which is an independent measurement service and research house monitoring the managed funds industry in Australia. This paper also utilises the Morgan Stanley Capital Indices (MSCI) data concerning equity and bond indices in Australia and the US. The US equity and bond indices are important since most of the international investments in the superannuation funds portfolio are analysed in US. For consistency, the returns for the Australian and the US equity and bond markets are also calculated. The same discrete returns formula is used. The MSCI data were from the DataStream.

4. **EMPIRICAL RESULTS**

Table 1 presents the results of preliminary diagnostics conducted on returns on the indices and superannuation funds. The highest mean statistics correspond to Australian Share Market, while the lowest mean correspond to Australian Super
Funds. The largest standard deviation is in the US Share Market and lowest standard deviation in the Australia Super Funds. The skewness statistics presented in row 3 indicate that all the time series are negatively skewed, with US Bond Market the most highly skewed and the least with Australian Share Market. The excess kurtosis statistics shown in row 4 reveal that all the time series are leptokurtic with US Share Market being the most leptokurtic and Australian Bond Market the least. The Jacque-Bera (JB) statistics in row 5 indicate that all the variables are characterised with non-normalities.

**TABLE 1. Descriptive statistics**

<table>
<thead>
<tr>
<th></th>
<th>Australian Super</th>
<th>Australian Share</th>
<th>Australian Bond</th>
<th>US Share</th>
<th>US Bond</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0002</td>
<td>0.0015</td>
<td>0.0013</td>
<td>0.0010</td>
<td>0.0012</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.0010</td>
<td>0.0180</td>
<td>0.0061</td>
<td>0.0240</td>
<td>0.0064</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.1739</td>
<td>-0.0982</td>
<td>-0.2092</td>
<td>-0.2742</td>
<td>-0.4514</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>3.5695</td>
<td>3.8529</td>
<td>3.4334</td>
<td>4.2353</td>
<td>3.6454</td>
</tr>
<tr>
<td>Jarque-Bera</td>
<td>8.4801</td>
<td>14.5868</td>
<td>6.9104</td>
<td>34.7815</td>
<td>23.4493</td>
</tr>
<tr>
<td>Probability</td>
<td>0.0144</td>
<td>0.0007</td>
<td>0.0316</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Table 2 presents the correlation between each market and the Australian superannuation funds. The highest correlation to Australian Super Funds is the Australian Share Market (85.35%) followed by US Share Market (68.83%), while US Bond Market is negatively correlated (-4.54%). The Australian Share Market is 56.30% correlated to US Share Market implying that these two share markets have a fairly high chance of moving in the same market direction, such as one market is going down, while another market will follow slightly. The Australian Bond Market is 60.97% correlated to the US Bond Market, which imply that both bond markets would move in the same directions.

The correlation between share markets and bond markets in general are negatively correlated. For example, the correlation of Australian Share Market with Australian Bond and US Bond Markets are -3.30% and -8.24%. While the results suggest both of the share and bond markets are moving in different directions of each other, this might provide investors an opportunity to diversify their portfolio by investing in markets that swing in different directions as their investment as a whole.
TABLE 2. Correlation matrix

<table>
<thead>
<tr>
<th></th>
<th>Australian Super</th>
<th>Australian Share</th>
<th>Australian Bond</th>
<th>US Share</th>
<th>US Bond</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australian Super</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Australian Share</td>
<td>0.8535</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Australian Bond</td>
<td>0.0723</td>
<td>-0.0330</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>US Share</td>
<td>0.6883</td>
<td>0.5630</td>
<td>-0.1325</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>US Bond</td>
<td>-0.0454</td>
<td>-0.0824</td>
<td>0.6097</td>
<td>-0.1662</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

In order to select the best specifications for the EGARCH (p,q) model, we have used the log-likelihood and two other information criterions (see Table 3). The log-likelihood and the Akaike Information Criterion (AIC) suggest the best specification is the EGARCH (2,1) model while Schwarz Information Criterion (SIC) supports the EGARCH (1,1) model. In this study, we will be using the EGARCH (2,1) model as two of the three selection criterions have supported this model specification.

TABLE 3. Comparison among the specifications of the EGARCH model.

<table>
<thead>
<tr>
<th></th>
<th>Log-likelihood</th>
<th>AIC</th>
<th>SIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>EGARCH(1,1)</td>
<td>2924.101</td>
<td>-12.7576</td>
<td>-12.6763*</td>
</tr>
<tr>
<td>EGARCH(2,1)</td>
<td>2925.218*</td>
<td>-12.7581*</td>
<td>-12.6678</td>
</tr>
<tr>
<td>EGARCH(1,2)</td>
<td>2924.528</td>
<td>-12.7550</td>
<td>-12.6648</td>
</tr>
<tr>
<td>EGARCH(2,2)</td>
<td>2925.312</td>
<td>-12.7541</td>
<td>-12.6548</td>
</tr>
</tbody>
</table>

The EGARCH(2,1) estimation results are reported in Table 4. The coefficients for all variables are highly significant at 5% level. The Australian Share Market has the highest coefficient, followed by Australian Bond Market and US Share Market. The US Bond Market, however, has a negatively coefficients that was similar in the correlation discussed in Table 2. One possible explanation for this result is that the regulatory bodies in setting a certain range for investment in certain asset classes. For example, the Australian Prudential Regulatory Authority sets a benchmark of about 10% of portfolio investment to cash, 15% to property, 25% to bonds and 50% to shares (APRA, 1999).
TABLE 4. Estimated parameters for EGARCH (2,1) model

<table>
<thead>
<tr>
<th></th>
<th>Coefficients</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Australian Share Market</td>
<td>0.0366</td>
<td>0.0000*</td>
</tr>
<tr>
<td>Australian Bond Market</td>
<td>0.0242</td>
<td>0.0000*</td>
</tr>
<tr>
<td>US Share Market</td>
<td>0.0120</td>
<td>0.0000*</td>
</tr>
<tr>
<td>US Bond Market</td>
<td>-0.0094</td>
<td>0.0093*</td>
</tr>
<tr>
<td>$\omega$</td>
<td>-0.1774</td>
<td>0.1900</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.2482</td>
<td>0.0147*</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>-0.1811</td>
<td>0.0786</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.0212</td>
<td>0.2278</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.9921</td>
<td>0.0000*</td>
</tr>
</tbody>
</table>

Note: * significant at 5%

\[
R_{SF} = 7.884 + 0.0366(\text{Australian Share Market}) + 0.0242(\text{Australian Bond Market}) + 0.0120(\text{US Share Market}) - 0.0094(\text{US Bond Market})
\] (5)

\[
\log(h_t) = -0.1774 + 0.0212|\phi_1 z_{t-1} + 0.9921|z_{t-1}| + 0.2482 \log h_{t-1} - 0.1811 \log h_{t-2}
\] (6)

In Table 4, the significant coefficients are $\beta_1$ and $\gamma$ suggesting persistence of volatility and a high coefficient for asymmetric volatility for the superannuation funds, which could indicate potential spillovers in volatility from other markets that was absorbed by the Australian superannuation funds. The asymmetric effect shows a high coefficient of 0.9921 implying that the Australian superannuation funds are reacting to different sources of news from different markets and adjust their portfolio accordingly.

Figure 1 presents the Actual, Fitted and Residuals graph for the EGARCH (2,1) model. The Actual plot of the data and Fitted plot is a close fit in terms of the movements within the time series data thus exhibiting a very good match ($r^2 = 0.89$). The residuals appear stationary with larger fluctuations during the period 1998 to 2001. The volatility is increasing at a reasonably steady momentum from 1997 to mid-2000 and decreasing from then on until mid-2001 and the volatility remained within a small range of fluctuations (see Figure 2).
Plots for other specifications of the EGARCH model that were tested in this study are similar to EGARCH(2,1) model, hence the graphs for other EGARCH model are not reported but are available upon request.

A plot of the realised volatility and the estimated volatility in Figure 3 reveal more information regarding the volatility at the different time periods, which could indicate certain events occurred during that point in time that could lead to increase in volatility. For instance, the first spike occurring in late 1997 could correspond to the
Asian crisis that could have an indirect impact to the superannuation funds investment portfolio as well the Russian crisis in late 1998 and September 11 attacks in 2001. Certain events such as the Dotcom boom and bust in mid-1999 and 2000, the bankruptcy of WorldCom and Delphi in 2002 and 2003 could have caused the volatility to increase. Interestingly, the realised volatility for the boom and bust of Dotcom and the bankruptcies are higher than the estimated volatility, this could imply that these events did not have a big influence on the returns of superannuation funds as compared to the crises. However, there are certain spikes in early 2000 and early 2001 that could not be identify relating to any events, which requires further studies to analyse these spikes.

**FIGURE 3. Realised Volatility and Estimated Volatility**

5. CONCLUSION

This study analysed the volatility of the Australian superannuation funds in relation to Australia and the US share and bond markets using an EGARCH model during the period 1997-2005. The findings suggest that asymmetric effects can be captured using EGARCH and EGARCH (2,1) model was the best fit to our data. The estimated parameters of the model reveal that Australian share market has higher influence on
the Australian superannuation funds portfolio returns, followed by US share market
then Australian bond market. The US bond market, however, has a negative
coefficient that could serve as a diversification asset within the superannuation funds
portfolio. The findings also reveal that there is persistence of volatility and
asymmetric effect that could imply potential spillovers from other markets that was
absorbed by the Australian superannuation funds.

There is a need for more sophisticated models to explain the data, in which this could
open the opportunities for further research into this field. Future studies could include
using Fourier series and power spectrum to provide more insights by transforming the
dataset into frequencies to produce richer information to explain certain recurring
events. Other areas could include leading and lagging of the portfolio in response to
the volatility to identify whether investors are anticipating for the fluctuations of the
volatility by adjusting their portfolio.

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