Idiosyncratic volatility and momentum: the performance of Australian equity pension funds

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Abstract

We investigate the importance of idiosyncratic volatility for pricing of equity funds by using a comprehensive dataset of Australian retail equity pension funds from January 1995 to December 2008. We find strong evidence to support that idiosyncratic volatility is a significant pricing factor for returns of the equity funds implying that investors should consider idiosyncratic volatility when evaluating the performance of funds,. We also find strong evidence to support that idiosyncratic volatility is strongly associated with momentum effect of Australian equity pension funds as equity pension funds with high idiosyncratic volatilities exhibit a high momentum effect.

JEL Classification: G12

Key words: Asset pricing anomalies, risk factors, idiosyncratic volatility, momentum, equity fund performance, size, value and growth, Australian superannuation funds, pension funds

INTRODUCTION

The asset pricing role of idiosyncratic volatility is gaining increasing attention amongst academics researchers. Many studies have shown that idiosyncratic volatility is important in the pricing of stock returns (e.g., Goyal and Santa-Clara, 2003; Ang et al., 2009; Fu, 2009; Angelidis, 2010). Although the importance of idiosyncratic volatility in the pricing of stock returns is becoming more widely accepted, there are only a few studies that investigate the relationship between idiosyncratic volatility and returns of managed funds.

Managed funds have gained popularity over the past two decades. One major explanation for this increased popularity is that these funds offer diversification at lower costs due to higher economies of scale. Hence, managed funds are often anticipated as a well-diversified implying that idiosyncratic volatility is diversified away in and therefore should play no role in the pricing of fund returns. However, Campbell et al. (2001) find that idiosyncratic volatility increases over time and while the correlation between individual stock returns declines, thus suggesting a larger number of stocks is needed in a portfolio in order to maintain a given level of diversification over time. In relation to diversification of managed funds, the implication of Campbell et al. (2001) is that idiosyncratic volatility has become more difficult to diversify, and therefore fund managers will need to increase the number of securities in their portfolio(s) to achieve a given level of diversification. Ignoring the effect of increasing idiosyncratic volatility when forming portfolios will lead to the under diversification of funds. Therefore, idiosyncratic volatility should play a significant role in pricing of managed funds, especially for the funds with heavy investments in equities. A few studies have investigated this issue and report results that support this hypothesis. For example, Angelidis and Tessaromatis (2010) find Greek public pension funds are under-diversified due to the fact that equity funds tend to concentrate investment in a small number of domestic stocks; Wagner and Winter (2013) find strong evidence to support that idiosyncratic volatility is a pricing factor for the returns of managed funds which invest in the European stock market; and Vidal-Garcia and Vidal (2014) find strong evidence to support that idiosyncratic volatility cannot be fully diversified in UK mutual funds.

One of the first investigations in this area was undertaken by Jegadeesh and Titman (1993), who find that a zero investment trading strategy by long stocks with recent high returns and short stocks with recent low return will yield statistically significant profits. This market anomaly still exists and has been reported in more recent empirical studies. For example, Arena, Haggard and Yan (2008) investigate whether the momentum effect is associated with idiosyncratic volatility in the US stock market. They find that the stocks that exhibit a greater momentum effect are those stocks with high idiosyncratic volatilities and therefore suggest the momentum anomaly can be explained by idiosyncratic volatility. They also find the momentum effect is well pronounced in managed funds. Subsequently, we are motivated to examine the effect of idiosyncratic volatility in the pricing of fund returns and the association between the momentum effect and idiosyncratic volatility in managed funds.

In this paper, we investigate the asset pricing role of idiosyncratic volatility in pricing of Australian retail equity pension funds. Australian pension funds are also known as Australian superannuation funds (we use equity funds and superannuation funds interchangeably in this paper). The industry has shown strong growth after the introduction of the Superannuation Guarantee[1] in 1992, and it has become the fourth largest[2] private pension fund market in the world. Although several previous studies have studied various aspects of Australian pension funds, no study[3] to date has addressed the issue of idiosyncratic volatility with regard to the pricing of Australian equity pension fund returns. An investigation of these

[1] Under Superannuation Guarantee law, the employer must contribute a minimum 9% of an employee's earnings to a superannuation fund on the employee's behalf.
[2] According to the IBIS World Industry Report K7412.
[3] According to Authors' knowledge.

funds is also supported by the following: (1) according to the asset allocation default strategy statistics published by APRA, 26% of the total assets of Australian superannuation funds has been allocated to Australian stocks[4] indicating the possibility that some equity funds are not well diversified since they invest heavily in domestic stocks; and (2) the largest 20 stocks by market capitalization weight contribute approximately 46% of the whole Australian stock market[5] implying that investments by equity superannuation funds tend to be concentrated in a small number of domestic stocks. Therefore, idiosyncratic risk may play a role in the pricing of managed funds, especially for funds that invest heavily in equities. Using a comprehensive dataset of Australian retail equity pension funds from January 1995 to December 2008, we find strong evidence to support that idiosyncratic volatility is important in the pricing of the pension fund returns.

We follow risk the mimicking portfolio approach of Fama and French (1993) to sort the pension funds into six portfolios according to their size and idiosyncratic volatility. Then, we construct a pension fund idiosyncratic volatility mimicking factor (hereafter the idiosyncratic volatility factor) and fund size factor. These two factors contain pension fund specific information in relation to idiosyncratic volatility of the funds and size of the funds. The explanatory power of both factors are subsequently examined by using ten pension fund portfolios[6] sorted on past year returns.

Our results reveal several interesting findings. We find the idiosyncratic volatility factor is priced in the returns of ten fund portfolios sorted on past year returns indicating the possibility that some equity pension funds are not fully diversified. Under diversification of the pension funds can be due to two possible reasons: (1) the Australian stock market is dominated by large cap stocks especially the blue chip stocks, and some pension funds may

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[4] APRA Annual Statistics, June 2013.

[5] Source: www.spindices.com/indices/equity/sp-asx-20

[6] We follow Carhart (1997) to sort the pension funds into ten portfolios according to their past year returns.

invest heavily in these large stocks resulting in under diversification of their portfolios; or (2) the pension funds are not diversified due to the fund manager's investment style. For example, some pension funds only focus on one particular sector in the stock market by investing a large proportion of their capital in one sector or some fund managers may speculate on hot market sectors based on their expectations.

We also find that there is an interesting U-shaped pattern of idiosyncratic volatility when moving across momentum portfolios suggesting that winner funds and loser funds exhibit higher idiosyncratic volatility. This finding is consistent with Arena, Haggard and Yan (2008) as they find that winner stocks and loser stocks are the stocks with high idiosyncratic volatility. They suggest that high idiosyncratic volatility stocks have greater information uncertainty, so investors tend to under react to the news which is related to the stocks with high idiosyncratic volatility. Consequently, an under reaction by investors results in persisting momentum effects over time. Our results also support the notion that fund managers may under react to news which is related to stocks with high idiosyncratic volatilities, so that the evidence further confirms that the momentum effect of the funds is related to idiosyncratic volatility.

Our results further indicate that idiosyncratic volatility is a proxy for information uncertainty in the context of Zhang (2006). Zhang (2006) finds greater information uncertainty leads to higher returns following good new and lower returns following bad news because investors are more likely to have a delayed reaction to the news in the case when there is higher level of information uncertainty for the stocks. He also suggests that information uncertainty reduces the efficiency of the market. In other words, stocks with higher information uncertainty will have a slower reaction to the news, so stock price drift is observed. Our results support that high idiosyncratic volatility funds tend to have a slow reaction to news. Specifically, we find funds with high idiosyncratic volatility exhibit greater momentum effect.

Our initial sample period did not cover the US subprime mortgage crisis and the following Global Financial Crisis (hereafter GFC) in 2007-2008. During this period, stock returns became highly volatile and the level of information uncertainty increased. Therefore, as a robustness check, we extend our sample period until December 2008. Interestingly, we obtain similar results over the extended sample period, and we can therefore conclude the explanatory power of the idiosyncratic volatility mimicking factor in relation to the returns of Australian pension funds is robust. Moreover, our four-factor model captures greater variations in the returns of the funds which exhibit a high of momentum effect and high idiosyncratic volatilities than the Carhart four-factor model during both the initial sample period and the extended sample periods. This result supports the notion that our four-factor model provides a more accurate performance measurement for Australian equity pension funds by allowing investors to adjust idiosyncratic risk.

This study contributes to the academic literature in several ways. First, this paper finds strong evidence to support that idiosyncratic volatility is a pricing factor for the returns of Australian equity pension funds. Second, we redefine the meaning of idiosyncratic volatility. From a rational asset pricing perspective, idiosyncratic volatility represents the level of firm specific risk. In this paper, we redefine it from a behavioural finance perspective. Since investors tend to have delayed reactions to the news related to the pension funds with high idiosyncratic volatility, hence idiosyncratic volatility also measures the level of information uncertainty in the context of Zhang (2006) and Arena, Haggard and Yan (2008). The results indicate that pension funds with high idiosyncratic volatility and high information uncertainty are the funds exhibiting high momentum effect (both winners and losers).

Our empirical findings have two practical implications for investors and fund managers. First, idiosyncratic volatility cannot be ignored when forming the portfolios because ignoring idiosyncratic volatility may lead to under diversification of the portfolios. Moreover, fund managers should be cautious when evaluating the performance of their portfolios against the benchmark portfolios and should adjust their expected returns for idiosyncratic risk. Further, the fund size factor should be included in the model when evaluating performance of the funds because we also find that the fund size factor capture additional variations in returns of the pension funds.

The remainder of this paper is organised as follows. The next section reviews the previous literature. Section 3 outlines the methodology in this study. Section 4 describes the data. The empirical results are presented and discussed in Section 5. Section 6 provides the conclusion.

Literature Review

The Capital Asset Pricing Model (hereafter CAPM) is the most well-known asset pricing model. In general, it has been applied to estimate returns of stocks and measure performance of fund and it assumes that every investors hold a proportion of the well diversified market portfolio so that idiosyncratic volatility should be ignored.

Many researchers suggest that CAPM is simple, general and fails in its practical application due to its over-simplified assumptions. For example, Merton (1987) suggests that idiosyncratic volatility should be priced for stock returns. He argues that investors may not have complete information for every stock available in the market. Hence, these investors may hold underdiversified portfolios because they form portfolios from the known stocks which represent small subset of the total stocks available. Therefore, it is likely to be true that in the real world that not every investor holds fully diversified portfolios. This hypothesis attracted some interests from researchers, for example, Goetzmann and Kumar (2004) find that more than 25% of investors hold only one stock and less than 10% of the investors hold more than 10 stocks. Campbell et al. (2001) suggest that many investors in reality do not hold well diversified portfolios so idiosyncratic volatility should be priced in asset returns.

The association between idiosyncratic volatility and stock returns was identified during the1970's and the 1980's (see example, Friend, Westerfield and Granito, 1978; Levy, 1978; and Amihud and Mendelson, 1989). Idiosyncratic volatility has drawn additional attention since late 1990's. Malkiel and Xu (1997) for example find that idiosyncratic risk is priced for returns of U.S. stocks, but the market factor has little power in explaining the risk-return relationship. They suggest that portfolio managers are forced to buy/sell stocks when they are dropping in price. Hence, portfolio managers require extra returns for the idiosyncratic risk they've taken. Campbell et al. (2001) summarize the historical movements in market, industry and idiosyncratic firm level risk. They find that idiosyncratic firm level risk increased from 1962 to 1997 by using a disaggregated approach to study the risk of stocks at the market, industry and idiosyncratic firm level. They suggest that the number of stocks required to achieve a given level of diversification has increased since the correlation among individual stocks declined over the sample period. They also suggest that market level, industry and firm-level risk increases during economic downturns, especially firm-level risk. Goyal and Santa-Clara (2003) find that lagged equal-weighted average stock variance (largely idiosyncratic risk) is positively related to the value-weighted portfolio returns on the NYSE/AMEX/NASDAQ stocks. Bali, Cakici, Yan and Zhang (2005) replicated Goyal and Santa-Clara (2003) and suggest that the results of Goyal and Santa-Clara (2003) is driven by small stocks from NASDAQ and partly due to the liquidity premium. Ang et al. (2006) find a negative relationship between lagged idiosyncratic risk and the future average return of U.S. stocks. Ang et al. (2009) find the negative relationship between idiosyncratic volatility and stock return hold in 23 developed markets. Fu (2009) find a positive relationship between expected idiosyncratic volatility and US stock returns. Ooi, Wang and Webb (2009) examine the importance of idiosyncratic risk in the pricing of REIT stocks and find a significant positive relationship between expected idiosyncratic risk and the time-series returns.

Asset pricing models are not limited to price stock returns. They can also be applied to price returns of other classes of assets, such as managed funds. Based on the momentum effect reported in Jegadeesh and Titman (1993) and the methodology of Hendricks, Patel and Zeckhauser (1993), Carhart (1997) find that persisting performance of US equity funds can be explained by the momentum factor leading to the development of the Carhart four-factor model. Since then, the Carhart four-factor model has been widely applied to price returns of managed funds and evaluates performances of managed funds.

Jegadeesh and Titman (1993) find buying past winner stocks and selling past loser stocks give investors significant profit. However, to date, this market anomaly continues to exist. Conrad and Kual (1998) and Chordia and Shivakumar (2002) argue that momentum effect is related to the compensation to systematic risk, but other studies support behavioural explanation of the momentum effect (e.g., Hong, Lim and Stein, 2000; Jegadeesh and Titman, 2001).

Zhang (2006) investigates how information uncertainty contributes to persisting stock momentum. He argues that investors will underreact to the news in the case of high level of information uncertainty associated with the stocks, so that investors should have slow reactions to the news which are related to the stocks with higher level of information uncertainty implying that higher level of information uncertainty leads greater price drift.

More recently, Arena, Haggard and Yan (2008) find that higher momentum effects are associated with high idiosyncratic volatility stocks. They argue that momentum effect still exists until today after the publication of Jegadeesh and Titman (1993) because high idiosyncratic volatility stocks contain high level of firm specific information, so that investors have delayed reactions to the news which are related to these stocks. Hence, momentum effect still exists and high idiosyncratic volatility exhibit higher momentum. They further argue that another explanation for the persisting momentum profits is that investors are reluctant to arbitrage high idiosyncratic volatility stocks, because arbitragers have limited diversification opportunity and they are very unlikely to trade high idiosyncratic volatility stocks as they do not want any excess idiosyncratic volatility. Therefore, lack of arbitrage on high idiosyncratic volatility stocks also result momentum effect to persists over time.

The importance of idiosyncratic volatility in relation to performance/pricing of managed funds has not been investigated thoroughly in the lieterature. There are only a few studies have investigate the issue. For example, Wagner and Winter (2013) states the literature in this area is scarce. They investigate the asset pricing role of idiosyncratic volatility by augmenting an idiosyncratic factor to the Fama and French three-factor model and the Carhart four-factor model and they find strong evidence to support that idiosyncratic volatility is a significant pricing factor for the equity funds investing in European stock market. Vidal-Garcia and Vidal (2014) find idiosyncratic volatility cannot be fully diversified in UK mutual funds.

Data

The data are obtained from several databases. The historical weekly return indices, monthly return indices and historical annual fund sizes of Australian retail equity pension funds are supplied by Morningstar. The historical 90-day Bank Acceptable Bill rate is obtained from Reserve Bank of Australia to represent the risk free rate in Australia.

The stock market data, including monthly Australian stock return indices, monthly market capitalization of the stocks, monthly book-to-market equity ratio (hereafter BE/ME) of the stocks, S&P/ASX 200 index, are downloaded from DataStream. The stock momentum factor is obtained from Fama and French data websit[7] to proxy the momentum effect of Australian stocks.

In order to test the stability of the models, we choose January 1995 to December 2006 as our initial sample period. Then, we extend the sample period to December 2008 to cover a very volatile period of the US subprime mortgage crisis and the GFC. In order to avoid survivor bias, both dead and live pension funds and stocks are included our final sample. Pension funds and stocks disappeared during our sample period were included in the sample until they disappear. In our final sample, there are 122 funds in January 1995 and 1919 funds in December 2008.

Methodology

Construction of ten momentum portfolio

Following Hendricks, Patel and Zechhauser (1993) and Carhart (1997), we construct ten momentum portfolios based on average returns of the pension fund in the past year. Every January, pension funds are sorted into ten momentum portfolios. We hold the portfolios for one year, so that the ten momentum portfolios are rebalanced on annual basis. Portfolio 1 consists of the funds with highest past year returns, and portfolio 10 consists of the fund with lowest past year returns. Funds disappeared during the sample period are included in the sample until they disappear, so there is not a concern about survivor bias.

Idiosyncratic volatility estimation

[7] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#International

Following Angelidis (2010), idiosyncratic volatility is defined as the standard deviation of the regression residual ε_t from a single factor model[8]. The single factor model equation is the following:

$$R_{it} - r_{ft} = \alpha_i + \beta_i (R_{mt} - r_{ft}) + \varepsilon_{it} \tag{1}$$

Where R_{it} is the weekly return of a pension fund, R_{mt} is the weekly return of the market portfolio proxy, r_{ft} is the effective weekly risk-free rate and ε_{it} is the residual.

Then, the weekly excess returns of individual pension funds are regressed on the market premium $R_{mt} - r_{ft}$. Subsequently the regression residuals ε_t is extracted and the standard deviation of the regression residuals are calculated for every individual pension fund. Finally, weekly idiosyncratic volatility is transformed into monthly idiosyncratic volatility by multiplying the weekly idiosyncratic volatility by the square root of the number of weeks in that month.

Fund idiosyncratic volatility mimicking factor and fund size factor construction

Following portfolio risk mimicking approach of Fama and French (1993), pension funds are sorted into two portfolios (big and small), in January of each year based on their sizes in December of previous year. The pension funds are then sorted into three idiosyncratic volatility portfolios (Low, Medium, High). Low idiosyncratic volatility portfolio contains 1/3 low idiosyncratic volatility pension funds, high idiosyncratic volatility portfolio contains 1/3 high idiosyncratic volatility pension funds, and the rest of 1/3 pension funds are medium idiosyncratic volatility pension funds.

[8] Guo and Savickas (2008) and Bali, Cakici, Yan and Zhang (2005) suggest that CAPM based idiosyncratic volatility is very similar to Fama and French three-factor model based idiosyncratic volatility.

Six pension fund portfolios (H/B, H/S, M/B, M/S, L/B and L/S) are formed from the intersections of two size and three idiosyncratic volatility portfolios. For example, H/B portfolio contains high idiosyncratic volatility and big size pension funds. Monthly equally weighted returns of the six portfolios are calculated from January of year t to January of year t+1, and portfolios are reformed each year in January according to the size and idiosyncratic risk of the pension funds in the previous December.

The pension fund size factor is constructed as the monthly return of small pension fund portfolio minus the monthly return of big pension fund portfolio. This pension fund size factor mimics the risk factor in returns associated with fund size. The idiosyncratic volatility factor mimics the risk factor in returns associated with idiosyncratic volatility. It is constructed as the monthly return of high idiosyncratic risk pension funds minus the monthly return of low idiosyncratic risk pension funds.

Stock size factor and stock BE/ME factor construction

Carhart (1997) find strong evidence to support that a model consists of a market factor, a stock size factor, a stock BE/ME factor and a momentum factor captures great variations in the returns of equity funds. We choose the four-factor model as our base regression model.

We follow Fama and French (1993) to construct a size factor based on stock returns and a BE/ME factor based on stock returns. The method is summarized as the following: Stocks[9] are divided into two size portfolios and three BE/ME portfolios. The two size portfolios consist of (a) the top 50% of stocks (big) by market capitalisation; and (b) the bottom 50% stocks (small) by market capitalisation. The three BE/ME portfolios consist of (a) one-third high BE/ME stocks; (b) one-third medium BE/ME stocks; and (c) one-third low

[9] We include all the dead and live stocks in our initial sample in order to avoid survivor bias. In order to avoid thin trading effect for Australian stocks, following Guant (2004), stocks that had at least one trade in month were included in the final sample.

BE/ME stocks. Every January, the stocks are ranked and sorted into portfolios according to their size and BE/ME at December of previous year. The portfolios are rebalanced on an annual basis. The stock size factor is calculated as the monthly returns of the big size portfolio minus the monthly returns of the small size portfolio. The stock BE/ME factor is calculated as the monthly return of the high BE/ME portfolio minus the monthly returns of the low BE/ME portfolio.

Fund momentum factor construction

For robustness purpose, we also include a fund momentum factor in the regression model. This fund momentum factor is constructed as the average return of past winner fund portfolio minus the average return of past loser fund portfolio.

The regression models

In order to determine how much additional variations in the pension fund returns can be captured by the idiosyncratic volatility factor in the presence of the four factors, we choose the Carhart four-factor model as our base regression model. Then, we test whether the fund size factor and the idiosyncratic volatility factor can capture additional variations in the returns of the pension funds in the presence of the four factors. The regression equations are the followings:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + s_p SMB_t + h_p HML_t + w_p WML_t + \varepsilon_{pt} \quad (2)$$

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + s_{fp} FSMB_t + i_p HIMLI_t + w_p WML_t + \varepsilon_{pt} \quad (3)$$

t = 1,2…,T

Where r_{pt} is the monthly returns of a fund portfolio, r_{ft} is the monthly 90-day bank acceptable bill rate, r_{mt} is the monthly return of S&P/ASX 200 Index. SMB ,

HML , WML , $FSMB$, $HIMLI$, $FWML$ are risk mimicking factors for stock size, stock BE/ME, stock momentum, fund size and fund idiosyncratic volatility respectively.

Empirical Results

Descriptive statistics

Table 1 presents the descriptive statistics of the explanatory variables from the regression equations. All variables have positive mean returns except $HIMLI$ indicating high idiosyncratic volatility funds generated lower returns than low idiosyncratic volatility funds over the initial sample period. The negative sign of $HIMLI$ also indicates that investors are not compensated for taking higher level of idiosyncratic volatility because funds with high idiosyncratic volatility are expected to generated higher returns for compensation of the remaining idiosyncratic volatility remaining. The distributions of the explanatory variables are very close to normal distribution except WML.

Table 2 presents the correlations matrix for the explanatory variables. The significant correlation coefficients are between $\mathrm{r_{mt}} - \mathrm{r_{ft}}$ and FSMB (-0.58), SMB and HIMLI (0.22), HML and HIMLI (-0.15), WML and FSMB (0.16), FWML and WML (0.32). As values of the significant correlations coefficient are low, so there is not concern of multicollinarity for the regressions.

The descriptive statistics for the momentum returns, idiosyncratic volatility of the funds and size of the funds are presented in Table 3. In Table 3, the pension funds are equally sorted into ten portfolios based on their average returns in the past year. Portfolio 1 comprises the pension funds with highest returns in the previous year, and portfolio 10 comprises the pension funds with lowest returns in the previous year. Consistent with Carhart (1997), there is a monotonically decreasing trend in the monthly excess returns of the portfolio when moving from portfolio 1 to portfolio 10 indicating that there is strong momentum effect over the sample period.

A U-shaped pattern in idiosyncratic volatility column exists when moving across momentum portfolios. Figure 1 plots the idiosyncratic volatilities on the 10 momentum portfolios. We can see that the two extreme portfolios have highest idiosyncratic volatilities. Idiosyncratic volatility of Portfolio 1 (winners) is 0.027 per month, idiosyncratic volatility of Portfolio 10 (losers) is 0.0303 per month and portfolio 6 has lowest idiosyncratic volatility of 0.0209 per month. This result indicates that pension funds which exhibit high momentum effect have high idiosyncratic volatilities. This finding is consistent with Arena, Haggard and Yan (2008) as they find a similar U-shaped pattern in idiosyncratic volatilities of US stocks. They argue that because investors tend to under react to the news which are related to the stocks with high idiosyncratic volatilities, hence momentum effects are more pronounced by these stocks. By using Australian equity pension funds, we find strong evidence to support their argument. In Table 3, there are not clear patterns in size and standard deviation when moving across the momentum portfolios.

Regression results: January/1995-December/2006

The regression results from the Carhart four-factor model[10] are presented in Table 4. In the table, none of the intercepts are significant indicating that there are not any differences between realized returns and risk adjusted return for the equity pension funds. This finding is consistent with Bilson, Frino and Heaney (2004) as they only find weak evidence of superior performance in small Australia retail pension funds over the period of the 1991 to 2000. Wagner and Winter (2013) also find there are not superior performance for the equity mutual funds which invest in European stock market. Therefore, our results support that there is not

[10] See Equation (2).

superior performance in Australian retail equity pension funds over the period of January 1995 to December 2006.

In Table 4, all the coefficients of $r_{mt} - r_{ft}$ are significant, but there are not a trend when moving across momentum portfolios and the coefficients are generally between 0.6 and 0.7 suggesting that the market factor along does not explain the variations in the returns of the pension funds. Coefficients of SMB are significant in four out of ten cases and there are none significant coefficient for HML indicating that HML does explain any variations in the returns over the sample period. The finding is consistent with Bilson, Frino and Heaney (2004), as they find the explanatory power of the size factor is very limited to the returns of Australia superannuation funds and the BE/ME factor does not explain any significant variations in the returns of Australian superannuation funds.

There are six significant coefficients for the momentum factor WML in Table 4. There is a pattern in the coefficients of WML when moving across the momentum portfolios. The returns of the portfolios 1 and 2 are significantly and positively correlated with the stock market momentum factor WML and the returns of the portfolio 7 to 10 are significantly and negatively correlated with WML. The adjusted R-squared are between 49% and 90%. The adjusted R-squared indicates that the Carhart four-factor model explains less variations in the returns of winner and loser pension funds. The patterns in coefficients of WML and R-squared in Table 4 are consistent with Carhart (1997).

Table 5 presents the regression results based on another four-factor model [11] comprising a market factor $\mathrm{r_{mt}} - \mathrm{r_{ft}}$, a fund size factor $FSMB_t$, an idiosyncratic volatility factor $HIMLI_t$ and a momentum factor WML_t. The intercepts and the coefficients of $\mathrm{r_{mt}} - \mathrm{r_{ft}}$ are very similar to those of Table 4 as none of intercepts are significant and all of

[11] See Equation (3). In Equation (3), the stock size factor and stock BE/ME factor are replaced by a fund size factor and fund idiosyncratic volatility factor.

the coefficients of $r_{mt} - r_{ft}$ are significant, except the magnitude of the coefficients of $r_{mt} - r_{ft}$ is slightly larger than those if Table 4. Turning our attention to the coefficients of the fund size factor $FSMB_t$, all the coefficients are significant but there is not a pattern when moving across momentum portfolios. All the coefficients of $HIMLI_t$ are significant at 1% level and they also exhibit an U-shape pattern when moving across the portfolios. This finding is interesting because as portfolio 1, 2, 9 and 10 have the largest four coefficients, especially portfolio 1 and portfolio 10 have the two extreme coefficients, which indicate that (1) the funds exhibiting stronger momentum effect are more sensitive to idiosyncratic volatility, (2) these funds are possibly the less diversified equity pension funds compared the funds from other portfolios. This finding is consistent with the results reported in Table 3 as an U-shape pattern in idiosyncratic volatility is observed when moving cross fund portfolios in Table 3 and an U-shaped pattern in the coefficients of $HIMLI_t$ is also observed according to the regression analysis from Table 5.

The coefficients of WML are consistent with those of Table 4, as there is a decreasing pattern in the coefficients when moving from portfolio 1 to portfolio 10. The adjusted R-squared are larger compared to those in Table 4. The larger R-squared indicates than our four-factor model consisting of a market factor, a fund size factor, an idiosyncratic volatility factor and a momentum factor captures more variations in the returns of the Australian equity pensions funds than the Carhart four-factor model. If we look at the individual R-squared for each portfolio, it is obvious that this four-factor model captures more variations in the returns than the Carhart four-factor for the funds exhibiting stronger momentum effects (winners and losers). The improvement in the R-squared is possibly caused the association between idiosyncratic volatility and momentum because high momentum effect is associated with the funds with high idiosyncratic volatilities, so that the explanatory power of the regression model is improved by including an idiosyncratic volatility factor in the model.

In summary, the results from Table 5 provide strong evidence to support that the high momentum effect (both winners and losers) are associated with high idiosyncratic volatility for Australian equity pension funds. This finding is consistent with Arena, Haggard and Yan (2008) as they reports similar findings by using US stocks. We further confirm that momentum effect is associated with idiosyncratic volatility by using Australian equity pension funds. Arena, Haggard and Yan (2008) argues that investors tend to under react to the news which is related to stocks with high idiosyncratic volatility, our results support this argument in a way that fund managers also tend to under react to news which are related to the stocks with high idiosyncratic volatilities. Hence, momentum effect persists over time.

The results from Table 5 also support that idiosyncratic volatility is a proxy of information uncertainty. Zhang (2006) suggests persisting momentum effect in the US stock market is driven by the stocks with high information uncertainty because investors tend to have slower reactions to the news which are related to stocks with high information uncertainly. Arena, Haggard and Yan (2008) also suggest that high idiosyncratic volatility stocks have high level of information uncertainty in the US. Therefore, momentum effects persists over time because investors under react to the news which are related to the stocks with high idiosyncratic volatility. Our results are consistent with the findings of Zhang (2006) and Arena, Haggard and Yan (2008), and further support that idiosyncratic volatility is a proxy for information uncertainty.

Regression results: January/1995-December/2008

The initial sample period does not cover period of finical crisis, such as US subprime mortgage crisis and GFC. However, stock returns become highly volatile and idiosyncratic volatilities increase significantly during periods of bad market time[12], so we extend our initial sample to cover the periods of financial crisis in order to robust our results.

Table 6 presents the characteristics of the ten fund portfolios sorted one past year return including monthly excess returns, standard deviation of the returns, idiosyncratic volatilities of the funds and fund size. Compared to Table 3, monthly excess returns do not decrease monotonically when moving from portfolio 1 to portfolio 10, but the generally there is still a decreasing pattern when moving from portfolios 5 to 10. This pattern suggest that past losers continue to be losers in the following period, but past winners will not be winners in the following periods when the periods of crisis is included. The results suggest that momentum effect of Australian equity pension funds is more associated with the loser pension funds than the winner pension funds when periods of bad market time is included.

The regression results based on the Carhart four-factor model and our four-factor model for the extended sample period are presented in Table 7 and 8. In Table 7, the results are very similar to those of Table 4 in term of significance of the coefficients, magnitudes of the coefficients and patterns in the coefficients when moving across portfolios, except there are improvements in the adjusted R-squared for the funds exhibiting high level of momentum effects. Table 8 presents the regression results based on our factor-factor model for the extended sample period. There are not major differences between the results from Table 5 and Table 8 except there are improvements in the adjusted R-squared for the funds exhibiting higher level of momentum effects. Turning our attentions to the individual R-squared for each portfolio, it is obvious that our four-factor model captures more variations in the returns than the Carhart four-factor model for the funds exhibiting stronger momentum effects (winners and losers) for the extended sample period.

[12] See example, Campbell et al. (2001) and Ooi, Wang and Webb (2009).

The results of Table 8 are consistent with those of Table 5, the coefficients of HIMLI_t are significant at 1% level in Table 8 and an U-shape pattern is presented in these coefficients when moving across portfolios. The results in Table 8 provide further evidence to support the finding that the funds exhibiting stronger momentum effect are more sensitive to idiosyncratic volatility and indicate the funds exhibiting strongest momentum effect may be less diversified.

Conclusion

Using a comprehensive dataset of Australian retail equity pension funds from January 1995 to December 2008, we find strong evidence to support that idiosyncratic volatility cannot be ignored when measuring performance of Australian equity pension funds. Our results indicate that not all equity pension funds are well diversified, especially the funds exhibiting highest level of momentum effect tend to be the least diversified equity funds.

Another interesting finding is that there is an U-shaped pattern in idiosyncratic volatilities when moving across the momentum fund portfolios indicating that there is association between idiosyncratic volatility and momentum effect. In the context of Arena, Haggard and Yan (2008), this U-shaped pattern can be explained by behaviour of investors as investors tend to under react to news related to the stock with high idiosyncratic volatilities so that momentum effect persist over time. By using Australian equity pension funds, we find strong evidence to support their argument.

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Table 1 **Descriptive Statistics of the Explanatory Variables**
$r_{mt} - r_{ft}$ is the market excess return, SMB is the risk mimicking factor for stock size, $FSMB$ is the risk mimicking factor for pension fund size, HML is the risk mimicking factor for BE/ME of the stocks, $HIMLI$ is the risk mimicking factor for idiosyncratic volatility of the funds, WML is the momentum factor based on stock returns, $FWML$ is the momentum factor based on fund returns. The sample period is from January 1995 to December 2006.

	$r_{mt} - r_{ft}$	SMB	$FSMB$	HML	$HIMLI$	WML
Mean	0.62%	1.12%	0.07%	1.69%	-0.28%	0.94%
Median	0.93%	0.46%	0.04%	1.90%	-0.15%	1.37%
Maximum	7.17%	20.48%	2.62%	8.68%	3.91%	10.58%
Minimum	-11.27%	-15.89%	-1.96%	-7.05%	-4.00%	-37.42%
Std. Dev.	3.23%	4.31%	0.70%	2.69%	1.41%	5.33%
Skewness	-0.73	1.06	0.45	-0.16	-0.26	-3.33
Kurtosis	3.85	7.98	4.83	3.49	3.44	22.65
Jarque-Bera	17.10	175.55	25.03	2.09	2.84	2583.85
Observations	144	144	144	144	144	144

Table 2 **Correlation Matrix**
$r_{mt} - r_{ft}$ is the market excess return, SMB is the risk mimicking factor for stock size, $FSMB$ is the risk mimicking factor for pension fund size, HML is the risk mimicking factor for BE/ME of the stocks, $HIMLI$ is the risk mimicking factor for idiosyncratic volatility of the funds, WML is the momentum factor based on stock returns, $FWML$ is the momentum factor based on fund returns. The sample period is from January 1995 to December 2006.

	$r_{mt} - r_{ft}$	SMB	$FSMB$	HML	$HIMLI$
SMB	-0.01				
t-stat	-0.09				
$FSMB$	-0.58	0.09			
t-stat	-8.58	1.11			
HML	-0.07	-0.05	-0.01		
t-stat	-0.79	-0.62	-0.11		
$HIMLI$	-0.03	0.22	-0.06	-0.15	
t-stat	-0.33	2.68	-0.74	-1.78	
WML	-0.07	0.08	0.16	-0.03	-0.07
t-stat	-0.79	0.98	1.90	-0.31	-0.80

Table 3 **Characteristics of the Ten Portfolios Sorted on Past Returns**

Pension funds are sorted into to ten portfolios in January each year based on their average return in the previous year. The portfolio returns are equally weighted. Funds with the highest average past year returns comprise portfolio 1 and funds with the lowest average past year returns comprise portfolio 10. Monthly Excess Return is the monthly returns of the funds in excess of the risk free rate. Std Dev is the standard deviation of the portfolio over the sample periods. Idiovol is the equally weighted idiosyncratic volatilities of the individual pension funds in the portfolio. Size is the natural logarithm of average sizes of the pension funds. The sample period is from January 1995 to December 2006.

Portfolio	Monthly Excess Return	Std Dev	Idiovol	Size
1 (high)	0.58%	2.73%	0.0270	8.11
2	0.53%	2.49%	0.0249	8.15
3	0.47%	2.38%	0.0224	8.24
4	0.44%	2.49%	0.0222	8.06
5	0.42%	2.49%	0.0212	7.82
6	0.39%	2.48%	0.0209	8.14
7	0.27%	2.59%	0.0240	8.01
8	0.31%	2.73%	0.0273	7.99
9	0.20%	2.79%	0.0278	7.89
10 (low)	0.15%	3.10%	0.0303	7.91

Figure 1 **Plot of the average idiosyncratic volatilities of the ten momentum portfolios**

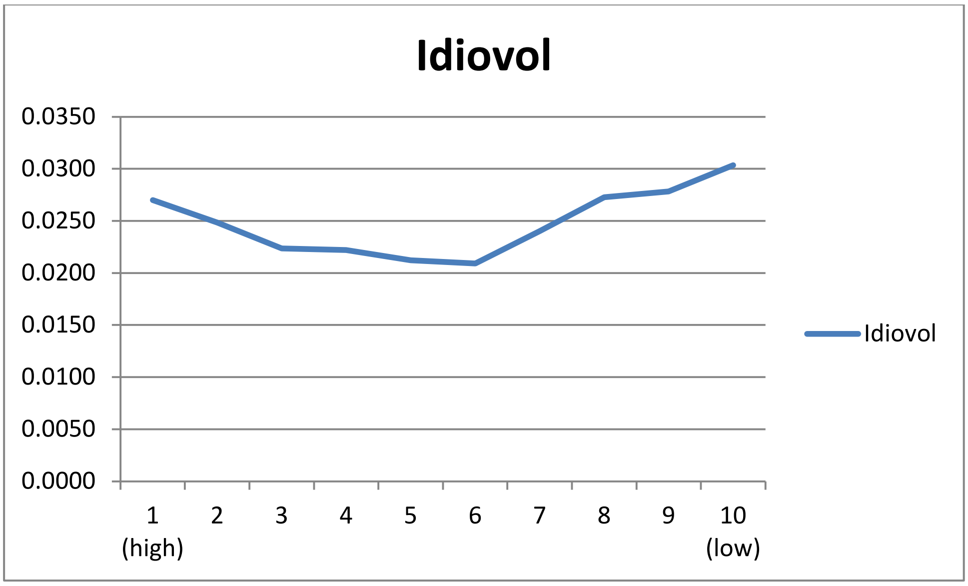

Table 4 **Regression results: the Carhart four-factor model**

Pension funds are sorted into to ten portfolios in January each year based on their average return in the previous year. The portfolio returns are equally weighted. Funds with the highest average past year returns comprise portfolio 1 and funds with the lowest average past year returns comprise portfolio 10. The sample period is from January 1995 to December 2006. The regression equation is the following:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + s_p SMB_t + h_p HML_t + w_p WML_t + \varepsilon_{pt}$$

Portfolio	α_p	$r_{mt} - r_{ft}$	SMB_t	HML_t	WML_t	Adj R-sq
1 (high)	0.0024	0.6075***	0.0447	-0.0809	0.0489*	57%
	1.33	13.49	1.32	-1.50	1.79	
2	0.0015	0.5713***	0.0547*	-0.0497	0.0525**	61%
	0.97	14.64	1.87	-1.06	2.21	
3	-0.0002	0.6779***	0.0501***	-0.0050	0.0178	85%
	-0.16	27.84	2.75	-0.17	1.20	
4	-0.0002	0.6968***	0.0380*	-0.0150	0.0161	82%
	-0.21	25.15	1.83	-0.45	0.96	
5	-0.0007	0.7262***	0.0291*	-0.0049	0.0050	90%
	-0.76	37.87	1.70	-0.18	0.36	
6	-0.0006	0.7101***	0.0053	0.0088	-0.0113	86%
	-0.63	29.10	0.29	0.30	-0.77	
7	-0.0008	0.7143***	-0.0022	-0.0264	-0.0421**	81%
	-0.68	24.50	-0.10	-0.75	-2.38	
8	0.0013	0.6537***	-0.0184	-0.0824*	-0.0611**	68%
	0.82	16.86	-0.63	-1.77	-2.60	
9	0.0004	0.5811***	0.0167	-0.0862	-0.0789***	54%
	0.21	12.49	0.48	-1.54	-2.79	
10 (low)	0.0000	0.5920***	0.0082	-0.0716	-0.1116***	49%
	-0.01	11.08	0.21	-1.11	-3.44	

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 5 **Regression results: a four-factor model**

Pension funds are sorted into to ten portfolios in January each year based on their average return in the previous year. The portfolio returns are equally weighted. Funds with the highest average past year returns comprise portfolio 1 and funds with the lowest average past year returns comprise portfolio 10. The sample period is from January 1995 to December 2006. The regression equation is the following:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + s_{fp}FSMB_t + i_pHIMLI_t + w_pWML_t + \varepsilon_{pt}$$

Portfolio	α_p	$r_{mt} - r_{ft}$	$FSMB_t$	$HIMLI_t$	WML_t	Adj R-sq
1 (high)	0.0019	0.7061***	0.6923***	0.5158***	0.0516**	65%
	1.35	14.11	2.97	5.51	2.07	
2	0.0017	0.6657***	0.6735***	0.5106***	0.0556***	70%
	1.43	15.92	3.47	6.53	2.67	
3	0.0006	0.7334***	0.4051***	0.3248***	0.0207	88%
	0.80	27.85	3.31	6.60	1.58	
4	-0.0007	0.8146***	0.9075***	0.2312***	0.0088	87%
	-0.84	28.15	6.74	4.27	0.61	
5	-0.0008	0.8047***	0.6679***	0.1783***	0.0093	89%
	-1.04	31.02	5.54	3.68	0.72	
6	-0.0006	0.7852***	0.5767***	0.2283***	-0.0161	89%
	-0.78	29.60	4.68	4.61	-1.22	
7	-0.0008	0.7614***	0.3223	0.3623***	-0.0403**	85%
	-0.87	24.03	2.19	6.12	-2.56	
8	-0.0004	0.7580***	0.7510	0.3799***	-0.0660***	73%
	-0.29	17.44	3.72	4.68	-3.05	
9	0.0000	0.6630***	0.5416	0.6447***	-0.0732***	66%
	0.01	13.43	2.36	6.99	-2.98	
10 (low)	-0.0005	0.7002***	0.7578	0.6398***	-0.1102***	60%
	-0.32	12.01	2.80	5.87	-3.80	

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 6 **Characteristics of the Ten Portfolios Sorted on Past Returns**

Pension funds are sorted into to ten portfolios in January each year based on their average return in the previous year. The portfolio returns are equally weighted. Funds with the highest average past year returns comprise portfolio 1 and funds with the lowest average past year returns comprise portfolio 10. Monthly Excess Return is the monthly returns of the funds in excess of the risk free rate. Std Dev is the standard deviation of the portfolio over the sample periods. Idiovol is the equally weighted idiosyncratic volatilities of the individual pension funds in the portfolio. Size is the natural logarithm of average sizes of the pension funds. The sample period is from January 1995 to December 2008.

Portfolio	Monthly Excess Return	Std Dev	Idiovol	Size
1 (high)	0.120%	3.35%	2.89%	8.10
2	0.122%	2.96%	2.61%	8.13
3	0.125%	2.90%	2.31%	8.22
4	0.130%	2.91%	2.28%	8.09
5	0.138%	2.83%	2.21%	7.90
6	0.125%	2.74%	2.22%	8.14
7	0.006%	2.77%	2.49%	8.00
8	-0.009%	2.92%	2.89%	7.97
9	-0.225%	3.17%	3.00%	7.87
10 (low)	-0.279%	3.44%	3.25%	7.92

Table 7 **Regression results: the Carhart four-factor model**

Pension funds are sorted into to ten portfolios in January each year based on their average return in the previous year. The portfolio returns are equally weighted. Funds with the highest average past year returns comprise portfolio 1 and funds with the lowest average past year returns comprise portfolio 10. The sample period is from January 1995 to December 2008. The regression equation is the following:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + s_p SMB_t + h_p HML_t + w_p WML_t + \varepsilon_{pt}$$

Portfolio	α_p	$r_{mt} - r_{ft}$	SMB_t	HML_t	WML_t	Adj R-sq
1 (high)	-0.0001	0.7532***	0.0472	-0.0854	0.0539*	70%
	-0.08	19.56	1.38	-1.58	1.97	
2	-0.0003	0.6685***	0.0525*	-0.0649	0.0474**	71%
	-0.18	19.88	1.75	-1.37	1.98	
3	-0.0011	0.7406***	0.0485***	-0.0081	0.0182	89%
	-1.19	36.61	2.69	-0.29	1.26	
4	-0.0003	0.7325***	0.0294	-0.0322	0.0063	86%
	-0.29	32.45	1.46	-1.01	0.39	
5	-0.0007	0.7262***	0.0291*	-0.0049	0.0050	90%
	-0.76	37.87	1.70	-0.18	0.36	
6	-0.0001	0.6976***	-0.0029	-0.0064	-0.0209	89%
	-0.14	35.79	-0.17	-0.23	-1.51	
7	-0.0006	0.6761***	-0.0081	-0.0289	-0.0490***	82%
	-0.49	27.17	-0.36	-0.83	-2.77	
8	0.0006	0.6558***	-0.0186	-0.0859*	-0.0690***	71%
	0.43	20.00	-0.64	-1.86	-2.96	
9	-0.0016	0.6519***	0.0214	-0.0948	-0.0856***	60%
	-0.84	15.52	0.57	-1.60	-2.86	
10 (high)	-0.0021	0.6889***	0.0160	-0.0810	-0.1228***	58%
	-0.98	14.76	0.38	-1.23	-3.70	

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 8 **Regression results: a four-factor model**

Pension funds are sorted into to ten portfolios in January each year based on their average return in the previous year. The portfolio returns are equally weighted. Funds with the highest average past year returns comprise portfolio 1 and funds with the lowest average past year returns comprise portfolio 10. The sample period is from January 1995 to December 2008. The regression equation is the following:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p(r_{mt} - r_{ft}) + s_{fp}FSMB_t + i_pHIMLI_t + w_pWML_t + \varepsilon_{pt}$$

Portfolio	α_p	$r_{mt} - r_{ft}$	$FSMB_t$	$HIMLI_t$	WML_t	Adj R-sq
1 (high)	0.0001	0.8199***	0.9761***	0.5058***	0.0539**	78%
	0.12	21.79	4.74	6.37	2.28	
2	0.0005	0.7239***	0.8575***	0.5057***	0.0496**	80%
	0.47	22.95	4.97	7.60	2.50	
3	0.0000	0.7741***	0.5208***	0.2746***	0.0201	92%
	-0.06	39.14	4.81	6.58	1.62	
4	-0.0006	0.8046***	0.8926***	0.1572***	-0.0013	90%
	-0.75	36.96	7.49	3.42	-0.09	
5	-0.0004	0.7724***	0.5850***	0.1081**	0.0009	91%
	-0.63	38.64	5.35	2.56	0.07	
6	0.0000	0.7274***	0.4130***	0.1443***	-0.0238**	90%
	0.03	35.09	3.64	3.30	-1.83	
7	-0.0002	0.6743***	0.0883	0.2493***	-0.0454***	84%
	-0.26	25.05	0.60	4.39	-2.69	
8	0.0000	0.6947***	0.5858***	0.3695***	-0.0709***	76%
	0.00	20.34	3.13	5.13	-3.31	
9	-0.0005	0.6756***	0.6006***	0.7563***	-0.0763***	75%
	-0.41	17.69	2.87	9.39	-3.19	
10 (low)	-0.0010	0.7404***	0.9309***	0.7595***	-0.1184***	73%
	-0.70	17.16	3.94	8.34	-4.38	

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.