Idiosyncratic Volatility, Stock Returns and Economy Conditions: The Role of Idiosyncratic Volatility in the Australian Stock Market

Bin Liu
Amalia Di Iorio

RMIT University
Melbourne Australia

Abstract

This study examines the importance of idiosyncratic volatility in asset pricing for Australian stock returns from 1993 to 2010. We form an idiosyncratic volatility mimicking factor. In the presence of the Fama-French three-factor we find that the idiosyncratic volatility mimicking factor is priced in Australian stock returns over the sample period, implying that this type of volatility is significant in the pricing of Australian stocks. Further, we find that idiosyncratic volatility is priced during both economy expansions and contractions and our model captures greater variations in Australian stock returns during expansions than contractions.

JEL Classification: G12

Key words: idiosyncratic volatility; asset pricing; stock returns; business cycles

Contact Authors:
Bin Liu, School of Economics, Finance and Marketing, RMIT University, phone: 9925 5858, fax: 9925 5986, bin.liu@rmit.edu.au
Amalia Di Iorio, Graduate School of Business and Law, RMIT University, phone: 9925 5900, fax: 9925 5986, amalia.diiorio@rmit.edu.au.
.

1. Introduction

The Capital Asset Pricing Model (hereafter CAPM) of Sharpe (1964) and Lintner (1965) suggests that only systematic risk is priced. This implies that idiosyncratic risk/volatility has no role in explaining asset returns. Specifically, given the assumptions of CAPM, idiosyncratic volatility is diversified away since investors hold a proportion of the well-diversified market portfolio. In reality, however, this is not always the case. Several studies have identified that for various reasons investors do not always hold well-diversified portfolios (see example Malkiel and Xu, 2002; Goetzmann and Kumar, 2004), and therefore systematic risk is not necessarily the only risk factor to be priced. In some cases idiosyncratic volatility has also been found to be priced.

Until recently, the role of idiosyncratic volatility in asset pricing has been ignored in the literature. Idiosyncratic volatility should play no role in asset pricing because under assumptions of CAPM idiosyncratic volatility is perfectly diversified away However, investors do not always hold well diversified portfolios and Merton (1987) suggests that investors are compensated for the holdings of underdiversified portfolios. Therefore, idiosyncratic volatility has attracted researcher's attentions. Indeed, several studies have found significant relationships between returns and idiosyncratic volatility that have created some interest, as well as some controversy. For example, Malkiel and Xu (1997, 2002), Goyal and Santa-Clara (2003) and Fu (2009) find idiosyncratic volatility is significantly and positively related to stock returns in the US. Conversely, Ang, Hoddrick, Xing and Zhang (2006) find a negative relationship between lagged idiosyncratic volatility and future average returns in the US. Further, Ang, Hoddrick, Xing and Zhang (2009) find that the negative relationship between lagged idiosyncratic volatility and future average returns is significant in the largest seven equity market. Interestingly, although the reported empirical results are mixed, most support that idiosyncratic volatility is an omitted pricing factor by CAPM.

In this paper, we examine the role of idiosyncratic volatility in pricing of Australian stocks. We follow Fama and French (1993) and Drew, Naughton and Veeraraghavan (2004) to construct an idiosyncratic volatility mimicking factor (hereafter idiosyncratic volatility factor). Our objective is to test whether this idiosyncratic volatility factor is priced in the presence of the Fama and French three-factor. Further, we examine the pricing ability of the idiosyncratic volatility factor in economy expansions and contractions. This is motivated by Campbell et al. (2001) and Ooi et al (2009) who suggest that the behaviour of idiosyncratic volatility is asymmetric during different market conditions.

This study contributes to the literature in several ways. First, we follow Drew, Naughton and Veeraraghavan (2004) by constructing an idiosyncratic volatility factor. However, unlike Drew et al (2004) who define the idiosyncratic volatility as the difference between total risk and the systematic risk of a stock, we define idiosyncratic volatility as the standard deviation of the regression residual of the Fama and French three-factor model. This definition has been implemented in several other studies, for example Ang, Hoddrick, Xing and Zhang (2009) and Fu (2009). In addition, we examine the pricing ability of the idiosyncratic volatility factor in presence of the Fama and French three-factor model. Second, we explore the stability of the idiosyncratic volatility factor enhanced model in different phases of business cycles. This is motivated by a number of studies in the asset pricing literature. For example, Campbell et al. (1997) report that idiosyncratic volatility increases during economic downturns, thus suggesting that the pricing ability of idiosyncratic volatility may not be stable. Lettau and Ludvigson (2001) find that stock returns vary in the different phases of business cycles and therefore argue that the pricing ability of idiosyncratic volatility factor may be affected. Ooi et al. (2009) also report that idiosyncratic volatility increases significantly during bad market cycles but decreases slightly during good market times. This evidence of the asymmetric behaviour of idiosyncratic volatility motivates us to explore the pricing ability of idiosyncratic volatility in different phases of the business cycle.

Our results reveal several interesting findings. First, the idiosyncratic volatility factor is priced for the returns of Australian stocks from 1993 to 2010. Second, the pricing ability of the idiosyncratic volatility remains strong even in the presence of the Fama and French three-factor. Third, we find that the Fama and French size factor is highly correlated with the idiosyncratic volatility factor. This may suggest that both factors capture similar information and therefore the idiosyncratic factor could replace the size factor in the three-factor model. This assertion is supported by the our three-factor model (the market risk factor, the book-to-market factor and the idiosyncratic volatility factor) as our three-factor model produces less mispricing than the Fama and French three-factor model over the sample period. Fourth, we find the idiosyncratic volatility factor is priced in both economy expansions and contractions, but our model captures greater variations of the stock returns during expansion than contractions.

Our empirical findings have several practical implications for the investor. First, idiosyncratic volatility should not be ignored when estimating the required rate of return and the cost of capital. Second, investors should match the idiosyncratic volatility of their portfolios with the benchmark portfolio when evaluating the performance of the portfolios. Third, due to the asymmetric nature of idiosyncratic volatility, investors should rebalance their portfolios according to different phases in the business cycle since changes in idiosyncratic volatility will affect the level of diversification of their portfolios.

The reminder of this paper is organized as follows. Section 2 outlines previous literature. The methods employed in this study are found in section 3. Section 4 describes the data. Section 5 presents the empirical test results. Finally, section 6 provides the conclusion.

2. Literature Review

According to the CAPM of Sharpe (1964) and Lintner (1965), only systematic risk is priced. Idiosyncratic risk is not priced because it is diversifiable. However, many researchers suggest that CAPM fails in its practical application, for example, Statmean (1980) finds that stocks with high book-to-market equity ratio generate higher average returns that CAPM fails to capture. Basu (1981) finds small stocks earn higher returns than estimated by CAPM, while Rosenberg, Reid and Lanstein (1985) find that the book-to-market equity ratio explains expected returns. Chan, Hamao and Lakonishok (1991) find that the book-to-market equity ratio also explains the average returns on Japanese stocks. These studies do not support CAPM empirically, and provide the impetus to investigate additional risk factors.

Fama and French (1992) report that size, and the book-to-market equity ratio are pricing factors for returns. This evidence suggests that these variables proxy different dimensions of stock risks and subsequently led to the development of the Fama and French (1993) three-factor model. Specifically, Fama and French (1993) find that risk mimicking factors for size and book-to-market equity ratio plus the market risk factor capture the variation in the stock returns, suggesting the risk mimicking factors of size and book-to-market equity ratio are firm-specific risks omitted by the market risk factor. Fama and French (1996, 1998) have confirmed and consolidated these findings.

The success of the Fama and French three-factor model indicates that unsystematic risk factors omitted by the CAPM could have significant explanatory power to the asset returns. Merton (1987) suggests that idiosyncratic risk should be priced if investors hold under-diversified portfolios. In reality, individual investors are not likely to hold well-diversified portfolios due to a number of reasons, for example, transaction costs, information costs and choice of investment style. Specifically, individual investors are reluctant to increase the level of diversification of their portfolios if they believe the transaction costs be greater than the benefits associated with further diversification. Moreover, information is costly, so it is impossible for individual investors and even institutional investors to collect and analyse all information about all securities in the market in a timely manner. Consequently, investors only have information for a subset of all securities and they subsequently construct portfolios heavily weighted in these securities. The outcome is that they therefore hold under-diversified portfolios. In some cases, investors are speculators who are willing to speculate on forthcoming information. These investors deliberately hold under-diversified portfolios as they expect high future returns to compensate the high idiosyncratic risk they assume. Finally, investment style may also lead to investors holding less than fully diversified portfolios. Campbell, Lettau, Malkiel and Xu (2001), for example, suggest that many individual investors hold a few stocks due to the restrictions of the corporate compensation plan. Goetzmann and Kumar (2004) report that more that 25% of investors hold only one stock and less than 10% of the investors hold more than 10 stocks, while Campbell, Lettau, Malkiel and Xu (2001) suggest that in order to achieve diversification investors must hold at least 50 randomly selected stocks in their portfolio. These studies support that notion that many investors do not hold well diversified portfolios and unsystematic risk is not fully diversified. Therefore, idiosyncratic risk should be priced.

The important role of idiosyncratic risk in asset pricing was first reported in the 1990's. Since then idiosyncratic volatility has drawn the attention of a number of researchers. For example, Malkiel and Xu (1997) find that idiosyncratic volatility is priced for U.S. stocks returns. They suggest that portfolio managers may be forced by the board of directors to buy or sell stocks when they dropping in price, so these portfolios managers require higher returns in order to compensate for the additional idiosyncratic risk they have assumed. Campbell et al. (2001) report that idiosyncratic volatility increased from 1962 to 1997. They suggest that the number of stocks to achieve given level of diversification has increased over the sample period. They also suggest that idiosyncratic volatility increases during economic downturns. The implication is that investors must increase the number of stocks they are holding in their portfolios in order to maintain the same level of diversification during economic contractions. Goyal and Santa-Clara (2003) find a positive relationship between idiosyncratic volatility and portfolio returns on the NYSE/AMEX/NASDAQ stocks. Bali, Cakici, Yan and Zhang (2005) replicated the study by Goyal and Santa-Clara (2003). They show that the positive relationship between idiosyncratic volatility and returns is driven by small stocks on the NASDAQ. The positive relationship does not hold for NYSE stocks. Fu (2005, 2009) report a positive relationship between expected idiosyncratic volatility and returns. However, contrary results are found by Ang et al. (2006, 2009). Their findings indicate that realized idiosyncratic volatility is negatively related to the stock returns in the U.S. and other developed countries. They suggest that there is an unidentified economic source which is driving the relationship between idiosyncratic volatility and return.

While a number of previous studies focus on the U.S. market, there are only a few research papers published that investigate the effect of idiosyncratic volatility on the pricing of Australian assets. Bollen, Skotnicki and Veeraraghavan (2009) follow the idiosyncratic volatility estimation method of Campbell et al. (1997) and find that idiosyncratic volatility is not priced in Australian stock market. Brockman et al. (2009) followed idiosyncratic volatility estimation method of Fu (2009), and examined idiosyncratic volatility in pricing of stocks in 44 countries including Australia. They report a significant positive relationship between expected idiosyncratic volatility and Australian stock returns.

We construct a 4-factor model by adding a risk mimicking factor for idiosyncratic volatility to the Fama and French (1993) 3-factor model. Our approach to construct the idiosyncratic volatility mimicking factor is similar to that implemented by Drew, Naughton and Veeraraghavan (2004), although we define idiosyncratic volatility differently. Following Xu and Malkiel (2003), Drew et al (2004) define idiosyncratic volatility as the difference between total risk and systematic risk. We, on the other hand, define idiosyncratic volatility as the standard deviation of the regression residual ε_t of the Fama and French (1993) three-factor model: $r_t - r_{ft} = \alpha_t + \beta_t (r_{mt} - r_{ft}) + s_t SMB_t + h_t HML_t + \varepsilon_t$, where $r_t - r_{ft}$ is the excess return of individual stocks, $r_{mt} - r_{ft}$ is the excess return of the market portfolio, SMB_t is the difference between returns of small stocks portfolio and large stocks portfolio, HML_t is the difference between returns of high book-to-market equity ratio stocks and low book-to-market equity ratio stocks. Our definition of idiosyncratic volatility is commonly used and widely accepted in many published research papers, for example Ang et al. (2006, 2009), Fu (2005, 2009) and Ooi et al. (2009). We construct a risk mimicking factor for idiosyncratic volatility. The idiosyncratic volatility mimicking factor $HIMLI_t$ is the difference in returns between high idiosyncratic volatility portfolio and low idiosyncratic volatility portfolio. This idiosyncratic volatility mimicking factor is tested in the asset pricing models.

This study is also motivated by empirical evidence that the HML_t factor of the Fama and French three factor model has weak explanatory power when implemented to test Australian stock returns. Previous studies suggest that the book to market equity ratio mimicking factor may not contribute as much as the size mimicking factor in explaining realized returns in Australia. For example, Gaunt (2004) reports 14 out of 25 significant HML_t factors and 21 out of 25 significant SMB_t factors. Faff (2004) supports these findings by reporting only 14 out of 24 significant cases of HML_t factors and 18 out of 24 significant SMB_t factors in his investigation of Australian industry portfolios. These studies suggest that for Australian stocks, the Fama and French three-factor model captures the variatons in the returns for Australian stocks, but the pricing ability of the Fama and French three-factor model is weaker for Australian stocks than U.S. stocks when compare these Australian empirical results to the results of Fama and French (1993, 1996). The weaker pricing ability of the Fama and French three-factor model for Australian stocks may be resulted by a missing pricing factor in the Fama and French three-factor model for Australian stocks. Hence, we are motivated to investigate whether or not the idiosyncratic volatility mimicking factor is a missing pricing factor in the Fama and French three-factor model for Australian stocks.

Moreover, we further investigate the stability of our idiosyncratic volatility mimicking factor in the pricing of stocks over business cycles during the sample period. Previous studies suggest that the behaviour of idiosyncratic volatility is asymmetric, for example Ooi et al. (2009) suggest that idiosyncratic volatility increases significantly during bad market times, but decreases slightly during good market times. Campbell et al. (2001) also suggest that idiosyncratic volatility is high during economy recessions. Due to the different behaviour of idiosyncratic volatility during different market times, the pricing ability of idiosyncratic volatility mimicking factor may be affected. Thus, we examine the pricing ability of the idiosyncratic volatility mimicking factor over the business cycles.

3. Method

3.1. Constructing Daily Fama and French Risk Mimicking Portfolios and Estimating Idiosyncratic Volatility

We follow Fama and French (1993) to construct daily SMB and HML portfolios. Companies are divided into two size portfolios and three book-to-market equity ratio portfolios. The two size portfolios consist of (i) the top 50% of companies (big) by market capitalization, and (ii) the bottom 50% companies (small) by market capitalization. The three book-to-market equity ratio portfolios consist of (i) 1/3 high book-to-market equity ratio companies, (ii) 1/3 medium book-to-market equity ratio companies, and (iii) 1/3 low book-to-market equity ratio companies. Every year t, the companies are ranked and sorted into portfolios according to their size and book-to-market equity ratio at December of year t-1. The daily SMB is calculated as the returns of the big size portfolio minus the returns of the small size portfolio. Daily HML is calculated as the returns of the high book-to-market equity ratio portfolio minus the returns of the low book-to-market equity ratio portfolio. The portfolios are rebalanced on an annual basis.

Then, following Ang et al (2009), we define idiosyncratic volatility as the standard deviation of regression residuals of the Fama and French (1993) three-factor model. Over the sample period, daily excess returns of stock i are regressed on the daily Fama and French (1993) three factors. The regression equation is the following:

$$r_t - r_{ft} = \alpha_t + \beta_t (r_{mt} - r_{ft}) + s_t SMB_t + h_t HML_t + \varepsilon_t \qquad (1)$$

Where r_t is the daily returns of stock i, r_{ft} is the daily 90-day bank acceptable bill rate, r_{mt} is the daily returns of S&P/ASX All Ordinary Index, SMB_t and HML_t are the daily returns of Fama and French (1993) risk factor mimicking portfolios for size and book-to-market ratio. Idiosyncratic volatility is estimated as the standard deviation of regression residual ε_t after regressing equation (1). Subsequently the standard deviation of daily regression residuals is transformed to a monthly value by multiplying the square root of the number of trading days in the month.

3.2. Constructing Monthly Risk Mimicking Portfolios for Size, Book-to-Market Equity Ratio and Idiosyncratic Volatility

We follow Fama and French (1993) to construct monthly SMB and HML. The monthly SMB is calculated as the returns of the big size portfolio minus the returns of the small size portfolio. The monthly HML is calculated as the returns of the high book-to-market equity ratio portfolio minus the returns of the low book-to-market equity ratio portfolio. The portfolios are rebalanced on an annual basis.

Then, following Drew, Naughton and Veeraraghavan (2006), we construct the risk mimicking portfolio HIMLI for idiosyncratic volatility. Three idiosyncratic volatility portfolios consist of 1/3 high idiosyncratic volatility companies, 1/3 medium idiosyncratic volatility companies and 1/3 low idiosyncratic volatility companies. Every year t, the companies are ranked and sorted into portfolios according to their idiosyncratic volatility at December of year t-1. Monthly HIMLI is calculated as the return of high idiosyncratic volatility portfolio minus return of low idiosyncratic volatility portfolio. As with the SMB and HML portfolios, the HIMLI portfolio is rebalanced on annual basis.

3.3. Idiosyncratic Volatility Enhanced Asset Pricing Models

The base model is idiosyncratic volatility enhanced two-factor model. The regression equation is the following:

$$r_t - r_{ft} = \alpha_t + \beta_t (r_{mt} - r_{ft}) + i_t HIMLI_t + \varepsilon_t \qquad (2)$$

The explanatory power of the risk mimicking portfolio for idiosyncratic volatility $HIMLI_t$ is tested in presence of size premia SMB_t or book to market equity premia HML and the market risk factor . The regression equations are the followings:

$$r_t - r_{ft} = \alpha_t + \beta_t (r_{mt} - r_{ft}) + s_t SMB_t + i_t HIMLI + \varepsilon_t \qquad (3)$$

$$r_t - r_{ft} = \alpha_t + \beta_t (r_{mt} - r_{ft}) + s_t HML_t + i_t HIMLI + \varepsilon_t \qquad (4)$$

The regression equation of an idiosyncratic volatility enhanced Fama and French three-factor model is the following:

$$r_t - r_{ft} = \alpha_t + \beta_t (r_{mt} - r_{ft}) + s_t SMB_t + h_t HML_t + i_t HIMLI + \varepsilon_t \qquad (5)$$

where r_t is the monthly returns of stock i, r_{ft} is the monthly 90-day bank acceptable bill rate, r_{mt} is the monthly return of S&P/ASX All Ordinary Index, SMB and HML are Fama and French risk factor mimicking portfolios for size and book-to-market ratio and $HIMLI_t$ is the monthly returns of risk mimicking portfolio for idiosyncratic volatility.

3.4. Idiosyncratic Volatility Enhanced Asset Pricing Model Over Business Cycles

Campbell et al. (2001) find that idiosyncratic volatility increases during economic downturns. In different states of business cycle, the idiosyncratic volatility enhanced models are:

$$r_t - r_{ft} = \alpha_t + \beta_t D_{\exp ansion}(r_{mt} - r_{ft}) + i_t D_{\exp ansion} HIMLI_t + \varepsilon_t \qquad (6)$$

$$r_t - r_{ft} = \alpha_t + \beta_t D_{contraction}(r_{mt} - r_{ft}) + i_t D_{contraction} HIMLI_t + \varepsilon_t \qquad (7)$$

where r_t is the monthly returns of stock i, r_{ft} is the monthly 90-day bank acceptable bill rate, r_{mt} is the monthly return of S&P/ASX All Ordinary Index, $HIMLI_t$ is a risk factor mimicking portfolios for idiosyncratic volatility. Alpha is the intercept of the regression model. $D_{\exp ansion}$ is a dummy variable which takes a value of unity in an expansionary phase of the business cycle [1] and a value of zero otherwise. $D_{contractio\,n}$ is a dummy variable which takes a value of unity in a contraction phase of the business cycle and a value of zero otherwise. Table 9 shows the phases of business cycles over the sample period.

[Insert Table 9 here]

3.5. Ten Equally Weighted Portfolios

At January of each year t, we construct ten portfolios of stocks based on idiosyncratic volatility at December of year t-1 with each portfolio comprising of an equal number of stocks. We hold the portfolios for one year, and rebalance them in January of year t+1. This provides a time series of monthly returns on each portfolio from 1993 to 2010.

[1] The business cycle classification is in accordance to the definitions provided by the Melbourne Institute of Applied Economics and Social Research on its website at http://melbourneinstitute.com/macro/reports/bcchronology.html

4. Data

Australian stock return data are obtained from Datastream for the period of January 1993 to December 2010. The 90-day Australian Bank Accepted Bill Rate is obtained from the website of the Reserve Bank of Australia to represent a proxy for the risk free rate in Australia. We use total return indices of the stocks to calculate the average returns of the stocks. We use ASX All Ordinaries Total Return Index to calculated average return of the market proxy. The total return index is the accumulation return index adjusted for dividends and other capital issues. Finally we use monthly market capitalization data to represent the size of stocks, and monthly market to book values to calculate the relevant book to market ratios.

The initial sample included active and dead companies listed on Australian Securities Exchange (hereafter ASX) during the sample period. In order to estimate monthly idiosyncratic volatility, daily return index for the stocks and the market proxy are obtained. Two filters were applied to obtain the final sample:

1. Following Guant (2004), only stocks that have at least one trade in a month were included to avoid any possible thin trading effects; and
2. Only stocks that had the following available data were included: daily and monthly total return index, monthly market capitalization and monthly market to book value.

Table 1 provides the number of stocks in the final sample and their equally-weighted average returns, equally-weighted average size, equally-weighted average book-to-market equity ratio and equally-weighted average idiosyncratic volatility during the sample period. Equally-weighted averages are used rather than value-weighed averages, since small stocks have high idiosyncratic volatilities (Bali, Cakici, Yan and Zhang (2005)), and therefore equally-weighted averages allow the idiosyncratic volatility effect of small stocks to be equally pronounced.. The smallest contribution of initial sample to the final sample is in 1993 (422 stocks), and the largest contribution is in 2008 (1773 stocks).

[Insert Table 1 here]

Table 2 presents the descriptive statistics of the relevant variables used in the regression equations. We observe that (i) the average market return is 0.95% per month from 1993 to 2010, and (ii) the monthly average excess return of the market proxy, average return of size mimicking portfolio, book-to-market equity ratio mimicking portfolio and idiosyncratic volatility mimicking portfolio are 0.49%, 1.24%, 1.88% and 1.61% respectively.

[Insert Table 2 here]

The monthly stock returns are ranked by idiosyncratic volatility in December and sorted into 10 idiosyncratic volatility ranked portfolios with an equal number of stocks in each portfolio. These portfolios are held for one year and rebalanced in the following year. Portfolio 1 comprises the stocks with highest idiosyncratic volatility and portfolio 10 comprises the stocks with lowest idiosyncratic volatility. Table 3 reports the summary statistics of 10 idiosyncratic volatility portfolios. Overall, it shows that monthly excess returns decrease monotonically when moving from high idiosyncratic volatility portfolio (portfolio 1) to low idiosyncratic volatility portfolio (portfolio 9). The standard deviation also decreases monotonically when moving from high idiosyncratic volatility portfolio (portfolio 1) to low idiosyncratic volatility portfolio (portfolio 9). Moreover, the average size is noted to increase when moving from the high idiosyncratic volatility portfolio (portfolio 1) to the low idiosyncratic volatility portfolio (portfolio 9). This finding is consistent with that reported by Bali, Cakici, Yan and Zhang (2005) who suggest that small companies have high idiosyncratic volatility. There is no such pattern in the BE/ME variable when moving from the high idiosyncratic volatility portfolio to the low idiosyncratic volatility portfolio.

[Insert Table 3 here]

Figure 1 shows the variation of the average idiosyncratic volatility over the sample period. We make several observations. First, the idiosyncratic volatility was high at the end of 1994. Following a 4 year downward drift, the volatility again reached a peak at the end of 1997. In 1997, Asian Financial Crisis caused a global stock market crash. This pattern was repeated two more times until the idiosyncratic volatility reached the highest peak in the end of 2008. This highest peak resulted by the Globe Financial Crisis which is the worst financial crisis since the Great Depression of 1930's

[Insert Figure 1 here]

Figure 2 shows the variation through time of the average idiosyncratic volatility and the market return over the sample period. In this case we note that the idiosyncratic volatility increases significantly when the market return drops but decreases slightly when the market return increases. This finding is consistent with Ooi, Wang and Webb (2009), who report that idiosyncratic volatility increases dramatically during bad market times and decreases marginally during good market times. From Figure 1 and 2, it is obvious that idiosyncratic volatility increased rapidly when there are sudden collapses in the stock market. The important implication of these results for an investment perspective is that the optimal level of portfolio diversification changes over different market conditions and investors must take this into consideration when rebalancing their portfolios.

[Insert Figure 2 here]

5. Empirical results

This section reports the results of the cross-sectional regression analysis. In section 5.1, we provide the results over the whole sample period. First, we report and analyse the results of a two-factor model: a market risk factor plus an idiosyncratic volatility mimicking factor. Second, we discuss two three-factor models: first model comprises a market risk factor, a size factor and an idiosyncratic volatility factor, second model comprises a market risk factor, a book-to-market factor and an idiosyncratic volatility factor. Third, we present the results of Fama and French three-factor model and a four-factor model. The results provide an insight into the pricing ability of the idiosyncratic volatility mimicking factor in Australia from 1993 to 2010. In section 5.22, we provide results of an analysis of the behaviour of idiosyncratic volatility during economy expansions and contractions.

5.1. Is Idiosyncratic Volatility Priced in Australian Stocks Returns?

Table 4 reports the results of a two-factor model. This two-factor model comprises a market risk factor and an idiosyncratic volatility factor. First, we observe that the intercepts are statistically significant in 3 out of 10 cases and all have positive signs. A significant intercept indicates that there is a pricing error caused by the asset pricing model. Therefore our findings indicate that the highest (Portfolio 1) and lowest idiosyncratic volatility portfolios (Portfolios 9 and 10) produce large positive abnormal returns. Second, all factor loadings of the market risk factor are statistically significant and positive as expected. The factor loadings do not, however, demonstrate a pattern when moving from high idiosyncratic volatility portfolios to low idiosyncratic volatility portfolios. Third, the coefficients of idiosyncratic volatility factor decrease monotonically when moving from the high idiosyncratic volatility portfolio to the low idiosyncratic volatility portfolio. This suggests that the higher the idiosyncratic volatility of the portfolio, the more sensitive the changes in return to changes in the idiosyncratic volatility factor. The returns of the idiosyncratic volatility portfolios are strongly and positively related to the idiosyncratic volatility factor except portfolio 10. This indicates that the idiosyncratic volatility factor captures variation in stock returns that is missed by the market risk factor and, therefore suggests that the market factor alone cannot explain the variation in the stock excess returns. The adjusted R-squared also exhibits a decreasing pattern from the high idiosyncratic volatility portfolio to the low idiosyncratic volatility portfolio. The adjusted R-squared is above 50% for all portfolios except portfolio 10. This indicates that the two factor model captures large proportions of variation in returns from portfolio 1 to 9, with the only exception being the lowest idiosyncratic volatility portfolio.

[Insert Table 4 here]

Table 5 and Table 6 show the results of two three-factor models. In table 5, the three-factor model comprises a market risk factor, a size factor (Fama and French SMB), and an idiosyncratic volatility factor. Table 5 shows the factor loading of this three-factor model and several important findings are observed. First, in 7 out of 10 cases, the intercepts are significant and 5 of these have negative signs. This indicates that high idiosyncratic volatility portfolios produce abnormal returns. Second, as expected, all factor loadings of the market risk factor are positive and significant and do not exhibit any pattern. The factor loadings of the market risk factor for portfolio 2 to 8 are very close to 1and portfolio 1 and 10 have smaller factor loadings than other portfolios. Third, the factor loadings of the size factor are positive and significant. There is a monotonically decreasing pattern in the factor loadings from portfolio 3 to portfolio 8 and portfolios 1 and 2 have bigger factor loadings than portfolio 10. This indicates that excess returns of the high idiosyncratic volatility portfolios are more sensitive to the changes in the size factor than low idiosyncratic volatility portfolios. Fourth, in 8 out of 10 cases, the idiosyncratic volatility factor has significant and positive factor loadings. A monotonically decreasing pattern in the factor loading is evident when moving from high idiosyncratic volatility portfolios to low idiosyncratic volatility portfolios, and the lowest idiosyncratic volatility portfolios have negative factor loadings. This indicates that the idiosyncratic volatility factor is priced in this three factor model and it captures the great variations in the excess returns of the idiosyncratic volatility portfolios. The adjusted R-squared shows a decreasing pattern again, but the values of adjusted R-squared of this three-factor model are greater than the adjusted R-squared values of the two-factor model. This indicates that there is an increase in the proportion of variation explained by the three-factor model.

[Insert Table 5 here]

Table 6 shows the factor loadings of a three-factor model that comprises a market risk factor, a book-to-market equity factor and an idiosyncratic volatility factor. First, surprisingly, the highest and lowest idiosyncratic volatility portfolios have significant positive intercepts which indicate abnormal returns are only available on two extreme cases. Second, as expected, the factor loadings of the market risk factor are significant and positive. There is no pattern when moving from the high idiosyncratic volatility portfolio to the low idiosyncratic volatility portfolio. Third, in 3 out of 10 cases, the book-to-market equity factor has a positive and significant factor loading. Fourth, again, the idiosyncratic volatility factor has a significant and positive factor loading except in the case of portfolio 10. There is a monotonically decreasing pattern in the factor loadings. The adjusted R-squared is above 50% except portfolio 10 which indicates that a large proportion of variation is explained by the model. The results from Table 5 and 6 suggest that the idiosyncratic volatility factor is priced in excess returns of Australian stocks.

[Insert Table 6 here]

Table 7 reports the results of the Fama and French three-factor model (Panel A) and a four-factor model (Panel B). The four-factor model comprises the well-documented Fama and French three factors and an additional idiosyncratic volatility factor. First, in panel A of table 7 we note that in 6 of 10 cases the intercept is significant and the highest and lowest idiosyncratic volatility portfolios (Portfolio 1 and Portfolio 10 respectively) have the largest positive abnormal returns. Portfolios 4 to 7 show negative abnormal returns. Second, the factor loadings of the market risk factor show consistency as they are significant, positive, and there is no pattern. In 8 out of 10 cases, the factor loadings of the market risk factor are close to 1, a finding that is consistent with many previous studies, including Gaunt (2004). Third, the size factor has significant and positive loadings, and we observe a monotonically decreasing pattern when moving from portfolio 1 to portfolio 10. This indicates that the size factor captures the variation in excess returns of the portfolios. Fourth, the explanatory power of HML is once again low. In 4 out of 10 cases, the factor loadings are significant with a negative factor loading for the high idiosyncratic volatility portfolio. The Adjusted R-squared values are high except for portfolio 10.

Consistent with the results of the Fama and French three-factor model, the four-factor model explains a greater proportion of the variation in the excess return of the portfolios. This is evidenced by high adjusted R-squared values. The intercepts, factor loadings of the market risk factor, size factor values and book-to-market equity factor values exhibit similar results as the Fama and French three-factor model. The interesting finding is that the idiosyncratic volatility factor is priced in this four-factor model and there is a monotonically decreasing pattern in the factor loadings when moving from highest idiosyncratic volatility portfolio (Portfolio 1) to the lowest idiosyncratic volatility portfolio (Portfolio 10). Both the loading of the size factor and the idiosyncratic volatility factor show monotonically decreasing patterns and these two factors capture most of variations of excess returns. The excess returns of high idiosyncratic volatility portfolios are positively related to the idiosyncratic volatility factor, while excess returns of the bottom two portfolios are negatively related to the idiosyncratic volatility factor.

Given these results, our findings suggest that idiosyncratic volatility was priced for Australian stock returns from 1993 to 2010. High (low) idiosyncratic volatility stocks are small (big) by size, have big (small) factor loadings on the size factor and idiosyncratic volatility factor. The book-to-market equity factor has weaker explanatory power than the size factor and the idiosyncratic volatility factor to the returns of Australian stocks.

[Insert Table 7 here]

5.2. A Three-Factor Model for Australian Stock Market

From Tables 4 to 7, which present the findings of our examination of explanatory power of idiosyncratic volatility in (i) the two-factor model (ii) the three-factor models and (iii) the four-factor model respectively, we find that the idiosyncratic volatility factor exhibits consistent explanatory power in relation to variation in the excess returns of the stocks. However, we note a stronger significant intercept when the size factor appears in the asset pricing model. This suggests that the size factor may cause a greater pricing error in the asset pricing model than does idiosyncratic volatility. For example there are 7 significant intercepts in Table 5 which reports the regression results of Equation 3 compared with 2 significant intercepts in Table 6 that presents the regression results of Equation 4.

Our analysis is based on portfolios, specifically size portfolios where the returns of small stocks minus the returns of big stock and idiosyncratic volatility as the returns of high idiosyncratic volatility stocks minus return of low idiosyncratic volatility stocks. However, Table 3 shows that high idiosyncratic volatility stocks are small stocks, so the idiosyncratic volatility factor may capture similar information as that captured by the size factor. Table 8 shows the correlation coefficients between the explanatory variables. The correlation between the size factor and the idiosyncratic volatility factor is significantly high at 67%. The high correlation between these two explanatory variables indicates a close but not exact relationship between them and may suggest that the t-statistics are unreliable. A simple solution to this multicollinearity problem is to omit one of two explanatory factors from the regression function.

Consequently, we compared the results of Fama and French three-factor model presented in table 7 and the regression results of the three-factor model reported in table 6. We find that both models capture a large proportion of variations in the excess returns of stock portfolios, but the three-factor model of Equation 4 is favourable over the Fama and French three-factor model due to the fact that there are fewer missing pricing for the three-factor model of Equation 4.

[Insert Table 8 here]

5.3. Is Idiosyncratic Volatility priced conditional on Business Cycles?

Previous studies have investigated the behaviour of idiosyncratic volatility in different market cycles. The empirical findings have been mixed. For example, Campbell et al. (2001) find that idiosyncratic volatility decreases during economy downturns, while Ooi et al (2009) report that idiosyncratic volatility increases dramatically during bad market times but decreases marginally during good market times. Notwithstanding these conflicting results, it is evident that differences in behaviour of idiosyncratic volatility during different business cycles may affect the pricing ability of the idiosyncratic volatility factor. Therefore, we extend our analysis in this paper to investigate the pricing ability of the idiosyncratic volatility factor during market expansions and contractions..

Our classification of Business Cycle phases in the Australian market is based on the definitions produced by the Melbourne Institute of Applied Economic and Social Research. Table 9 shows a summary of these phases over the sample period. There is a total of 144 months of expansion and 72 months of recession. We create an expansion dummy variable and a contraction dummy base on the information provided by Table 9 and we use a two-factor model to test the stability of the pricing ability of the idiosyncratic volatility factor. The two-factor model comprises a market risk factor and an idiosyncratic volatility factor. The two-factor model is selected among all the models used in this study because the market risk factor is the most stable pricing factor.

Table 10 reports the factor loadings for the two-factor model during expansions and contractions. During expansions, there is evidence of three mispricings by the two-factor model. The abnormal returns are positive and large abnormal returns were evident for the highest and lowest idiosyncratic volatility portfolios. There is no pattern in the factor loadings of the market risk factor and they are all significantly different from zero. In 9 out of 10 cases, the factor loadings of the idiosyncratic volatility factor are significant and positive, except the factor loading for portfolio 10. We observe a monotonically decreasing pattern in the factor loadings which suggests that the idiosyncratic volatility factor is priced and captures the variation in the excess returns of the portfolios during expansions. The adjusted R-squared values are lower than those presented in Table 4, but they are all above 30% except R-squared for portfolio 10 (what is the R squared here?) which suggests that the two-factor model captures the variations in the excess returns.

[Insert Table 10 here]

During contractions, there are 9 significant intercepts. Hence, the two-factor model exhibits greater mispricing during contractions than during expansions. All the factor loadings of the market risk factor are significant and positive. There is no pattern in the factor loadings of the market risk factor. The factor loadings of the idiosyncratic volatility factor show a monotonically decreasing pattern from portfolio 1 to portfolio 7. The adjusted R-squared values are much lower than those of the two-factor model during expansions. Based on the results provided in Table 10, we conclude that the idiosyncratic volatility factor is priced in both expansions and contractions, but there is more mispricing produced by the two-factor model during contractions.

6. Conclusion

Investors do not always hold well-diversified portfolios. This could be due to a number of reasons, including high transaction costs, and lack of information. Therefore, idiosyncratic risk is not fully diversified so investors should be compensated for the idiosyncratic risk. Hence, idiosyncratic volatility should be priced in the asset pricing models. This study examines the role of idiosyncratic volatility in the pricing of Australian stocks from 1993 to 2010. We find that the idiosyncratic volatility mimicking factor captures information omitted by the Fama and French three-factor model. Further, we show that the idiosyncratic volatility mimicking factor is priced in different business cycle phases.

Our main findings are summarized as follows. First, we show that the idiosyncratic volatility mimicking factor is priced for Australian stock returns from 1993 to 2010. There are patterns in the factor loadings of the idiosyncratic volatility mimicking factor when moving from high idiosyncratic volatility portfolios to low idiosyncratic portfolios which suggests that the idiosyncratic volatility mimicking factor captures variations in the return of the portfolios. The factor loadings of the market risk factor and the Fama and French size factor are positive, significant and consistent with previous findings in the literature. The pricing ability of the Fama and French book-to-market equity factor is weaker than other pricing factors in our asset pricing models. Second, we provide evidence to show that the idiosyncratic volatility mimicking factor is a stronger pricing factor than the Fama and French size factor for Australian stock returns due to the fact that our three-factor model comprising a market risk factor, a book-to-market equity factor and an idiosyncratic volatility factor that capture large proportion of variation in Australian stock returns and our three-factor model produces fewer mispricing than the Fama and French three-factor model over the same sample period. Third, we also show that the idiosyncratic volatility mimicking factor is priced during economy expansions and contractions. However, our two-factor model produces more mispricing during contractions than expansions. The main goal of this paper is to explore the pricing role of the idiosyncratic volatility, so further work is needed to explain the asymmetric behaviour of idiosyncratic volatility during good and bad economic cycles.

The findings of this study provide a number of important implications for investors. First, investors should consider the level of idiosyncratic volatility remaining in their portfolio if they are not well-diversified when estimating the required rate of return and/or evaluating the performance of these portfolios. Second, investors should rebalance their portfolios during different economic phases, specifically expansions and contractions. This is due to the asymmetric behaviour of the idiosyncratic volatility. Holding a constant number of stocks in different phases of business cycle may result in under-diversification of the portfolio as idiosyncratic volatility increases significantly during bad times.

References

Ang, A., R. J. Hodrick, et al. (2006). The cross section of volatility and expected returns. *The Journal of Finance*, 61(1): 259-299.

Ang, A., R. J. Hodrick, et al. (2009). High idiosyncratic volatility and low returns: International and further US evidence. *Journal of Financial Economics*, 91(1): 1-23.

Bali, T. G., N. Cakici, et al. (2005). Does idiosyncratic risk really matter? *The Journal of Finance,* 60(2): 905-929.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance*, 32(3): 663-682.

Bollena, B., A. Skotnickia, et al. (2009). Idiosyncratic volatility and security returns: Australian evidence. *Applied Financial Economics*, 19(19): 1573-1579.

Brockman, P., Schutte, M. G., & Yu, W (July 11, 2009). Is idiosyncratic risk priced? *The international evidence*. *Working paper.* SSRN: http://ssrn.com/abstract=1364530

Campbell, J. Y., M. Lettau, et al. (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *The Journal of Finance*, 56(1): 1-43.

Chan, L. K. C., Y. Hamao, et al. (1991). Fundamentals and stock returns in Japan. *Journal of finance*: 1739-1764.

Drew, M. E., T. Naughton, et al. (2004). Is idiosyncratic volatility priced? Evidence from the Shanghai Stock Exchange. *International Review of Financial Analysis,* 13(3): 349-366.

Faff, R. (2004). A simple test of the Fama and French model using daily data: Australian evidence. *Applied Financial Economics*, 14(2): 83-92.

Fama, E. F. and K. R. French (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2): 427-465.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, 33(1): 3-56.

Fama, E. F. and K. R. French (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance,* 51(1): 55-84.

Fama, E. F. and K. R. French (1998). Value versus growth: The international evidence. *The Journal of Finance,* 53(6): 1975-1999.

Fu, F. (2005). Idiosyncratic risk and the cross-section of expected stock returns, *Working paper,* University of Rochester.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics,* 91(1): 24-37.

Gaunt, C. (2004). Size and book to market effects and the Fama French three factor asset pricing model: evidence from the Australian stock market. Accounting & Finance, 44(1): 27-44.

Goetzmann, W. N. and A. Kumar (2004). Why do individual investors hold under-diversified portfolios. *Yale University and University of Notre Dame Working Paper*.

Goyal, A. and P. Santa-Clara (2003). Idiosyncratic risk matters! *Journal of finance, 58*: 975-1007.

Lettau, M. and S. Ludvigson (2001). Resurrecting the (C) CAPM: A cross-sectional test when risk premia are time-varying. *Journal of Political Economy, 109*: 1238-1287.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics, 43*: 13-37.

Malkiel, B. G. and Y. Xu. (2002). Idiosyncratic risk and security returns. *University of Texas at Dallas (November 2002).*

Malkiel, B. G. and Y. Xu (1997). Risk and return revisited. *The Journal of Portfolio Management*, 23(3): 9-14.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *Journal of Finance, 42*: 483-510.

Ooi, J. T. L., J. Wang, et al. (2009). Idiosyncratic risk and REIT returns. *The Journal of Real Estate Finance and Economics,* 38(4): 420-442.

Rosenberg, Barr, K. Reid and R. Lanstein, (1985). Persuasive evidence of market inefficiency. *Journal of Portfolio Management,* 11(3): 9-16.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3): 425-442.

Stattman, D. (1980). Book values and stock returns. *The Chicago MBA: a journal of selected papers,* 4: 25-45.

Xu, Y., & Malkiel, B. G. (2003). Investigating the behaviour of idiosyncratic volatility. *Journal of Business, 76*, 613-644.

Table 1: Yearly Summary Statistics

This table shows the average number of stocks, average monthly return, average size (in millions) of the companies, average monthly BE/ME, and average monthly idiosyncratic volatility over the sample period.

Summary Statistics

Year	Number of Stocks	Return	Size	BE/ME	Idiovol
1993	422	0.0628	474	0.8564	0.1620
1994	480	0.0152	524	0.6741	0.1540
1995	529	0.0261	490	0.7701	0.1463
1996	737	0.0351	415	0.7110	0.1606
1997	822	-0.0087	435	0.7763	0.1712
1998	862	0.0029	514	0.9112	0.1954
1999	888	0.0480	637	0.8776	0.1983
2000	980	0.0182	655	0.7970	0.2106
2001	1083	-0.0003	619	1.0780	0.2162
2002	1111	0.0035	603	1.0110	0.2032
2003	1141	0.0433	573	0.9398	0.1972
2004	1255	0.0227	634	0.7465	0.1638
2005	1380	0.0065	716	0.7481	0.1705
2006	1485	0.0313	797	0.7193	0.1839
2007	1612	0.0237	912	0.6014	0.1860
2008	1773	-0.0649	723	0.8178	0.2591
2009	1771	0.0736	617	1.2262	0.2556
2010	1746	0.0179	765	0.8234	0.1989

Table 2: Descriptive Statistics of the Relevant Variables
Descriptive Statistics

Variables	Mean	Median	Max	Min	Std Dev	Skewness	Kurtosis
Market Proxy Returns	0.0095	0.0154	0.1096	-0.1324	0.0412	-0.5617	3.4739
Ln(SIZE)	6.4003	6.4289	6.8851	5.9192	0.2225	-0.1007	2.4080
BE/ME	0.8381	0.7954	1.6546	0.5295	0.1840	1.5099	6.2722
Idiovol	0.1907	0.1858	0.3664	0.1227	0.0385	1.0994	5.0976
RMRF	0.0049	0.0107	0.1069	-0.1366	0.0412	-0.5453	3.4619
SMB	0.0124	0.0080	0.2048	-0.1589	0.0400	0.9796	7.6364
HML	0.0188	0.0186	0.0926	-0.0705	0.0274	0.1265	3.6542
HIMLI	0.0161	0.0096	0.4411	-0.2828	0.0755	1.1904	9.7565

Table 3: Summary Statistics of ten Idiosyncratic Volatility Portfolios

Portfolio	Monthly Excess Return	Std Dev	Size (millions)	BE/ME
1(high)	4.16%	11.67%	21	0.5994
2	1.81%	9.57%	38	0.5767
3	1.57%	8.71%	59	0.6433
4	1.07%	7.79%	68	0.5977
5	0.95%	6.62%	176	0.6497
6	0.62%	5.81%	334	0.6638
7	0.67%	5.02%	970	0.6467
8	0.72%	4.43%	1327	0.6818
9	0.96%	3.98%	2215	0.6628
10(low)	1.51%	5.55%	1249	0.5376

Table 4: Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10. The dependent variable is the equal-weighed excess return of the stocks. RMRF is the excess return on the accumulative ASX All Ordinary Index, SMB is Fama and French risk factor mimicking portfolios for size. HIMLI is a risk factor mimicking portfolio for idiosyncratic volatility. Alpha is the intercept of the regression model.

$$r_t - r_{ft} = \alpha_t + \beta_t (r_{mt} - r_{ft}) + i_t HIMLI + \varepsilon_t$$

	2-Factor Model			
Portfolio	Alpha	RMRF	HIMLI	ADJ R-sq
1(high)	0.0207***	0.5542***	1.1314***	0.67
	-4.4	-4.69	-17.54	
2	0.0001	0.7387***	0.8976***	0.75
	-0.03	-8.77	-19.53	
3	0	0.8213***	0.7310***	0.71
	(-0.01)	-10.01	-16.32	
4	-0.0028	0.7955***	0.6001***	0.67
	(-0.91)	-10.19	-14.08	
5	-0.0016	0.7532***	0.4624***	0.66
	(-0.60)	-11.11	-12.5	
6	-0.0026	0.8753***	0.2825***	0.67
	(-1.12)	-14.92	-8.82	
7	-0.0001	0.8492***	0.1664***	0.66
	(-0.07)	-16.54	-5.94	
8	0.0023	0.7567***	0.0784***	0.57
	-1.13	-14.91	-2.83	
9	0.0053***	0.6434***	0.0722***	0.52
	-2.75	-13.34	-2.74	
10(low)	0.0133***	0.3595***	-0.0004	0.06
	-3.57	-3.83	(-0.01)	

Table 5: Regression statistics from the 3-factor model

Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10. The dependent variable is the equal-weighed excess return of the stocks. RMRF is the excess return on the accumulative ASX All Ordinary Index, SMB is Fama and French risk factor mimicking portfolios for size. HIMLI is a risk factor mimicking portfolios for idiosyncratic volatility. Alpha is the intercept of the regression model.

$$r_t - r_{ft} = \alpha_t + \beta_t (r_{mt} - r_{ft}) + s_t SMB_t + i_t HIMLI + \varepsilon_t$$

	3-Factor Model				
Portfolio	Alpha	RMRF	SMB	HIMLI	ADJ R-sq
1(high)	0.0161***	0.6856***	0.6402***	0.8812***	0.69
	(3.46)	(5.79)	(4.13)	(10.15)	
2	-0.0066**	0.9323***	0.9426***	0.5292***	0.83
	(-2.31)	(12.88)	(9.94)	(9.96)	
3	-0.0074***	1.0335***	1.0333***	0.3272***	0.83
	(-2.83)	(15.65)	(11.94)	(6.75)	
4	-0.0089***	0.9708***	0.8538***	0.2665***	0.77
	(-3.32)	(14.31)	(9.60)	(5.35)	
5	-0.0068***	0.9042***	0.7354***	0.1750***	0.76
	(-2.93)	(15.30)	(9.49)	(4.04)	
6	-0.0061***	0.9763***	0.4915***	0.0904**	0.72
	(-2.79)	(17.63)	(6.77)	(2.23)	
7	-0.0028	0.9259***	0.3735***	0.0205	0.70
	(-1.42)	(18.63)	(5.73)	(0.56)	
8	0.0002	0.8170***	0.2938***	-0.0365	0.61
	(0.10)	(16.18)	(4.44)	(-0.98)	
9	0.0025	0.7238***	0.3916***	-0.0808**	0.60
	(1.38)	(15.80)	(6.52)	(-2.40)	
10(low)	0.0101***	0.4522***	0.4513***	-0.1767**	0.11
	(2.71)	(4.77)	(3.63)	(-2.54)	

Table 6: Regression statistics from the 3-factor model

Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10. The dependent variable is the equal-weighed excess return of the stocks. RMRF is the excess return on the accumulative ASX All Ordinary Index, HML is Fama and French risk factor mimicking portfolios for book-to-market ratio. HIMLI is a risk factor mimicking portfolios for idiosyncratic volatility. Alpha is the intercept of the regression model.

$$r_t - r_{ft} = \alpha_t + \beta_t (r_{mt} - r_{ft}) + s_t HML_t + i_t HIMLI + \varepsilon_t$$

	3-Factor Model				
Portfolio	Alpha	RMRF	HML	HIMLI	ADJ R-sq
1(high)	0.0190***	0.5633***	0.0863	1.1334***	0.66
	(3.27)	(4.70)	(0.50)	(17.50)	
2	0.0030	0.7234***	-0.1458	0.8940***	0.75
	(0.73)	(8.50)	(-1.20)	(19.43)	
3	-0.0028	0.8359***	0.1388	0.7344***	0.71
	(-0.69)	(10.08)	(1.17)	(16.37)	
4	-0.0039	0.8013***	0.0552	0.6015***	0.67
	(-1.02)	(10.13)	(0.49)	(14.05)	
5	-0.0040	0.7661***	0.1220	0.4654***	0.66
	(-1.21)	(11.18)	(1.24)	(12.57)	
6	-0.0041	0.8835***	0.0778	0.2844***	0.67
	(-1.44)	(14.88)	(0.91)	(8.86)	
7	-0.0030	0.8645***	0.1453*	0.1699***	0.66
	(-1.20)	(16.76)	(1.97)	(6.09)	
8	-0.0006	0.7718***	0.1438*	0.0818***	0.58
	(-0.22)	(15.14)	(1.97)	(2.97)	
9	0.0015	0.6633***	0.1896***	0.0768***	0.53
	(0.66)	(13.80)	(2.75)	(2.95)	
10(low)	0.0151***	0.3502***	-0.0880	-0.0025	0.06
	(3.27)	(3.68)	(-0.65)	(-0.05)	

Table 7: Regression statistics from Fama French 3-factor model

Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10. The dependent variable is the equal-weighed excess return of the stocks RMRF is the excess return on the accumulative ASX All Ordinary Index, SMB and HML are Fama and French risk factor mimicking portfolios for size and book-to-market ratio. Alpha is the intercept of the regression model.

$$r_t - r_{ft} = \alpha_t + \beta_t (r_{mt} - r_{ft}) + s_t SMB_t + h_t HML_t + \varepsilon_t \,,$$

			FF 3-Factor Model				
Portfolio	Monthly Excess Return	Std Dev	Alpha	RMRF	SMB	HML	ADJ R-sq
1(high)	4.83%	15.28%	0.020466	1.140771	1.75724	-0.33069	0.54
			3.018374	8.59116	13.01424	-1.64998	
2	1.81%	9.57%	0.0018	1.1683	1.6313	-0.5062	0.77
			0.4420	14.9955	20.5916	-4.3046	
3	1.57%	8.71%	-0.0049	1.1966	1.4509	-0.1715	0.79
			-1.4195	17.8568	21.2931	-1.6952	
4	1.07%	7.79%	-0.0057	1.0963	1.1974	-0.2001	0.74
			-1.6862	16.5210	17.7445	-1.9975	
5	0.95%	6.62%	-0.0057	0.9929	0.9581	-0.0796	0.74
			-1.9754	17.5088	16.6135	-0.9297	
6	0.62%	5.81%	-0.0054	1.0212	0.6070	-0.0481	0.72
			-2.0370	19.6923	11.5107	-0.6151	
7	0.67%	5.02%	-0.0041	0.9454	0.3952	0.0659	0.70
			-1.7319	20.5535	8.4489	0.9492	
8	0.72%	4.43%	-0.0016	0.8085	0.2426	0.0989	0.61
			-0.6627	17.3168	5.1102	1.4028	
9	0.96%	3.98%	0.0000	0.6954	0.2827	0.1404	0.60
			0.0224	16.3411	6.5341	2.1857	
10(low)	1.51%	5.55%	0.0127	0.3385	0.2380	-0.1181	0.09
			2.7950	3.8000	2.6273	-0.8786	

Table 8: Regression statistics from the 4-factor model

Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10. The dependent variable is the equal-weighed excess return of the stocks RMRF is the excess return on the accumulative ASX All Ordinary Index, SMB and HML are Fama and French risk factor mimicking portfolios for size and book-to-market ratio. HIMLI is a risk factor mimicking portfolios for idiosyncratic volatility. Alpha is the intercept of the regression model.

$$r_t - r_{ft} = \alpha_t + \beta_t (r_{mt} - r_{ft}) + s_t SMB_t + h_t HML_t + i_t HIMLI + \varepsilon_t$$

			4-Factor Model					
Portfolio	Monthly Excess Return	Std Dev	Alpha	RMRF	SMB	HML	HIMLI	ADJ R-sq
1(high)	4.83%	15.28%	0.016879	0.682835	0.647028	-0.03993	0.877537	0.69
			3.002011	5.729811	4.09298	-0.23711	9.928205	
2	1.81%	9.57%	-0.0003	0.9084	1.0013	-0.3412	0.4980	0.84
			-0.0827	12.8002	10.6363	-3.4018	9.4615	
3	1.57%	8.71%	-0.0062	1.0289	1.0445	-0.0650	0.3213	0.83
			-1.9677	15.4813	11.8470	-0.6921	6.5173	
4	1.07%	7.79%	-0.0068	0.9628	0.8736	-0.1153	0.2560	0.77
			-2.1035	14.1343	9.6682	-1.1974	5.0665	
5	0.95%	6.62%	-0.0064	0.9027	0.7392	-0.0223	0.1730	0.76
			-2.2887	15.1652	9.3620	-0.2646	3.9189	
6	0.62%	5.81%	-0.0058	0.9749	0.4948	-0.0187	0.0887	0.72
			-2.1878	17.4809	6.6877	-0.2379	2.1449	
7	0.67%	5.02%	-0.0042	0.9311	0.3606	0.0749	0.0273	0.70
			-1.7738	18.6459	5.4442	1.0619	0.7369	
8	0.72%	4.43%	-0.0015	0.8233	0.2784	0.0895	-0.0283	0.61
			-0.6123	16.2423	4.1411	1.2491	-0.7531	
9	0.96%	3.98%	0.0003	0.7320	0.3715	0.1172	-0.0701	0.60
			0.1551	15.9819	6.1142	1.8099	-2.0643	
10(low)	1.51%	5.55%	0.0135	0.4394	0.4826	-0.1822	-0.1934	0.12
			3.0076	4.6175	3.8231	-1.3548	-2.7394	

Table 9: Correlation coefficients between independent variables

Correlation	MKT	SMB	HML	HIMLI
MKT	1			

SMB	0.0287	1		
	(0.42)	-----		
HML	-0.1801**	0.0798	1	
	(-2.68)	(1.17)	-----	
HIMLI	0.3258***	0.6688***	-0.1180	1
	(5.04)	(13.16)	(-1.74)	-----

Table 10: Phases of Australian Business Cycle over the Sample Period
Source: original data is downloaded from website of Melbourne Institute of Applied Economic and Social Research. Website address: [http://melbourneinstitute.com/macro/reports/bachronologyhtml]

Start month	End month	Phases of Business Cycle	Number of months
Jan-93	Aug-95	Expansion	32
Sep-95	Feb-97	Contraction	18
Mar-97	Jun-00	Expansion	40
Jul-00	Feb-01	Contraction	8
Mar-01	May-04	Expansion	39
Jun-04	Feb-06	Contraction	21
Mar-06	Jan-07	Expansion	11
Feb-07	Feb-09	Contraction	25
Mar-09	Dec-10	Expansion	22

Table 11: Conditioning Idiosyncratic Volatility Premia on Economy Conditions

Stocks are sorted on December each year from 1992 to 2010 into 10 decile portfolios based on their December idiosyncratic volatility. Stocks with highest idiosyncratic volatility comprise decile 1 and stocks with lowest idiosyncratic volatility comprise decile 10. The dependent variable is the equal-weighed excess return of the portfolios. RMRF is the excess return on the accumulative ASX All Ordinary Index, HIMLI is a risk factor mimicking portfolios for idiosyncratic volatility. Alpha is the intercept of the regression model. $D_{\exp ansion}$ is a dummy variable which takes a value of unity in the period if expansionary phase of the business cycle is identified by Melbourne Institute of Applied Economic and Social Research and a value of zero otherwise. $D_{contractio\,n}$ is a dummy variable which takes a value of unity in the period if expansionary phase of the business cycle is identified and a value of zero otherwise. The business cycle classification is downloaded from the website of the Melbourne Institute of Applied Economics and Social Research.

$$r_t - r_{ft} = \alpha_t + \beta_t D_{\exp ansion}(r_{mt} - r_{ft}) + i_t D_{\exp ansion} HIMLI + \varepsilon_t$$
$$r_t - r_{ft} = \alpha_t + \beta_t D_{contraction}(r_{mt} - r_{ft}) + i_t D_{contraction} HIMLI + \varepsilon_t$$

2-Factor Model								
	Expansions				Contractions			
Portfolio	Alpha	RMRF	HIMLI	ADJ R-sq	Alpha	RMRF	HIMLI	ADJ R-sq
1(high)	0.0239***	0.4919***	1.1095***	0.51	0.0389***	0.6541**	1.1766***	0.14
	(4.20)	(2.79)	(13.10)		(5.26)	(1.97)	(4.53)	
2	0.0028	0.6992***	0.8691***	0.55	0.0158***	0.7853***	0.9885***	0.18
	(0.62)	(5.05)	(13.05)		(2.68)	(2.97)	(4.76)	
3	0.0021	0.8626***	0.6842***	0.52	0.0136**	0.6934***	0.9163***	0.18
	(0.51)	(6.60)	(10.88)		(2.53)	(2.88)	(4.85)	
4	-0.0007	0.8023***	0.5438***	0.45	0.0087*	0.7126***	0.8551***	0.22
	(-0.17)	(6.46)	(9.10)		(1.85)	(3.37)	(5.16)	
5	0.0000	0.7642***	0.4195***	0.44	0.0080**	0.6808***	0.6530***	0.21
	(0.01)	(7.19)	(8.21)		(1.98)	(3.77)	(4.62)	
6	-0.0015	0.8418***	0.2638***	0.42	0.0053	0.9170***	0.3604***	0.23
	(-0.49)	(8.87)	(5.78)		(1.54)	(5.89)	(2.95)	
7	0.0006	0.8398***	0.1439***	0.42	0.0060**	0.8400***	0.2688**	0.24
	(0.24)	(10.15)	(3.62)		(2.01)	(6.25)	(2.55)	
8	0.0029	0.7027***	0.0708*	0.32	0.0069***	0.8480***	0.1154	0.24
	(1.13)	(8.95)	(1.88)		(2.64)	(7.19)	(1.25)	
9	0.0054**	0.6201***	0.0831**	0.33	0.0096***	0.7067***	0.0033	0.18
	(2.41)	(8.87)	(2.47)		(3.88)	(6.40)	(0.04)	
10(low)	0.0135***	0.3065**	0.0102	0.03	0.0152***	0.4726***	-0.0520	0.03
	(3.53)	(2.60)	(0.18)		(4.07)	(2.82)	(-0.40)	

Figure 1: Time path of average idiosyncratic volatility over the sample period.

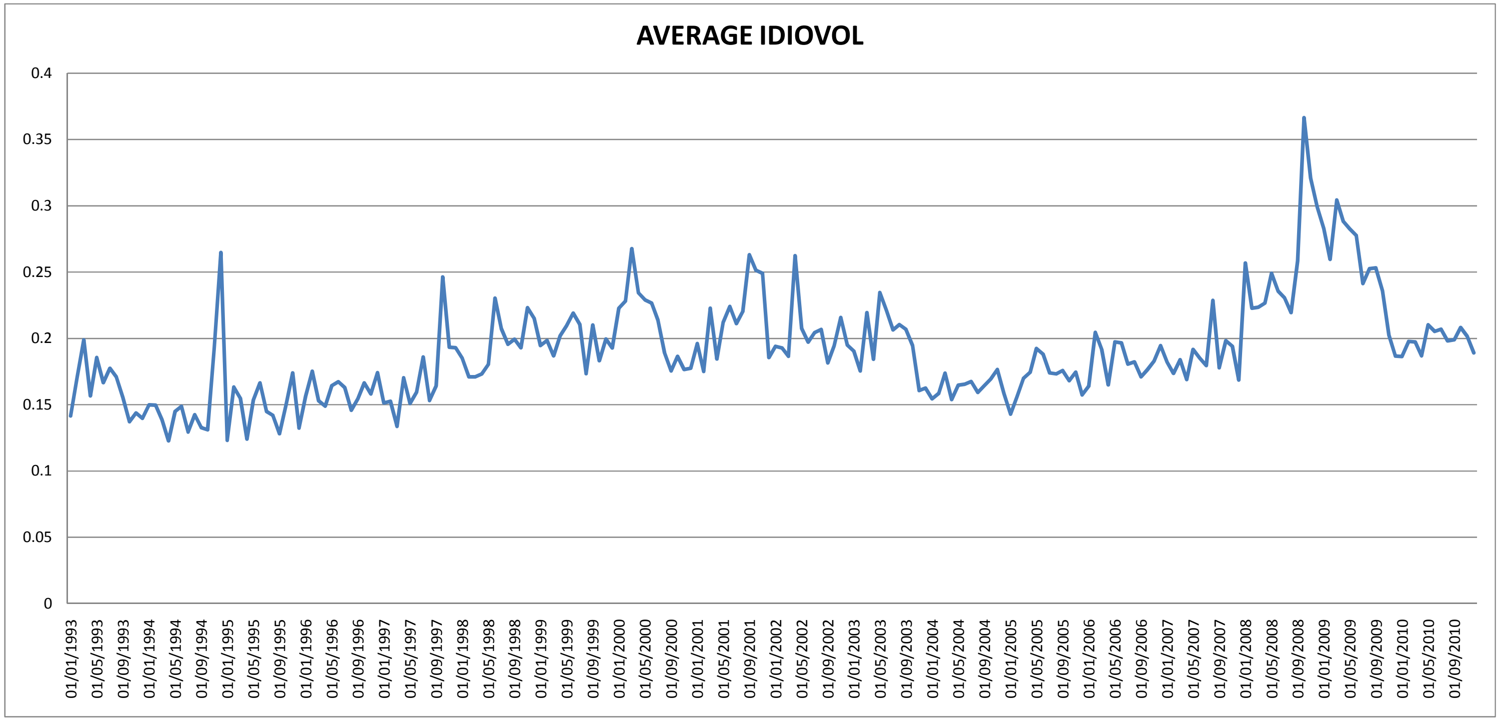

Figure 2: Time path of average idiosyncratic volatility and the market proxy return.