Using Ordinary Least Squares Regression and Quantile Regression to test the Capital Asset Pricing Model and the Fama and French Model in the Australian Equity Market

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USING ORDINARY LEAST SQUARES REGRESSION AND QUANTILE REGRESSION TO TEST THE CAPITAL ASSET PRICING MODEL AND THE FAMA AND FRENCH MODEL IN THE AUSTRALIAN EQUITY MARKET

A Dissertation Submitted to the Faculty of Business and Law in Edith Cowan University in Fulfilment of the Requirements for the Degree of BACHELOR OF FINANCE IN HONOURS

June, 2011

By

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Abstract

Many studies have tested the CAPM and the Fama and French model in the Australian security market using the Ordinary Least Squares (OLS) method. However, this regression method just focuses on the relationship between means in the dataset, and equity market usually has some extreme situations in the tails. In this study, quantile regression will be used as well as OLS to provide a more comprehensive picture. This research will also compare the domestic and overseas indices in testing the CAPM and the Fama and French model. A twenty-year data sample composed of the 50 largest companies' equity returns will be analyzed in the first-pass regression. In the second-pass regression, results estimated in the first-pass regression under OLS and quantile regression will be used as the independent variables, to check the relationship between different factors and the subsequent equity return. Seventeen portfolios will be sorted according to the methodology of Fama and MacBeth (1974) to generate a cross-sectional dataset. The regression power and testing results will be compared between different regression methods and datasets. The empirical results generally demonstrate that the international dataset has performed better than the domestic dataset; and factors estimated by quantile regression in the first-pass regression have better explanatory power for the subsequent equity returns in the second-pass regression.
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Chapter 1. Introduction

The relationship between risk and return on equity has been a controversial topic for researchers across many decades. Among several theories and models, the Capital Asset Pricing Model (CAPM) and the Fama and French model are two core models used in Modern Portfolio Theory.

1.1. General Background

The Capital Asset Pricing Model, a crucial finding in modern finance, was proposed by Sharpe, Treynor, Lintner and Mossin (1964). It is a model for pricing an individual share or a portfolio, and its key formula is:

$$\bar{R}_i = R_f + \beta_i (\bar{R}_m - R_f)$$  (1)

where $\bar{R}_i$ is the expected return on the equity; $R_f$ stands for the return which is 100% certain and has no risk involved, and Treasury bill rate could be a proxy for it; $R_m$ is the return of the “market portfolio”, and could be represented by the return on the equity market index; beta is a measure of market risk calculated by:

$$\beta_i = \frac{\text{Cov}(R_i, R_m)}{\sigma^2_m}$$  (2)

where $\text{Cov} (R_i, R_m)$ is the covariance between the equity return and the market portfolio’s return, $\sigma^2_m$ is the variance of the return on the market portfolio. Betas vary according to different categories of companies. The beta for the whole market is 1, and when shares have betas larger than 1 it means that they have higher risk than the market. Companies belonging to this category including some mining companies,
since they usually have more volatile returns. Conversely, the share prices of banks usually have lower volatility than the market, since the banking industry is more stable than other industries. The CAPM is based on investors' rational behaviour, which implies that higher risk yields higher return, and vice versa.

After the CAPM was proposed in the 1960s, there were many tests of whether the CAPM explains and predicts equity returns very well. Although the results of early tests support the CAPM (e.g., Black, Jensen and Scholes, 1972, Fama and MacBeth, 1974), there are also some criticisms on the process of testing the CAPM (e.g., Roll, 1977). Studies subsequently indicate that beta is not the only determinant in explaining the relationship between risk and return: Fama and French (1992; 1993) found that beta is less important for explaining share returns than the size effect and book-to-market ratios.

Fama and French revealed the relationship between share return and other factors in the formula below:

$$E(R_{it}) - R_{ft} = b_i[E(R_{Mt})-R_{ft}] + s_iE(SMB_i) + h_iE(HML_i) \tag{3}$$

where SMB means the difference between the return on small-and-big stock portfolios, and HML stands for the difference between the simple average returns on high and low book-to-market portfolios.

As one of the contradictions of the CAPM, the size effect proposed by Banz (1981) indicates that market equity (a stock's price times shares outstanding) adds to the explanation of the cross-section of average returns provided by market betas. Another contradiction of the Sharpe-Linter model (equation 1) revealed by Stattman (1980) is that the positive relationship between average returns on U.S. equities and the ratio of a firm's book value of common equity (BE) to its market value (ME). Fama and
French (1993) assessed previous research and suggested two mimic factors defined below:

Size: The portfolio SMB (small minus big), which is meant to mimic the risk factor in returns related to size, is the difference between the simple average of returns on the three small-stock portfolios and the simple average of the returns on the three big-stock portfolios each month. SMB in fact is the difference between the returns on small and big-stock portfolios with about the same weighted-average book-to-market equity.

BE/ME: The portfolio HML (high minus low) is the difference between the simple average of the returns on the two high BE/ME portfolios and the average of returns on the two low BE/ME portfolios. It is meant to mimic the risk factor in returns related to book-to-market (BM) equity (Fama and French, 1993).

1.2. OLS and Quantile Regression

Several researchers have tested the CAPM and the Fama and French model, and their methods normally involve ordinary least square regression (OLS). OLS is a method used to estimate the following equation:

\[ Y_t = \alpha + \beta X_t + e_t \]  

The intercept alpha represents the value of Y when X is 0, and the slope coefficient beta measures the change of Y for a unit change of X, and e is the error term. OLS minimizes the sum of squares of the vertical distances of actual points in the scatter diagram from the predicted regression line. This method has been widely used in research; however, an important prior assumption is that the dataset should be normally distributed. If not, the result could be inaccurate.
Although the CAPM assumes that equity returns are normal distributed, in fact they are fat tailed (Fama, 1976). Using only OLS to test the CAPM and Fama and French model could be misleading because it may be sensitive to outliers. That is the motivation for this research: using quantile regression as well as OLS to test the CAPM and the Fama and French model.

Quantile regression is an old idea in statistical history: it was first proposed by Boscovitch in the 18th century, but was ignored until Koenker and Bassett (1978) proposed and operationalized the idea more systematically. Unlike OLS which uses the “mean” as the benchmark to run regression, quantile regression uses the “median” as the benchmark, and researchers can run regressions on different quantiles in the dataset centered on the quantile of interest. It is therefore to some extent a process of running regressions across each segment of the whole dataset. The quantile regression method focuses on the absolute residual values instead of squares of the vertical distances, as used in OLS. This new approach is less sensitive to outliers and gives a more complete picture of the relationship across the full distribution rather than just around the mean.

1.3. Research Design and Significance

This study focuses on the explanatory and predictive power of the CAPM and the Fama and French model in equity market, thus quantitative analysis will be utilized. Generally, this research can be divided into two segments: the first-pass regression, which includes both OLS and quantile regression to generate betas, the slope coefficients of size and BM factor; and the second-pass regression, which uses OLS to check the relationship between subsequent equity return and factors estimated from the first-pass regression.

Few researchers have tested the CAPM or the Fama and French model using quantile regression (e.g. Barnes and Hughes, 2002), although several have used OLS for this
purpose. Within the latter group, a large amount of research including Fama and French (1992, 1993) questioned the explanatory power of beta in the CAPM (e.g. Roll, 1977, Ross, 1976, Fama and French, 2004). Compared with the CAPM, the Fama and French model works slightly better to evaluate the risk and return relationship in equities (Bartholdy and Peare, 2002). This study will use both OLS and quantile regression to check the number and percentage of significant betas in the first-pass regression. Most of the previous testing results use U.S. datasets and apply only OLS. Research comparing the explanatory power of the CAPM and the Fama and French model in Australia is far less common. This research will test these models over the last twenty year including the period of Global Financial Crisis, which will provide an important additional test to research comparing the CAPM and the Fama and French model.

Quantile regression divides the dataset into different segments and provides a more comprehensive picture of the regression results. It is interesting to check whether these coefficients remain the same over different quantiles. Since OLS only focuses on the average point in the dataset, the slope coefficients in quantile regression may be significant in other areas of the distribution. The comparison of results is a key point of this research, since quantile regression is a new method applied in this study.

This study also focuses on the overall performance of different datasets. In equation (1), \( R_m \) stands for the return on “market portfolio”. The important point here is, which index could represent the “market portfolio” to provide a better result in testing the CAPM and the Fama and French model: domestic or overseas? Theoretically the international dataset will work better, since an important implication in the CAPM is that the “market portfolio” should include the “entire” assets in the world; also, it should involve different kinds of investments such as equity, bond, derivative and real estate. This assumption is unrealistic and cannot be achieved, so that people usually use equity index as a proxy for the “market portfolio” to test the CAPM. This research will use a “benchmark” dataset on French’s website (French, n.d.) as well as the
Australian All Ordinaries index in the first-pass regression, to determine which index has better explanatory power. The detailed description of the benchmark index is demonstrated in section 3.3 below.

Another important component in this paper is using subsequent returns to test the previous beta estimated by OLS and quantile regression. It is the second-pass of testing the CAPM and the Fama and French model. This study will rank the slope coefficients from the first-pass regression and sort them into different portfolios, and check the relationship between the subsequent real return and the different factors such as beta, the coefficient of size and BM factor. Results estimated by quantile regression in the first-pass regression would have more explanatory power in the second-pass regression if coefficients estimated by this new method involve more detailed information of the distribution in the dataset.

This paper has six main chapters. Chapter two offers a brief literature review, which includes the major research in U.S. and Australia; chapter three introduces the research methodology and data collecting process in this study; chapter four provides the first-pass regression results and analysis; chapter five involves the results of second-pass regression, and finally chapter six provides the overall conclusions for this study.
Chapter 2. Literature Review

This section covers three areas: the original CAPM and Fama and French model, recent results of testing the CAPM and the Fama and French model, and quantile regression.

2.1. The CAPM and the Fama and French Model

The CAPM and the Fama and French model are important components in asset pricing models: the former was proposed in 1960s, while the latter was proposed in 1990s. The CAPM model is the key component in Modern Portfolio Theory (MPT). Markowitz (1952, 1959) proposed that portfolio return is a weighted average of rate of return of individual stocks, but portfolio risk is not the weighted average of risk of individual stocks because of the correlation and coefficients between the individual assets in the portfolio. Investors need to make a trade-off between return and risk to achieve their utilities. They should decide which level of risk and return they can accept when they look for efficient portfolios. An important conclusion in Markowitz's theory is that risk can by reduced by diversification. Equation (5) explains the weighted return for an n-asset portfolio, and equation (6) reveals the risk for a two-asset portfolio:

\[ E(R_p) = w_1 E(R_1) + \ldots + w_n E(R_n) \]  

(5)

\[ \sigma_p^2 = w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2 w_1 w_2 \sigma_1 \sigma_2 \rho_{12} \]  

(6)

where the \( R_p \) indicates return, \( \sigma_p^2 \) indicates risk, \( w \) indicates the weighting of shares in the portfolio, and \( \rho_{12} \) denotes the correlation coefficient of these two equities.
The covariance term in equation (6) will become much larger when the share numbers increase in the portfolio, which is a limitation in Markowitz’s model. Based on his theory, Sharpe (1964) proposed the Single Index Model (SIM) which breaks the return into two parts: a unique part and a market-related part. The SIM assumes zero correlation between residuals of individual company returns, and beta is the only factor used to explain returns.

\[ r_i = \alpha_i + \beta_i r_M + e_i \]  

There are three components in equation (7): alpha, which is the intercept of the formula; beta, the part of return determined by market performance, and an error term. The SIM solves Markowitz’s problem of infinite covariance terms in the formula for calculating risk:

\[ \sigma_i^2 = \beta_i^2 \sigma_M^2 + \sigma^2(e_i) \]  

where \( \sigma_i^2 \) means the total risk of security, and it is decided by market risk \( \sigma_M^2 \) and unique risk \( \sigma^2(e_i) \). Market risk, also called the systematic variance, cannot be diversified while unique risk can be reduced by diversification.

Sharpe proposed the capital-market line and the security-market line to evaluate the risk-return relationship. In the capital-market line, price is divided into two components: the price of time, which is the intercept on the axis; and the price of risk, which is the additional expected return per unit of risk borne. Based the capital-market line, the security-market line (equation 1) is proposed which demonstrates the relationship between beta and equity return. Lintner (1965) used the Lagrange approach and got a similar conclusion to Sharpe, which leads to equation (1), the key
There are many tests of how well the CAPM explains share returns. Early tests include Black, Jensen and Scholes (1972) and Fama and MacBeth (1974). Black et al. (1972) used all stocks traded on NYSE during the year 1926-1965, and found that: (1), the relationship between beta and return is positive and linear; (2), the intercept that the CAPM produces is higher than the risk-free rate; (3) the R-square for the beta is 0.98, which is close to one. This means that beta is the only determinant of equity risk-return relationship. Fama and MacBeth (1974) regressed the portfolio returns on three factors: the $\hat{\beta}$ estimated by the first-pass regression, the variable $\bar{\beta}$ and residual variance $s_t$. Factors $\hat{\beta}$ and $s_t$ are used to test the linearity relationship between beta and equity return, and residual variance that cannot be explained by the CAPM. Their results indicate that it is not suitable to reject the hypothesis that risk-averse investors attempt to hold efficient portfolios, as well as the investor who hold portfolios assume that the relationship between risk and return is linear. However, Roll (1977) argued that the only test of the CAPM is a test of the efficiency of the “market portfolio”: if the chosen market portfolio is ex-post efficient, the return will be an exact linear function of beta, otherwise the relationship between return and beta will not be linear. Thus, the CAPM “has never been tested”. Fama and French (2004) indicated that the CAPM has never been an empirical success: there is no market proxy in the real world works like the “market portfolio” in tests of the CAPM, which leads to the result that this model does not work in applications. After the 1970s, research has demonstrated that variables such as size, price-to-earnings ratios and momentum could add to the explanation of average returns provided by beta (e.g. Banz, 1981, Ball, 1978). Fama and French concluded these findings and proposed the new three-factor model.

While the CAPM indicates that beta is the only determinant of return on shares, research in the late 1970s and 1980s indicated that size, leverage, earnings-price ratios and book-to-market ratio (BM) help to explain the cross-sectional return in the U.S. equity market. Fama and French evaluated the joint roles of these factors, and finally
included beta, size and and BM factor as the determinants of share return. Fama and
French (1992) argued that beta has a strong correlation with the size effect. To
disentangle beta and the size effect, they subdivided size portfolios on the basis of
pre-ranking betas, and found a strong relationship between size and average return but
no relationship between beta and average return. Another finding is that the
book-to-market effect is even stronger than the size effect, which indicated a strong
relationship between equity return and the book-to-market ratio. Overall, stocks which
have a small size tend to have larger returns than equities with a bigger size, and low
book-to-market-equity firms remain more profitable than high book-to-market-equity
firms. The three-factor model absorbs the effect of other factors such as leverage and
earnings-price ratios in explaining the cross-sectional equity return.

Fama and French (1996) tested the explanatory power of the model compared with the
CAPM, and their results indicated that the three-factor-model explains the pattern in
returns observed when portfolios are formed on earnings/price, cash flow/price and
sales growth. As well, the Fama and French model captures the reversal of long-term
returns. Fama and French also indicated that the model captures priced default risk to
explain equity return.

Fama and French (1995) extended their three-factor-model from explaining equity
returns to profitability: they provided evidence that the size and book-to-market factors
are related to firm profits. Firms with a high book-to-market ratio tend to be
persistently distressed; while with low book-to-market ratio have a strong relationship
with sustained strong profitability. On the other hand, small stocks tend to be less
profitable than big stocks within book-to-market groups. They concluded that there are
size and book-to-market factors in earnings like those in returns. However the results
of Fama and French discussed above are all based on the U.S. data, although they
extended their three-factor-model into international markets later. Fama and French
(1998) examined value and growth across 13 countries including Australia. According
to their results, Australia has the largest difference between the annual return on the
extreme book-to-market portfolios: the highest book-to-market portfolio return is 17.62%, while the lowest is 5.3%, a difference of 12.32%. These results indicate that the Fama and French model works not only in U.S., but also in many countries including Australia.

2.2. Australian Research

Australian research of testing the CAPM focus on not only the traditional CAPM, but also the conditional CAPM proposed by Jagannathan and Wang (1996). The conditional CAPM involves market premium and human capital as two important factors in determining the cross-sectional equity return. There are some debates on whether the conditional CAPM explains the equity return well; however, results of testing traditional CAPM are roughly similar: its explanatory power in the Australian equity market is low. Durack, Durand and Maller (2004) revealed that results of OLS tests of the CAPM are consistent with recent U.S. research: the evidence of priced beta is marginal and the R-square is low (0.0725).

A number of local studies also focus on testing the Fama and French model, and their results generally reveal that the size effect is the best documented and least ambiguous among all the factors in explaining the equity return. (Gaunt, 2004, Kassimatis, 2008, Brailsford and O’ Brien, 2008, O’ Brien, Brailsford and Gaunt, 2009, Gharghori, Chan and Faff, 2007).

Gaunt (2004) tested the Fama and French model in the Australian equity market and found that the smallest stock portfolio appears to produce large positive abnormal returns, which means the size effect exists in the Australian security market. Kassimatis (2008) indicated that the returns of SMB are significant in explaining realized returns; after time variation effects have been considered, the size effect is diminished but still exists. Brailsford and O’ Brien (2008) ran a two-factor model
including beta and size to formally examine the impact of size, and found significant exposure to the size factor among the combinations of size and performance portfolios. Gharghori et al. (2007) found evidence of the size effect that returns decrease when the dataset moves from the small size portfolio to the big size portfolio. O’ Brien et al. (2009) used a new approach to control the interaction of these factors to test the Fama and French model’s performance in Australian market. The key to their approach is to disentangle the interactional effect of the three factors by triple-sorting the portfolios. After analyzing the results from the OLS regression, they revealed that the size premium is the strongest among the factors in the Fama and French model. Therefore the size factor explains the equity return well in the Australian equity market.

Compared with the size factor, the book-to-market (BM) effect on the Australian equity market is vague. Halliwell et al. (1999) covered the period 1979-1990 and found a positive relationship between book-to-market and excess return. The explanatory power of the BM factor in this paper is weak, as shown by two points: (1), the relationship still exists after using the Fama and French model to generate expected returns; and (2), the positive relationship is mainly restricted within the largest three size quintiles; which means the relationship could be a mixture of size and book-to-market effect. Gaunt (2004) obtained a similar result to Halliwell et al. and Fama and French (1998), with some evidence of a book-to-market effect as abnormal returns increase monotonically from the lowest to highest BM portfolios in the period 1991-2000. Kassimatis (2008) indicated that for the largest four size quintiles, raw returns in the high book-to-market portfolio are greater than those in the low book-to-market portfolio. Gharghori et al. (2007) revealed that the book-to-market and size factors are negatively correlated, and there is a significant positive relationship between HML and returns in the period 1993-2004. Finally, O’ Brien et al. (2009) documented the BM effect that portfolios composed by high book-to-market ratios tend to have higher returns than portfolios with low BM ratios after the interaction effects in the Fama and French model have been controlled.
2.3. Quantile Regression: Original Model and Application in Finance

Compared with OLS, quantile regression is more suitable for testing the CAPM and the Fama and French model since it is less sensitive to outliers. The reason is that this regression method is the median regression rather than the average, which minimizes a sum of symmetrically (in the median) or asymmetrically weighted (in other quantiles such as 0.1, 0.2, 0.8, 0.9) absolute residuals instead of squares of the vertical distances in OLS.

Koenker and Bassett (1978) revealed that the value of “estimators superior to least squares for the non-Gaussian linear model is a well kept secret in most of the econometrics literature”, and the “dogma of normality” seems largely attributable to a kind of wishful thinking. To overcome the shortcoming of OLS regression they proposed the quantile regression method, which could be expressed as below:

Let \( \{y_t: t=1,\ldots,T\} \) be a random sample on a random variable Y having distribution function \( F \). Then the \( \theta \)th sample quantile, \( 0<\theta<1 \), could be defined as any solution to the minimization problem:

\[
\min_{b \in \mathbb{R}} \left[ \sum_{t \in \{t: y_t \geq b\}} \theta |y_t - b| + \sum_{t \in \{t: y_t < b\}} (1-\theta) |y_t - b| \right].
\] (9)

Let \( \{x_t: t=1,\ldots,T\} \) denotes a sequence of K-vectors of a known design matrix. Suppose \[ y_t: t=1,\ldots,T \]is a random sample on the regression process \( u_t = y_t - x_t \beta \), which has distribution function \( F \). The \( \theta \)th regression quantile, \( 0<\theta<1 \), is defined as any solution to the minimization problem:
Koenker and Bassett explained the concept and background of the original idea of quantile regression. Koenker and Hallock (2001) in another research regarded quantile regression as an optimization problem. Just as the sample mean can be defined as the solution to the problem of minimizing a sum of squared residuals, the median could be defined as the solution to the problem of minimizing a sum of absolute residuals. For the quantiles other than median, this can be defined as minimizing a sum of asymmetrically weighted absolute residuals:

$$\min_{b \in \mathbb{R}^k} \left[ \sum_{t \in \{i: y_i \geq x_i b\}} \theta |y_i - x_i b| + \sum_{t \in \{i: y_i < x_i b\}} (1 - \theta) |y_i - x_i b| \right].$$ \hspace{1cm} (10)

where the function $\rho_{\tau} (\cdot)$ is the tilted absolute function that yields the $\tau$th sample quantile as its solution, and $\xi (x, \beta)$ is formulated as a linear function of parameters. These parameters can be solved efficiently by linear programming methods.

Quantile regression focuses not only on the median but also different segments of the dataset, thus it appears to be a better statistical method especially for testing the CAPM and the Fama and French model than OLS. Another important aspect is that this regression method could probably provide more accurate results for the second pass of testing the CAPM and the Fama and French model. This research uses a symmetric weighting scheme to combine the coefficients in all the quantile levels (0.1-0.9). The combination result involves not only the median of the distribution, but also the information of tails in the dataset. Theoretically coefficients estimated in this way could have more explanatory power compared with OLS, which only focuses on the average of the distribution. Section 3.4 below provides the detailed explanation.
As a more effective tool than OLS in analyzing the extremes of a distribution, quantile regression has been applied to the research areas including asset-pricing, mutual-fund management and risk evaluation. Barnes and Hughes (2002) used the equity prices of 1093 firms from the Center for Research in Security Prices database across 1028 consecutive trading days, and ran quantile regression to test the performance of the CAPM. Their results demonstrated that the coefficients vary significantly across different quantiles, and that beta is a strongly significant cross-sectional explanatory variable for firms that underperform and over perform vis-à-vis the mean, but insignificant for firms with average performance.

There are also some Australian studies using quantile regression method. Allen, Gerrans, Singh and Powell (2009) used the quantile regression method to estimate the CAPM parameters for some S&P/ASX equities. They analyzed 43 stocks in S&P/ASX 50 during the period 2006-2008 and indicated that: 1, the behaviour of market factor is different around median observations when the distribution reaches extremes; 2, betas of equity vary substantially across the quantiles. Allen and Singh (2010) used the technique of Data Envelopment Analysis (DEA) applied to the Fama and French model, to select equities from Dow Jones Industrial Index. Quantile regression method has been applied in this research to estimate the coefficients and form portfolios. Their results indicate that: stocks selected by quantile regression model have a higher return than the ones selected by OLS during the same period.

Research in portfolio management and mutual-fund involve the quantile regression method as well. Gowlland, Xiao and Zeng (2009) adopted the quantile regression method to estimate two commonly used factors: book-to-price factor and medium-term momentum factor. They applied these two factors to evaluate the risk-return relationship in U.S. small-cap stocks. The relationship between the book-to-price factor and the subsequent one-month return is different across the quantiles, and generally, factors in the lower quantiles have a closer relationship with equity return than in higher quantiles. For the medium-term momentum factor, the estimated values of slope
coefficient are volatile across the quantiles. These results are important for portfolio managers to construct artificial portfolios. Bassett and Chen (2001) introduced quantile regression as a complement to the standard analysis in identifying portfolio’s style. They proposed using quantile regression to identify patterns in the fund’s entire return distribution, and indicated that the style of mutual funds classified by OLS and quantile regression could be different. A portfolio’s style depends on how a factor influences the entire distribution, and cannot be described by a single regression result based on the average in the dataset when quantile regression approach has been adopted.

Some researchers have used quantile regression as a technique in the estimation of value at risk (VaR) for financial institutions. Engle and Mangaelli (1999) proposed a conditional autoregressive specification for VaR, and the unknown parameters in this model are estimated by quantile regression. Their results indicate that the applications to the real data demonstrate the ability of this new model to adapt to new risk environments, and quantile regression has played an important role since it can observe the different behaviours of the tails in the distribution.

2.4. Summary

The CAPM is an important method for evaluating the relationship between risk and return. Results from Black et al. (1972) and Fama and MacBeth (1974) demonstrate strong support for the CAPM, however research on testing the CAPM has received many criticisms (e.g. Roll, 1977). Fama and French (1992, 1993) used the size and book-to-market factors to evaluate equity returns, first model by evaluating share returns in the U.S. market, and then by estimating profitability (Fama and French, 1995) across 13 countries including Australia (Fama and French, 1998). Their results indicate that the three-factor model can explain the abnormal returns for which the CAPM cannot provide a satisfactory explanation (Fama and French, 1996).
The performance of the CAPM in the Australian equity market is poor. As for the Fama and French model, many Australian researchers have found a strong size effect in the Australian equity market. However, compared with the size effect, the book-to-market effect is vague and weak, and most of the book-to-market effects are restricted to large quintiles.

Compared with OLS, quantile regression proposed by Koenker and Bassett (1978) could provide a more comprehensive analysis in evaluating risk-return relationship of equity market, since it is less sensitive to outliers. It can produce results across different quantiles such as 0.1 and 0.9, and thus is suitable to test the non-normal distributed equity returns.

Quantile regression can be applied to research areas such as asset-pricing, mutual fund management and risk evaluation. U.S. and Australian research have already used quantile regression to test the CAPM, and the result demonstrates that betas vary significantly across different quantiles. This regression method is also beneficial in the areas of portfolio-style classification, portfolio selection, mutual-fund management and risk-evaluation.
Chapter 3. Methodology and Data

To test the CAPM and the Fama and French model, the 50 largest companies in Australia will be chosen according to their market capitalizations. A table for the companies involved in this research is provided in Appendix A2. Chapter three has five major sections. Section 3.1 introduces the assumption in this research and defines the research questions. Section 3.2 demonstrates the process of the first-pass and second-pass regression. Section 3.3 introduces four models for the first-pass regression, and both OLS and quantile regression will be run using time-series data for each company. Section 3.4 involves the methodology of combining the quantile regression results in the first-pass of testing the CAPM and the Fama and French model. This section also includes the models of the second-pass regression, and the method of sorting different equities into portfolios. Finally section 3.5 demonstrates the way to generate the original data in this research.

3.1. Assumption and Research Questions

This research complies with the assumptions of the CAPM and the Fama and French model, which include: quadratic utility function, homogenous expectations from investors, no capital market frictions such as tax and transaction costs, short sales are allowed, investors can borrow and lend at risk-free rate, investments are infinitely divisible and all assets are marketable. Another assumption in quantile regression as well as OLS is that the error terms are independently and identically distributed. In the second-pass regression, an important assumption is that the relationship between the equity return and different factors is linear. Six key questions will be addressed in this research:

- What are the numbers and percentages of significant betas and other factors under OLS and quantile regression?
• Which dataset explains equity returns better for the CAPM and the Fama and French model, domestic or international?

• Is beta for each company constant or not across the quantiles?

• Is the Jensen Alpha (the intercept) under OLS positive or negative? This is a by-product of this research, which measures whether these particular equities in this study perform better than the market index or not.

• In the second-pass of testing the CAPM and the Fama and French model, previous results under which dataset have more explanatory power for the subsequent equity returns?

• Among the first-pass regression results from OLS and quantile regression, which one could provide a more convincing result in the second-pass regression?

3.2. The Process of First-pass and Second-pass Regression

The methodology of testing the CAPM provided by Black, Jensen and Scholes(1972) and Fama and MacBeth (1974) involves two major steps: the first-pass regression and the second-pass regression. The first-pass regression of testing the CAPM regresses the equity or portfolio return on the market return in a time-series dataset, and the regression line is called the characteristic line. The slope coefficient of the characteristic line is the beta for the particular share or portfolio. For the Fama and French model, the first-pass regression regresses the equity return on the market return, the size factor and the book-to-market (BM) factor. The calculation method for the size factor and BM factor has been mentioned in section 1.1. This research will use both OLS and quantile regression method in the first-pass regression.

For testing the CAPM, the second-pass regression regresses the return of the equity or
portfolio on the beta estimated by the first-pass regression in a cross-sectional dataset. This process checks the relationship between the equity return and the beta, and the regression line is called the security-market line (SML). For the Fama and French model, this research regresses the portfolio returns on the slope coefficients of size factor and BM factor estimated by the first-pass regression respectively. Coefficients evaluated by OLS and quantile regression in the first-pass regression will be applied in the second-pass of testing the CAPM and the Fama and French model, as well as the results estimated in the domestic and international datasets. Section 3.3 and 3.4 below reveal the detailed information.

3.3. The First-pass Regression Models

The first-pass regression uses time-series data for each company in 1989-2009. The 20-year timeline has been divided into four segments, and each of them contains five years time-series data. This study uses both OLS and quantile regression methods to run the first-pass regression in the domestic and international dataset.

**Model 1: Testing the CAPM in the Domestic Dataset**

\[ H_0: \hat{\beta}_t = 0. \text{ (Beta estimated by the domestic dataset does not explain equity return)} \]

\[ H_1: \hat{\beta}_t \neq 0. \text{ (Beta estimated by the domestic dataset explains equity return)} \]

\[ R_{it} = \alpha_i + \hat{\beta}_t (R_{mt} - R_{ft}) + \varepsilon_{it} \quad (12) \]

\( R_{it} \) = individual company’s monthly return

\( R_{ft} \) = 90 day bank bills in Australia

\( \alpha_i \) = intercept of regression

\( \hat{\beta}_t \) = slope factor of excess market return
Model 2: Testing the CAPM in the International Dataset

\[ R_{it} - R_{ft} = \tilde{\alpha}_t + \tilde{\beta}_t (R_{mt} - R_{ft}) + \tilde{\varepsilon}_{it} \]  \hspace{1cm} (13)

where:

- \( R_{it} \) = individual company’s monthly return
- \( R_{ft} \) = one-month Treasury bill rate from Ibbotson Associates, has been transferred into Australian dollar
- \( R_{mt} \) = the value-weighted return on all NYSE, AMEX, and NASDAQ stocks from CRSP, has been transferred into Australian dollar
- \( \tilde{\alpha}_t \) = intercept of regression
- \( \tilde{\beta}_t \) = slope factor of excess market return
- \( \tilde{\varepsilon}_{it} \) = error term

**H0:** \( \tilde{\beta}_t = 0 \) (Beta estimated by the international dataset does not explain equity return)

**H1:** \( \tilde{\beta}_t \neq 0 \) (Beta estimated by the international dataset explains equity return)

Model 3: Testing the Fama and French Model in the Domestic Dataset

\[ R_{it} = \tilde{\alpha}_t + \tilde{\beta}_t (S - B) + \tilde{\gamma}_t (H - L) + \tilde{\varepsilon}_{it} \]  \hspace{1cm} (14)

where:

- \( R_{it} \) = individual company’s monthly return
- \( R_{ft} \) = 90 day bank bills rate in Australia

**H0:** \( \tilde{\beta}_t = \tilde{\varepsilon}_t = \tilde{\gamma}_t = 0 \) (Slope coefficients estimated by the domestic dataset do not explain equity return)

**H1:** \( \tilde{\beta}_t \neq \tilde{\varepsilon}_t \neq \tilde{\gamma}_t \neq 0 \) (Slope coefficients estimated by the domestic dataset explain equity return)
\( \alpha_t \) = intercept of regression

\( \beta_t \) = slope factor of excess market return

\( R_{mt} \) = monthly return of All Ordinaries

\( \xi_t \) = slope of the size factor

\( \eta_t \) = slope of the book-to-market ratio factor

\( S-B \) = the difference of monthly return between S&P/ASX 300 and S&P/ASX 20 index

\( H-L \) = the book-to-market ratio factor from French’s website, limited to the year 2007

**Model 4: Testing the Fama and French Model in the International Dataset**

H0: \( \beta_t = \xi_t = \eta_t = 0 \). (Slope coefficients estimated by the international dataset do not explain equity return)

H1: \( \beta_t \neq \xi_t \neq \eta_t \neq 0 \). (Slope coefficients estimated by the international dataset explain equity return)

\[ R_{it} - R_{ft} = \tilde{\alpha}_t + \tilde{\beta}_t (R_{mt} - R_{ft}) + \tilde{\xi}_t \bar{S} + \tilde{\eta}_t (H - L) + \varepsilon_{it} \] (15)

\( R_{it} \) = individual company’s monthly return

\( R_{ft} \) = one-month Treasury bill rate from Ibbotson Associates, has been transferred into Australian dollar

\( \tilde{\alpha}_t \) = intercept of regression

\( \tilde{\beta}_t \) = slope factor of excess market return

\( \tilde{\xi}_t \) = slope of the size factor

\( \tilde{\eta}_t \) = slope of the book-to-market ratio factor
S-B = the size factor from French’s website, has been transferred into Australian dollar
H-L = the book-to-market ratio factor from French’s website, has been transferred into
Australian dollar

3.4. Results Combination, Portfolio Formation and the Second-pass Regression Models

After the first-pass regression, results estimated under OLS and quantile regression will be applied in the second-pass of testing the CAPM and the Fama and French model. Due to the lack of numbers of sorted portfolios in this research, OLS will be applied only in the second-pass regression. Theoretically the first-pass regression results provided by the quantile regression should have more explanatory power compared with OLS: in contrast to OLS estimates around the mean, combining the quantile regression coefficients by certain weighting schemes could probably have the advantage to yield more robust measurements of effect of the factors. Following with the methodology provided by Allen and Singh (2010), this study uses a symmetric weighting scheme to combine the different coefficients provided by the quantile regression at each of the quantile levels (0.1-0.9). A single coefficient for each of the three factors will be provided after the combination of quantile regression results:

\[
\beta_t = 0.04\beta_{(0.1,t)} + 0.06\beta_{(0.2,t)} + 0.1\beta_{(0.3,t)} + 0.15\beta_{(0.4,t)} + 0.3\beta_{(0.5,t)} + 0.15\beta_{(0.6,t)} \\
+ 0.1\beta_{(0.7,t)} + 0.06\beta_{(0.8,t)} + 0.04\beta_{(0.9,t)}
\]

(16)

\[
s_t = 0.04s_{(0.1,t)} + 0.06s_{(0.2,t)} + 0.1s_{(0.3,t)} + 0.15s_{(0.4,t)} + 0.3s_{(0.5,t)} + 0.15s_{(0.6,t)} \\
+ 0.1s_{(0.7,t)} + 0.06s_{(0.8,t)} + 0.04s_{(0.9,t)}
\]

(17)

\[
h_t = 0.04h_{(0.1,t)} + 0.06h_{(0.2,t)} + 0.1h_{(0.3,t)} + 0.15h_{(0.4,t)} + 0.3h_{(0.5,t)} + 0.15h_{(0.6,t)} \\
+ 0.1h_{(0.7,t)} + 0.06h_{(0.8,t)} + 0.04h_{(0.9,t)}
\]

(18)
This paper uses Fama and MacBeth (1974)'s methodology to sort the different equities into portfolios. Fifty equities are grouped into seventeen portfolios in the second-pass regression. Among the seventeen portfolios, sixteen of them contain three equities and one of them contains two equities. The procedure of forming portfolios is on the basis of ranked values of $\hat{\beta}_t$, $s_i$ and $f_i$ for individual securities. However the process could result in a regression phenomenon that in a cross section of $\hat{\beta}_t$, high observed $\hat{\beta}_t$ tends to be above the corresponding true $\beta_t$, and low observed $\hat{\beta}_t$ tends to be below the true $\beta_t$. This phenomenon could be avoided to some extent by forming portfolios from ranked $\hat{\beta}_t$ computed from data for one time period but then using a subsequent period to obtain the $\hat{\beta}_p$ for these portfolios that are used to test the two-parameter model (Fama and MacBeth, 1974).

This research follows Fama and MacBeth (1974) to use the Blume (1970)'s method to calculate the betas and other factors of the portfolios. For any portfolio $p$, defined by the weights $x_{tp}$,

$$\hat{\beta}_p = \frac{\text{c}\text{o}\text{v}(\hat{R}_p, \bar{R}_m)}{\text{c}\text{o}\text{v}(\hat{R}_t, \bar{R}_m)} = \sum_{i=1}^{N} x_{tp} \frac{\text{c}\text{o}\text{v}(\hat{R}_i, \bar{R}_m)}{\text{c}\text{o}\text{v}(\hat{R}_t, \bar{R}_m)} = \sum_{i=1}^{N} x_{tp} \hat{\beta}_i.$$  

(19)

The $\hat{\beta}_p$ can be much more precise estimated of true $\beta$'s than the $\hat{\beta}_t$ if the errors in $\hat{\beta}_t$ are substantially less than perfectly positively correlated.

<table>
<thead>
<tr>
<th>Table 1: Portfolio Formation, Estimation and Testing Periods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Periods</td>
</tr>
<tr>
<td>Real return in testing period</td>
</tr>
<tr>
<td>No. of equity in portfolios</td>
</tr>
<tr>
<td>No. of portfolios</td>
</tr>
</tbody>
</table>
Table 1 above has demonstrated that three testing periods are generated to run the second-pass of testing the CAPM and the Fama and French model. The real return of equity and risk-free rate one-year lagged are used as the dependent variable, and the independent variable contains betas estimated by OLS and quantile regression in previous time-period. The formula below has the detailed explanation:

\[ R_{p(t+1)} - R_{f(t+1)} = \tilde{\alpha}_j + \tilde{\gamma} \beta_{pt} + \tilde{\varepsilon}_{it} \]  \hspace{1cm} (20)

For the testing period 1, the \( R_{p(t+1)} \) is the real return of the portfolio in 2000, and the \( R_{f(t+1)} \) is the risk-free rate at the same time. A reason for using the real equity return one-year lagged in the second-pass regression is that this research focuses on the predictive power of the independent variable. The slope coefficient \( \tilde{\gamma} \) will be significant if any independent variable estimated in 1995-1999 (e.g., portfolio beta, the coefficient of size or BM factor in the first-pass regression) has some explanatory power for the subsequent real equity return (2000). The independent variable in equation (20) is the beta of the portfolio estimated in the previous time period 1995-1999. The portfolio forming process is based on the equities’ beta values in 1989-1994, as suggested by Fama and MacBeth (1974). This study uses the adjusted R-square as the benchmark to check the statistical explanatory power of the security-market line (SML).

As for the Fama and the French model, this research checks the relationship between the real equity return and the size and book-to-market factor individually. The formulas of the second-pass regression are listed below:

\[ R_{p(t+1)} - R_{f(t+1)} = \tilde{\alpha}_j + \tilde{\gamma} S_{pt} + \tilde{\varepsilon}_{it} \] \hspace{1cm} (21)

\[ R_{p(t+1)} - R_{f(t+1)} = \tilde{\alpha}_j + \tilde{\gamma} h_{pt} + \tilde{\varepsilon}_{it} \] \hspace{1cm} (22)

where \( S_{pt} \) and \( h_{pt} \) are coefficients of size and BM factor in the first-pass regression.
3.5. Data Collection

This research chooses a 20-year timeline from 1989 to 2010 and divides them into four segments. The reason for using a 5-year time-period window to test CAPM and the Fama and French model is that generally it could provide more accurate results than other timelines (Bartholdy and Peare, 2002). Fifty companies' monthly share prices are chosen from Datastream. There are two reasons for choosing monthly data instead of weekly or daily: 1), the SMB and HML factors proposed by Fama and French (1992) are calculated by monthly data; 2), some shares have activities such as issuing dividends, stop trading in some days or having other situations to make the trading days not the same. Using the weekly or daily data could cause inconsistency of dates across the 50 companies.

This study uses the 90-day bank bills rate as a proxy for the risk free rate in Australia, and the one-month Treasury bill rate from Ibbotson Associates for the overseas markets. The factors for testing the Fama and French model in the first-pass regression, SMB and HML, are drawn from French’s website (French, n.d.). These factors are not perfect for the Australian equity market: the BM factor is limited to 2007; and there is no SMB factor for the Australian security market. This research uses the difference of monthly returns between S&P/ASX300 and S&P/ASX20 as a proxy for the size factor, since SMB means the difference between returns in small and large companies. The S&P/ASX300 is composed of 300 Australian companies and the S&P/ASX20 is composed of the 20 largest Australian companies. The difference of monthly returns between them is then a suitable proxy for the size factor.

The number of firms in the dataset may not be enough to reflect the whole Australian equity market, since this paper uses a timeline of 20 years and many companies do not have such a long trading history. For the limited BM factor, this study focuses on the results evaluated from the international dataset in 2005-2009.
Chapter 4. The First-pass Regression Results

4.1. The Performance of the CAPM across Different Quantiles

Over the 20-year period, 12.5% of the betas under the CAPM are significant according to OLS regression. Most of the betas are insignificant in the period 1989-1994 and 2000-2004: the percentages of significant results are only 4% and 7% respectively. However, during the period of 2005-2009, which is the boom period in the equity market following the Global Financial Crisis (GFC), the result for the first-pass regression is the best over the 20 years: 14 out of 50 companies' betas are significant in the domestic dataset, and 11 out of 50 betas are significant in the international data. Compared with the OLS, an important result in quantile regression is that the betas for each company vary substantially across the quantiles. The blue and the black lines in Figure 1 demonstrate OLS and quantile estimates respectively.

**Figure 1: ANZ's Betas for the CAPM during 2005-2009 in the Domestic Dataset**
Figure 1 reveals the variation of betas for the particular equity ANZ. It is obvious that the slope coefficient changes substantially across the quantiles from 1.14 to 0.01. This result indicates that using one regression coefficient based on the average of the distribution to evaluate equities’ risk-return relationship could be inaccurate. Figure 2 below stacks the betas of quantile regression in the 50 companies together:

**Figure 2: Domestic Betas for the CAPM in 2005-2009**

![Domestic betas for the CAPM in 2005-2009](image)

Figure 2 demonstrates the variation of betas from -1 to 2.5 in the domestic dataset during the period 2005-2009. Not only betas for ANZ vary substantially across the quintiles, all the companies in this research have variable betas according to the result of quantile regression. The slope coefficients vary substantially from, for example, 2.06 at quantile 0.1 to 0.03 at quantile 0.8 (beta for Campbell Brothers). Many shares such as Leighton Holdings and GPT have extreme betas at quantile 0.1 and 0.9. Compared with the extreme values of betas in the tails, the overall variation of betas is flat when the quantiles are close to the median. This result is consistent with Barnes and Hughes (2002) and Allen et al. (2009). The answer for the third research question is clear: the betas are not constant across quantiles.
As for the significant numbers of betas, quantile regression also provides a more comprehensive picture since this method divides the dataset into different segments. Each company in this research has nine slope coefficients from quantile 0.1 to 0.9. The general result is consistent with OLS: both the domestic and international dataset demonstrate that the CAPM performs best in the first-pass regression during the period 2005-2009. This time period not only contains the largest number of significant betas, but also the largest number of positive significant betas. Most of the significant coefficients in period 1995-1999 are negative, and this phenomenon will be discussed in section 4.5. Table two reveals the numbers of significant betas in domestic and international datasets under quantile regression during the period 1989-2009. Note that the total numbers of betas estimated in each five-year time period are 50 and 450 respectively for OLS and quantile regression.

Table 2: Numbers and Percentages of Significant Betas in the Domestic and International Dataset Estimated by Quantile Regression

[Note: the regression formula is: $R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \epsilon_{it}$. Dome. and Inter. in this table represent “domestic” and “international” respectively.]

<table>
<thead>
<tr>
<th>Period</th>
<th>Dome. beta</th>
<th>Significant percentage</th>
<th>Inter. beta</th>
<th>Significant percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Significant no.</td>
<td>1989-1994</td>
<td>58</td>
<td>12.89%</td>
<td>91</td>
</tr>
<tr>
<td>Positive sig. no.</td>
<td>108</td>
<td>24.00%</td>
<td>86</td>
<td>19.11%</td>
</tr>
<tr>
<td>Significant no.</td>
<td>1995-1999</td>
<td>3</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>Positive sig. no.</td>
<td>2000-2004</td>
<td>74</td>
<td>16.44%</td>
<td>27</td>
</tr>
<tr>
<td>Significant no.</td>
<td>2005-2009</td>
<td>132</td>
<td>30.89%</td>
<td>116</td>
</tr>
</tbody>
</table>

Note: the regression formula is: $R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \epsilon_{it}$. Dome. and Inter. in this table represent “domestic” and “international” respectively.
According to OLS results, the significant numbers between domestic and international beta are close to each other: during the twenty-year time period, 27 out of 200 domestic betas are significant; while the number in the international dataset is 23. However Table 2 above indicates that the international dataset performed slightly better in the quantile regression: overall, 395 international betas are significant, and the significant number in the domestic dataset is 379. Results estimated in the latter dataset have more significant ratios in the periods 1995-1999 and 2005-2009, and overall the significant percentages of betas in the international dataset are not as variable as those in domestic dataset in different periods.

4.2. Betas in the Fama and French Model across Different Quantiles

The overall performance of the market factor in the Fama and French model and the CAPM has some consistencies, generally, the correlation between the betas estimated by the CAPM and the Fama and French model under both the OLS and quantile regression is larger than 0.8. Like the variance of betas in the CAPM across the quantiles, betas in the Fama and French model also vary significantly; however, the general tendency is similar to the CAPM in the same period.

It is apparent that Figure 3 and Figure 4 have some similarities, especially for equities such as Adelaide Brighton, Anglo and Coca-Cola. For the share Coca-Cola (the blue panel), both of these two figures reveal that betas in lower quantile have extreme values: approximately 1.6 from the result of the CAPM and 2.0 from the Fama and French model. Anglo (the purple panel) has larger values of beta in quantile 0.2-0.8, and betas in the tails are much smaller in both of these two figures. As for other companies, the moving tendency of betas across the quantile is generally similar. The colour for each company in Figure 3 and Figure 4 is the same.
Figure 3 & 4: International Betas in the CAPM and the Fama and French model in 1995-1999

International beta for CAPM in 1995-1999:
- Adelaide brighton
- ALUMINA
- ALESO
- ANGLO
- BHP
- ABERDEEN LEADERS
- AMCOR
- ANSELL
- ANZ
- BOQ
- BLACKMORES
- BRAMABLES
- CALTEX AUSTRALIA
- CAMPBELL BROTHERS
- CARLTON
- INVESTMENTS
- COAL & ALLD.INDS

International beta for FF in 1995-1999:
- Adelaide brighton
- ALUMINA
- ALESO
- ANGLO
- BHP
- ABERDEEN LEADERS
- AMCOR
- ANSELL
- ANZ
- BOQ
- BLACKMORES
- BRAMABLES
- CALTEX AUSTRALIA
- CAMPBELL BROTHERS
- CARLTON INVESTMENTS
- COAL & ALLD.INDS
- COCA-COLA
- COFFEE INTERNATIONAL
- COUNTRY ROAD
- COVENTRY GROUP
- CRANE
- CSR
- CUDECO
- ELDERS
- ENERGY RES. OF AUS
- GOWING BROS
- GPT
- HILLS
- ILUKA RESOURCES
- KRESTA HOLDINGS
Results from OLS demonstrate that the number of significant beta values in the CAPM is larger than in the Fama and French model. 27 betas out of 200 in the domestic dataset are significant in the twenty-year time period, and the significant number in the international dataset is 23 under the CAPM. In the Fama and French model, 17 betas in domestic dataset are significant, while in the international dataset the significant number is 15. However quantile regression provides a different picture in Table 3 below.

Table 3: Comparison of the Market Factors in the CAPM and the Fama and French Model under Quantile Regression

[Note: this table compares the numbers and percentages of significant slope coefficient \( \hat{\beta} \) in the CAPM and the Fama and French model respectively.]

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1989-1994</td>
<td>58</td>
<td>12.8%</td>
<td>91</td>
<td>20.22%</td>
<td>93</td>
<td>20.67%</td>
<td>111</td>
<td>24.67%</td>
</tr>
<tr>
<td>Positive sig.no.</td>
<td>40</td>
<td></td>
<td>13</td>
<td></td>
<td>50</td>
<td></td>
<td>22</td>
<td></td>
</tr>
<tr>
<td>1995-1999</td>
<td>108</td>
<td>24.00%</td>
<td>86</td>
<td>19.11%</td>
<td>138</td>
<td>30.67%</td>
<td>118</td>
<td>26.22%</td>
</tr>
<tr>
<td>Positive sig.no.</td>
<td>3</td>
<td>27.00%</td>
<td>9</td>
<td>9.00%</td>
<td>9</td>
<td>9.00%</td>
<td>2</td>
<td>2.00%</td>
</tr>
<tr>
<td>2000-2004</td>
<td>74</td>
<td>16.44%</td>
<td>90</td>
<td>21.78%</td>
<td>111</td>
<td>24.67%</td>
<td>146</td>
<td>32.44%</td>
</tr>
<tr>
<td>Positive sig.no.</td>
<td>32</td>
<td>46.00%</td>
<td>69</td>
<td>21.78%</td>
<td>69</td>
<td>21.78%</td>
<td>116</td>
<td>32.44%</td>
</tr>
<tr>
<td>2005-2009</td>
<td>139</td>
<td>30.89%</td>
<td>120</td>
<td>26.57%</td>
<td>129</td>
<td>28.67%</td>
<td>88</td>
<td>19.56%</td>
</tr>
<tr>
<td>Positive sig.no.</td>
<td>138</td>
<td>116.00%</td>
<td>63</td>
<td>28.67%</td>
<td>63</td>
<td>28.67%</td>
<td>61</td>
<td>19.56%</td>
</tr>
<tr>
<td>Sum of sign. no./total no. of betas</td>
<td>379/1800</td>
<td>21.06%</td>
<td>395/1800</td>
<td>21.94%</td>
<td>471/1800</td>
<td>26.17%</td>
<td>463/1800</td>
<td>25.72%</td>
</tr>
</tbody>
</table>

It is apparent that betas estimated by the Fama and French model have larger significant numbers and percentages than those in the CAPM in both the domestic and international datasets during three time periods: 1989-1994, 1995-1999 and 2000-2004. The CAPM performs better than the Fama and French model only in 2005-2009. Both of these two models demonstrate that results estimated from international dataset have a better performance in period 1989-1994 and 2000-2004.
4.3. The Size Factor across Different Quantiles

Both OLS and quantile regressions demonstrate that the size factor is the least ambiguous among all the factors in the first-pass regression; this means that it is the best factor for explaining the risk-return relationship in the Fama and French model if the benchmark is the significant numbers. This result is consistent with previous research (Gaunt, 2004, Kassimatis, 2008, Brailsford and O’ Brien, 2008, O’ Brien, Brailsford and Gaunt, 2009, Gharghori, Chan and Faff, 2007). The size factor has more significant numbers in OLS among the three factors: overall 59 out of 400 size factors are significant. The number of significant betas in the CAPM and in the Fama and French model are 50 and 32, respectively. For comparison, the equivalent number for b-m factors is 39. As for results in different datasets, 36 out of 200 size factors in the international dataset are significant according to OLS, while in the domestic dataset the number is 23.

Similar to the variance of betas in the CAPM, the coefficient of size factor also varies substantially across the quantiles. Below is an example of the size factors’ variance in the quantile regression:

Figure 5: The Size Factor According to the International Dataset in 2000-2004
A limitation in this research is that there is no available data for the SMB factor in the Australian security market, and this study uses the difference of returns between S&P/ASX300 and S&P/ASX20 as a proxy. Accordingly, the slope coefficient of domestic size factor has a much larger variance compared with the international size coefficient. However, based on the number of significant coefficients in the quantile regression, the size factor is also the best factor in explaining risk-return relationship in the Fama and French model.

Table 4: Numbers and Percentages of Significant Size Factors in Different Datasets under Quantile Regression

[Note: the numbers and percentages of significant slope coefficient $\widehat{\beta}$ are generally larger than betas in Table 3.]

<table>
<thead>
<tr>
<th>Period</th>
<th>Dome. size</th>
<th>Significant percentage</th>
<th>Inter. size</th>
<th>Significant percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Significant no.</td>
<td>1989-1994</td>
<td>144</td>
<td>32.00%</td>
<td>167</td>
</tr>
<tr>
<td>Positive sig.</td>
<td>20</td>
<td></td>
<td></td>
<td>164</td>
</tr>
<tr>
<td>Significant no.</td>
<td>1995-1999</td>
<td>94</td>
<td>20.89%</td>
<td>114</td>
</tr>
<tr>
<td>Positive sig.</td>
<td>59</td>
<td></td>
<td></td>
<td>93</td>
</tr>
<tr>
<td>Significant no.</td>
<td>2000-2004</td>
<td>107</td>
<td>23.78%</td>
<td>146</td>
</tr>
<tr>
<td>Positive sig.</td>
<td>75</td>
<td></td>
<td></td>
<td>116</td>
</tr>
<tr>
<td>Significant no.</td>
<td>2005-2009</td>
<td>129</td>
<td>28.67%</td>
<td>71</td>
</tr>
<tr>
<td>Positive sig.</td>
<td>83</td>
<td></td>
<td></td>
<td>30</td>
</tr>
</tbody>
</table>

Table 4 demonstrates that the slope coefficients of size factor estimated by the international dataset perform better than in the domestic dataset along the timeline except during 2005-2009 under quantile regression. Among these four time periods, period 1989-1994 captures the largest significant number and percentage of the size factor. The number of significant values (absolute and percentage of total) for the size factor is the largest among the three factors in the Fama and French model.
4.4. The Book-to-Market Factor across Different Quantiles

The first-pass regression demonstrates that the BM effect is not as influential as the size effect. According to the OLS result, 39 out of 400 b-m coefficients are significant. Results of quantile regression in Table 5 indicate that the b-m factor performs slightly better than the CAPM in Table 2, but the effect is vague compared with the size factor. This is also in accordance with the previous research (e.g., Halliwell, 1999, Gaunt, 2004). Besides, the variance of coefficients across the quantiles is also substantial (see Appendix A1).

Table 5: Numbers and Percentages of Significant b-m Factors in Different Datasets under Quantile Regression

[Note: the number and percentage of significant slope coefficient in the international dataset during 2005-2009 are much larger than other values in Table 5]

<table>
<thead>
<tr>
<th>Period</th>
<th>Dome. b-m</th>
<th>Significant percentage</th>
<th>Inter. b-m</th>
<th>Significant percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1989-1994</td>
<td>108</td>
<td>24.00%</td>
<td>86</td>
<td>19.11%</td>
</tr>
<tr>
<td>Positive sig.no.</td>
<td>92</td>
<td></td>
<td>76</td>
<td></td>
</tr>
<tr>
<td>1995-1999</td>
<td>76</td>
<td>16.89%</td>
<td>109</td>
<td>24.22%</td>
</tr>
<tr>
<td>Positive sig.no.</td>
<td>34</td>
<td></td>
<td>87</td>
<td></td>
</tr>
<tr>
<td>2000-2004</td>
<td>90</td>
<td>20.00%</td>
<td>120</td>
<td>26.67%</td>
</tr>
<tr>
<td>Positive sig.no.</td>
<td>19</td>
<td></td>
<td>92</td>
<td></td>
</tr>
<tr>
<td>2005-2009</td>
<td>105</td>
<td>23.33%</td>
<td>157</td>
<td>34.89%</td>
</tr>
<tr>
<td>Positive sig.no.</td>
<td>32</td>
<td></td>
<td>154</td>
<td></td>
</tr>
<tr>
<td>Sum of sign. no./total no. of BM coefficients</td>
<td>379/1800</td>
<td>21.06%</td>
<td>472/1800</td>
<td>26.22%</td>
</tr>
</tbody>
</table>

The international data in period 2005-2009 is more robust than the domestic data since the Australian b-m factors on French’s website (French, n.d.) are limited to 2007. It should be noticed that the b-m factor performs relatively well during this period,
especially in the international dataset. This result provides some evidence that the b-m factor is weighted more than other time periods when the economy experiences a recession.

Similar to the size factor, the b-m factor has more significant results in the international than the domestic dataset. In OLS, the number of significant coefficients in the domestic dataset is 11; however, the number in the international dataset is 28. Table 5 above also reveals that the b-m factor under the quantile regression performs better in the international dataset except in period 1989-1994.

4.5. Negative Beta

This section focuses on the results of testing the CAPM model. It is surprising to find out that there are many negative betas in both OLS and quantile regression, especially in the period 1995-2004. Among the 108 significant betas in the domestic dataset during 1995-1999, only three are positive. In the international dataset, 27 out of 86 significant results are positive. Another example is in 2000-2004: 32 out of 74 significant betas in the domestic dataset are positive; while 46 out of 98 significant coefficients in the international dataset are positive. This extreme situation was not sustained after 2004, since in 2005-2009 138 out of 139 significant results are positive in the domestic dataset and 116 out of 120 results are positive in the international dataset.

Ross and Westerfield (1988) explained that the asset with a negative beta has a negative risk premium, which means that the expected return on the particular asset is less than the risk-free rate of return on T-bills. In the U.S. market, Tinic and West (1984) found a negative risk-return relationship for several months during the 1980s. Coggin and Hunter (1985) revealed a negative relation between betas and returns for large firms. Fama and Schwert (1977) documented that fitted values of the risk
premium sometimes are negative in the U.S. equity market. Cloninger, Waller, Bendeck and Lee (2004) used data gleaned from the CRSP tapes, and betas were derived for all NYSE/AMEX firms during the period 1987-1995; the number of negative beta securities ranged from 354 (1988) to 961 (1995), representing an average of 10% of total betas. For European markets, Hawawini (1983) found a negative risk and return relationship in the French stock market. The number of negative betas can be substantial not only in the U.S. and European market, but also in the Asian equity market: Mok et al. (1990) found a negative risk-return relationship for the period 1980-1989 after investigating the returns of 37 Hong Kong Index constituent stocks. Chui (1991) indicated a negative risk-return relationship for the period 1980-1990 using weekly returns of 33 stocks. Generally, the empirical results show that the risk-return relationship in Hong Kong for the period 1980-2000 is negative and the movement of stocks is asymmetric. All the findings above contradict the prediction of the unconditional CAPM.

This research reveals that the situation of negative betas also exists in the Australian equity market according to both OLS and quantile regression results. The result of negative beta, to some extent, reflects that the explanatory power of the CAPM is low. This is consistent with the adjusted R-square; overall the average of the adjusted R-square for the CAPM during the twenty-year is very low; and in some cases the adjusted R-square is even negative.

There are also explanations of negative betas under the CAPM framework. Ross and Westerfield (1984) argued that the opposite movements of a negative beta makes negative beta assets particularly valuable additions to any portfolio, “because they are such valuable additions, they must offer lower expected returns or they would offer an arbitrage opportunity that all investors would flock to.” (Ross and Westerfield, 1984). Boudoukh et al. (1993) indicated that risk-averse investors are willing to hold a market portfolio that is riskier but earns a lower return than the risk-free asset in periods of high expected inflation, especially in the downward sloping term structures. From a
consumption-based asset pricing perspective, the implication of negative beta is that
the conditional covariance between the marginal rate of substitution and the excess
return on the market is positive. Thus, negative risk-return relationships can still occur
when investors are risk-averse and hence the CAPM is not contradicted. (Boudoukh et
al, 1993).

Overall, this study reveals that negative betas were common during the period
1995-2004. Although there are some explanations for negative betas, the low adjusted
R-square and the similarity in the Asian equity market document the weak explanatory
power of the CAPM.

4.6. The Jensen Alpha in CAPM and the Fama and French

Model under OLS

The Jensen alpha is useful for evaluating mutual-fund performance. This research
focuses on the equity performance, and the Jensen alpha is a by-product of checking
this performance. As a result, only the Jensen Alpha estimated by OLS will be
analyzed in this study. This part of result answers the fourth research question. Under
the Jensen Alpha framework, the CAPM and the Fama and French model are the
benchmarks for evaluating the risk-return relationship. According to the formula
\[ R_i - R_f = \alpha_j + \beta_1 (R_m - R_f) + \beta_2 (S - B) + \beta_3 (H - L) \]
\[ \alpha_j \] is positive when the particular equity or the portfolio outperforms the market; and vice versa. Table 6 below
demonstrates the overall performance of the 50 equities.

The average Jensen Alpha values in the fifty companies are generally negative in
period 1989-1994, 1995-1999 and 2005-2009 under OLS, which means that overall the
fifty equities outperformed the market only in the period 2000-2004. The general
tendency of median values is consistent with mean values: most of them over the
twenty-year period are negative.
Table 6: Summary of the Jensen Alpha in Different Time Periods Estimated by the CAPM and the Fama and French Model

<table>
<thead>
<tr>
<th></th>
<th>Mean Value</th>
<th>Median Value</th>
<th>Maximum</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1989-1994</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( a1 ) = The Jensen Alpha estimated by the CAPM in the domestic dataset</td>
<td>-0.0047</td>
<td>-0.0043</td>
<td>0.0280</td>
<td>-0.0389</td>
</tr>
<tr>
<td>( a2 ) = The Jensen Alpha estimated by the CAPM in the international dataset</td>
<td>-0.0012</td>
<td>-0.0007</td>
<td>0.0371</td>
<td>-0.0433</td>
</tr>
<tr>
<td>( a3 ) = The Jensen Alpha estimated by the FF Model in the domestic dataset</td>
<td>-0.0070</td>
<td>-0.0061</td>
<td>0.0254</td>
<td>-0.0501</td>
</tr>
<tr>
<td>( a4 ) = The Jensen Alpha estimated by the FF Model in the international dataset</td>
<td>-0.0015</td>
<td>-0.0012</td>
<td>0.0371</td>
<td>-0.0426</td>
</tr>
<tr>
<td><strong>1995-1999</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( a1 ) = The Jensen Alpha estimated by the CAPM in the domestic dataset</td>
<td>-0.0018</td>
<td>-0.0016</td>
<td>0.0252</td>
<td>-0.0465</td>
</tr>
<tr>
<td>( a2 ) = The Jensen Alpha estimated by the CAPM in the international dataset</td>
<td>-0.0020</td>
<td>-0.0006</td>
<td>0.0255</td>
<td>-0.0534</td>
</tr>
<tr>
<td>( a3 ) = The Jensen Alpha estimated by the FF Model in the domestic dataset</td>
<td>-0.0002</td>
<td>0.0017</td>
<td>0.0262</td>
<td>-0.0515</td>
</tr>
<tr>
<td>( a4 ) = The Jensen Alpha estimated by the FF Model in the international dataset</td>
<td>-0.0002</td>
<td>-0.0001</td>
<td>0.0261</td>
<td>-0.0577</td>
</tr>
<tr>
<td><strong>2000-2004</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( a1 ) = The Jensen Alpha estimated by the CAPM in the domestic dataset</td>
<td>0.0045</td>
<td>0.0046</td>
<td>0.0502</td>
<td>-0.0358</td>
</tr>
<tr>
<td>( a2 ) = The Jensen Alpha estimated by the CAPM in the international dataset</td>
<td>0.0049</td>
<td>0.0050</td>
<td>0.0515</td>
<td>-0.0365</td>
</tr>
<tr>
<td>( a3 ) = The Jensen Alpha estimated by the FF Model in the domestic dataset</td>
<td>0.0040</td>
<td>0.0038</td>
<td>0.0506</td>
<td>-0.0385</td>
</tr>
<tr>
<td>( a4 ) = The Jensen Alpha estimated by the FF Model in the international dataset</td>
<td>0.0014</td>
<td>0.0017</td>
<td>0.0456</td>
<td>-0.0609</td>
</tr>
<tr>
<td><strong>2005-2009</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( a1 ) = The Jensen Alpha estimated by the CAPM in the domestic dataset</td>
<td>-0.0015</td>
<td>-0.0016</td>
<td>0.0306</td>
<td>-0.0489</td>
</tr>
<tr>
<td>( a2 ) = The Jensen Alpha estimated by the CAPM in the international dataset</td>
<td>-0.0003</td>
<td>-0.0002</td>
<td>0.0301</td>
<td>-0.0482</td>
</tr>
<tr>
<td>( a3 ) = The Jensen Alpha estimated by the FF Model in the domestic dataset</td>
<td>0.0117</td>
<td>0.0059</td>
<td>0.0847</td>
<td>-0.0231</td>
</tr>
<tr>
<td>( a4 ) = The Jensen Alpha estimated by the FF Model in the international dataset</td>
<td>-0.0012</td>
<td>0.0003</td>
<td>0.0310</td>
<td>-0.0517</td>
</tr>
</tbody>
</table>
Although this research uses individual equity instead of portfolios in mutual funds to run the regression, the Jensen Alpha result is generally consistent with Jensen (1967): the mean and median values overall are negative, with the extreme values fluctuated from -0.061 to 0.085. The performance of equities among different time-periods is irregular: the situations where “winners tend to perform well and losers tend to perform poorly” and “winners tend to perform poorly and losers tend to perform well” both exist in this study, based on Jensen Alpha as the benchmark of equity performance. Some equities such as Mount, could have a negative Jensen Alpha and a low rank among the 50 equities during the period 1989-2004, and suddenly have a high rank and outperform the market in 2005-2009.

There are some discrepancies between the values of the Jensen Alpha estimated under different datasets (domestic or international datasets) and models (the CAPM or the Fama and French model); however, the ranks evaluated by these models are generally similar for the same time period: the ranking list has less discrepancy than three or four ranks, and some of the companies have the same rank in the CAPM and the Fama and French model.

### 4.7. Overall Comparison between the CAPM and FF Model

The results of OLS reveal that both of these models performed poorly during the period 1989-1994 and 2000-2004 relative to the other two time periods. Below is a table which summarises the number of significant coefficients under OLS:

**Table 7: Numbers of Significant Factors under OLS during the 20-Years**

[Note: the total number for each factor during one period is 50. The bold numbers are the largest significant numbers among the eight factors. Generally, the size factor in the international dataset outperforms other factors during the same period.]
The Fama and French model has more significant size coefficients than the beta in the CAPM during the period 1989-1994: 11 out of 50 size factors in the domestic dataset are significant; and 22 out of 50 size coefficients are significant in the international data. The performance of BM factor is slightly better than the CAPM in the international dataset. The percentages for significant outcomes are: 12.5% for beta in the CAPM, 8% for beta in the Fama and French model, 14.75% for the size factor and 9.75% for the BM factor, and 10.83% overall in the three-factor model.

Another important benchmark for evaluating the performance of these two models is the R-square. This study uses the adjusted R-square to compare the performance of the CAPM and the Fama and French model since the latter contains more than one factor:

**Table 8: The Adjusted R-square for the CAPM and the Fama and French Model under OLS**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Average of adjusted R square for the CAPM in the domestic dataset</td>
<td>-0.0007</td>
<td>0.0183</td>
<td>0.0017</td>
<td>0.0222</td>
</tr>
<tr>
<td>Average of adjusted R square for the CAPM in the international dataset</td>
<td>0.0066</td>
<td>0.0049</td>
<td>0.0055</td>
<td>0.0185</td>
</tr>
<tr>
<td>Average of adjusted R square for the FF in the domestic dataset</td>
<td>0.0339</td>
<td>0.0260</td>
<td>0.0038</td>
<td>0.0098</td>
</tr>
<tr>
<td>Average of adjusted R square for the FF in the international dataset</td>
<td>0.0494</td>
<td>0.0148</td>
<td>0.0294</td>
<td>0.0349</td>
</tr>
</tbody>
</table>
The overall performance of the CAPM and the Fama and French model in the first-pass regression is very poor according to the average of adjusted R-square in Table 8: the largest mean adjusted R-square of the fifty equities is only 0.0494. However, results in Table 8 are consistent with the previous conclusion: firstly, the adjusted R-squares in the international dataset are generally larger than in the domestic dataset; secondly, the Fama and French model generally has larger adjusted R-squares than the CAPM. The result that the three-factor model performs better than the CAPM is consistent with Fama and French (1996) and Bartholdy and Peare (2002).

Quantile regression reveals more significant coefficients than OLS: some of the insignificant factors around the mean here are significant at tails (0.1, 0.2, 0.8, 0.9). Table 9 summarizes the significant numbers of coefficients in the quantile regression. Betas estimated in the Fama and French model have larger significant percentages than those estimated in the CAPM except in the period 2005-2009. The size factor performs best among all the factors during the period 1989-1994 in both domestic and international datasets; during 1995-1999 and 2000-2004 it is also the best factor for explaining equity return and risk in the international dataset. Overall, the three factor model performs better than the CAPM: 2725 out of 10800 coefficients are significant under the Fama and French model (25.23% in total); while 774 out of 3600 betas are significant under the CAPM (21.5% in total). These results indicate that both the CAPM and the Fama and French model show some promise under the quantile regression; however, many coefficients of the market factor are negative. After deleting the negative betas, 11.53% of betas are significant in the CAPM model, while 10.42% of the betas in the Fama and French model are significant.

The international dataset performs better than the domestic dataset based on the total number of significant coefficients in the 20-year timeline except 2005-2009. During 2000-2004, all the factors (beta, size and BM) in the international dataset have larger significant percentages than those in the domestic dataset.
<table>
<thead>
<tr>
<th></th>
<th>Dome. beta</th>
<th>FF domes. beta</th>
<th>Domes. size</th>
<th>Domes. BM</th>
<th>Inter. beta</th>
<th>FF inter. beta</th>
<th>Inter. size</th>
<th>Inter. BM</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1989-1994</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Significant no.</td>
<td>58</td>
<td>93</td>
<td>144</td>
<td>108</td>
<td>91</td>
<td>111</td>
<td>167</td>
<td>86</td>
</tr>
<tr>
<td>Positive sig.no.</td>
<td>40</td>
<td>50</td>
<td>20</td>
<td>92</td>
<td>13</td>
<td>22</td>
<td>164</td>
<td>76</td>
</tr>
<tr>
<td>Percentage of sig. no.</td>
<td>12.89%</td>
<td>20.67%</td>
<td>32.00%</td>
<td>24.00%</td>
<td>20.22%</td>
<td>24.67%</td>
<td>37.11%</td>
<td>19.11%</td>
</tr>
<tr>
<td>Sum of significant no. in different datasets</td>
<td>403</td>
<td>455</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>1995-1999</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Significant no.</td>
<td>108</td>
<td>138</td>
<td>94</td>
<td>76</td>
<td>86</td>
<td>118</td>
<td>114</td>
<td>109</td>
</tr>
<tr>
<td>Positive sig.no.</td>
<td>3</td>
<td>9</td>
<td>59</td>
<td>34</td>
<td>27</td>
<td>50</td>
<td>93</td>
<td>87</td>
</tr>
<tr>
<td>Percentage of sig. no.</td>
<td>24.00%</td>
<td>30.67%</td>
<td>20.89%</td>
<td>16.89%</td>
<td>19.11%</td>
<td>26.22%</td>
<td>25.33%</td>
<td>24.22%</td>
</tr>
<tr>
<td>Sum of significant no. in different datasets</td>
<td>416</td>
<td>427</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>2000-2004</strong></td>
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<td></td>
<td></td>
<td></td>
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<tr>
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<td>111</td>
<td>107</td>
<td>90</td>
<td>98</td>
<td>114</td>
<td>146</td>
<td>120</td>
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<tr>
<td>Positive sig.no.</td>
<td>32</td>
<td>69</td>
<td>75</td>
<td>19</td>
<td>46</td>
<td>51</td>
<td>116</td>
<td>92</td>
</tr>
<tr>
<td>Percentage of sig. no.</td>
<td>16.44%</td>
<td>24.67%</td>
<td>23.78%</td>
<td>20.00%</td>
<td>21.78%</td>
<td>25.33%</td>
<td>32.44%</td>
<td>26.67%</td>
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<tr>
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<td>382</td>
<td>478</td>
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<td><strong>2005-2009</strong></td>
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<tr>
<td>Significant no.</td>
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<td>129</td>
<td>129</td>
<td>105</td>
<td>120</td>
<td>88</td>
<td>71</td>
<td>157</td>
</tr>
<tr>
<td>Positive sig.no.</td>
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<td>83</td>
<td>32</td>
<td>116</td>
<td>61</td>
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<td>154</td>
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<tr>
<td>Percentage of sig. no.</td>
<td>30.89%</td>
<td>28.67%</td>
<td>28.67%</td>
<td>23.33%</td>
<td>26.67%</td>
<td>19.56%</td>
<td>15.78%</td>
<td>34.89%</td>
</tr>
<tr>
<td>Sum of significant no. in different datasets</td>
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</table>
It is noteworthy that the size factor did not perform as well during 2005-2009, a boom period following with the GFC, as in the preceding periods. During 2005-2007, the equity index (All Ordinaries) increased from 4721.08 to 6853.57, while after 2008, the index slumped from 6853.57 to 3111.74. It is a time period which contains two extreme situations: extreme increase and decline. The performance of size factor here is not as influential as before; however, both the CAPM and the book-to-market ratio which had a fair performance previously performed better in this period.

4.8. Summary

According to the percentages of significant coefficients and the adjusted R-square under OLS, the CAPM did not perform adequately in explaining the risk-return relationship in the first-pass regression: the adjusted R-squares in Table 8 are very low. This attracts researchers to find other models or use other regression methods to explain realized returns. The Fama and French model has performed better in this study probably because it incorporates two important factors: size and the b-m ratio. The size factor, which has been regarded as the best factor in explaining the risk-return relationship, had the largest number of significant results among the three factors in both OLS and quantile regression. The performance of the b-m factor is vague compared with the size factor; however, under the quantile regression it yielded slightly more significant results than beta in the CAPM. The effect of the size and BM factor in explaining equity return is consistent with previous Australian research in section 2.2. Overall the average of adjusted R-square for the Fama and French model in Table 8 is larger than CAPM.

This study identified some negative betas in OLS and quantile regression. The situation of negative betas exists not only in the Australian equity market, but also in the U.S., European and Asian markets. Section 4.5 has provided some discussions for negative betas.
Quantile regression in this research provides more results than OLS since this regression method demonstrates the situation of different quantiles in the dataset. Another finding in this study is that the coefficients, including betas in the CAPM and all the factors in the Fama and French model, vary substantially across the quantile. This result is in accordance with previous U.S. and Australian research (e.g., Barnes and Hughes, 2002, Allen et al, 2009). Generally the result demonstrates that the international dataset has performed better. The first three research questions, including the numbers and percentages of significant factors, the performance of different datasets and the variation of factors, have been answered in chapter 4.

The average values of Jensen Alpha in these fifty equities are negative during the 20-year timeline except in 2000-2004. Generally, the ranking lists provided by the CAPM and the Fama and French model are similar. This is also the answer for the fourth research question.
This research also runs the second pass regression to check the predictive power of the CAPM and the Fama and French model. Both OLS and quantile regression result in the first-pass regression will be used as the independent variable in the second-pass regression. After the combination of quantile regression results in section 3.4, nine values across the quantile (0.1-0.9) become one slope coefficient. This coefficient contains not only the information in the median, but also in the tails. To interpret the second-pass regression results, four tables are generated according to different independent variables. Each table contains three time periods and four panels. Table 10 below reveals the statistic results of the second-pass regression under the CAPM.

5.1. The Predictive power of Betas in Different Models

An assumption in the second-pass of testing the CAPM is that the relationship between the equity return and beta is linear. In Table 10, the coefficient $\gamma$ varies from -0.0642 to 0.1966 during 1995-2009. Six out of twelve coefficients are positive. If the benchmark is that the relationship between equity return and beta is positive and linear, betas estimated from the international dataset in the first-pass regression previously perform better than those in the domestic dataset, since the former provides more positive coefficients. The implication that the international dataset performs better does not change according to the value of adjusted R-square. Under OLS, the adjusted R-squares in the international dataset are larger than those in the domestic dataset in 2000-2004 and 2005-2009; same as those in Panel C&D over 1995-1999 and 2000-2004. However, overall the adjusted R-squares are much lower than the results provided by Black, Jensen and Scholes (1972). Black et al. revealed that the R-square for beta is 0.98, and beta is the only determinant in evaluating equity risk and return relationship. Some of the adjusted R-squares here are even negative, which means the predictive power of the CAPM is poor in those particular periods.
<table>
<thead>
<tr>
<th>PERIOD</th>
<th>$\hat{\beta}_1$</th>
<th>t(\hat{\beta}_1)</th>
<th>p(\hat{\beta}_1)</th>
<th>Standard Error</th>
<th>Adjusted R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995-1999</td>
<td>-0.0210</td>
<td>-0.0346</td>
<td>0.1881</td>
<td>0.0298</td>
<td>0.0219</td>
</tr>
<tr>
<td>2000-2004</td>
<td>0.0143</td>
<td>1.0098</td>
<td>0.0121 **</td>
<td>0.0322</td>
<td>0.0215</td>
</tr>
<tr>
<td>2005-2009</td>
<td>0.0109</td>
<td>0.7643</td>
<td>0.0253</td>
<td>0.0235</td>
<td>0.0232</td>
</tr>
<tr>
<td>1995-1999</td>
<td>0.0212</td>
<td>0.0125</td>
<td>0.0219</td>
<td>0.0192</td>
<td>0.0189</td>
</tr>
<tr>
<td>2000-2004</td>
<td>-0.0102</td>
<td>-0.0135</td>
<td>0.0179</td>
<td>0.0200</td>
<td>0.0196</td>
</tr>
<tr>
<td>2005-2009</td>
<td>0.0005</td>
<td>0.0042</td>
<td>0.0027</td>
<td>0.0023</td>
<td>0.0023</td>
</tr>
<tr>
<td>1995-1999</td>
<td>-0.0144</td>
<td>-0.0144</td>
<td>0.0104</td>
<td>0.0204</td>
<td>0.0162</td>
</tr>
<tr>
<td>2000-2004</td>
<td>0.0020</td>
<td>0.0299</td>
<td>0.0230</td>
<td>0.0196</td>
<td>0.0230</td>
</tr>
<tr>
<td>2005-2009</td>
<td>0.0024</td>
<td>0.0179</td>
<td>0.0216</td>
<td>0.0203</td>
<td>0.0203</td>
</tr>
<tr>
<td>1995-1999</td>
<td>-0.0084</td>
<td>-0.0084</td>
<td>0.0139</td>
<td>0.0207</td>
<td>0.0187</td>
</tr>
<tr>
<td>2000-2004</td>
<td>0.0019</td>
<td>0.0196</td>
<td>0.0196</td>
<td>0.0187</td>
<td>0.0187</td>
</tr>
<tr>
<td>2005-2009</td>
<td>-0.0002</td>
<td>-0.0058</td>
<td>0.0032</td>
<td>0.0125</td>
<td>0.0025</td>
</tr>
</tbody>
</table>
The poor performance of the CAPM is in accordance with previous Australian study: Durack et al. (2004) indicated that the adjusted R-square for the traditional CAPM is 0.0725. The average values of adjusted R-square during these three testing periods in Panel A-D are 0.0479, 0.0193, 0.0505 and 0.1173 respectively, which are close to the result proposed by Durack et al. (2004).

This research also focuses on the comparison between OLS and quantile regression results. There are some similar results in Table 10 according to these two regression methods. Both of them provide negative coefficients in the same period: 1995-1999 and 2005-2009 in the domestic dataset, and 2005-2009 in the international dataset. The values of coefficients estimated by these two methods are close, however betas evaluated by the quantile regression provides two significant coefficients $\hat{\gamma}$ at 5% level, while only one coefficient is significant at 10% level by betas estimated by OLS. In this case quantile regression has provided a better result than OLS. Previous research such as Allen and Singh (2010) and Bassett and Chen (2001) indicate that factors estimated by quantile regression have more explanatory power than OLS in the area of portfolio management. This study provides similar results that factors in the CAPM and the Fama and French model (revealed in sections below) evaluated by quantile regression have better explanatory power to the subsequent equity returns.

Most of the intercepts are positive and significant in Table 10, which means that 1), the estimated intercepts are larger than the real risk-free rate; 2) a part of return cannot be fully explained by beta. The former is consistent with the result provided by Black, Jensen and Scholes (1972), Lintner (1966) and Fama and MacBeth (1974). Compared with intercepts estimated by OLS in the same dataset and time period, all the results estimated by betas under the quantile regression previously are closer to zero. Table 11 below reveals the results for the second-pass regression in testing the market factor under the Fama and French model. The slope coefficient $\hat{\gamma}$ is significant at 1% level during 2000-2004 in Panel C. Some intercepts, such as intercepts over the period 2000-2004 in all the four panels, are also significant in different statistical levels.
Table 11: Summary Results For the Second-pass Regression in Testing the Market Factor among the FF Model

\[ R_{p(t+1)} - R_{f(t+1)} = \alpha_j + \gamma_{\text{FFR}} + \varepsilon_t \]

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively.

<table>
<thead>
<tr>
<th>PERIOD</th>
<th>( \hat{\alpha}_j )</th>
<th>( \hat{\gamma} )</th>
<th>( t(\hat{\alpha}_j) )</th>
<th>( t(\hat{\gamma}) )</th>
<th>( p(\hat{\alpha}_j) )</th>
<th>( p(\hat{\gamma}) )</th>
<th>Standard Error</th>
<th>Adjusted R square</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A:</strong> ( \beta_{\text{F}} ) estimated by the domestic dataset under OLS in the first-pass regression</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995-1999</td>
<td>-0.0183</td>
<td>-0.0342</td>
<td>-2.0841</td>
<td>-1.4855</td>
<td>0.0547 **</td>
<td>0.1581</td>
<td>0.0178</td>
<td>0.0701</td>
</tr>
<tr>
<td>2000-2004</td>
<td>0.0130</td>
<td>0.0148</td>
<td>2.1322</td>
<td>0.5111</td>
<td>0.0499 **</td>
<td>0.6167</td>
<td>0.0250</td>
<td>-0.0484</td>
</tr>
<tr>
<td>2005-2009</td>
<td>-0.0040</td>
<td>-0.0032</td>
<td>-0.8175</td>
<td>-0.2627</td>
<td>0.4264</td>
<td>0.7964</td>
<td>0.0194</td>
<td>-0.0618</td>
</tr>
<tr>
<td><strong>Panel B:</strong> ( \beta_{\text{F}} ) estimated by the international dataset under OLS in the first-pass regression</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995-1999</td>
<td>-0.0079</td>
<td>0.0623</td>
<td>-1.5822</td>
<td>1.8410</td>
<td>0.1345</td>
<td>0.0855 *</td>
<td>0.0200</td>
<td>0.1299</td>
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<tr>
<td>2000-2004</td>
<td>0.0161</td>
<td>0.0428</td>
<td>2.5068</td>
<td>0.6707</td>
<td>0.0242 **</td>
<td>0.5126</td>
<td>0.0244</td>
<td>-0.0356</td>
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<tr>
<td>2005-2009</td>
<td>-0.0038</td>
<td>0.0069</td>
<td>-0.5969</td>
<td>0.1789</td>
<td>0.5595</td>
<td>0.8604</td>
<td>0.0242</td>
<td>-0.0644</td>
</tr>
<tr>
<td><strong>Panel C:</strong> ( \beta_{\text{F}} ) estimated by the domestic dataset under quantile regression in the first-pass regression</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995-1999</td>
<td>-0.0210</td>
<td>-0.0405</td>
<td>-2.4128</td>
<td>-1.7971</td>
<td>0.0291 **</td>
<td>0.0925 *</td>
<td>0.0178</td>
<td>0.1223</td>
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<tr>
<td>2000-2004</td>
<td>0.0084</td>
<td>0.0640</td>
<td>2.0831</td>
<td>3.7564</td>
<td>0.0548 **</td>
<td>0.0019 ***</td>
<td>0.0160</td>
<td>0.4504</td>
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<tr>
<td>2005-2009</td>
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<td>-0.0111</td>
<td>-0.7184</td>
<td>-0.6708</td>
<td>0.4835</td>
<td>0.5126</td>
<td>0.0224</td>
<td>-0.0356</td>
</tr>
<tr>
<td><strong>Panel D:</strong> ( \beta_{\text{F}} ) estimated by the international dataset under quantile regression in the first-pass regression</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995-1999</td>
<td>-0.0091</td>
<td>0.0391</td>
<td>-1.9453</td>
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<td>2005-2009</td>
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<td>-0.0527</td>
<td>0.0893</td>
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<td>0.9300</td>
<td>0.2373</td>
<td>0.0239</td>
<td>0.0312</td>
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</table>
Some slope coefficients $\tilde{y}$ in Table 11 are similar to those in Table 10, especially over the period 1995-1999 and 2000-2004 in Panel A; as well as the period 1995-1999 and 2005-2009 in Panel C. This is in accordance with the first-pass regression results, since the correlation between betas estimated by the CAPM and the Fama and French model is close to one. Seven out of twelve coefficients in Table 11 are positive. The adjusted R-square is generally low, while an exception is Panel C in 2000-2004. It is difficult to interpret which dataset performs better from the results in Table 11: betas evaluated by the international dataset in Panel B generally perform better than in Panel A; however, betas estimated by the domestic dataset in Panel C roughly have a better performance than in Panel D.

As for the performance of results estimated by different regression methods, betas estimated by quantile regression in the first-pass regression have a better predictive power according to the adjusted R-square: all of them are larger than those in OLS except 1995-1999 in the international dataset. The adjusted R-squares under quantile regression during the period 2005-2009 are generally lower than previous time period in Table 10 and 11. This result is inconsistent with the first-pass regression, since the numbers of significant betas are the largest during this particular time period under both of these two regression methods; however it conforms to the empirical result that during the period of the Global Financial Crisis, all the models stopped working when the financial conditions have changed substantially. The inconsistency between the results of first and second-pass regression reveals that beta could explain current return well does not equal to it has a strong predictive power.

5.2. The Coefficient of Size Factor in Explaining Equity Returns

The size factor in the first-pass regression has the largest number of significant coefficients among all the factors in both OLS and quantile regression. However, the slope coefficient $\hat{y}$ estimated in the first-pass regression does not have a very strong
Table 12: Summary Results For the Second-pass Regression in Testing the Size Factor among the FF Model

\[ R_{p(t+1)} - R_{f(t+1)} = \hat{\alpha}_j + \gamma \tilde{s}_{pt} + \tilde{\xi}_{pt} \]

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively.

<table>
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<tr>
<th>PERIOD</th>
<th>( \hat{\alpha}_j )</th>
<th>( \hat{\gamma} )</th>
<th>( t(\hat{\alpha}_j) )</th>
<th>( t(\hat{\gamma}) )</th>
<th>( p(\hat{\alpha}_j) )</th>
<th>( p(\hat{\gamma}) )</th>
<th>Standard Error</th>
<th>Adjusted R square</th>
</tr>
</thead>
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<tr>
<td><strong>Panel A</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>1995-1999</td>
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<td>-2.4749</td>
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<td>0.0059</td>
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<td><strong>Panel B</strong></td>
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<td>2000-2004</td>
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<td>2005-2009</td>
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<td><strong>Panel C</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995-1999</td>
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<td>0.0087</td>
<td>-2.0654</td>
<td>1.9959</td>
<td>0.0566 **</td>
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<tr>
<td>2000-2004</td>
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<td>-0.0014</td>
<td>1.7580</td>
<td>-0.2930</td>
<td>0.0974 *</td>
<td>0.7735</td>
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<tr>
<td>2005-2009</td>
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<td>-0.0090</td>
<td>-0.2230</td>
<td>-1.2364</td>
<td>0.8265</td>
<td>0.2353</td>
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<tr>
<td><strong>Panel D</strong></td>
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<td></td>
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</tr>
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<td>-0.2292</td>
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<td>0.8218</td>
<td>0.0173</td>
<td>-0.0629</td>
</tr>
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<td>2005-2009</td>
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<td>-1.1188</td>
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<td>0.2808</td>
<td>0.1002 *</td>
<td>0.0198</td>
<td>0.1145</td>
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</tbody>
</table>
predictive power in the second-pass regression. A major difference of the predictive power between beta and spt in Table 11 and 12 is that spt estimated by the domestic dataset performs much better than the international dataset. A potential reason is that this research uses the difference between S&P/ASX 300 and S&P/ASX 20 index as a proxy of domestic size factor, which is different from the calculating method by Fama and French. The predictive power of spt in the second-pass regression is inconsistent with its performance in the first-pass regression: overall the values of adjusted R-square are close in Table 11 and 12, which means that spt does not have a significant performance in Table 12 compared with the betas in the Fama and French model.

Among the twelve coefficients (\(\bar{y}\)), five out of the six negative results are estimated by the spt from quantile regression. The negative coefficient of the size factor conforms to previous study (e.g., Fama and French, 1992, 1993) that an inverse relationship exists between the size of the firms and the equity return. The adjusted R-squares in Panel D are larger than those in Panel B in all the three time periods. Only one coefficient is significant at 5% level in Panel A and B, while three coefficients are significant at 10% level under the results evaluated by quantile regression. For the intercepts, spt estimated by quantile regression previously provide more significant coefficients in the second-pass regression: three out of six intercepts are significant in Panel C and D, with two results significant at 5% level. Only one intercept is significant at 5% level in Panel A and B.

5.3. The Coefficient of BM Factor in Predicting Equity Returns

According to the result of second-pass regression, coefficients of BM factors (hpt) estimated previously in the international dataset have more predictive power than those in the domestic dataset. An important reason is that the dataset on French’s website (French, n.d.) for the BM factor in Australia is limited to 2007, so that the hpt estimated from the domestic dataset in the first-pass regression is less accurate. This is
Table 13: Summary Results For the Second-pass Regression in Testing the BM Factor among the FF Model

\[ R_{p(t+1)} - R_{f(t+1)} = \tilde{\alpha}_i + \gamma h_{m,t} + \tilde{\varepsilon}_t \]

Note: *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively.

<table>
<thead>
<tr>
<th>PERIOD</th>
<th>( \tilde{\alpha}_i )</th>
<th>( \tilde{\gamma} )</th>
<th>( t(\tilde{\alpha}_i) )</th>
<th>( t(\tilde{\gamma}) )</th>
<th>( p(\tilde{\alpha}_i) )</th>
<th>( p(\tilde{\gamma}) )</th>
<th>Standard Error</th>
<th>Adjusted R square</th>
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<tr>
<td>Panel A: ( \hat{h}_m ) estimated by the domestic dataset under OLS in the first-pass regression</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995-1999</td>
<td>-0.0057</td>
<td>0.0752</td>
<td>-1.8809</td>
<td>3.8848</td>
<td>0.0795 *</td>
<td>0.0015 **</td>
<td>0.0124</td>
<td>0.4683</td>
</tr>
<tr>
<td>2000-2004</td>
<td>0.0115</td>
<td>-0.0021</td>
<td>1.9404</td>
<td>-0.0993</td>
<td>0.0714 *</td>
<td>0.0222</td>
<td>0.0174</td>
<td>-0.0660</td>
</tr>
<tr>
<td>2005-2009</td>
<td>-0.0040</td>
<td>-0.0048</td>
<td>-0.6154</td>
<td>-0.1164</td>
<td>0.5475</td>
<td>0.9089</td>
<td>0.0230</td>
<td>-0.0657</td>
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<tr>
<td>Panel B: ( \hat{h}_m ) estimated by the international dataset under OLS in the first-pass regression</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995-1999</td>
<td>-0.0059</td>
<td>-0.0311</td>
<td>-0.9080</td>
<td>-0.9820</td>
<td>0.3782</td>
<td>0.3417</td>
<td>0.0171</td>
<td>-0.0022</td>
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<tr>
<td>2000-2004</td>
<td>0.0121</td>
<td>0.0139</td>
<td>2.1365</td>
<td>0.2535</td>
<td>0.0495 **</td>
<td>0.8034</td>
<td>0.0217</td>
<td>-0.0621</td>
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<tr>
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<td>-0.0190</td>
<td>0.3371</td>
<td>-0.8004</td>
<td>0.7407</td>
<td>0.4360</td>
<td>0.0192</td>
<td>-0.0230</td>
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<tr>
<td>Panel C: ( \hat{h}_m ) estimated by the domestic dataset under quantile regression in the first-pass regression</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995-1999</td>
<td>-0.0040</td>
<td>0.0721</td>
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<td>4.3033</td>
<td>0.2621</td>
<td>0.0006 **</td>
<td>0.0140</td>
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<td>2000-2004</td>
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<td>-0.0522</td>
<td>0.2603</td>
<td>-1.8102</td>
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<td>0.0176</td>
<td>0.1246</td>
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<tr>
<td>2005-2009</td>
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<td>0.0212</td>
<td>-0.3139</td>
<td>1.2451</td>
<td>0.7579</td>
<td>0.2322</td>
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<tr>
<td>Panel D: ( \hat{h}_m ) estimated by the international dataset under quantile regression in the first-pass regression</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1995-1999</td>
<td>-0.0127</td>
<td>0.0146</td>
<td>-2.1201</td>
<td>0.5442</td>
<td>0.0511 **</td>
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<td>0.0184</td>
<td>-0.0460</td>
</tr>
<tr>
<td>2000-2004</td>
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<td>1.5434</td>
<td>3.1327</td>
<td>0.1436</td>
<td>0.0068 **</td>
<td>0.0145</td>
<td>0.3552</td>
</tr>
<tr>
<td>2005-2009</td>
<td>0.0075</td>
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<td>0.9335</td>
<td>-1.6669</td>
<td>0.3654</td>
<td>0.1163</td>
<td>0.0182</td>
<td>0.1000</td>
</tr>
</tbody>
</table>
consistent with the adjusted R-square in period 2005-2009: the results in Panel A and Panel C are only -0.0657 and 0.0332 respectively.

The hpt factor estimated by the first-pass regression from the domestic dataset has more predictive power in the period 1995-1999, since the adjusted R-square is relatively high; however, after the period 1995-1999, hpt estimated from the international dataset performs better according to the number of significant coefficient $\gamma$ and adjusted R-square. Over the period 2000-2004, none of the coefficient $\gamma$ is significant in Panel A and B and the p-values are generally close to one; however, two slope coefficients are significant at 1% level and another one is significant at 10% level during the period 1995-1999 and 2000-2004 in Panel C and D, which is consistent with previous conclusion that hpt estimated from quantile regression previously has a better performance in explaining subsequent equity returns. The coefficients $\gamma$ range from -0.0522 to 0.1259 during the year 1995-2009, and six out of twelve are positive.

5.4. Summary

The second pass of testing the CAPM and the Fama and French model in this research follows Fama and MacBeth (1974)'s methodology to sort the equities into different portfolios. For the coefficients (beta, spt and hpt) estimated from the first-pass regression, this research runs the regression for each of them individually to check the regression power in explaining subsequent equity returns. Due to the lack of data in the listed Australian companies, the number of portfolios is much less than it in Fama and MachBeth’s research. In contrast with the results of Black, Jensen and Scholes (1972), the relationship between beta and equity return is not always positive in this research: some negative coefficients $\gamma$ have been provided in Table 10 and 11. Overall the adjusted R-square is low in the second-pass regression, although in some cases the slope coefficients are significant at different levels. For example, the coefficient of the beta in Panel C and D during 2000-2004 (Table 10), the coefficient of the spt over
1995-1999 in Panel A (Table 12), and the coefficient of the hpt estimated by domestic
dataset in 1995-1999 (Table 13) are all significant at 5% level. Some reasons are
provided for the low adjusted R-square. Firstly, this result indicates that the predictive
power of both the CAPM and the Fama and French factors is low. Secondly, a reason
for the poor result in the performance is the shortage of data: only 17 portfolios are
formed in this research, due to the reason that many companies listed in the Australian
equity market do not have a formal trading history back to 1989.

Betas and the hpt estimated by the international dataset in the first-pass regression
roughly performed better in the second-pass regression than the domestic dataset;
however for the size factor, spt evaluated by the domestic dataset perform better. An
important reason is that the calculating method of the size factor in the first-pass
regression is different. Results estimated by quantile regression contain more
information in the tails than OLS, and overall they have a better performance except
for some special cases according to the adjusted R-squares and p-values of the
coefficient $\tilde{y}$. Unfortunately quantile regression cannot “save” the CAPM and the
Fama and French model: generally the regression power is still low. No model could
fully explain the subsequent equity price in the real world: unrealistic assumptions and
investors’ behaviours make asset-pricing models fragile in explaining and predicting
equity returns. The answers for the last two research questions are clear: factors
estimated by quantile regression and international dataset have a better performance.
Chapter 6. Conclusion

This research uses both OLS and quantile regression method to run the first-pass regression of testing the CAPM and the Fama and French model in the Australian equity market during the year 1989-2009. In the second part of this study, the methodology of sorting different equities into portfolios provided by Fama and MacBeth (1974) has been applied to run the second-pass regression. Compared with other Australian research, this study fulfils the gaps that using a twenty-year timeline to test these two models, which includes the period of global financial crisis; also the quantile regression method has been applied as a new testing method in this study. Another important aspect in this research is that two datasets have been used to run the first and second-pass regression. Different results from domestic dataset and international dataset have been compared and analyzed in this study.

The performance of the CAPM is poor according to the result of first-pass regression under OLS. During the twenty-year timeline, this model performs best in the period 1995-1999 and, surprisingly, 2005-2009 especially in the domestic dataset. Compared with the CAPM, the Fama and French model performs slightly better since it has larger adjusted R-squares under OLS and higher percentages of significant coefficients under the quantile regression. The result that Fama and French model performs better than the CAPM is consistent with previous research by Fama and French (1996) and Bartholdy and Peare (2002). The number of significant betas in the first-pass regression estimated by the international dataset is generally larger than it in the domestic dataset in both OLS and quantile regression, which indicates that the international dataset has a better explanatory power in explaining local companies' equity returns.

The size factor has the largest significant number in the first-pass regression under OLS and quantile regression. Both the size factor and BM factor estimated in the
international dataset perform better than the market factor under the quantile regression. The coefficients of the factors vary substantially across the quantile, and this violates the hallmark of the CAPM that there should be a single market price of beta risk for all stocks.

The second-pass regression has demonstrated that the predictive power of the CAPM and the Fama and French model is low. Some of the results under the second-pass regression contradict with those in the first-pass regression. The size factor, which has performed best in the first-pass regression, does not have a significant performance in the second-pass regression. Although the beta under the CAPM over 2005-2009 has the largest significant number in the twenty-year timeline, its performance in the second-pass regression is poor. Fortunately, overall first-pass regression results estimated by quantile regression provides more significant coefficients ($\hat{\beta}$) and larger adjusted R-squares than OLS in the second-pass regression, since it involves more detailed information of distribution in the dataset; also results estimated from the international dataset in the first-pass regression roughly perform better than those in the domestic dataset. These two important conclusions are consistent with results in the first-pass regression.

There are still some questions remained in this research. Firstly, this research cannot avoid Roll's critique (1977) that there is no suitable index to represent the "market portfolio". The international dataset could provide better results in the first and second-pass regression in testing the CAPM; however, this conclusion in effect indicates that the return and standard deviation of the value-weighted index of all NYSE, AMEX and NASDAQ stocks are more "efficient" than the All Ordinaries index. Secondly, some detailed explanations need to be addressed for the contradictions between the first-pass regression and second-pass regression, such as the low predictive power of spt in section 5.2. Thirdly, this research cannot cover enough companies in the two-pass regression tests since some Australian companies do not have a formal trading history back to 1989, and the imperfect dataset on French's
website (French, n.d.) could make the regression result less accurate. Finally, companies involved in this research generally have large market capitalizations, which could result in some biases, especially in the aspect of testing the size factor. Further study still needs to be addressed.
References


Appendix

A1. Thirty-two figures are generated by the coefficients estimated in the first-pass of testing the CAPM and the Fama and French model under the quantile regression. The general tendency in the quantile regression could be viewed in these pictures: coefficients vary substantially across the quintiles, and extreme values are generally in the tails. Betas for the CAPM and the Fama and French model in the same period have similar moving tendency.

Regression formula: $R_{it} - R_{ft} = \alpha_i + \bar{\beta}_t (R_{mt} - R_{ft}) + \varepsilon_{it}$. Factor stacked: $\bar{\beta}_t$
Regression formula: \( R_{it} - R_{ft} = \alpha_t + \tilde{\beta}_t (R_{mt} - R_{ft}) + \tilde{\sigma}_t (S - B) + \tilde{\mu}_t (H - L) + \tilde{\varepsilon}_{it} \). Factor stacked: \( \tilde{\beta}_t \).
Regression formula: $R_{it} - R_{ft} = \bar{\alpha}_t + \bar{\beta}_t (R_{mt} - R_{ft}) + \bar{s}_t (S - B) + \bar{h}_t (H - L) + \bar{\varepsilon}_t$. Factor stacked: $\bar{s}_t$
Regression formula: $R_{it} - R_{ft} = \tilde{\alpha}_i + \tilde{\beta}_i (R_{mt} - R_{ft}) + \tilde{s}_t (S - B) + \tilde{h}_t (H - L) + \tilde{\epsilon}_{it}$. Factor stacked: $\tilde{h}_t$
Regression formula: $R_{tt} - R_{ft} = \alpha_t + \beta_t (R_{mt} - R_{ft}) + \varepsilon_{tt}$  
Factor stacked: $\hat{\beta}_t$
Regression formula: $R_{it} - R_{ft} = \alpha_j + \beta_t^i (R_{mt} - R_{ft}) + \delta_t (S - B) + \eta_t (H - L) + \xi_{it}$. Factor stacked: $\beta_t^i$.
Regression formula: $R_{it} - R_{ft} = \alpha_i + \beta_t(R_{mt} - R_{ft}) + \delta_t(S - B) + \pi_t(H - L) + \varepsilon_{it}$. Factor stacked: $\delta_t$
Regression formula: $R_{it} - R_{ft} = \tilde{\alpha}_t + \tilde{\beta}_t (R_{mt} - R_{ft}) + \tilde{\gamma}_t (S - B) + \tilde{\eta}_t (H - L) + \tilde{\epsilon}_{it}$. Factor stacked: $\tilde{h}_t$.
Regression formula: $R_{tt} - R_{ft} = \beta_t (R_{mt} - R_{ft}) + \varepsilon_{it}$. Factor stacked: $\beta_t$. 

Domestic beta for CAPM in 2000-2004

International beta for CAPM in 2000-2004
Regression formula: $R_{it} - R_{ft} = \tilde{\alpha}_t + \tilde{\beta}_t (R_{mt} - R_{ft}) + \tilde{\sigma}_t (S - B) + \tilde{\nu}_t (H - L) + \tilde{\varepsilon}_{it}$. Factor stacked: $\tilde{\beta}_t$
Regression formula: $R_{it} - R_{ft} = \alpha_t + \beta_t (R_{mt} - R_{ft}) + \delta_t (S - B) + \bar{h}_t (H - L) + \tilde{\epsilon}_{it}$. Factor stacked: $\delta_t$
Regression formula: $\tilde{R}_{it} - R_{ft} = \tilde{\alpha}_j + \tilde{\beta}_j (R_{mt} - R_{ft}) + \tilde{\xi}_j (S - B) + \tilde{\eta}_j (H - L) + \varepsilon_{it}$. Factor stacked: $\tilde{h}_i$. International b-m in 2000-2004

Domestic b-m in 2000-2004

[Diagram showing domestic and international b-m movements from 2000 to 2004]
Regression formula: $R_{it} - R_{ft} = \alpha_i + \bar{\beta}_t (R_{mt} - R_{ft}) + \epsilon_{it}$. Factor stacked: $\bar{\beta}_t$.
Regression formula: $R_{it} - R_{ft} = \bar{\alpha}_i + \bar{\beta}_t(R_{mt} - R_{ft}) + \bar{s}_t(S - B) + \bar{h}_t(H - L) + \varepsilon_{it}$. Factor stacked: $\bar{\beta}_t$
Regression formula: $R_{it} - R_{ft} = \alpha_i + \beta_t(R_{mt} - R_{ft}) + \bar{s}_t(S - B) + \bar{h}_t(H - L) + \bar{\varepsilon}_t$. Factor stacked: $\bar{s}_t$
Regression formula: \( R_{it} - R_{ft} = \alpha_t + \beta_t (R_{mt} - R_{ft}) + \delta_t (S - B) + \tilde{h}_t (H - L) + \tilde{e}_{it} \). Factor stacked: \( \tilde{h}_t \)
A2. This research tried to involve as many companies as possible to test the CAPM and the Fama and French model in the Australian equity market, since more companies will provide a more intact picture of testing results. Another important factor is the timeline, since it is not worth running analysis with less than a ten-year history. As a result, there is a trade-off between company numbers and trading history, and the result is fifty largest companies according to their market capitalizations with a twenty-year trading history have been included in the research. The table below contains the names of the fifty companies.

<table>
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<tr>
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<td>REECE AUSTRALIA</td>
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<td>ST BARTA</td>
<td>WESFARMERS</td>
<td>WESTPAC BANKING</td>
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