# Emerging Countries Stock Markets: An analysis using an extension Of the Three-Factor CAPM

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**BY**

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# Chapter 1 - Introduction

The stock markets of India and South Korea became partly liberalized in 1992. But has this liberalization led to stock market efficiency? The overall goal of this paper is to test if the stock markets in these two countries are truly informationally efficient in the Fama (1970, 1991) sense. The stock markets being informationally efficient implies that the stock prices already contain all the information about the fundamental value of the firms and thus there is no new information to be discovered by looking elsewhere. The business of discovering information about the value of traded stocks is a highly competitive one. The higher the competition the greater the dissemination of information and thus the smaller the chance of a single entity discovering new information and cashing in. When the competition is extremely high, the ability to discover and cash in and make abnormal profits (profits over-and-above that which is required for the risk taken) on new information is almost non-existent. The only way one can earn additional profits is by taking additional risks. A stock market existing in this situation is said to be informationally efficient. Now stock market liberalization throws opens the stock markets to the world. Thus there is greater competition in the endeavor to discover new information and make an abnormal profit out of it. Thus one should expect that the stock markets in these liberalized countries should become informationally efficient soon after they throw their doors open.

Our first objective (Objective A) is to see if our model, which accounts for all possible risk factors, is able to explain the returns to portfolios formed, based on various criteria. However if we find that the intercept of our model for a certain country is consistently significantly different from zero, implying that the model is consistently leaving a large unexplained return, we should conclude that the stock market in that country is not informationally efficient.

Our second objective (Objective B) is to test for the presence of serial correlation in the returns to portfolios. If there is serial correlation in a significant majority of the portfolios, then the returns to the portfolios is predictable. Entities could cash in on this piece of information and make abnormal profits. Thus we would have to conclude that the stock market in that country is not informationally efficient

Our third objective (Objective C) is to test for the presence of time-varying conditional variance in the returns of the portfolios and to see if this compensated for in the average returns to the portfolios. If we find that there is time-varying conditional variance in the returns and this variance is, in the majority of the cases, not compensated for in the average returns, then we would have to conclude that the stock market in that country is to a certain extent not efficient. The reason is that portfolios that display time-varying conditional variance in the pattern of their returns are riskier than those that do not and should justifiably earn more returns than those that do not.

Our fourth objective is to test whether low Price-to-Cash Flow (PCF) (Objective D1), high Book Value-to-Market Value ratio (BE/ME) (Objective D2), high Earnings-to-Price ratio (EP) (Objective D3), and low market captilization (Objective D4) are typical of distressed firms and vice versa. We also test whether our model is able to capture the pattern of returns of portfolios formed on ranks of PCF, BE/ME, EP, and low market capitalization in a meaningful manner.

Our fifth objective is to test if there is any abnormal cyclical pattern in long-term returns (DeBondt and Thaler, 1985) (Objective E1), and any continuation pattern in short-term returns (Jegadeesh and Titman, 1993) (Objective E2). We also test if our model is able to capture the pattern of returns of portfolios formed on ranks of long-term and short-term past returns in a meaningful manner i.e. firms with high long-term past returns should be strong firms whereas firms with high short-term past returns should be distressed firms.

**India's stock market regulations for foreign investors**

In India, the stock market was liberalized in September 1992. After liberalization, foreign institutional investors such as banks, insurance companies, fund management companies, and pension funds can purchase shares directly once they are given authorization. However in order to get authorization, the foreign institutional investors need to first register with the Securities and Exchange Board of India (SEBI), and then get permission from the Reserve Bank of India (RBI). The whole process of getting authorization takes about a month. Foreign investors are allowed to buy in total a maximum of 24 percent of the share capital of the quoted stock. The RBI regularly publishes a list of all the stocks that have reached the 24 percent limit. Dividend income and interest income is taxed at the rate of 20 percent each, while long-term profit is taxed at the rate of 10 percent. There are no restrictions of the repatriation of interest, dividend income, and the originally invested capital. The settlement period is a maximum of ten working days.

**South Korea's stock market regulations for foreign investors**

Since 1992, South Korea's stock market has been open to foreign investors. Until December 1994 foreign investors were allowed to purchase directly only up to 10 percent of the share capital of the quoted stock. Until December 1994 foreigners were not allowed to purchase stocks of certain strategically important companies such as the Pohang Iron and Steel (POSCO), and the Korea Electric Power Company (KEPCO). The general restriction of 10 percent was raised to 12 percent in December 1994, and then to 15 percent in the beginning of 1995. Furthermore, the government allowed up to 10-percent investment in those strategically important companies such as POSCO and KEPCO. The repatriation of interest, dividend income, and the originally invested capital is largely unrestricted. Dividend income is taxed at 16.125 percent and interest income at 12.9 percent, while long-term profits are free from taxes for foreign investors. The settlement period is a maximum of two working days. At the end of 1994, KEPCO and POSCO were listed on the New York Stock Exchange. These two stocks were the first two foreign stocks to be listed in a foreign stock exchange. The government gave permission to companies such as Korea Mobile Telecom, Samsung Electronics, Goldstar, Hyundai Motor, and Daewoo Corporation to introduce ADRs or GDRs on foreign stock exchanges. In 1995, Korea Mobile Telecom and Daewoo Corporation issued GDRs on the London Stock Exchange.

A few very large industrial corporations and conglomerates, such as Hyundai and Daewoo dominate the stock market. These corporations and conglomerates are called *chaebols*. In 1990, the ten largest *chaebols* produced 77.3 percent of the GDP, and the fifty largest *chaebols* as much as 99.7 percent of the GDP.

# Chapter 2 – Literature Review

Until the 1980s the One-Factor CAPM (henceforth referred to as simply the CAPM) of Sharpe(1964) and Lintner(1965) was regarded as a very good measure of risk and consequently it was regarded as a model that could explain why some stocks, portfolios, fund managers, etc. earn higher average returns than other stocks, portfolios, fund managers, etc. The CAPM theory states that stocks can only earn a high average return if they have a high market beta. Beta drives average returns because beta measures how much adding a bit of the stock to a diversified portfolio increases the volatility of the portfolio, and investors care only about portfolio returns. The assumption that investors care only about portfolio returns is quite an unrealistic assumption. Investors, like typical people, care about their overall wealth, which comes not only from investing but also from earning a living. Let us take an example of how caring about overall wealth can lead to stocks with the same market beta having different average returns expectations. During recessions people lose jobs and thus have only one source of income, i.e. their income from investing. With this in mind let us compare two stocks A and B with the same market beta. Let us suppose A does well (Company A's earnings goes up) during a recession while B does badly. Investors will quite naturally prefer A to B. The investors will bid up the price of stock A, or, equivalently they are willing to hold stock A at a lower expected average return. The investors will bid down the price of stock B, or, equivalently they are willing to hold stock B at a higher expected average return. Thus stock A and stock B will have very different average returns expectations although they have the same market beta. Given this fact about investors caring about their overall wealth and not just the portfolio returns it is quite surprising that the CAPM proved to be empirically very successful for so long. It was able to capture the pattern of average returns earned by most stocks, portfolios, fund managers, etc.

From the 1980s researchers have been finding patterns of average returns stocks, portfolios, etc. that are not captured by the CAPM i.e. these patterns cannot be explained by the beta of these stocks, portfolios, etc., or by their tendency to move with the market as a whole. The patterns in average returns that are not explained by the CAPM are typically called anomalies. Basu (1983) found that low price-earnings ratio (P/E) stocks experienced returns in excess of what could be explained by the CAPM, whereas high P/E ratio stocks experienced returns lower than what could be explained by the CAPM. Basu found this result even after accounting for the size effect. Banz (1981) and Reinganum (1981) found that small-cap stocks experienced returns in excess of what could be explained by the CAPM. DeBondt and Thaler (1985) found that stocks with abnormally low long-term returns (average returns in three years) experience abnormally high long-term future returns (average returns in the next three years) and vice versa. Jegadeesh and Titman (1983) found that stocks with abnormally low short-term returns (average returns in one year) experience low short-term future returns (average returns in the next one year) and vice versa. Lakonishok, Shleifer, and Vishny (LSV 1994) found a strong positive relationship between average return and book-to-market equity ratio (BE/ME), and cash flow/price ratio (C/P); these relationships could not be explained by the CAPM.

In a paper in 1992, Fama and French evaluate the joint roles of market beta, size, EP ratio, financial leverage, and BE/ME in the cross section of average returns on the NYSE, AMEX, and NASDAQ stocks. In their multivariate tests they find that the negative relationship between size and average returns continues to hold even after other variables are included in the model. They also find that the positive relationship between BE/ME and average returns continues to hold when other variables are included in the model. Furthermore they find that when both, the size and BE/ME, variables are included in the model, the BE/ME variable has a consistently stronger role in explaining average returns. They conclude that size and BE/ME equity capture the cross-sectional variation in average stock returns associated with size, EP, BE/ME equity, and financial leverage.

In a paper in 1995, Fama and French show that high BE/ME firms have low earnings on assets relative to low BE/ME firms for four years before and at least five years after the ranking dates. Thus high BE/ME stocks are relatively distressed stocks and low BE/ME stocks are relatively strong stocks. In the same paper they found that controlling for BE/ME, small-cap stocks have low earnings on assets relative to large-cap stocks. Thus small-cap stocks are relatively distressed stocks and large-cap stocks are relatively strong stocks. In times of a credit crunch, liquidity crunch, flight to quality, or similar "bad" events, stocks in financial distress will do badly. But these are just the times when people do not want to hear the news that the stocks are doing badly. These firms' earnings have high sensitivities to credit crunches, liquidity crunches, flights to quality, etc., and so the returns to the stocks of these firms should compensate the investors for these high sensitivities. Thus the investors can only be induced to hold these stocks if the prices of these stocks are low, or equivalently the returns on these stocks are high. They (Fama and French) use the HML[1] (High minus Low) portfolio returns to mimic the returns to the real, macroeconomic, aggregate, nondiversifiable risk factor related to BE/ME. They use the SMB[2] (Small minus Big) portfolio returns to mimic the returns to the real, macroeconomic, aggregate, nondiversifiable risk factor related to market capitalization. They do a multiple regression with the returns on portfolios formed on rankings of BE/ME and rankings of market capitalization as the dependent variables and the returns to the market portfolio, the returns to the SMB portfolio, and the returns to the HML portfolio as the independent variables. In order to avoid spurious common return variation that might be induced by the fact that the HML portfolio is constructed from the BE/ME portfolios and the SMB portfolio is constructed from the market-capitalization portfolios, they do a set of regressions using different stocks in the dependent and independent variable. They do a second set of regressions using the same stocks in the dependent and independent variable. They find that in both sets of regressions, stocks with positive slopes on HML are the high BE/ME stocks and are thus relatively distressed whereas stocks with negative slopes on HML are the low BE/ME stocks and are thus relatively strong. They also find that in both sets of regressions, stocks with positive slopes on SMB are the small-cap stocks and are thus relatively distressed whereas stocks with negative slopes on SMB are the large-cap stocks and are thus relatively strong.

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[1] The HML portfolio return is the difference between the return on a portfolio of high book-to-market (BE/ME) stocks and the return on a portfolio of low BE/ME stocks. Both portfolios are about the same weighted average size and thus the HML portfolio should be free of the size effect.

[2] The SMB portfolio return is the difference between the return on a portfolio of small-cap stocks and the return on a portfolio of large-cap stocks. Both portfolios are about the same weighted average BE/ME and thus the SMB portfolio should be free of the BE/ME effect.

In a paper in 1996, Fama and French show that many of the abnormal returns patterns seen in the 1980s and 1990s are in reality not abnormal returns patterns at all. These abnormal return patterns are due to a misspecification of the expected-returns model. These so-called anomalies are related and can be captured by a model that, unlike the CAPM, includes not only the market risk factor but includes other risk factors as well. Specifically, they show that when they add two other variables, SMB and HML, the resultant three-factor model is able to capture most of these abnormal return patterns. Specifically, the expected excess return on a portfolio is,

$$E(R_t) - R_{f,t} = b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + \varepsilon_t$$

They form twenty-five size-BE/ME portfolios. They then do a regression of the excess returns of these portfolios on the three dependent variables. They find that the intercept is not significantly different from zero for twenty-four of the portfolios. They find that the model captures most of the variation in the average returns. The average $R^2$ of the twenty-five regressions is 0.93. They find that portfolios with stocks of small firms load positively on the SMB variable (i.e. the coefficient of SMB is significantly positive) irrespective of what the BE/ME is, whereas portfolios of stocks of the biggest firms load negatively on the SMB variable irrespective of what the BE/ME is. They also find that portfolios of stocks with low BE/ME load negatively on the HML variable irrespective of what the size is, whereas portfolios of stocks with the highest BE/ME load positively on the HML variable irrespective of what the size is.

Fama and French form ten portfolios on the deciles of the C/P. They then regress the excess returns of these portfolios on the three dependent variables. They find that none of the intercepts are significantly different from zero. The average $R^2$ of the ten regressions is 0.94. Higher C/P portfolios load positively on SMB and HML and vice versa.

Fama and French form ten portfolios each on the deciles of BE/ME and EP. Here too, higher BE/ME and higher EP load positively on SMB and HML and vice versa. The average $R^2$ of the BE/ME and EP regressions is 0.94 and 0.93 respectively. Given the evidence in Fama & French (1995) that positive slopes on HML proxy for distress whereas negative slopes on HML proxy for strength, one can infer that high C/P, BE/ME, and EP are typical of stocks that are distressed whereas low C/P, BE/ME, and EP are typical of stocks that are strong.

In order to check if their model is able to capture the pattern of returns observed by DeBondt and Thaler (1985) Fama and French form ten equal-weight portfolios on deciles of monthly long-term (up to five years) past returns. Their results confirm the strong reversal in the average returns found by DeBondt and Thaler. They also find that their three-factor model is able to explain this pattern of average return. The intercepts of all ten regressions are not significantly different from zero. Also, long-term losers load more on SMB and HML and thus are small and distressed stocks. The model predicts that since long-term losers are small and distressed, these losers will have higher average returns in the future.

In order to check if their model is able to capture the pattern of returns observed by Jegadeesh and Titman (1993) Fama and French form ten equal-weight portfolios on deciles of monthly short-term (up to one year) past returns. Their results do not confirm the strong continuation of average returns found by Jegadeesh and Titman. The intercepts of the regression are strongly negative for short-term losers and strongly positive for short-term winners. Also, short-term losers load more on SMB and HML and thus behave like small and distressed stocks. Thus, as in the case of long-term past returns, here too the model predicts losers will have higher average return in the future.

# Chapter 3 – The Model

The model says that the expected return on a portfolio in excess of the risk-free rate $[E(R_t) - R_{f,t}]$ is explained by a few factors: a) the expected excess return of the market portfolio $[E(R_{m,t}) - R_{f,t}]$; b) the rate of change in the exchange rate $PCER_t$; c) the difference between the returns on a portfolio of small-cap stocks and the returns on a portfolio of large-cap stocks $[SMB_t$, small minus big$]$; d) the difference between the return on a portfolio of high-book-to-market stocks and the returns on a portfolio of low-book-to-market stocks $[HML_t$, high minus low$]$; and e) a function of the conditional variance $h_t$, $[F(h_t)]$. This model is fitted with autocorrelated error terms and an IGARCH term. Specifically, the expected excess return on portfolio *i* is,

$$E(R_t) - R_{f,t} = b[E(R_{m,t}) - R_{f,t}] + eE[PCER_t] + sE[SMB_t] + hE[HML_t] + \delta F(h_t) + \nu_t \qquad (1)$$

$$\nu_t = -\phi_1 \nu_{t-1} - \phi_2 \nu_{t-2} - \ldots\ldots\ldots\ldots -\phi_p \nu_{t-p} + \varepsilon_t \qquad (2)$$

$$\varepsilon_t = \sqrt{(h_t)}\, e_t \qquad (3)$$

$$h_t = \kappa + \alpha \varepsilon_{t-1}^2 + \gamma h_{t-1} \qquad \kappa > 0 \qquad (4)$$

$$\alpha + \gamma = 1 \qquad (5)$$

$$e_t \sim IN(0,1) \qquad (6)$$

The $[E(R_{m,t}) - R_{f,t}]$ variable is used to explain that part of the returns to an asset of the firm that is due to the market risk faced by the firm.

The $E[PCER_t]$ variable is used because we calculate the rate of returns to the various portfolios whose values are measured in US dollars rather than in the local currency. The variable captures variations in the returns to the portfolios that are due to exchange rate fluctuations.

The SMB variable is used to explain that part of the returns to small stocks that is not explained by the market returns. It is used to mimic the common risk factor related to size. Adding this variable is in line with the evidence from Huberman and Kandel (1987) that there is covariation in the returns on small stocks that is not captured by the market return and is compensated in average returns. Fama and French (1995) show that small-cap stocks tend to have lower earnings on book equity than do big-cap stocks, after controlling for BE/ME. They also show that the slope of the SMB serves as a good proxy for the size effect in average returns. Small-cap stocks tend to have positive slopes on SMB, whereas big-cap stocks tend to have negative slopes on SMB. Using the SMB variable is better than using market capitalization to capture the size effect in average returns because the regression slopes on SMB are factor loadings and thus are risk factor sensitivities.

The HML variable is used to explain that part of the returns to distressed stocks that is not explained by the market returns. It is used to mimic the common risk factor related to BE/ME. Adding this variable is in line with the evidence from Chan and Chen (1991) that there is covariation in returns to distressed stocks that is not captured by the market returns and is compensated in average returns. Fama and French (1995) show that BE/ME and the slope of the HML are good proxies for relative distress. They show that weak firms with persistently low earnings tend to have high BE/ME and positive slopes on HML, whereas strong firms with persistently high earnings tend to have low BE/ME and negative slopes on HML. Using the HML variable is better than using BE/ME to capture the value effect in average returns because the regression slopes on HML are factor loadings and thus are risk factor sensitivities.

We add AR error terms to correct for the autocorrelation in the data for two reasons. The first reason is that it is used to test for the presence of serial correlation in the returns. If there were a pre-dominance of serial correlation in the returns, it would indicate that the stock market is not informationally efficient. In the presence of autocorrelation: a) statistical tests of the significance of estimated parameters, and the confidence limits for the predicted values are not correct, b) the estimates of the regression coefficients are not as efficient as they would be if the autocorrelation were corrected for, c) the residuals contain information which is not being used to improve the explanatory power of the model.

We add a GARCH(1,1) term for two reasons. The first reason is that it is used to test for the presence of time-varying connditional variance. The second reason is that the GARCH(1,1) term would account for time-varying conditional variance if it were present. We need to account for it because in the presence of such changing variances: a) statistical tests of the significance of estimated parameters, and the confidence limits for the predicted values are not correct, b) the estimates of the regression coefficients are not as efficient as they would be if the autocorrelation were corrected for, c) the residuals contain information which is not being used to improve the explanatory power of the model. We specifically add an IGARCH term because we want to test to see whether the shocks to the variance of the error term have permanent effects on the conditional variance of the error term.

The $F(h_t)$ variable is used to test if the time-varying conditional variance is compensated for in the average return to the portfolio. Adding this variable is in line with the insight from Engle, Lilien, and Robins (1987). Risk-averse agents require additional compensation for taking additional risks. Thus, a part of the returns that investors receive should be an increasing function of the time-varying conditional variance of returns.

In our model we use the multiplicative conditionally heteroskedastic error term

$\varepsilon_t = e_t \sqrt{(h_t)}$, where $h_t \equiv \kappa + \alpha\, \varepsilon^2_{t-1} + \gamma h_{t-1}$.

This implies that $\varepsilon^2_{t-1} = e^2_t (\kappa + \alpha\varepsilon^2_{t-1} + \gamma h_{t-1})$.

Now since $e_t$ is white-noise, it is independent of $\varepsilon_{t-1}$ and $h_{t-1}$.

Thus $E_{t-1}(\varepsilon^2_t) = E_{t-1} e^2_t\, E_{t-1}(\kappa + \alpha\varepsilon^2_{t-1} + \gamma h_{t-1})$

where $E_{t-1}$ is the expected value given information upto time t - 1.

Or, $E_{t-1}(\varepsilon^2_t) = E\, e^2_t (\kappa + \alpha\varepsilon^2_{t-1} + \gamma h_{t-1})$

Now, $E\, e^2_t = 1$.

Thus, $E_{t-1}(\varepsilon^2_t) = \kappa + \alpha\varepsilon^2_{t-1} + \gamma h_{t-1}$.

Thus the conditional variance of $\varepsilon_t$ is dependent on the realized values of $\varepsilon^2_{t-1}$ and $h_{t-1}$.

Now, $h_t = \kappa + \alpha\varepsilon^2_{t-1} + \gamma h_{t-1}$.

Adding $\varepsilon_t^2$ to both sides and rewriting the expression we get

$$h_t + \varepsilon_t^2 = \kappa - \gamma(\varepsilon_{t-1}^2 - h_{t-1}) + \gamma\varepsilon_{t-1}^2 + \alpha\varepsilon_{t-1}^2 + \varepsilon_t^2 .$$

Or, $\varepsilon_t^2 = \kappa + (\gamma + \alpha)\varepsilon_{t-1}^2 + \omega_t - \gamma\omega_{t-1}$ (7)

where $\omega_t \equiv \varepsilon_t^2 - h_t$ .

Now $h_t$ is the forecast of $\varepsilon_t^2$ based on its own lagged values and thus $\omega_t \equiv \varepsilon_t^2 - h_t$ is the error associated with the forecast. Thus $\omega_t$ is a white-noise process. Expression (7) is basically an ARMA(1,1) process in $\varepsilon_t^2$, in which the autoregressive coefficient is $(\gamma + \alpha)$ while the moving average coefficient is $\gamma$.

We use the iterated expectations technique to find the forecast function of $\varepsilon_t^2$. We get

$E_t\varepsilon_{t+j}^2 = (\gamma + \alpha)^j\{\varepsilon_t^2 - \kappa/(1-\gamma-\alpha)\} + \kappa/(1-\gamma-\alpha)$ (8)

Our IGARCH(1,1) model imposes the condition that a = 1.

Limit$[E_t\varepsilon_{t+j}^2,\ \gamma + \alpha$ □$1] = j\kappa + \varepsilon_t^2$ (9)

Thus, $E_t\varepsilon_{t+j}^2$ has a unit autoregressive root. Thus $E_t\varepsilon_{t+j}^2$ is not covariance stationary. Therefore shocks to $\varepsilon_t^2$ do not die out, but persist. In the behavior of its conditional expectation, $\varepsilon_t^2$ looks very much like a linear random walk with drift $\kappa$. However, as Nelson (1990) pointed out, the behavior of $\varepsilon_t^2$ in other respects is very different from a linear random walk. In an IGARCH(1,1) model with $\kappa = 0$, $\varepsilon_t^2$ converges to zero *almost surely*, i.e. P(|Limit$[\varepsilon_t^2,\ t \to \infty] - 0\ | > \delta) = 0$ for any arbitrary □ $> 0$; and in an IGARCH(1,1) model with $\kappa > 0$, $\varepsilon_t^2$ is strictly stationary and ergodic. Therefore $\varepsilon_t^2$

does not behave like a linear random walk, since linear random walks diverge *almost surely*.

# Chapter 4 – The Methodology

In this chapter, we explain the process of portfolio formation and regression estimation. The weekly Three-month US Treasury Bill rate data is from the Federal Reserve Bank. The rest of the data is from the International Finance Corporation's (IFC) *Emerging Market Data Base* (EMDB). Our weekly returns data on all the variables is from June 25th 1993 to June 26th 1998. We have 261 observations for each variable. $R_{f,t}$ is the Three-month US Treasury Bill rate. $R_{m,t}$ is the IFCG market index weekly returns of the country under study. In our analysis the dependent variable $F(h_t)$ is just the square root of $h_t$, i.e. $F(h_t) = \sqrt{(h_t)}$.

**Portfolio Formation**

The explanatory returns to SMB and HML are formed in the following way. In the last week of June of each year t the listed stocks of the country are allocated to two groups (small or big, S or B) based on whether the stock's market equity (ME, stock price times shares outstanding) in the last week of June is below or above the median ME. In the same week of June of each year t, in an independent sort, the stocks are allocated to three book-to-market equity (BE/ME) groups (low, medium, or high; L, M, or H) based on whether the stock fell below the twenty-five percentile, between the twenty-five percentile and the seventy-five percentile, or above the seventy-five percentile. Six size-BE/ME portfolios (SL, SM, SH, BL, BM, BH) are created from the stocks in the intersection of the two size and three BE/ME groups. Value-weighted monthly returns on the portfolios are calculated from that year's July to the following year's June. SMB is the difference, each week, between the average of the returns on the three small-stock portfolios (SL, SM, SH) and the average of the returns on the three big-stock portfolios (BL, BM, BH). HML is the difference between the average of the returns on the two high-BE/ME portfolios (SH and BH) and the average of the returns on the two low-BE/ME portfolios (SL and BL).

We form five categories of dependent returns which we have named SZDT, EP, PCF SE36, and SE12.

The sixteen portfolios in the SZDT (Size and Distress) category are formed in the following way. In the last week of June of each year t the listed stocks of the country are given ranks 1 through 4 depending on their ME in that last week. Stocks with smaller MEs are given lower ranks. In the same week, in an independent sort, the stocks are given ranks 1 through 4 depending on their BE/ME in that week. Stocks with smaller BE/MEs are given lower ranks. The sixteen portfolios are formed from stocks in the intersection the ME ranks and the BE/ME ranks. Equal-weight weekly returns on the portfolios are calculated from that year's July to the following year's June.

The ten portfolios in the EP category are formed in the following way. In the last week of June of each year t the listed stocks of the country are given ranks 1 through 10 depending on their Earnings-Price (EP) ratio in that last week. Stocks with smaller EPs are given lower ranks. Equal-weight weekly returns on the portfolios are calculated from that year's July to the following year's June.

The ten portfolios in the PCF category are formed in the following way. In the last week of June of each year t the listed stocks of the country are given ranks 1 through 10 depending on their Price-Cash Flow (PCF) ratio in that last week. Stocks with smaller PCF are given lower ranks. Equal-weight weekly returns on the portfolios are calculated from that year's July to the following year's June.

The ten portfolios in the SE36 category are formed in the following way. In the last week of June of each year t the mean of the monthly returns from thirty-six months before that June to one month before that June (36-1) is calculated for each stock. The stocks are then given a rank 1 through 10 depending on their mean return. Stocks with smaller mean returns are given lower ranks. Equal-weight weekly returns on the portfolios are calculated from that year's July to the following year's June.

The ten portfolios in the SE12 category are formed in the following way. In the last week of June of each year t the mean of the monthly returns from twelve months before that June to one month before that June (13-1) is calculated for each stock. The stocks are then given a rank 1 through 10 depending on their mean return. Stocks with smaller mean returns are given lower ranks. Equal-weight weekly returns on the portfolios are calculated from that year's July to the following year's June.

**Regression Method**

$$E(R_t) - R_{f,t} = b[E(R_{m,t}) - R_{f,t}] + E[PCER_t] + sE[SMB_t] + hE[HML_t] + \delta\sqrt{(h_t)} + \nu_t \qquad (1)$$

$$\nu_t = -\phi_1\nu_{t-1} - \phi_2\nu_{t-2} - \ldots\ldots\ldots\ldots\ldots -\phi_p\nu_{t-p} + \varepsilon_t \tag{2}$$

$$\varepsilon_t = \sqrt{(h_t)}\, e_t \tag{3}$$

$$h_t = \kappa + \alpha\varepsilon_{t-1}^2 + \gamma h_{t-1} \qquad \kappa > 0 \tag{4}$$

$$\alpha + \gamma = 1 \tag{5}$$

$$e_t \sim IN(0,1) \tag{6}$$

We first use the Ordinary Least Square (OLS) procedure to regress $[E(R_t) - R_{f,t}]$ on $[E(R_{m,t}) - R_{f,t}]$, $E[PCER_t]$, $E[SMB_t]$, and $E[HML_t]$. We then use the OLS procedure again to regress $[E(R_t) - R_{f,t}]$ on $[E(R_{m,t}) - R_{f,t}]$, $E[PCER_t]$, $E[SMB_t]$, $E[HML_t]$ and the lagged error terms (from lag one to lag thirteen) of the first regression. We drop the lagged error term with the smallest non-significant t-value and then re-estimate the model. Once again, we drop the lagged error with the smallest non-significant t-value and re-estimate the model. We repeat this procedure until there are no more lagged error terms with non-significant t-values in the model. We use the five-percent level of significance as our criterion for determining the significance of the lagged error terms. We then use the Maximum Likelihood Estimation (MLE) method to regress $[E(R_t) - R_{f,t}]$ on $[E(R_{m,t}) - R_{f,t}]$, $E[PCER_t]$, $E[SMB_t]$, $E[HML_t]$ the significant lagged error terms, $\sqrt{(h_t)}$, and the IGARCH(1,1) error term.

# Chapter 5 – Findings from South Korea's Stock Market

In this chapter, we present the results on our study of the South Korean stock market. This chapter is divided into five sections. In each section we present our findings on a certain category of portfolios. The categories of portfolios are SZDT, EP, PCF, SE36, and SE12. Each section is organized in the following way. We first present the means of out-of-sample returns along with their corresponding p-values. We then present the AIC and SC goodness-of-fit measures for the three categories of models, namely the One-Factor, the Three-Factor, and the Multi-Factor models. We then present the adjusted R-Squares for all three categories of models. We then present our estimation of the parameters of the three categories of models. We also present the Durbin-Watsons for the Multi-factor category of models.

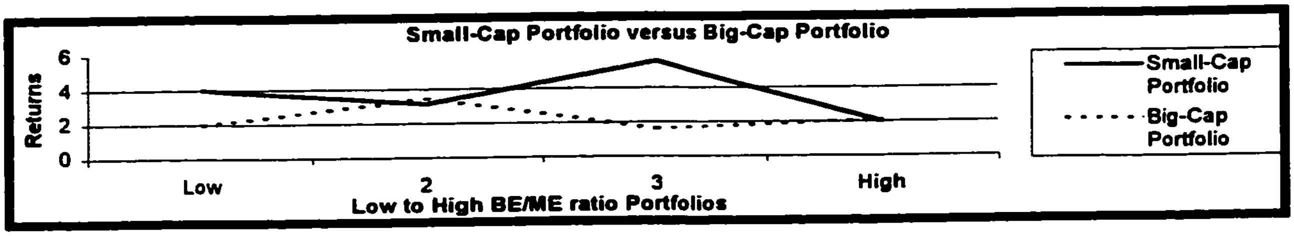
### 1. Tests on the 16 SZDT Portfolios

Table 5.1.1 shows the average out-of-sample returns to the 16 portfolios along with their corresponding p-values.

**Table 5.1.1**

**Summary Statistics**

| BE/ME \ Size | Low BE/ME | 2 | 3 | High BE/ME | | Low BE/ME | 2 | 3 | High BE/ME |
|---|---|---|---|---|---|---|---|---|---|
| | Means of Out-of-Sample Returns | | | | | p-values | | | |
| Small Mkt. Cap. | 4.02 | 3.13 | 5.57 | 1.99 | | 0.01 | 0.05 | 0.03 | 0.12 |
| 2 | 4.06 | 3.34 | 2.36 | 2.19 | | 0.01 | 0.01 | 0.05 | 0.18 |
| 3 | 4.10 | 3.10 | 2.61 | 1.28 | | 0.14 | 0.01 | 0.03 | 0.20 |
| Big Mkt. Cap | 1.95 | 3.45 | 1.61 | 2.07 | | 0.24 | 0.05 | 0.08 | 0.04 |



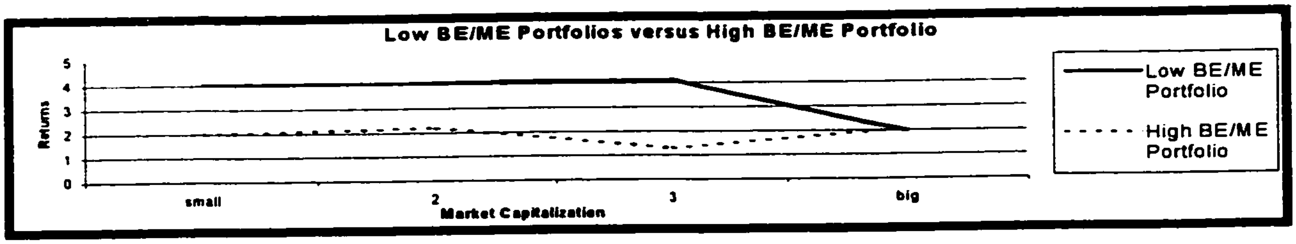



Table 5.1.1 shows that small stocks tend to have greater average out-of-sample returns than big stocks which is in line with the Fama-French findings for the American stock market. However, unlike the Fama-French findings for the American stock market, low BE/ME stocks tend to have greater average out-of-sample returns than high BE/ME stocks.

Table 5.1.2 presents the Akaike Information Criterion and the Schwarz Criterion, two goodness of fit measures of the estimated models.

**Table 5.1.2**

**Akaike Information Criterion (AIC)**

| | One-Factor CAPM | | | | Three-Factor CAPM | | | | Multi-Factor CAPM | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME |
| Small Mkt. Cap. | 1,562 | 1,502 | 1,697 | 1,604 | 1,214 | 1,346 | 1,453 | 1,376 | 888 | 990 | 1,045 | 983 |
| 2 | 1,482 | 1,389 | 1,382 | 1,479 | 1,133 | 1,281 | 1,210 | 1,344 | 795 | 906 | 901 | 983 |
| 3 | 1,503 | 1,213 | 1,334 | 1,224 | 1,352 | 1,147 | 1,254 | 1,216 | 921 | 810 | 943 | 889 |
| Big Mkt. Cap. | 1,627 | 1,126 | 982 | 1,442 | 1,267 | 1,099 | 981 | 1,383 | 939 | 740 | 671 | 1,061 |

**The Schwarz Criterion (SC)**

| | One-Factor CAPM | | | | Three-Factor CAPM | | | | Multi-Factor CAPM | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME |
| Small Mkt. Cap. | 1,572 | 1,512 | 1,707 | 1,614 | 1,232 | 1,364 | 1,470 | 1,394 | 935 | 1,033 | 1,084 | 1,040 |
| 2 | 1,493 | 1,400 | 1,393 | 1,490 | 1,151 | 1,299 | 1,228 | 1,362 | 831 | 949 | 937 | 1,022 |
| 3 | 1,514 | 1,223 | 1,344 | 1,234 | 1,370 | 1,165 | 1,272 | 1,233 | 974 | 853 | 983 | 925 |
| Big Mkt. Cap. | 1,638 | 1,137 | 993 | 1,453 | 1,285 | 1,117 | 999 | 1,401 | 978 | 776 | 714 | 1,093 |

A study of the tables shows that the Multi-Factor model has the best fit. The Three-Factor CAPM generally has a better fit than the One-Factor CAPM. On average, the AIC for the Three-factor model is 11 percent smaller than that for One-factor models, whereas the AIC for the Multi-factor models is 36 percent smaller than that for the One-factor models. . On average, the SC for the Three-factor model is 10 percent smaller than that for One-factor models, whereas the SC for the Multi-factor models is 33 percent smaller than that for the One-factor models.

Table 5.1.3 presents the adjusted R-Square of the regression models.

**Table 5.1.3**

| Adjusted R-Square | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | One-Factor CAPM | | | | Three-Factor CAPM | | | | Multi-Factor CAPM | | | |
| | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME |
| Small Mkt. Cap. | 0.68 | 0.73 | 0.61 | 0.69 | 0.91 | 0.85 | 0.85 | 0.87 | 0.92 | 0.85 | 0.84 | 0.87 |
| 2 | 0.72 | 0.78 | 0.79 | 0.73 | 0.92 | 0.85 | 0.89 | 0.84 | 0.92 | 0.86 | 0.89 | 0.84 |
| 3 | 0.73 | 0.87 | 0.81 | 0.85 | 0.85 | 0.90 | 0.86 | 0.85 | 0.83 | 0.90 | 0.86 | 0.85 |
| Big Mkt. Cap. | 0.56 | 0.89 | 0.94 | 0.70 | 0.89 | 0.90 | 0.94 | 0.76 | 0.88 | 0.90 | 0.94 | 0.76 |

The Adjusted R-Squares of the Multi-Factor CAPM regressions and the Three-Factor CAPM regressions average 0.87, whereas the Adjusted R-Square of the One-Factor CAPM regressions average 0.76. This shows that both the Multi-Factor CAPMs and the Three-Factor CAPMs have better explanatory power than the One-Factor CAPMs.

Table 5.1.4 shows the regression estimates of the One-Factor CAPM along with their corresponding p-values.

**Table 5.1.4**

**One-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + e_t$$

| BE/ME \ Size | Low BE/ME | 2 | 3 | High BE/ME | | Low BE/ME | 2 | 3 | High BE/ME |
|---|---|---|---|---|---|---|---|---|---|
| | **a** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | -1.46 | -1.30 | -2.14 | -1.60 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **2** | -1.28 | -0.93 | -1.37 | -0.90 | | 0.00 | 0.01 | 0.00 | 0.02 |
| **3** | -0.65 | -0.48 | -0.77 | -1.00 | | 0.12 | 0.04 | 0.01 | 0.00 |
| **Big** Mkt. Cap | -0.28 | -0.22 | -0.11 | 0.46 | | 0.59 | 0.28 | 0.46 | 0.21 |
| | **e** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | -0.90 | -0.92 | -1.49 | -1.19 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **2** | -0.63 | -0.36 | -0.69 | -0.48 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **3** | -0.43 | -0.10 | -0.27 | -0.18 | | 0.00 | 0.21 | 0.01 | 0.03 |
| **Big** Mkt. Cap | -0.03 | 0.10 | 0.03 | 0.27 | | 0.88 | 0.15 | 0.54 | 0.03 |
| | **b** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | 0.76 | 0.76 | 0.64 | 0.76 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **2** | 0.81 | 0.90 | 0.79 | 0.89 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **3** | 0.97 | 0.97 | 0.92 | 0.87 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **Big** Mkt. Cap | 0.96 | 0.99 | 1.01 | 1.01 | | 0.00 | 0.00 | 0.00 | 0.00 |

Ten of the sixteen intercepts were negative and significant at the 5 percent level of significance. The portfolios of only the big firms have non-significant intercepts. Thus, generally, the models are not able to capture the pattern of portfolio returns. The market betas of the small firms are generally smaller than of those of the big firms. Thus, big firms seem to be more volatile than the small firms are. However, we shall see later that the difference in volatility disappears once we bring in all the risk factors.

Table 5.1.5 shows the regression estimates of the Three-Factor CAPM along with their corresponding p-values.

**Table 5.1.5**

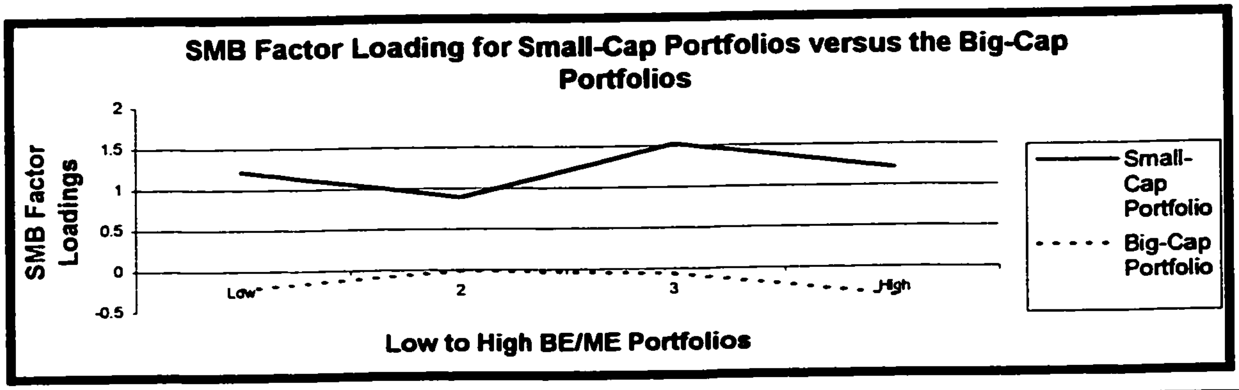
**Three-Factor CAPM Time-Series Regression Estimates**

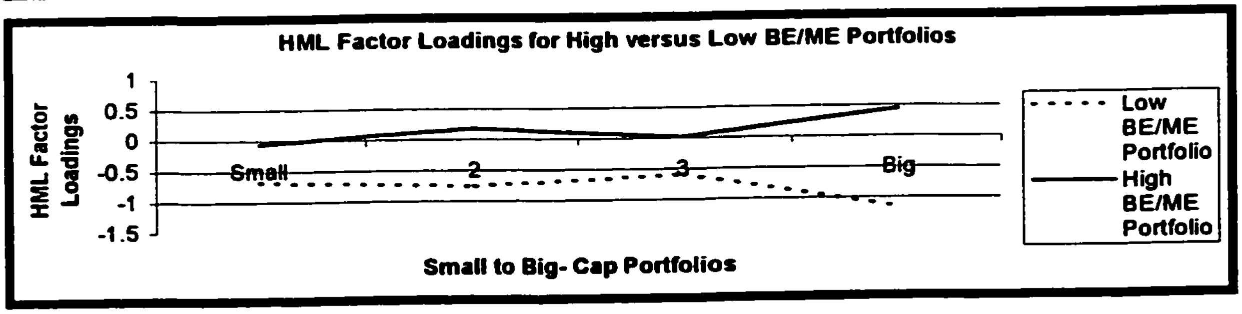
$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + e_t$$

| BE/ME \ Size | Low BE/ME | 2 | 3 | High BE/ME | | Low BE/ME | 2 | 3 | High BE/ME |
|---|---|---|---|---|---|---|---|---|---|
| | a | | | | | p-values | | | |
| Small Mkt. Cap. | -0.07 | -0.32 | -0.50 | -0.37 | | 0.76 | 0.31 | 0.19 | 0.26 |
| 2 | -0.17 | -0.24 | -0.59 | -0.24 | | 0.40 | 0.38 | 0.01 | 0.44 |
| 3 | 0.27 | -0.08 | -0.21 | -0.84 | | 0.40 | 0.72 | 0.41 | 0.00 |
| Big Mkt. Cap | -0.22 | -0.18 | -0.17 | 0.00 | | 0.42 | 0.35 | 0.27 | 0.99 |
| | e | | | | | p-values | | | |
| Small Mkt. Cap. | -0.01 | -0.27 | -0.37 | -0.29 | | 0.92 | 0.02 | 0.01 | 0.01 |
| 2 | 0.04 | 0.11 | -0.14 | 0.04 | | 0.62 | 0.28 | 0.11 | 0.75 |
| 3 | 0.13 | 0.16 | 0.09 | -0.07 | | 0.25 | 0.04 | 0.32 | 0.45 |
| Big Mkt. Cap | -0.19 | 0.09 | -0.01 | 0.02 | | 0.05 | 0.21 | 0.79 | 0.90 |
| | b | | | | | p-values | | | |
| Small Mkt. Cap. | 0.99 | 0.93 | 0.92 | 0.97 | | 0.00 | 0.00 | 0.00 | 0.00 |
| 2 | 1.00 | 1.01 | 0.92 | 1.00 | | 0.00 | 0.00 | 0.00 | 0.00 |
| 3 | 1.12 | 1.04 | 1.01 | 0.90 | | 0.00 | 0.00 | 0.00 | 0.00 |
| Big Mkt. Cap | 0.98 | 0.99 | 1.00 | 0.93 | | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 5.1.5 Continued**

| BE/ME / Size | Low BE/ME | 2 | 3 | High BE/ME | | Low BE/ME | 2 | 3 | High BE/ME |
|---|---|---|---|---|---|---|---|---|---|
| | s | | | | | p-values | | | |
| Small Mkt. Cap. | 1.22 | 0.89 | 1.52 | 1.21 | | 0.00 | 0.00 | 0.00 | 0.00 |
| 2 | 0.92 | 0.64 | 0.74 | 0.70 | | 0.00 | 0.00 | 0.00 | 0.00 |
| 3 | 0.76 | 0.35 | 0.50 | 0.16 | | 0.00 | 0.00 | 0.00 | 0.00 |
| Big Mkt. Cap | -0.22 | -0.01 | -0.06 | -0.35 | | 0.00 | 0.77 | 0.04 | 0.00 |
| | h | | | | | p-values | | | |
| Small Mkt. Cap. | -0.68 | -0.38 | -0.47 | -0.06 | | 0.00 | 0.00 | 0.00 | 0.32 |
| 2 | -0.76 | -0.20 | -0.15 | 0.18 | | 0.00 | 0.00 | 0.00 | 0.00 |
| 3 | -0.59 | -0.20 | -0.21 | 0.01 | | 0.00 | 0.00 | 0.00 | 0.84 |
| Big Mkt. Cap | -1.16 | -0.18 | -0.01 | 0.45 | | 0.00 | 0.00 | 0.76 | 0.00 |



Fourteen of the sixteen intercepts are not significantly different from zero at the 5 percent level of significance. This shows that in general risk factors are adequately priced leaving no abnormal return to the portfolios. The market betas of the portfolios are all close to one. This shows that the stocks generally move in step with the market.

We also see that the small firms have positive coefficients on the SMB portfolios, whereas big firms have a low and negative coefficient on the SMB portfolio. Thus small firms do receive a small-firm risk premium. We see that high BE/ME (value) stocks have a positive coefficient on the HML portfolio, whereas the lower the BE/ME the more negative the coefficient is on the HML portfolio. This shows that value stocks are given the value risk premium.

Table 5.1.6 shows the regression estimates of the Multi-Factor CAPM along with their corresponding p-values.

**Table 5.1.6**

**Multi-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + \delta\sqrt{(h_t)} + -\phi_1 v_{t-1} - \phi_2 v_{t-2} - \ldots - \phi_{53} v_{t-53} + \sqrt{(h_t)}\, e_t$$

$$h_t = \kappa + \alpha\varepsilon_{t-1}^2 + \gamma h_{t-1} \qquad \kappa > 0$$

$$\alpha + \gamma = 1$$

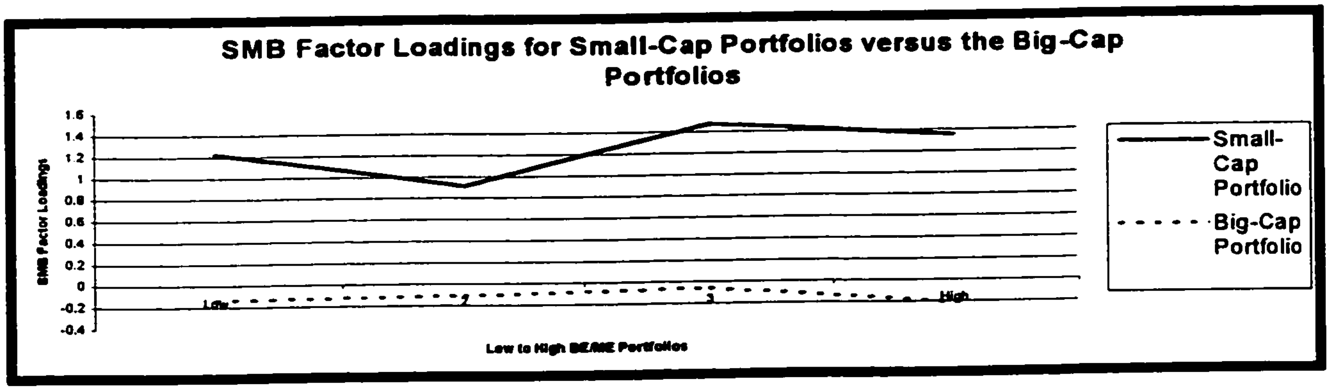
| BE/ME \ Size | Low BE/ME | 2 | 3 | High BE/ME | | Low BE/ME | 2 | 3 | High BE/ME |
|---|---|---|---|---|---|---|---|---|---|
| | **a** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | -0.20 | 2.96 | -0.21 | -0.08 | | 0.73 | 0.40 | 0.68 | 0.87 |
| **2** | 0.10 | 0.10 | -0.39 | -0.63 | | 0.80 | 0.79 | 0.82 | 0.37 |
| **3** | 0.22 | -0.45 | -0.50 | -0.57 | | 0.52 | 0.30 | 0.29 | 0.31 |
| **Big** Mkt. Cap | -0.59 | -0.03 | -0.88 | -2.14 | | 0.22 | 0.92 | 0.02 | 0.01 |
| | **e** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | 0.01 | -0.35 | -0.23 | -0.28 | | 0.91 | 0.00 | 0.23 | 0.01 |
| **2** | -0.08 | 0.01 | -0.14 | 0.00 | | 0.43 | 0.90 | 0.10 | 0.97 |
| **3** | -0.12 | 0.13 | -0.11 | 0.04 | | 0.40 | 0.09 | 0.31 | 0.71 |
| **Big** Mkt. Cap | -0.15 | -0.07 | 0.03 | -0.05 | | 0.06 | 0.47 | 0.57 | 0.70 |
| | **b** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | 0.98 | 0.94 | 1.03 | 0.97 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **2** | 0.98 | 0.97 | 0.93 | 0.96 | | 0.00 | 0.00 | 0.00 | 0.00 |

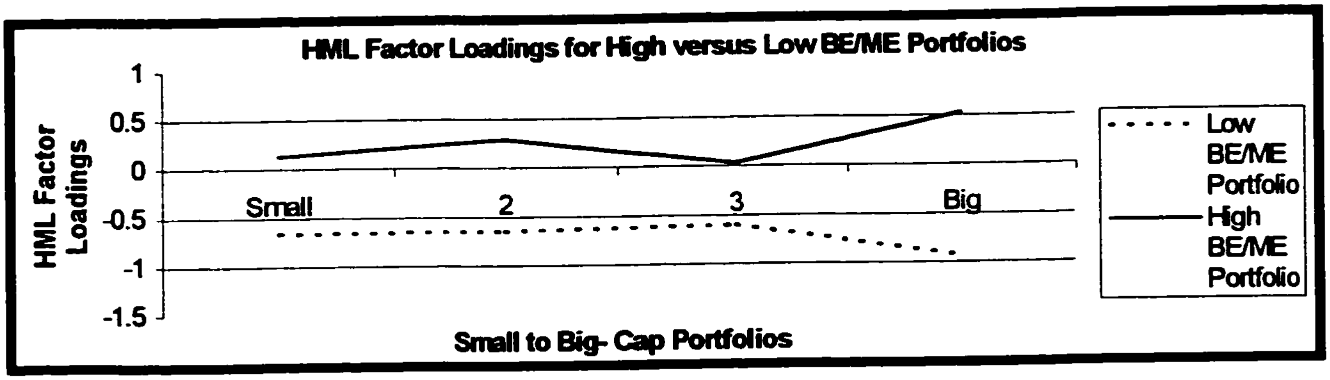
| Table 5.1.6 Continued | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| BE/ME / Size | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME |
| 3 | 1.04 | 1.05 | 0.95 | 0.98 | 0.00 | 0.00 | 0.00 | 0.00 |
| Big Mkt. Cap | 0.96 | 0.95 | 1.02 | 0.85 | 0.00 | 0.00 | 0.00 | 0.00 |
| | s | | | | p-values | | | |
| Small Mkt. Cap. | 1.22 | 0.91 | 1.47 | 1.35 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2 | 0.87 | 0.68 | 0.74 | 0.75 | 0.00 | 0.00 | 0.00 | 0.00 |
| 3 | 0.35 | 0.35 | 0.33 | 0.20 | 0.00 | 0.00 | 0.00 | 0.00 |
| Big Mkt. Cap | -0.14 | -0.11 | -0.06 | -0.21 | 0.03 | 0.01 | 0.12 | 0.00 |
| | h | | | | p-values | | | |
| Small Mkt. Cap. | -0.66 | -0.25 | -0.32 | 0.13 | 0.00 | 0.00 | 0.00 | 0.06 |
| 2 | -0.65 | -0.25 | -0.15 | 0.29 | 0.00 | 0.00 | 0.00 | 0.00 |
| 3 | -0.60 | -0.20 | -0.05 | 0.03 | 0.00 | 0.00 | 0.34 | 0.52 |
| Big Mkt. Cap | -0.93 | -0.13 | -0.01 | 0.53 | 0.00 | 0.00 | 0.70 | 0.00 |
| | delta | | | | p-values | | | |
| Small Mkt. Cap. | -0.01 | -1.07 | 0.04 | -0.11 | 0.97 | 0.39 | 0.79 | 0.54 |
| 2 | -0.18 | -0.19 | -0.09 | 0.05 | 0.36 | 0.19 | 0.91 | 0.81 |
| 3 | -0.13 | 0.20 | -0.01 | 0.06 | 0.35 | 0.25 | 0.96 | 0.81 |
| Big Mkt. Cap | 0.09 | -0.17 | 0.49 | 0.45 | 0.51 | 0.32 | 0.03 | 0.02 |

**Table 5.1.6 Continued**

| BE/ME \ Size | Low BE/ME | 2 | 3 | High BE/ME | | Low BE/ME | 2 | 3 | High BE/ME |
|---|---|---|---|---|---|---|---|---|---|
| | **k** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | 0.19 | 0.08 | 0.57 | 0.21 | | 0.33 | 0.56 | 0.13 | 0.16 |
| **2** | 0.08 | 0.55 | 0.03 | 5.10 | | 0.27 | 0.15 | 0.48 | 0.03 |
| **3** | 0.52 | 1.08 | 4.74 | 0.39 | | 0.07 | 0.11 | 0.00 | 0.13 |
| **Big** Mkt. Cap | 6.34 | 0.15 | 0.15 | 4.35 | | 0.09 | 0.13 | 0.15 | 0.06 |
| | **alpha** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | 0.14 | 0.03 | 0.24 | 0.11 | | 0.11 | 0.27 | 0.01 | 0.03 |
| **2** | 0.11 | 0.20 | 0.02 | 0.87 | | 0.04 | 0.02 | 0.43 | 0.00 |
| **3** | 0.32 | 0.45 | 1.00 | 0.24 | | 0.00 | 0.00 | 0.00 | 0.01 |
| **Big** Mkt. Cap | 0.90 | 0.19 | 0.23 | 0.67 | | 0.00 | 0.02 | 0.02 | 0.00 |
| | **gamma** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | 0.86 | 0.97 | 0.76 | 0.89 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **2** | 0.89 | 0.80 | 0.98 | 0.13 | | 0.00 | 0.00 | 0.00 | 0.39 |
| **3** | 0.68 | 0.55 | 0.00 | 0.76 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **Big** Mkt. Cap | 0.10 | 0.81 | 0.77 | 0.33 | | 0.64 | 0.00 | 0.00 | 0.03 |

| Durbin Watson to check for Autocorrelation | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Durbin Watson | | | | p-value for negative autocorrelation | | | | p-value for positive autocorrelation | | | |
| | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME |
| Small Mkt. Cap. | 2.27 | 2.33 | 2.12 | 2.10 | 0.01 | 0.00 | 0.16 | 0.19 | 0.99 | 1.00 | 0.84 | 0.81 |
| 2 | 2.18 | 2.12 | 2.30 | 2.01 | 0.07 | 0.15 | 0.01 | 0.45 | 0.93 | 0.85 | 0.99 | 0.55 |
| 3 | 2.12 | 2.19 | 2.11 | 2.20 | 0.16 | 0.06 | 0.17 | 0.05 | 0.84 | 0.94 | 0.83 | 0.95 |
| Big Mkt. Cap. | 2.19 | 1.79 | 2.21 | 2.19 | 0.06 | 0.96 | 0.04 | 0.05 | 0.94 | 0.04 | 0.96 | 0.95 |




Fourteen of the sixteen intercepts are not significantly different from zero at the 5 percent level of significance. These model also show that in general risk factors are adequately priced leaving no abnormal return to the portfolios. We also see that the market betas are all significant and close to one. Thus, all the stocks generally move in step with the market.

We see that the small stocks are given its small stock risk premium (i.e. positive loadings on the SMB risk factors). We also see that the high BE/ME (value) stocks are given its value risk premium (i.e. positive loadings on the HML risk factors).

The alpha and gamma coefficients are significantly different from zero at the 5 percent level of significance. This shows that there is time varying conditional variance in the stock returns. However we see that the coefficients for delta are all not significantly different from zero; this may be either because the risk associated with a changing variance is not compensated for, or because this risk is somehow captured by and compensated for in a higher premium to some of the other risk factors. We see that the gamma is generally given a higher weight than the alpha; this implies that in predicting the current residual variance, more importance is given to the one period past estimate of the residual variance than what is given to the one period past squared residual.

Only two of the sixteen portfolios show significant negative autocorrelation when measured at the one- percent level of significance. This shows that in general autocorrelation did not pose a problem.

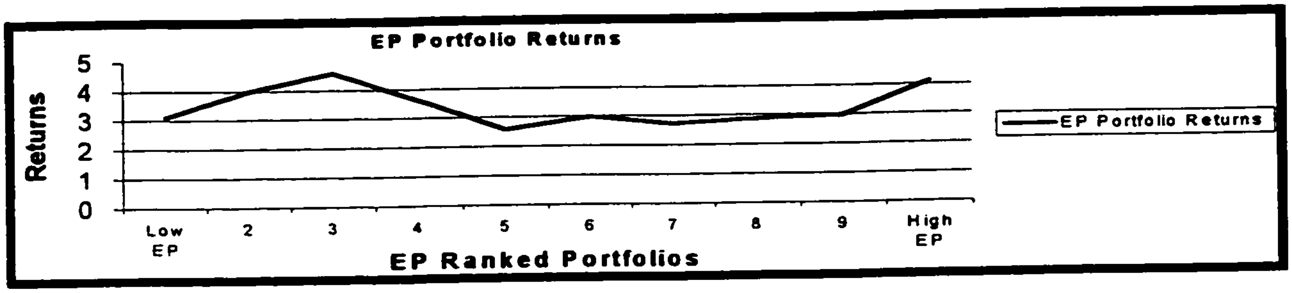
**2. Tests on the 10 EP Portfolios**

Table 5.2.1 shows the average out-of-sample returns to the 10 portfolios along with their corresponding p-values.

**Table 5.2.1**

**Summary Statistics**

| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
|---|---|---|---|---|---|---|---|---|---|---|
| **Returns** | 3.10 | 3.97 | 4.57 | 3.62 | 2.58 | 2.98 | 2.73 | 2.87 | 2.95 | 4.10 |
| **p-value** | 0.03 | 0.01 | 0.03 | 0.02 | 0.01 | 0.02 | 0.01 | 0.03 | 0.02 | 0.01 |




The average out-of-sample returns to the portfolios formed based on the EP ratio, do not show any trend, and average around 3.35 percent.

Table 5.2.2 presents the Akaike Information Criterion and the Schwarz Criterion, two goodness of fit measures of the estimated models.

**Table 5.2.2**

| Goodness-of-Fit | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
| **Akaike Information Criterion** | | | | | | | | | | |
| One-Factor | 1,442 | 1,427 | 1,314 | 1,355 | 1,227 | 1,231 | 1,237 | 1,294 | 1,166 | 1,251 |
| Three-Factor | 1,239 | 1,254 | 1,252 | 1,211 | 1,064 | 1,072 | 1,086 | 1,036 | 1,049 | 1,089 |
| Multi-Facor | 931 | 913 | 850 | 815 | 709 | 731 | 777 | 715 | 697 | 758 |
| **Schwarz Criterion** | | | | | | | | | | |
| One-Factor | 1,453 | 1,438 | 1,325 | 1,365 | 1,237 | 1,241 | 1,248 | 1,304 | 1,176 | 1,262 |
| Three-Factor | 1,257 | 1,272 | 1,270 | 1,228 | 1,082 | 1,090 | 1,104 | 1,054 | 1,067 | 1,106 |
| Multi-Facor | 966 | 953 | 900 | 868 | 748 | 774 | 819 | 754 | 747 | 797 |

A study of the tables shows that the Multi-Factor model has the best fit. The Three-Factor CAPM generally has a better fit than the One-Factor CAPM. On average, the AIC for the Three-factor model is 12 percent smaller than that for One-factor models, whereas the AIC for the Multi-factor models is 39 percent smaller than that for the One-factor models. . On average, the SC for the Three-factor model is 12 percent smaller than that

for One-factor models, whereas the SC for the Multi-factor models is 36 percent smaller than that for the One-factor models.

Table 5.2.3 presents the adjusted R-Square of the regression models.

**Table 5.2.3**

| Adjusted R-Square | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
| One-Factor | 0.77 | 0.77 | 0.80 | 0.80 | 0.86 | 0.87 | 0.87 | 0.83 | 0.88 | 0.84 |
| Three-Factor | 0.89 | 0.88 | 0.85 | 0.89 | 0.92 | 0.93 | 0.92 | 0.94 | 0.92 | 0.91 |
| Multi-Facor | 0.90 | 0.88 | 0.83 | 0.90 | 0.93 | 0.94 | 0.93 | 0.94 | 0.93 | 0.92 |

The Adjusted R-Squares of the Multi-Factor CAPM regressions and the Three-Factor CAPM regressions average 0.91, whereas the Adjusted R-Square of the One-Factor CAPM regressions average 0.81. This shows that both the Multi-Factor CAPMs and the Three-Factor CAPMs have better explanatory power than the One-Factor CAPMs.

Table 5.2.4 shows the regression estimates of the One-Factor CAPM along with their corresponding p-values.

**Table 5.2.4**

**One-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + e_t$$

| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
|---|---|---|---|---|---|---|---|---|---|---|
| **a** | -0.55 | -1.08 | -0.94 | -0.83 | -0.99 | -0.66 | -0.62 | -0.90 | -0.65 | -0.72 |
| **p-value** | 0.13 | 0.00 | 0.00 | 0.01 | 0.00 | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **e** | -0.42 | -0.54 | -0.24 | -0.32 | -0.37 | -0.43 | -0.35 | -0.49 | -0.25 | -0.20 |
| **p-value** | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 |
| | | | | | | | | | | |
| **b** | 0.97 | 0.87 | 0.88 | 0.92 | 0.86 | 0.93 | 0.92 | 0.84 | 0.90 | 0.89 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

The intercepts of nine of the ten models are significant and negative at the 5 percent level of significance. Thus, the model is not able to capture the pattern of returns of the portfolios. The intercepts do not show any trend across portfolios. The market betas of all the portfolios are less than one. Thus, portfolios built on a sort of stocks based on the ranks of EP ratio all show less volatility than the market portfolio.

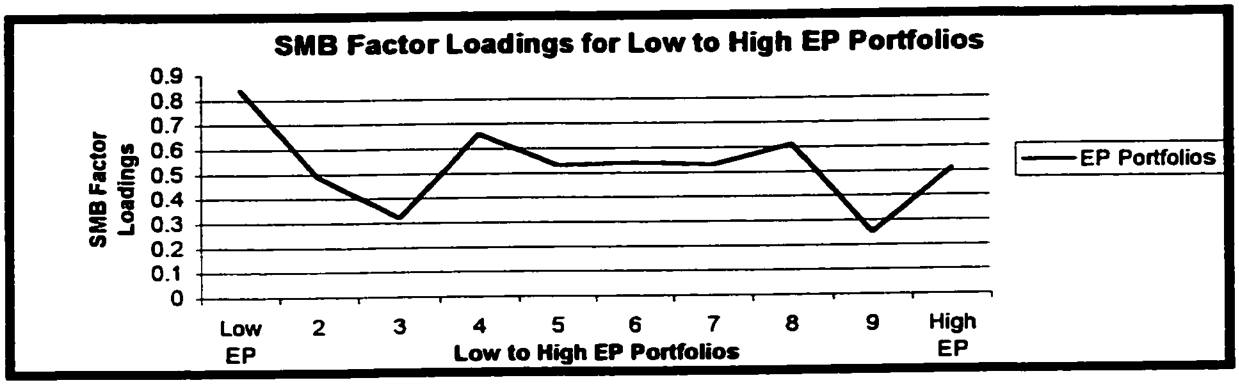
Table 5.2.5 shows the regression estimates of the Three-Factor CAPM along with their corresponding p-values.

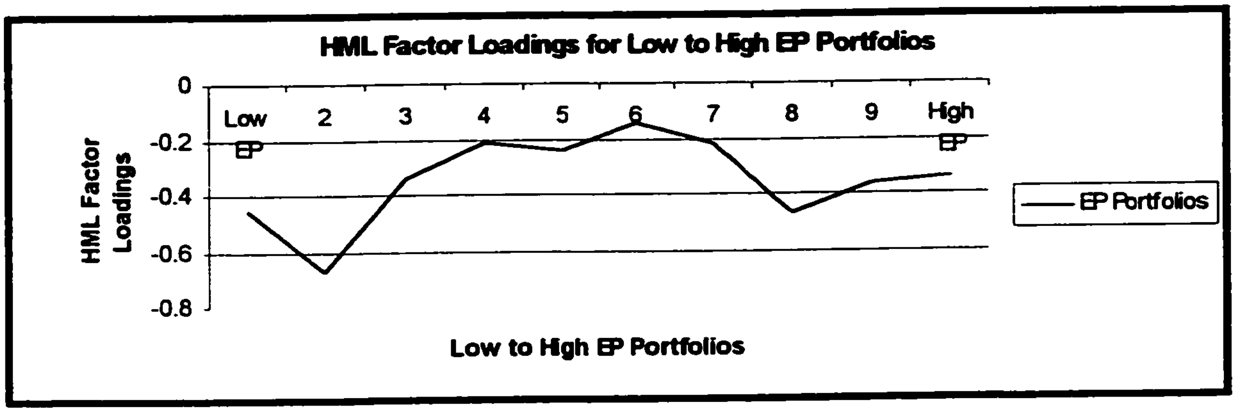
**Table 5.2.5**

**Three-Factor CAPM Time-Series Regression Estimates**

$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + e_t$

| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
|---|---|---|---|---|---|---|---|---|---|---|
| **a** | 0.40 | -0.43 | -0.54 | -0.11 | -0.40 | -0.08 | -0.03 | -0.18 | -0.32 | -0.13 |
| **p-value** | 0.11 | 0.10 | 0.04 | 0.64 | 0.03 | 0.66 | 0.86 | 0.31 | 0.07 | 0.51 |
| | | | | | | | | | | |
| **e** | 0.20 | -0.19 | 0.00 | 0.16 | 0.02 | -0.03 | 0.04 | -0.05 | -0.07 | 0.18 |
| **p-value** | 0.03 | 0.05 | 0.98 | 0.06 | 0.77 | 0.67 | 0.61 | 0.45 | 0.29 | 0.01 |
| | | | | | | | | | | |
| **b** | 1.13 | 0.98 | 0.94 | 1.05 | 0.96 | 1.02 | 1.02 | 0.97 | 0.96 | 1.00 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **s** | 0.84 | 0.49 | 0.32 | 0.66 | 0.53 | 0.54 | 0.53 | 0.61 | 0.25 | 0.51 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **h** | -0.45 | -0.67 | -0.34 | -0.21 | -0.24 | -0.14 | -0.22 | -0.47 | -0.36 | -0.34 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |




We see that nine of the ten intercepts are not significantly different from zero at the 5 percent level of significance. Thus, the model is able to capture the pattern of returns to the portfolios and the risks of the portfolios are priced adequately. The market betas of the portfolios range from 0.94 to 1.13. Low EP stocks are greater than one and thus more volatile than the market whereas high EP stocks are less than one and thus less volatile than the market.

The low EP portfolios earn a higher small-firm risk premium (i.e. greater positive loadings on the SMB risk factor) than the high EP portfolios; thus low EP portfolios seem to consist of more small firms than the high EP portfolios. On the other hand, the low EP portfolios endure a higher low-distress penalty (i.e. more negative loadings on the HML risk factor) than the high EP portfolios; thus, low EP portfolios seem to consist of lower BE/ME stocks i.e. growth stocks, than the high EP portfolios. Thus, the low EP portfolios seem to consist of smaller, healthier, but more volatile stocks than the big EP portfolios.

Table 5.2.6 shows the regression estimates of the Multi-Factor CAPM along with their corresponding p-values.

**Table 5.2.6**

**Multi-Factor CAPM Time-Series Regression Estimates**

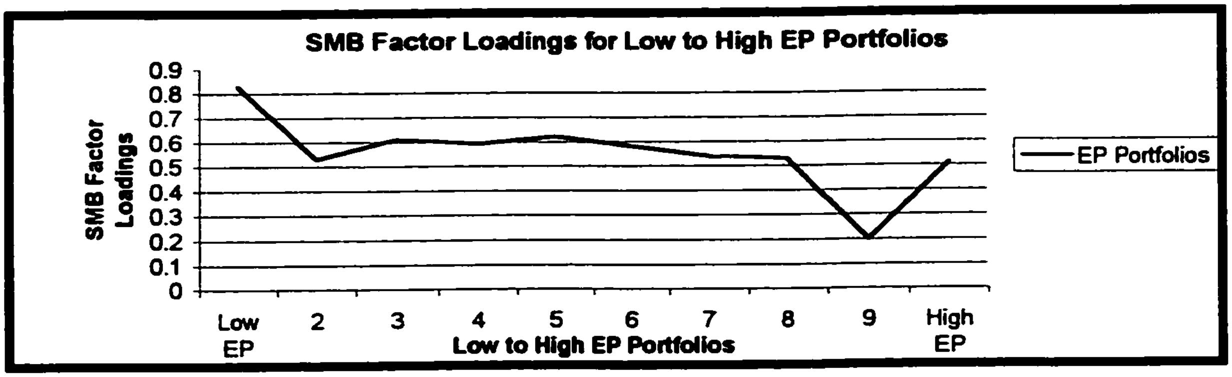
$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + \delta\sqrt{(h_t)} + -\phi_1 v_{t-1} - \phi_2 v_{t-2} - \dots - \phi_{53} v_{t-53} + \sqrt{(h_t)}\, e$$

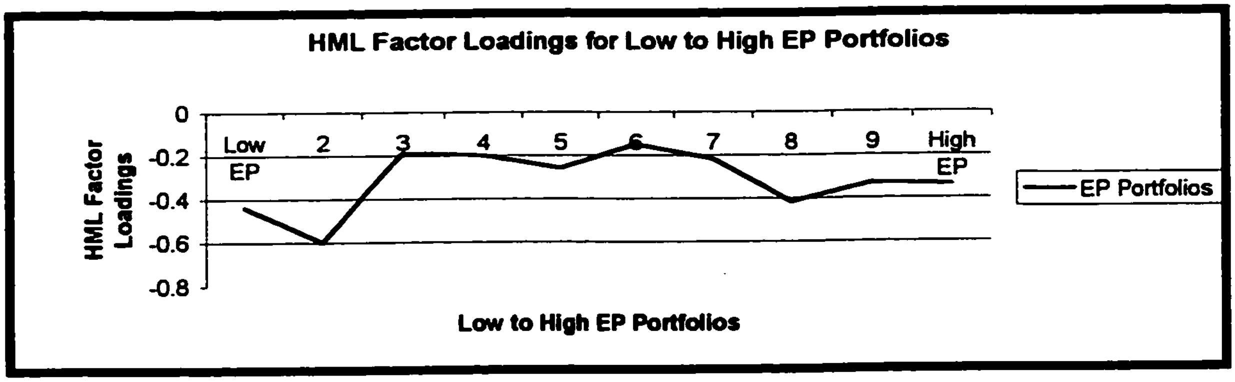
$$h_t = \kappa + \alpha\varepsilon_{t-1}^2 + \gamma h_{t-1} \qquad \kappa > 0$$

$$\alpha + \gamma = 1$$

| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
|---|---|---|---|---|---|---|---|---|---|---|
| **a** | -0.18 | 0.82 | -0.61 | 0.00 | -0.32 | -0.63 | -0.25 | -0.76 | -0.48 | -0.58 |
| **p-value** | 0.79 | 0.46 | 0.07 | 1.00 | 0.18 | 0.26 | 0.72 | 0.04 | 0.12 | 0.14 |
| | | | | | | | | | | |
| **e** | 0.20 | -0.18 | 0.22 | 0.17 | 0.16 | 0.00 | 0.04 | -0.05 | -0.08 | 0.11 |
| **p-value** | 0.03 | 0.02 | 0.01 | 0.03 | 0.02 | 0.98 | 0.59 | 0.51 | 0.15 | 0.15 |
| | | | | | | | | | | |
| **b** | 1.13 | 0.97 | 1.00 | 1.04 | 1.01 | 1.01 | 1.04 | 0.97 | 0.95 | 0.96 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **s** | 0.83 | 0.53 | 0.61 | 0.59 | 0.62 | 0.58 | 0.54 | 0.53 | 0.20 | 0.51 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **h** | -0.44 | -0.60 | -0.19 | -0.20 | -0.26 | -0.15 | -0.22 | -0.42 | -0.33 | -0.34 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

| Table 5.2.6 Continued | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
| delta | 0.26 | -0.52 | 0.16 | -0.06 | 0.09 | 0.26 | 0.15 | 0.30 | 0.07 | 0.14 |
| p-value | 0.33 | 0.22 | 0.24 | 0.73 | 0.52 | 0.33 | 0.68 | 0.08 | 0.70 | 0.48 |
| | | | | | | | | | | |
| k | 0.06 | 0.03 | 0.52 | 0.42 | 0.11 | 0.14 | 0.07 | 0.60 | 0.31 | 0.28 |
| p-value | 0.43 | 0.53 | 0.10 | 0.23 | 0.13 | 0.54 | 0.55 | 0.19 | 0.21 | 0.18 |
| | | | | | | | | | | |
| alpha | 0.08 | 0.03 | 0.31 | 0.22 | 0.21 | 0.12 | 0.08 | 0.38 | 0.28 | 0.27 |
| p-value | 0.09 | 0.29 | 0.00 | 0.04 | 0.00 | 0.42 | 0.41 | 0.00 | 0.04 | 0.03 |
| | | | | | | | | | | |
| gamma | 0.92 | 0.97 | 0.69 | 0.78 | 0.79 | 0.88 | 0.92 | 0.62 | 0.72 | 0.73 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **Durbin Watson to test for Autocorrelation** | | | | | | | | | | |
| d | 2.25 | 2.24 | 2.48 | 1.85 | 2.22 | 2.17 | 2.12 | 1.97 | 1.92 | 2.14 |
| p-value (for - corr) | 0.98 | 0.98 | 1.00 | 0.13 | 0.97 | 0.93 | 0.85 | 0.41 | 0.26 | 0.88 |
| p-value (for + corr) | 0.02 | 0.02 | <.0001 | 0.87 | 0.03 | 0.07 | 0.15 | 0.59 | 0.74 | 0.12 |




Nine of the ten intercepts are not significantly different from zero at the 5 percent level of significance. Thus the risks seem to be adequately priced and the model is able to capture the pattern of returns of the portfolios. The market betas of the portfolios range from 0.95 to 1.13. The market betas of the low EP stocks are greater than one and thus more volatile than the market whereas high EP stocks are less than one and thus less volatile than the market.

The low EP portfolios earn a higher small-firm risk premium (i.e. greater positive loadings on the SMB risk factor) than the high EP portfolios; thus low EP portfolios seem to consist of more small firms than the high EP portfolios. On the other hand, the low EP portfolios endure a higher low-distress penalty (i.e. more negative loadings on the HML risk factor) than the high EP portfolios; thus, low EP portfolios seem to consist of lower BE/ME stocks i.e. growth stocks, than the high EP portfolios.

The alpha coefficients are not always significantly different from zero at the 5 percent level of significance but the gamma coefficients are always significantly different from zero at the 5 percent level of significance. However we see that the coefficients for delta are all not significantly different from zero at the 5 percent level of significance; this may be either because the risk associated with a changing variance is not compensated for, or because this risk is somehow captured by and compensated for in a higher premium to some of the other risk factors. We see that the gamma is always given a higher weight than the alpha; this implies that in predicting the current residual variance, more importance is given to the one period past estimate of the residual variance than what is given to the one period past squared residual.

Only one of the ten portfolios showed significant positive autocorrelation when measured at the one- percent level of significance. This shows that in general autocorrelation did not pose a problem.

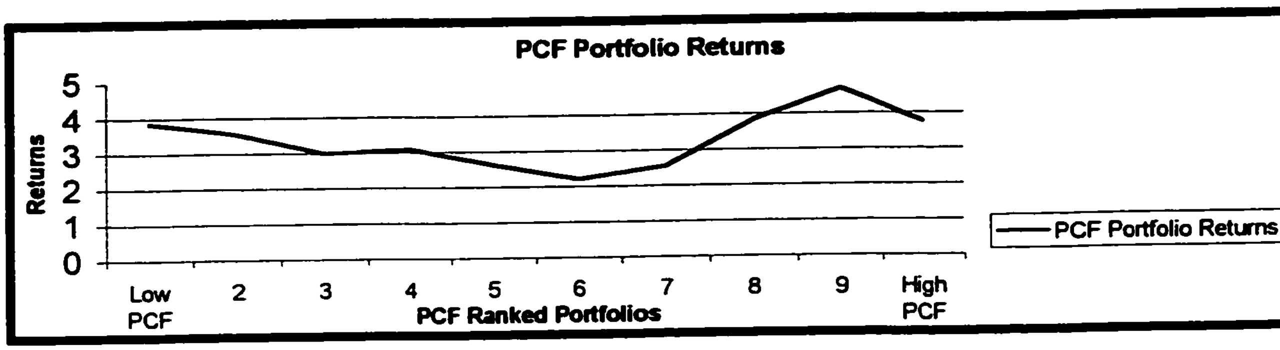
Thus the low EP portfolios seem to consist of smaller, healthier, but more volatile stocks than the big EP portfolios, with a significant conditionally heteroskedastic error term.

### 3. Tests on the 10 PCF Portfolios

Table 5.3.1 shows the average out-of-sample returns to the 10 portfolios along with their corresponding p-values.

**Table 5.3.1**

| Summary Statistics | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Low PCF** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High PCF** |
| **Returns** | 3.86 | 3.54 | 2.99 | 3.10 | 2.62 | 2.20 | 2.55 | 3.84 | 4.71 | 3.76 |
| **p-value** | 0.01 | 0.01 | 0.02 | 0.03 | 0.02 | 0.05 | 0.02 | 0.02 | 0.02 | 0.02 |




The average out-of-sample returns on the portfolios formed based on the PCF ratio show a clear trend with the Low and High PCF portfolios having a higher average return than the middle-ranked portfolios.

Table 5.3.2 presents the Akaike Information Criterion and the Schwarz Criterion, two goodness of fit measures of the estimated models.

**Table 5.3.2**

| Goodness-of-Fit | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
| **Akaike Information Criterion** | | | | | | | | | | |
| **One-Factor** | 1,27 3 | 1,144 | 1,206 | 1,137 | 1,260 | 1,357 | 1,462 | 1,277 | 1,297 | 1,513 |
| **Three-Factor** | 1,07 6 | 1,027 | 1,096 | 1,016 | 1,087 | 1,191 | 1,256 | 1,190 | 1,201 | 1,331 |
| **Multi-Facor** | 755 | 701 | 774 | 693 | 775 | 839 | 896 | 866 | 880 | 990 |
| **Schwarz Criterion** | | | | | | | | | | |
| **One-Factor** | 1,283 | 1,155 | 1,217 | 1,148 | 1,270 | 1,368 | 1,473 | 1,288 | 1,308 | 1,524 |
| **Three-Factor** | 1,093 | 1,045 | 1,114 | 1,033 | 1,104 | 1,209 | 1,274 | 1,207 | 1,219 | 1,349 |
| **Multi-Facor** | 791 | 740 | 806 | 736 | 807 | 878 | 938 | 906 | 916 | 1,029 |

A study of the tables shows that the Multi-Factor model has the best fit. The Three-Factor CAPM generally has a better fit than the One-Factor CAPM. On average, the AIC for the Three-factor model is 11 percent smaller than that for One-factor models, whereas the AIC for the Multi-factor models is 37 percent smaller than that for the One-factor models. . On average, the SC for the Three-factor model is 11 percent smaller than that

for One-factor models, whereas the SC for the Multi-factor models is 34 percent smaller than that for the One-factor models.

Table 5.3.3 presents the adjusted R-Square of the regression models.

**Table 5.3.3**

| Adjusted R-Square | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
| One-Factor | 0.83 | 0.90 | 0.87 | 0.90 | 0.84 | 0.81 | 0.73 | 0.83 | 0.83 | 0.73 |
| Three-Factor | 0.92 | 0.93 | 0.91 | 0.94 | 0.92 | 0.90 | 0.88 | 0.88 | 0.89 | 0.87 |
| Multi-Facor | 0.92 | 0.94 | 0.91 | 0.94 | 0.92 | 0.91 | 0.87 | 0.88 | 0.89 | 0.87 |

The Adjusted R-Squares of the Multi-Factor CAPM regressions average 0.91and that of the Three-Factor CAPM regressions average 0.90, whereas the Adjusted R-Square of the One-Factor CAPM regressions average 0.83. This shows that both the Multi-Factor CAPMs and the Three-Factor CAPMs have better explanatory power than the One-Factor CAPMs.

Table 5.3.4 shows the regression estimates of the One-Factor CAPM along with their corresponding p-values.

**Table 5.3.4**

| One-Factor CAPM Time-Series Regression Estimates | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| $E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + e_t$ | | | | | | | | | | |
| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
| a | -0.89 | -0.40 | -0.63 | -0.63 | -0.83 | -1.15 | -1.25 | -0.93 | -0.80 | -0.51 |
| p-value | 0.00 | 0.06 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.22 |
| e | -0.38 | -0.27 | -0.35 | -0.27 | -0.22 | -0.52 | -0.51 | -0.26 | -0.30 | -0.50 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| b | 0.84 | 0.93 | 0.88 | 0.92 | 0.91 | 0.87 | 0.84 | 0.88 | 0.93 | 0.97 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Nine of the ten intercepts are significant and negative at the 5 percent level of significance. This shows that the model is not able to capture the pattern of returns to the portfolios. The intercepts do not show any trend across portfolios. The market betas of all the portfolios are less than one. Thus, portfolios built on a sort of stocks based on the PCF ratio all show less volatility than the market portfolio.

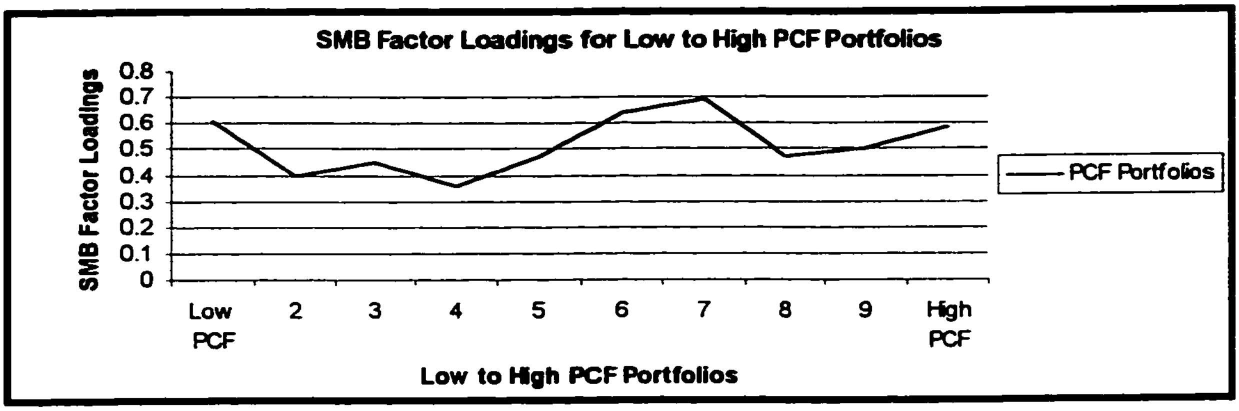
Table 5.3.5 shows the regression estimates of the Three-Factor CAPM along with their corresponding p-values.

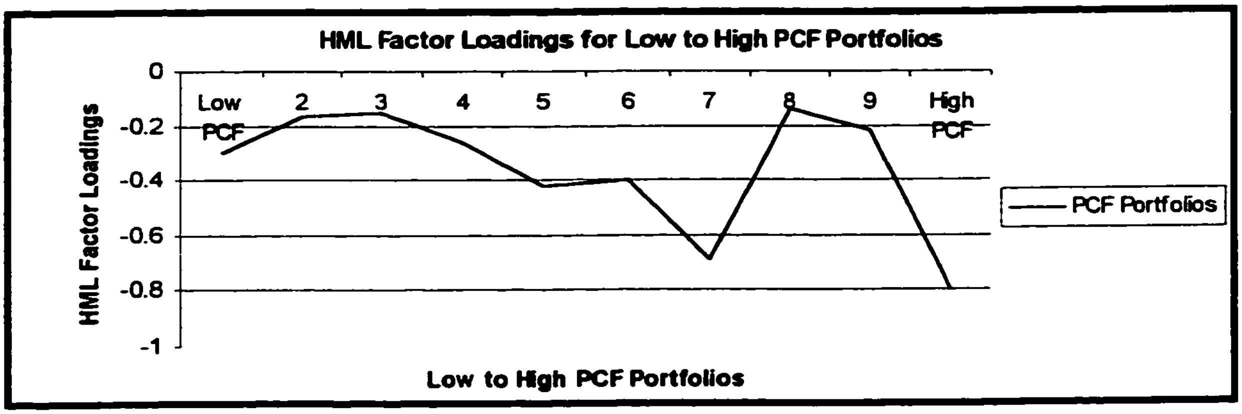
**Table 5.3.5**

**Three-Factor CAPM Time-Series Regression Estimates**

$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + e_t$

| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
|---|---|---|---|---|---|---|---|---|---|---|
| **a** | -0.20 | 0.05 | -0.14 | -0.20 | -0.26 | -0.41 | -0.38 | -0.42 | -0.25 | 0.27 |
| **p-value** | 0.28 | 0.75 | 0.45 | 0.22 | 0.17 | 0.08 | 0.15 | 0.07 | 0.29 | 0.37 |
| | | | | | | | | | | |
| **e** | 0.06 | 0.03 | -0.01 | -0.01 | 0.12 | -0.05 | 0.00 | 0.09 | 0.07 | -0.07 |
| **p-value** | 0.33 | 0.67 | 0.83 | 0.92 | 0.07 | 0.58 | 0.97 | 0.28 | 0.41 | 0.54 |
| | | | | | | | | | | |
| **b** | 0.96 | 1.01 | 0.96 | 1.00 | 1.01 | 0.99 | 0.99 | 0.97 | 1.02 | 1.11 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **s** | 0.61 | 0.40 | 0.45 | 0.36 | 0.47 | 0.64 | 0.69 | 0.47 | 0.50 | 0.59 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **h** | -0.30 | -0.17 | -0.15 | -0.26 | -0.42 | -0.40 | -0.69 | -0.14 | -0.22 | -0.80 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |




We see that no intercepts are significantly different from zero at the 5 percent level of significance. Thus the risks of the portfolios are adequately priced. The market betas of the portfolios range from 0.96 to 1.11. There does not seem to be any trend across market betas.

All ten portfolios are given a small-firm risk premium (i.e. positive loadings on the SMB risk factor). The premium, however, does not show any pattern across the ten portfolios. All ten portfolios endure a low-distress penalty (i.e. negative loadings on the HML risk factor), with the firms with the highest ratio enduring a much higher low-distress penalty than the firm with the lowest ratio does. Thus, the firms with the highest ratio consist of lower BE/ME ratios than what the firms with the lowest ratios do.

Table 5.3.6 shows the regression estimates of the Multi-Factor CAPM along with their corresponding p-values.

**Table 5.3.6**

**Multi-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + \delta\sqrt{(h_t)} + -\phi_1 v_{t-1} - \phi_2 v_{t-2} - \ldots - \phi_{53} v_{t-53} + \sqrt{(h_t)}\, e$$

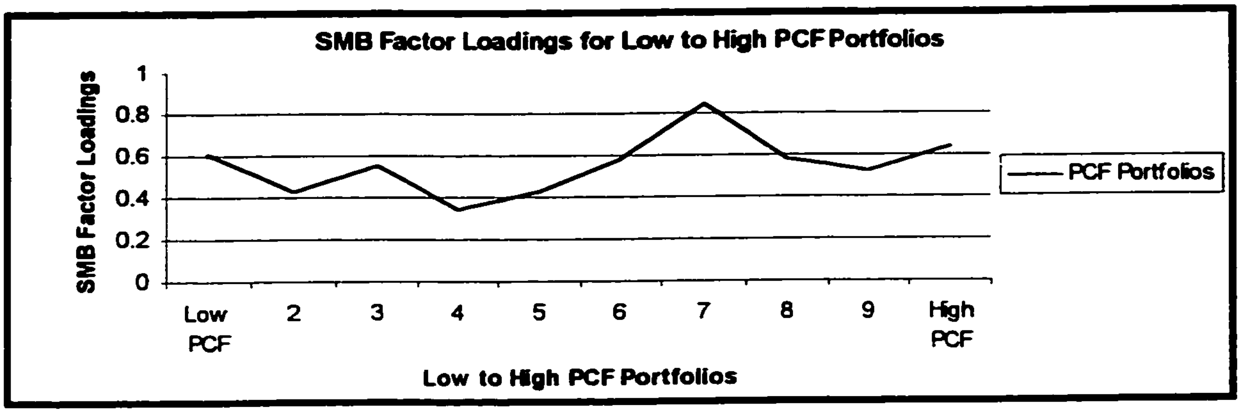
$$h_t = \kappa + \alpha\varepsilon_{t-1}^2 + \gamma h_{t-1} \qquad \kappa > 0$$

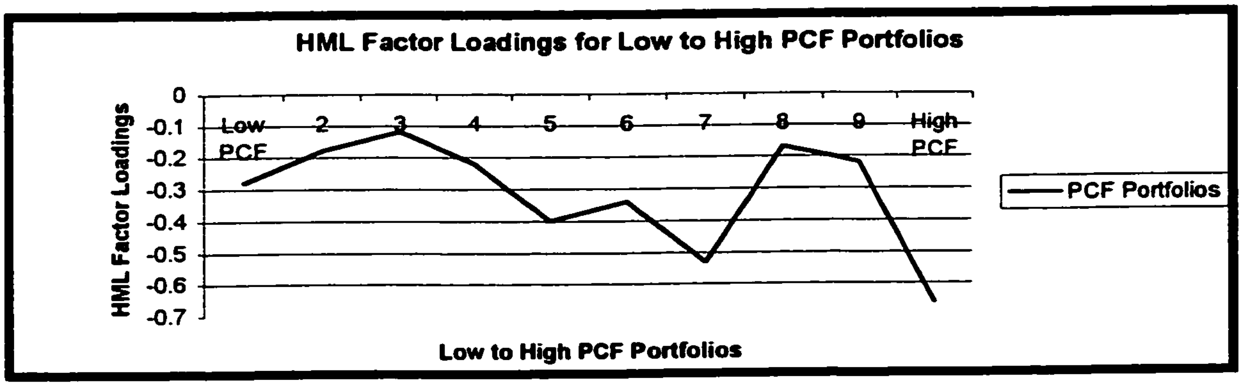
$$\alpha + \gamma = 1$$

| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
|---|---|---|---|---|---|---|---|---|---|---|
| a | -1.08 | -0.22 | -5.63 | -0.31 | -0.23 | 0.31 | -0.04 | -0.56 | 0.01 | -0.11 |
| p-value | 0.00 | 0.49 | 0.58 | 0.49 | 0.60 | 0.43 | 0.92 | 0.27 | 0.99 | 0.81 |
| | | | | | | | | | | |
| e | -0.01 | -0.05 | 0.05 | 0.08 | 0.08 | -0.05 | 0.02 | 0.24 | 0.11 | -0.11 |
| p-value | 0.91 | 0.39 | 0.36 | 0.16 | 0.32 | 0.53 | 0.86 | 0.00 | 0.20 | 0.35 |
| | | | | | | | | | | |
| b | 0.92 | 0.98 | 0.98 | 1.02 | 1.00 | 1.00 | 1.01 | 1.07 | 1.04 | 1.08 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| s | 0.61 | 0.43 | 0.55 | 0.34 | 0.43 | 0.58 | 0.85 | 0.58 | 0.52 | 0.64 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| h | -0.28 | -0.18 | -0.12 | -0.22 | -0.40 | -0.34 | -0.53 | -0.17 | -0.22 | -0.66 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 5.3.6 Continued**

| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
|---|---|---|---|---|---|---|---|---|---|---|
| delta | 0.36 | 0.09 | 2.69 | 0.13 | -0.01 | -0.28 | -0.06 | 0.26 | -0.09 | 0.09 |
| p-value | 0.03 | 0.66 | 0.60 | 0.54 | 0.95 | 0.06 | 0.68 | 0.24 | 0.69 | 0.52 |
| | | | | | | | | | | |
| k | 0.18 | 0.27 | 0.00 | 0.32 | 0.11 | 0.27 | 0.19 | 0.35 | 0.37 | 0.10 |
| p-value | 0.06 | 0.20 | 0.57 | 0.20 | 0.15 | 0.07 | 0.38 | 0.14 | 0.16 | 0.25 |
| | | | | | | | | | | |
| alpha | 0.26 | 0.30 | 0.00 | 0.18 | 0.16 | 0.26 | 0.12 | 0.22 | 0.22 | 0.12 |
| p-value | 0.00 | 0.05 | 0.00 | 0.02 | 0.02 | 0.00 | 0.20 | 0.03 | 0.02 | 0.01 |
| | | | | | | | | | | |
| gamma | 0.74 | 0.70 | 1.00 | 0.82 | 0.84 | 0.74 | 0.88 | 0.78 | 0.78 | 0.88 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **Durbin Watson to test for Autocorrelation** | | | | | | | | | | |
| d | 2.31 | 1.98 | 1.92 | 1.94 | 1.81 | 1.81 | 2.30 | 2.24 | 2.10 | 2.14 |
| p-value (for - corr) | 0.01 | 0.56 | 0.71 | 0.68 | 0.94 | 0.94 | 0.01 | 0.02 | 0.20 | 0.12 |
| p-value (for + corr) | 0.99 | 0.44 | 0.29 | 0.32 | 0.06 | 0.06 | 0.99 | 0.98 | 0.80 | 0.88 |




Nine of the ten intercepts were not significantly different from zero at the 5 percent level of significance. Thus the risks seem to be adequately priced and the models were able to capture the pattern of returns to the portfolios. The market betas of the portfolios range from 0.92 to 1.08. High PCF stocks are greater than one and thus more volatile than the market whereas low PCF stocks are less than one and thus less volatile than the market.

All ten portfolios are given a small-firm risk premium (i.e. positive loadings on the SMB risk factors). The premium, however, does not show any pattern across the ten portfolios. All ten portfolios endure a low-distress penalty (i.e. negative loadings on the HML risk factors), with the firms with the highest ratio enduring a much higher low-distress penalty than the firm with the lowest ratio does. Thus, the firms with the highest ratio consist of lower BE/ME ratios than what the firms with the lowest ratios do. Thus, higher ratio stocks are indeed stocks of stronger firms.

The alpha and the gamma coefficients are significantly different from zero at the 5 percent level of significance. However we see that nine out of the ten coefficients for delta are not significantly different from zero at the 5 percent level of significance; this may be either because the risk associated with a changing variance is not compensated for, or because this risk is somehow captured by and compensated for in a higher premium to some of the other risk factors. We see that the gamma is always given a higher weight than the alpha; this implies that in predicting the current residual variance, more importance is given to the one period past estimate of the residual variance than what is given to the one period past squared residual.

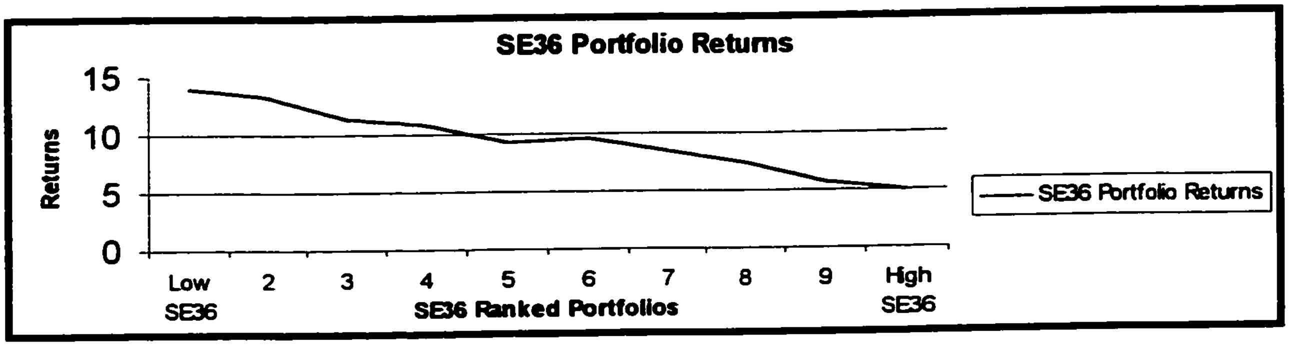
Only two of the ten portfolios showed significant negative autocorrelation when measured at the one- percent level of significance. This shows that in general autocorrelation did not pose a problem.

### 4. Tests on the 10 SE36 Portfolios

Table 5.4.1 shows the average out-of-sample returns to the 10 portfolios along with their corresponding p-values.

**Table 5.4.1**

| Summary Statistics | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
| Returns | 13.93 | 13.21 | 11.31 | 10.88 | 9.27 | 9.57 | 8.41 | 7.50 | 5.61 | 4.94 |
| p-value | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.04 | 0.05 |




The average out-of-sample returns on the portfolios formed based on the 36 months prior returns show a very clear trend with long-term losers coming back to earn much higher returns than long-term winners. Thus there is a strong reversal in average long-term returns. The average out-of-sample returns to all ten portfolios are a high 9.46 percent.

Table 5.4.2 presents the Akaike Information Criterion and the Schwarz Criterion, two goodness of fit measures of the estimated models.

**Table 5.4.2**

| Goodness-of-Fit | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
| **Akaike Information Criterion** | | | | | | | | | | |
| One-Factor | 1,497 | 1,459 | 1,395 | 1,457 | 1,337 | 1,313 | 1,248 | 1,231 | 1,262 | 1,167 |
| Three-Factor | 1,287 | 1,263 | 1,189 | 1,196 | 1,215 | 1,181 | 1,173 | 1,172 | 1,149 | 1,146 |
| Multi-Facor | 980 | 922 | 833 | 844 | 891 | 872 | 861 | 857 | 809 | 789 |
| **Schwarz Criterion** | | | | | | | | | | |
| One-Factor | 1,508 | 1,470 | 1,406 | 1,468 | 1,348 | 1,323 | 1,259 | 1,242 | 1,273 | 1,178 |
| Three-Factor | 1,304 | 1,281 | 1,207 | 1,214 | 1,233 | 1,199 | 1,192 | 1,190 | 1,167 | 1,164 |
| Multi-Facor | 1,016 | 961 | 879 | 883 | 933 | 904 | 896 | 889 | 852 | 829 |

A study of the tables shows that the Multi-Factor model has the best fit. The Three-Factor CAPM generally has a better fit than the One-Factor CAPM. On average, the AIC for the Three-factor model is 10 percent smaller than that for One-factor models, whereas the AIC for the Multi-factor models is 35 percent smaller than that for the One-factor models. . On average, the SC for the Three-factor model is 10 percent smaller than that

for One-factor models, whereas the SC for the Multi-factor models is 33 percent smaller than that for the One-factor models.

Table 5.4.3 presents the adjusted R-Square of the regression models.

**Table 5.4.3**

| Adjusted R-Square | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
| One-Factor | 0.74 | 0.74 | 0.79 | 0.74 | 0.83 | 0.82 | 0.86 | 0.87 | 0.86 | 0.89 |
| Three-Factor | 0.88 | 0.87 | 0.90 | 0.90 | 0.89 | 0.89 | 0.89 | 0.89 | 0.91 | 0.90 |
| Multi-Facor | 0.88 | 0.88 | 0.91 | 0.90 | 0.90 | 0.89 | 0.90 | 0.89 | 0.90 | 0.90 |

The Adjusted R-Squares of the Multi-Factor CAPM regressions average 0.90 and that of the Three-Factor CAPM regressions average 0.89, whereas the Adjusted R-Square of the One-Factor CAPM regressions average 0.81. This shows that both the Multi-Factor CAPMs and the Three-Factor CAPMs have better explanatory power than the One-Factor CAPMs.

Table 5.4.4 shows the regression estimates of the One-Factor CAPM along with their corresponding p-values.

**Table 5.4.4**

**One-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + e_t$$

| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
|---|---|---|---|---|---|---|---|---|---|---|
| a | -0.78 | -0.53 | -0.74 | -0.79 | -0.50 | -1.01 | -0.40 | -0.93 | -0.61 | -0.27 |
| p-value | 0.06 | 0.17 | 0.03 | 0.04 | 0.10 | 0.00 | 0.11 | 0.00 | 0.02 | 0.21 |
| | | | | | | | | | | |
| e | -0.47 | -0.22 | -0.50 | -0.45 | -0.28 | -0.44 | -0.29 | -0.32 | -0.30 | -0.11 |
| p-value | 0.00 | 0.08 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.12 |
| | | | | | | | | | | |
| b | 0.96 | 0.96 | 0.91 | 0.89 | 1.00 | 0.86 | 0.94 | 0.92 | 0.94 | 0.99 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

The intercepts of the regression models of five of the ten portfolios are significant and negative at the 5 percent level of significance. This shows that in general the models were not able to capture the pattern of returns to the portfolios. The intercepts do not show any trend across portfolios. The market betas of all the portfolios are less than or equal to one. Thus portfolios built on a sort of stocks based on the past 36-months stock returns all show less volatility than the market portfolio.

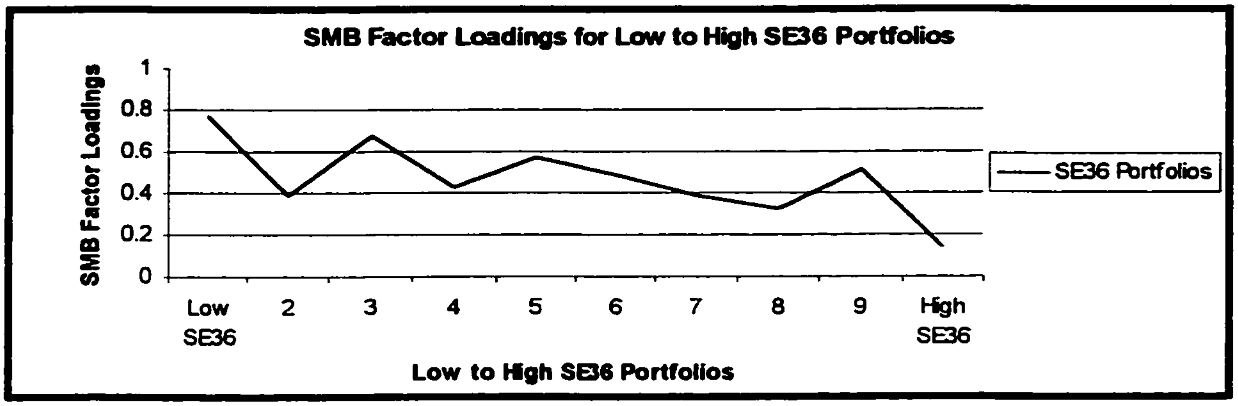
Table 5.4.5 shows the regression estimates of the Three-Factor CAPM along with their corresponding p-values.

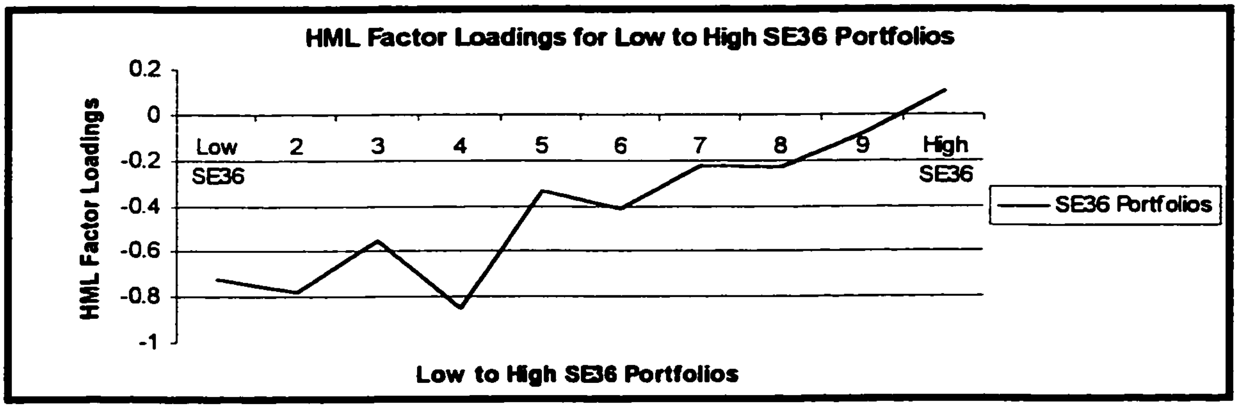
**Table 5.4.5**

**Three-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + c[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + e_t$$

| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
|---|---|---|---|---|---|---|---|---|---|---|
| a | 0.17 | 0.06 | 0.08 | -0.14 | 0.15 | -0.42 | 0.05 | -0.55 | -0.08 | -0.16 |
| p-value | 0.54 | 0.83 | 0.73 | 0.55 | 0.53 | 0.07 | 0.83 | 0.01 | 0.70 | 0.45 |
| | | | | | | | | | | |
| c | 0.10 | 0.06 | 0.00 | -0.14 | 0.13 | -0.09 | 0.00 | -0.09 | 0.07 | -0.01 |
| p-value | 0.34 | 0.53 | 0.99 | 0.11 | 0.12 | 0.29 | 0.96 | 0.29 | 0.37 | 0.85 |
| | | | | | | | | | | |
| b | 1.12 | 1.07 | 1.05 | 1.01 | 1.11 | 0.96 | 1.01 | 0.98 | 1.03 | 1.00 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| s | 0.77 | 0.39 | 0.68 | 0.43 | 0.57 | 0.49 | 0.39 | 0.32 | 0.51 | 0.14 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| h | -0.72 | -0.78 | -0.55 | -0.85 | -0.33 | -0.41 | -0.22 | -0.23 | -0.08 | 0.10 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.01 |




We see that nine out of the ten intercepts are not significantly different from zero at the 5 percent level of significance. Thus the risks of the portfolios are adequately priced and the models are able to capture the pattern of returns to the portfolios. The market betas of the portfolios range from 0.96 to 1.12, with the low SE36 portfolios in the high end of the range whereas the high SE36 portfolios in the low end of the range. Thus, the low SE36 portfolios (i.e. the losers) are much more volatile than the high SE36 portfolios (i.e. the winners).

All ten portfolios are given a small-firm risk premium (i.e. positive loadings on the SMB risk factor), with the low SE36 portfolios receiving a higher premium than the high SE36 portfolios. Thus the low SE36 portfolios consist of smaller stocks relative to the high

SE36 portfolios. The high SE36 portfolios earn a high-distress premium (i.e. positive loadings on the HML risk factor) whereas the low SE36 portfolios endure a low-distress penalty. Thus, high SE36 portfolios consist of higher BE/ME ratios stocks relative to low SE36 portfolios and are thus compensated for it.

Thus, the low SE36 stocks are smaller, lower-distressed, and more volatile than the high SE36 stocks.

Table 5.4.6 shows the regression estimates of the Multi-Factor CAPM along with their corresponding p-values.

**Table 5.4.6**

**Multi-Factor CAPM Time-Series Regression Estimates**

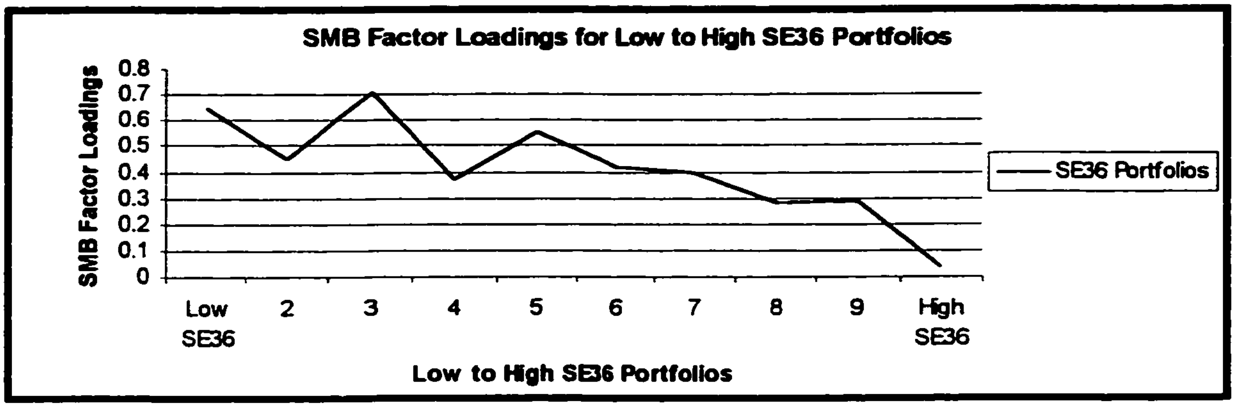
$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + \delta\sqrt{(h_t)} + -\phi_1 v_{t-1} - \phi_2 v_{t-2} - \dots - \phi_{53} v_{t-53} + \sqrt{(h_t)}\, e$$

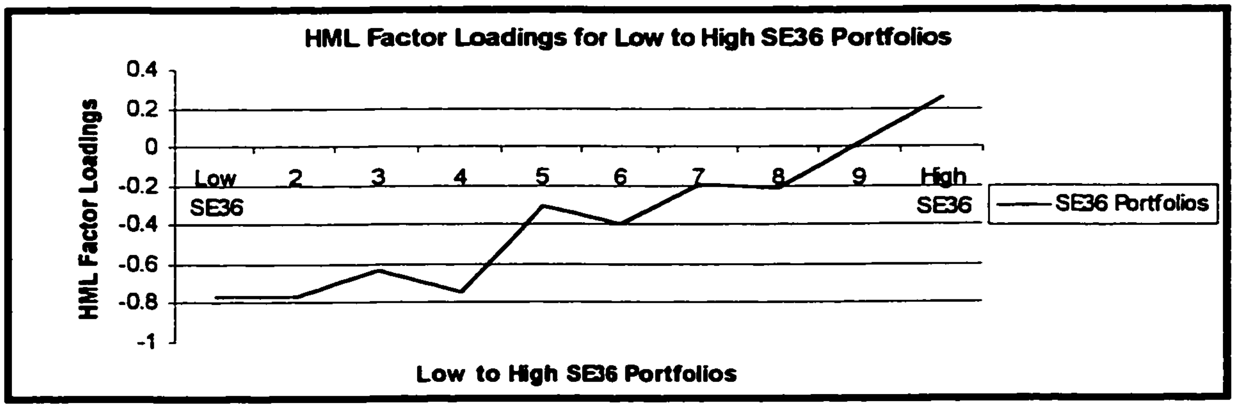
$$h_t = \kappa + \alpha\varepsilon^2_{t-1} + \gamma h_{t-1} \qquad \kappa > 0$$

$$\alpha + \gamma = 1$$

| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
|---|---|---|---|---|---|---|---|---|---|---|
| a | 4.73 | 0.19 | 0.22 | -0.09 | 0.61 | 0.42 | -0.66 | -0.25 | -0.36 | 0.56 |
| p-value | 0.35 | 0.65 | 0.45 | 0.85 | 0.40 | 0.20 | 0.15 | 0.69 | 0.28 | 0.34 |
| | | | | | | | | | | |
| e | 0.14 | 0.01 | -0.08 | -0.06 | 0.12 | -0.11 | -0.02 | -0.08 | -0.14 | 0.07 |
| p-value | 0.09 | 0.96 | 0.38 | 0.53 | 0.23 | 0.05 | 0.83 | 0.36 | 0.18 | 0.35 |
| | | | | | | | | | | |
| b | 1.17 | 1.08 | 1.02 | 1.05 | 1.11 | 0.98 | 1.03 | 1.01 | 1.01 | 0.98 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| s | 0.65 | 0.45 | 0.71 | 0.37 | 0.56 | 0.42 | 0.40 | 0.28 | 0.29 | 0.04 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.34 |
| | | | | | | | | | | |
| h | -0.77 | -0.76 | -0.63 | -0.74 | -0.31 | -0.40 | -0.19 | -0.21 | 0.02 | 0.26 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.73 | 0.00 |

| Table 5.4.6 Continued | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
| delta | -0.68 | 0.00 | -0.14 | 0.08 | -0.17 | -0.30 | 0.33 | 0.00 | 0.06 | -0.39 |
| p-value | 0.10 | 0.98 | 0.23 | 0.69 | 0.56 | 0.01 | 0.09 | 0.99 | 0.69 | 0.09 |
| | | | | | | | | | | |
| k | 21.97 | 0.29 | 0.08 | 0.65 | 0.05 | 2.42 | 0.22 | 0.28 | 0.53 | 0.24 |
| p-value | 0.58 | 0.29 | 0.16 | 0.15 | 0.38 | 0.00 | 0.17 | 0.38 | 0.01 | 0.40 |
| | | | | | | | | | | |
| alpha | 0.64 | 0.19 | 0.16 | 0.25 | 0.08 | 1.00 | 0.18 | 0.12 | 0.46 | 0.11 |
| p-value | 0.02 | 0.05 | 0.01 | 0.01 | 0.05 | 0.00 | 0.00 | 0.21 | 0.00 | 0.17 |
| | | | | | | | | | | |
| gamma | 0.36 | 0.81 | 0.84 | 0.75 | 0.92 | 0.00 | 0.82 | 0.88 | 0.54 | 0.89 |
| p-value | 0.19 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **Durbin Watson to test for Autocorrelation** | | | | | | | | | | |
| d | 2.32 | 2.33 | 2.39 | 2.12 | 2.08 | 1.92 | 2.13 | 2.00 | 2.15 | 2.05 |
| p-value (for - corr) | 0.00 | 0.00 | 0.00 | 0.16 | 0.24 | 0.74 | 0.13 | 0.48 | 0.11 | 0.31 |
| p-value (for + corr) | 1.00 | 1.00 | 1.00 | 0.84 | 0.76 | 0.26 | 0.87 | 0.52 | 0.89 | 0.69 |




We see that no intercepts were significantly different from zero at the 5 percent level of significance. Thus the risks of the portfolios are adequately priced and the models were able to capture the pattern of returns to the portfolios. The market betas of the portfolios range from 0.98 to 1.17, with the low SE36 portfolios in the high end of the range whereas the high SE36 portfolios in the low end of the range. Thus the low SE36 portfolios are much more volatile than the high SE36 portfolios.

All ten portfolios are given a small-firm risk premium (i.e. positive loadings on the SMB risk factors), with the low SE36 portfolios receiving a higher premium than the high SE36 portfolios. Thus the low SE36 portfolios consist of smaller stocks relative to the high SE36 portfolios. The high SE36 portfolios earn a high-distress premium (i.e.

positive loadings on the HML risk factors) whereas the low SE36 portfolios endure a low-distress penalty. Thus, high SE36 portfolios consist of higher BE/ME ratios stocks relative to low SE36 portfolios and thus were given a compensation for it.

The alpha and the gamma coefficients are significantly different from zero at the 5 percent level of significance. However we see that nine out of the ten coefficients for delta are not significantly different from zero at the 5 percent level of significance; this may be either because the risk associated with a changing variance is not compensated for, or because this risk is somehow captured by and compensated for in a higher premium to some of the other risk factors. We see that the gamma is always given a higher weight than the alpha; this implies that in predicting the current residual variance, more importance is given to the one period past estimate of the residual variance than what is given to the one period past squared residual.

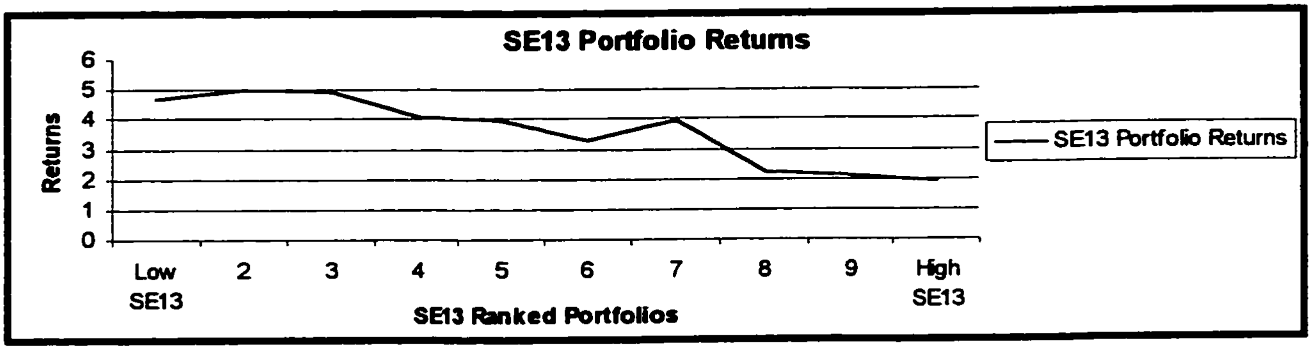
The lowest three SE36 portfolios showed significant negative autocorrelation when measured at the one- percent level of significance. Thus, autocorrelation did pose a slight problem for this category of portfolios.

## 5. Tests on the 10 SE12 Portfolios

Table 5.5.1 shows the average out-of-sample returns to the 10 portfolios along with their corresponding p-values.

**Table 5.5.1**

| Summary Statistics | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Low SE12** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High SE12** |
| **Returns** | 4.66 | 5.02 | 4.95 | 4.10 | 3.94 | 3.31 | 3.96 | 2.25 | 2.14 | 1.91 |
| **p-value** | 0.04 | 0.02 | 0.02 | 0.02 | 0.01 | 0.02 | 0.02 | 0.07 | 0.08 | 0.09 |




The average out-of-sample returns on the portfolios formed based on the 12 months prior returns show a very clear trend with short-term losers coming back to earn higher returns than short-term winners. Thus there is a strong reversal in average short-term returns. The average out-of-sample return to all ten portfolios is 3.62 percent.

Table 5.5.2 presents the Akaike Information Criterion and the Schwarz Criterion, two goodness of fit measures of the estimated models.

**Table 5.5.2**

| Goodness-of-Fit | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low SE12 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE12 |
| **Akaike Information Criterion** | | | | | | | | | | |
| One-Factor | 1,575 | 1,430 | 1,417 | 1,382 | 1,268 | 1,186 | 1,208 | 1,195 | 1,109 | 1,374 |
| Three-Factor | 1,287 | 1,200 | 1,210 | 1,142 | 1,111 | 1,062 | 1,133 | 1,134 | 1,044 | 1,295 |
| Multi-Facor | 938 | 868 | 875 | 790 | 797 | 766 | 803 | 797 | 740 | 904 |
| **Schwarz Criterion** | | | | | | | | | | |
| One-Factor | 1,586 | 1,441 | 1,428 | 1,393 | 1,278 | 1,196 | 1,219 | 1,206 | 1,120 | 1,384 |
| Three-Factor | 1,305 | 1,218 | 1,228 | 1,160 | 1,129 | 1,080 | 1,151 | 1,152 | 1,062 | 1,313 |
| Multi-Facor | 981 | 911 | 922 | 832 | 840 | 802 | 842 | 840 | 772 | 939 |

A study of the tables shows that the Multi-Factor model has the best fit. The Three-Factor CAPM generally has a better fit than the One-Factor CAPM. On average, the AIC for the Three-factor model is 12 percent smaller than that for One-factor models, whereas the AIC for the Multi-factor models is 37 percent smaller than that for the One-factor models. . On average, the SC for the Three-factor model is 11 percent smaller than that

for One-factor models, whereas the SC for the Multi-factor models is 34 percent smaller than that for the One-factor models.

Table 5.5.3 presents the adjusted R-Square of the regression models.

**Table 5.5.3**

| Adjusted R-Square | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low SE12 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE12 |
| One-Factor | 0.64 | 0.76 | 0.74 | 0.78 | 0.86 | 0.89 | 0.88 | 0.88 | 0.91 | 0.80 |
| Three-Factor | 0.88 | 0.90 | 0.88 | 0.91 | 0.92 | 0.93 | 0.91 | 0.91 | 0.93 | 0.86 |
| Multi-Facor | 0.89 | 0.90 | 0.89 | 0.92 | 0.93 | 0.93 | 0.91 | 0.91 | 0.93 | 0.85 |

The Adjusted R-Squares of the Multi-Factor CAPM regressions average 0.91 and that of the Three-Factor CAPM regressions average 0.90, whereas the Adjusted R-Square of the One-Factor CAPM regressions average 0.81. This shows that both the Multi-Factor CAPMs and the Three-Factor CAPMs have better explanatory power than the One-Factor CAPMs.

Table 5.5.4 shows the regression estimates of the One-Factor CAPM along with their corresponding p-values.

**Table 5.5.4**

**One-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + e_t$$

| | Low SE12 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE12 |
|---|---|---|---|---|---|---|---|---|---|---|
| a | -1.04 | -0.87 | -1.09 | -0.98 | -0.76 | -0.52 | -0.16 | -0.56 | -0.53 | -1.07 |
| p-value | 0.03 | 0.02 | 0.00 | 0.00 | 0.00 | 0.02 | 0.50 | 0.01 | 0.01 | 0.00 |
| | | | | | | | | | | |
| e | -0.42 | -0.41 | -0.31 | -0.43 | -0.47 | -0.32 | -0.08 | -0.30 | -0.33 | -0.53 |
| p-value | 0.01 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.29 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| b | 0.88 | 0.90 | 0.86 | 0.88 | 0.90 | 0.95 | 1.02 | 0.95 | 0.93 | 0.89 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

The intercepts of the regression models of nine of the ten portfolios are significant and negative at the 5 percent level of significance. This shows that the model is not able to capture the pattern of returns to the portfolios. The intercepts do not show any trend across portfolios. The market betas of all the portfolios except one are less than one. Thus portfolios built on a sort of stocks based on the past 12-months stock returns all show less volatility than the market portfolio.

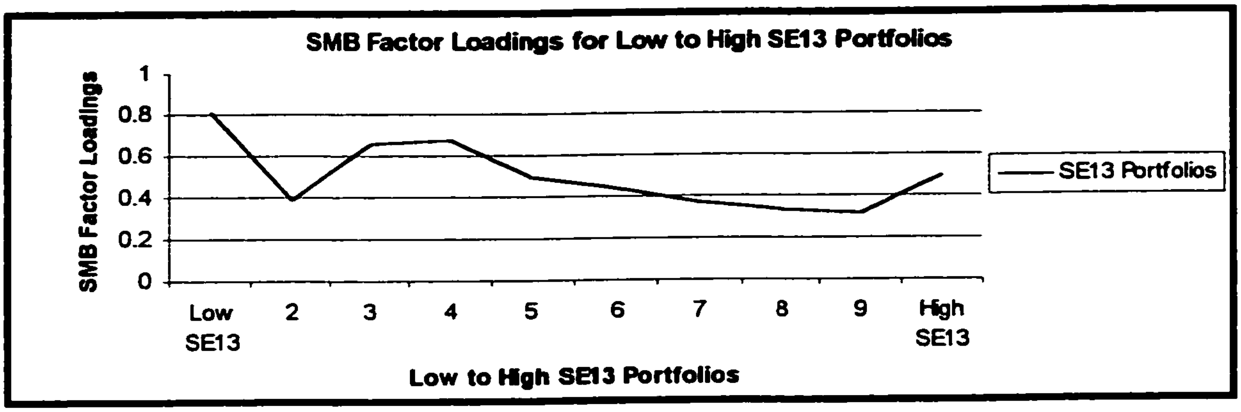
Table 5.5.5 shows the regression estimates of the Three-Factor CAPM along with their corresponding p-values.

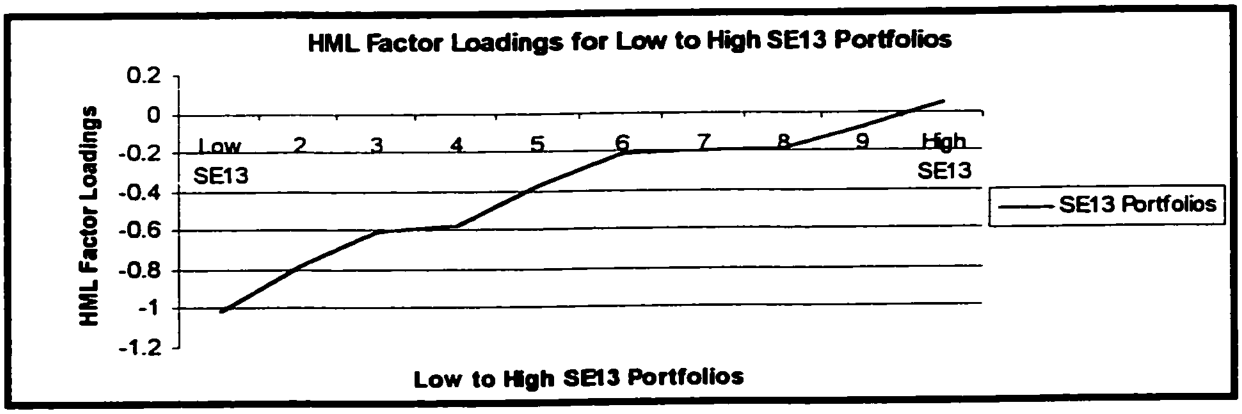
**Table 5.5.5**

**Three-Factor CAPM Time-Series Regression Estimates**

$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + e_t$

| | Low SE12 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE12 |
|---|---|---|---|---|---|---|---|---|---|---|
| a | 0.02 | -0.29 | -0.28 | -0.15 | -0.17 | -0.02 | 0.26 | -0.19 | -0.20 | -0.57 |
| p-value | 0.93 | 0.23 | 0.25 | 0.46 | 0.40 | 0.89 | 0.20 | 0.37 | 0.25 | 0.04 |
| e | 0.17 | -0.13 | 0.17 | 0.07 | -0.10 | 0.00 | 0.19 | -0.06 | -0.10 | -0.16 |
| p-value | 0.08 | 0.13 | 0.04 | 0.36 | 0.18 | 0.97 | 0.01 | 0.41 | 0.10 | 0.11 |
| b | 1.07 | 1.00 | 1.00 | 1.02 | 1.00 | 1.04 | 1.09 | 1.01 | 0.99 | 0.97 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| s | 0.81 | 0.39 | 0.66 | 0.68 | 0.50 | 0.44 | 0.37 | 0.33 | 0.31 | 0.50 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| h | -1.02 | -0.78 | -0.61 | -0.58 | -0.37 | -0.21 | -0.20 | -0.19 | -0.08 | 0.05 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.33 |




We see that none of the ten intercepts is significantly different from zero at the 5 percent level of significance. Thus the risks of the portfolios were adequately priced and the model is able to capture the pattern of returns to the portfolios. The market betas of the portfolios range from 0.97 to 1.09, with the low SE12 portfolios in the high end of the range whereas the high SE12 portfolios in the low end of the range. Thus the low SE12 portfolios are more volatile than the high SE12 portfolios.

All ten portfolios are given a small-firm risk premium (i.e. positive loadings on the SMB risk factors), with the low SE12 portfolios receiving a higher premium than the high SE12 portfolios. Thus the low SE12 portfolios consist of smaller stocks relative to the high SE12 portfolios. The high SE12 portfolios earn a high-distress premium (i.e.

positive loadings on the HML risk factors) whereas the low SE12 portfolios endure a low-distress penalty. Thus high SE12 portfolios consists of higher BE/ME ratios stocks relative to low SE12 portfolios and are thus compensated for it.

Thus the low SE12 stocks are smaller, lower-distressed, and more volatile than the high SE12 stocks.

Table 5.5.6 shows the regression estimates of the Multi-Factor CAPM along with their corresponding p-values.

**Table 5.5.6**

**Multi-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{ft} = a + e[PCER_t] + b[E(R_{mt}) - R_{ft}] + sE[SMB_t] + hE[HML_t] + \delta\sqrt{(h_t)} + -\phi_1 v_{t-1} - \phi_2 v_{t-2} - \dots - \phi_{53} v_{t-53} + \sqrt{(h_t)}\, e$$

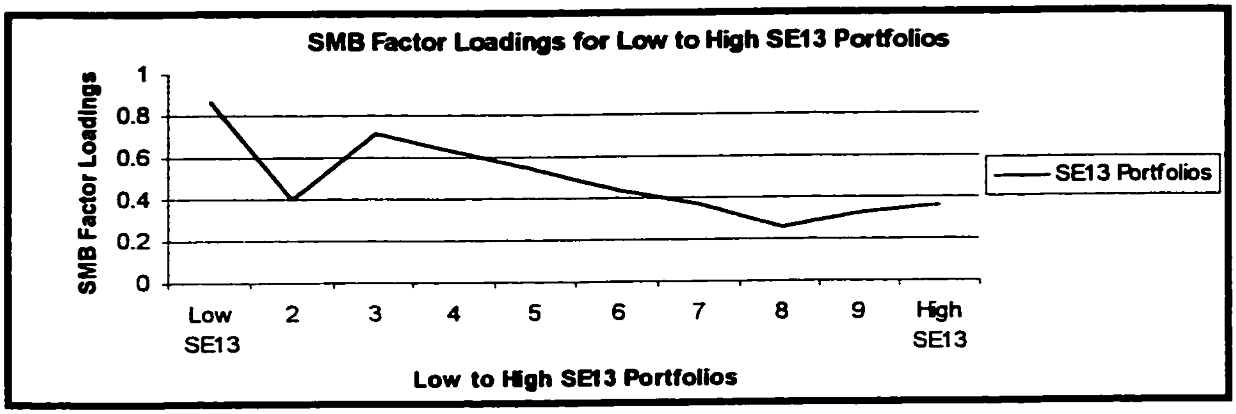
$$h_t = \kappa + \alpha\varepsilon^2_{t-1} + \gamma h_{t-1} \qquad \kappa > 0$$

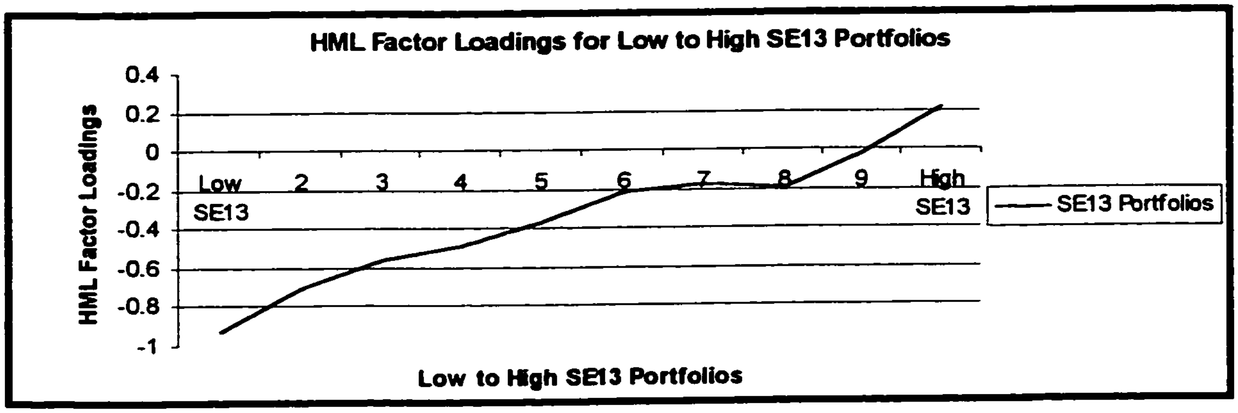
$$\alpha + \gamma = 1$$

| | Low SE12 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE12 |
|---|---|---|---|---|---|---|---|---|---|---|
| **a** | 0.57 | -0.13 | -0.19 | -0.26 | -0.91 | -0.96 | -0.58 | -0.62 | -0.23 | -0.02 |
| **p-value** | 0.47 | 0.75 | 0.69 | 0.61 | 0.07 | 0.30 | 0.23 | 0.20 | 0.75 | 0.97 |
| | | | | | | | | | | |
| **e** | 0.20 | -0.19 | 0.22 | -0.03 | -0.04 | -0.02 | 0.16 | -0.07 | -0.21 | -0.09 |
| **p-value** | 0.05 | 0.03 | 0.02 | 0.80 | 0.61 | 0.76 | 0.04 | 0.28 | 0.09 | 0.40 |
| | | | | | | | | | | |
| **b** | 1.13 | 0.97 | 1.01 | 1.00 | 1.01 | 1.03 | 1.08 | 1.00 | 0.95 | 1.03 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **s** | 0.87 | 0.40 | 0.71 | 0.63 | 0.54 | 0.44 | 0.37 | 0.26 | 0.32 | 0.36 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **h** | -0.93 | -0.70 | -0.56 | -0.49 | -0.37 | -0.21 | -0.17 | -0.19 | -0.02 | 0.22 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.61 | 0.00 |

**Table 5.5.6 Continued**

| | Low SE12 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE12 |
|---|---|---|---|---|---|---|---|---|---|---|
| **delta** | -0.09 | -0.13 | -0.01 | -0.09 | 0.40 | 0.48 | 0.40 | 0.17 | -0.08 | -0.03 |
| **p-value** | 0.77 | 0.43 | 0.95 | 0.73 | 0.09 | 0.34 | 0.09 | 0.41 | 0.84 | 0.83 |
| | | | | | | | | | | |
| **k** | 0.04 | 0.25 | 0.05 | 0.09 | 0.17 | 0.02 | 0.14 | 0.36 | 0.03 | 0.39 |
| **p-value** | 0.38 | 0.21 | 0.32 | 0.34 | 0.31 | 0.62 | 0.24 | 0.46 | 0.54 | 0.11 |
| | | | | | | | | | | |
| **alpha** | 0.04 | 0.18 | 0.07 | 0.08 | 0.17 | 0.05 | 0.14 | 0.15 | 0.05 | 0.19 |
| **p-value** | 0.23 | 0.03 | 0.01 | 0.05 | 0.05 | 0.34 | 0.02 | 0.29 | 0.38 | 0.00 |
| | | | | | | | | | | |
| **gamma** | 0.96 | 0.82 | 0.93 | 0.92 | 0.83 | 0.95 | 0.86 | 0.85 | 0.95 | 0.81 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **Durbin Watson to test for Autocorrelation** | | | | | | | | | | |
| **d** | 2.44 | 2.28 | 2.04 | 2.00 | 2.31 | 2.05 | 2.23 | 2.22 | 2.11 | 1.83 |
| **p-value (for - corr)** | 0.00 | 0.01 | 0.35 | 0.47 | 0.01 | 0.33 | 0.03 | 0.04 | 0.18 | 0.91 |
| **p-value (for + corr)** | 1.00 | 0.99 | 0.65 | 0.53 | 0.99 | 0.67 | 0.97 | 0.96 | 0.82 | 0.09 |




We see that none of the intercepts was significantly different from zero at the 5 percent level of significance. Thus the risks of the portfolios were adequately priced and the models were able to capture the pattern of returns to the portfolios. The market betas of the portfolios range from 0.95 to 1.13, with the lowest SE12 portfolios in the high end of the range whereas the higher SE12 portfolios in the low end of the range. Thus the low SE12 portfolios are much more volatile than the high SE12 portfolios.

All ten portfolios are given a small-firm risk premium (i.e. positive loadings on the SMB risk factors), with the low SE12 portfolios receiving a higher premium than the high SE12 portfolios. Thus the low SE12 portfolios consist of smaller stocks relative to the high SE12 portfolios. The high SE12 portfolios earn a high-distress premium (i.e.

positive loadings on the HML risk factors) whereas the low SE12 portfolios endure a low-distress penalty. Thus high SE12 portfolios consists of higher BE/ME ratios stocks relative to low SE12 portfolios and are thus compensated for it.

Six of the alpha coefficients and all the gamma coefficients are significantly different from zero at the 5 percent level of significance. However we see that all ten coefficients for delta are not significantly different from zero at the 5 percent level of significance; this may be either because the risk associated with a changing variance is not compensated for, or because this risk is somehow captured by and compensated for in a higher premium to some of the other risk factors. We see that the gamma is always given a higher weight than the alpha; this implies that in predicting the current residual variance, more importance is given to the one period past estimate of the residual variance than what is given to the one period past squared residual.

Three of the ten SE12 portfolios show significant negative autocorrelation when measured at the one- percent level of significance. Thus, autocorrelation did pose a slight problem for this category of portfolios.

# Chapter 6 – Findings from India's Stock Market

In this chapter, we present the results on our study of the Indian stock market. This chapter is divided into five sections. In each section we present our findings on a certain category of portfolios. The categories of portfolios are SZDT, EP, PCF, SE36, and SE12. Each section is organized in the following way. We first present the means of out-of-sample returns along with their corresponding p-values. We then present the AIC and SC goodness-of-fit measures for the three categories of models, namely the One-Factor, the Three-Factor, and the Multi-Factor models. We then present the adjusted R-Squares for all three categories of models. We then present our estimation of the parameters of the three categories of models. We also present the Durbin-Watsons for the Multi-factor category of models.

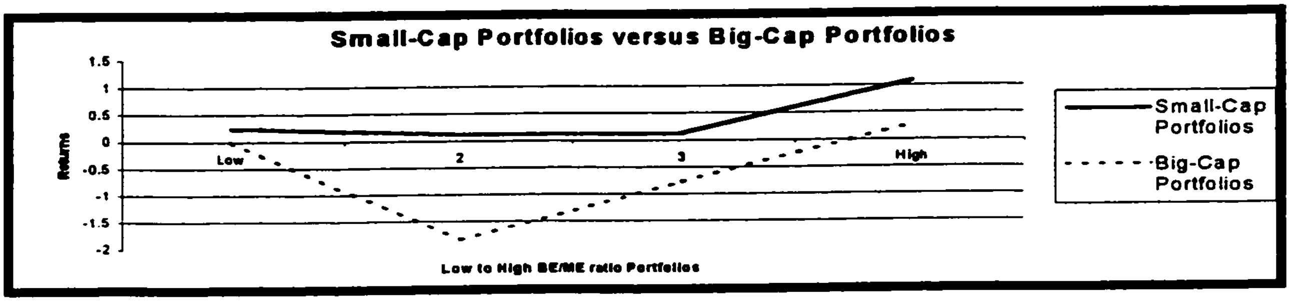
## 1. Tests on the 16 SZDT Portfolios

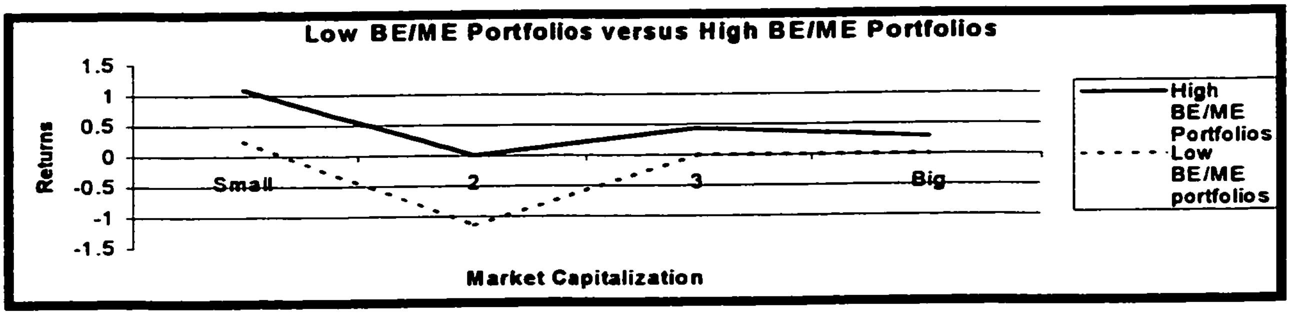
Table 6.1.1 shows the average out-of-sample returns to the 16 portfolios along with their corresponding p-values.

**Table 6.1.1**

**Summary Statistics**

| BE/ME \ Size | Low BE/ME | 2 | 3 | High BE/ME | | Low BE/ME | 2 | 3 | High BE/ME |
|---|---|---|---|---|---|---|---|---|---|
| | **Means of Out-of-Sample Returns** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | 0.25 | 0.11 | 0.13 | 1.09 | | 0.76 | 0.92 | 0.88 | 0.41 |
| **2** | -1.15 | -0.89 | -0.20 | NA | | 0.21 | 0.22 | 0.80 | NA |
| **3** | NA | -0.78 | 0.00 | 0.44 | | NA | 0.30 | 1.00 | 0.44 |
| **Big** Mkt. Cap | NA | -1.84 | -0.77 | 0.28 | | NA | 0.09 | 0.25 | 0.65 |



We see that the average out-of-sample returns to the small-cap portfolios are greater than the returns to the big-cap portfolios. We also see that the average out-of-sample returns to the high BE/ME portfolios are greater than the returns to the low BE/ME portfolios. These findings are very much in line with what the theory suggests. It must be noted though that none of the returns are significantly different from zero at the 5 percent level of significance.

Table 6.1.2 presents the Akaike Information Criterion and the Schwarz Criterion, two goodness of fit measures of the estimated models.

**Table 6.1.2**

**Akaike Information Criterion (AIC)**

| | One-Factor CAPM | | | | Three-Factor CAPM | | | | Multi-Factor CAPM | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME |
| Small Mkt. Cap. | 1,606 | 1,399 | 1,551 | 1,506 | 1,440 | 1,308 | 1,542 | 1,464 | 908 | 1,000 | 1,154 | 1,126 |
| 2 | 1,577 | 1,669 | 1,515 | 1,459 | 1,539 | 1,656 | 1,496 | 1,375 | 974 | 986 | 1,073 | 987 |
| 3 | 1,410 | 1,790 | 1,517 | 1,187 | 1,324 | 1,790 | 1,515 | 1,184 | 979 | 949 | 1,039 | 828 |
| Big Mkt. Cap. | 1,125 | 1,437 | 1,121 | 1,118 | 1,116 | 1,434 | 1,121 | 1,108 | 816 | 949 | 764 | 770 |

**The Schwarz Criterion (SC)**

| | One-Factor CAPM | | | | Three-Factor CAPM | | | | Multi-Factor CAPM | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME |
| Small Mkt. Cap. | 1,616 | 1,410 | 1,562 | 1,517 | 1,458 | 1,326 | 1,560 | 1,482 | 948 | 1,040 | 1,193 | 1,162 |
| 2 | 1,588 | 1,680 | 1,526 | 1,469 | 1,556 | 1,674 | 1,514 | 1,392 | 1,013 | 1,015 | 1,105 | 1,023 |
| 3 | 1,421 | 1,800 | 1,528 | 1,197 | 1,342 | 1,807 | 1,532 | 1,202 | 1,022 | 981 | 1,081 | 867 |
| Big Mkt. Cap. | 1,135 | 1,448 | 1,132 | 1,129 | 1,133 | 1,452 | 1,139 | 1,125 | 866 | 978 | 818 | 806 |

A study of the tables shows that the Multi-Factor model has the best fit. The Three-Factor CAPM generally has a better fit than the One-Factor CAPM. On average, the AIC for the Three-factor model is 3 percent smaller than that for One-factor models, whereas the AIC for the Multi-factor models is 33 percent smaller than that for the One-factor models. . On average, the SC for the Three-factor model is 2 percent smaller than that for One-factor models, whereas the SC for the Multi-factor models is 31 percent smaller than that for the One-factor models.

Table 6.1.3 presents the adjusted R-Square of the regression models.

**Table 6.1.3**

| Adjusted R-Square | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | One-Factor CAPM | | | | Three-Factor CAPM | | | | Multi-Factor CAPM | | | |
| | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME |
| Small Mkt. Cap. | 0.32 | 0.51 | 0.37 | 0.44 | 0.64 | 0.66 | 0.40 | 0.53 | 0.63 | 0.67 | 0.41 | 0.53 |
| 2 | 0.33 | 0.25 | 0.33 | 0.26 | 0.43 | 0.30 | 0.39 | 0.47 | 0.42 | 0.29 | 0.38 | 0.47 |
| 3 | 0.50 | 0.24 | 0.35 | 0.62 | 0.65 | 0.25 | 0.37 | 0.63 | 0.65 | 0.23 | 0.38 | 0.63 |
| Big Mkt. Cap. | 0.55 | 0.53 | 0.71 | 0.62 | 0.57 | 0.54 | 0.71 | 0.64 | 0.64 | 0.54 | 0.73 | 0.65 |

The Adjusted R-Squares of the Multi-Factor CAPM regressions average 0.52 and the Three-Factor CAPM regressions average 0.51, whereas the Adjusted R-Square of the One-Factor CAPM regressions average just 0.43. This shows that both the Multi-Factor CAPMs and the Three-Factor CAPMs have better explanatory power than the One-Factor CAPMs.

Table 6.1.4 shows the regression estimates of the One-Factor CAPM along with their corresponding p-values.

**Table 6.1.4**

**One-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + e_t$$

| BE/ME / Size | Low BE/ME | 2 | 3 | High BE/ME | | Low BE/ME | 2 | 3 | High BE/ME |
|---|---|---|---|---|---|---|---|---|---|
| | **a** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | -0.97 | -0.52 | -0.28 | 0.08 | | 0.07 | 0.16 | 0.56 | 0.86 |
| **2** | -1.01 | -0.76 | -1.18 | -1.80 | | 0.05 | 0.22 | 0.01 | 0.00 |
| **3** | -0.41 | -0.21 | -0.95 | -1.07 | | 0.27 | 0.79 | 0.04 | 0.00 |
| **Big** Mkt. Cap | 0.45 | -0.01 | -0.69 | -1.38 | | 0.27 | 0.97 | 0.00 | 0.00 |
| | **e** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | 0.08 | 2.24 | -2.42 | -2.56 | | 0.98 | 0.28 | 0.38 | 0.31 |
| **2** | -1.95 | -3.33 | -1.76 | -2.25 | | 0.50 | 0.34 | 0.49 | 0.33 |
| **3** | 0.81 | -6.45 | -1.66 | -0.54 | | 0.70 | 0.14 | 0.52 | 0.69 |
| **Big** Mkt. Cap | 2.61 | 0.80 | -0.23 | -0.54 | | 0.29 | 0.72 | 0.85 | 0.65 |
| | **b** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | 0.97 | 0.98 | 0.97 | 1.02 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **2** | 0.93 | 0.91 | 0.83 | 0.63 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **3** | 0.99 | 1.08 | 0.88 | 0.80 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **Big** Mkt. Cap | 1.09 | 1.10 | 0.88 | 0.71 | | 0.00 | 0.00 | 0.00 | 0.00 |

Seven of the sixteen models had intercepts that are significantly different from zero at the 5 percent level of significance and negative. This shows that generally the models are not being able to capture the pattern of returns of the portfolios or are not being able to capture all the risk factors associated with the returns. The market betas range from 0.63 to 1.09; the biggest firms with the lowest BE/ME ratios and the smallest firms with the biggest BE/ME ratios are more volatile than the market, whereas the smallest firms with the lowest BE/ME ratios and the biggest firms with the highest BE/ME ratios are less volatile than the market.

Table 6.1.5 shows the regression estimates of the Three-Factor CAPM along with their corresponding p-values.

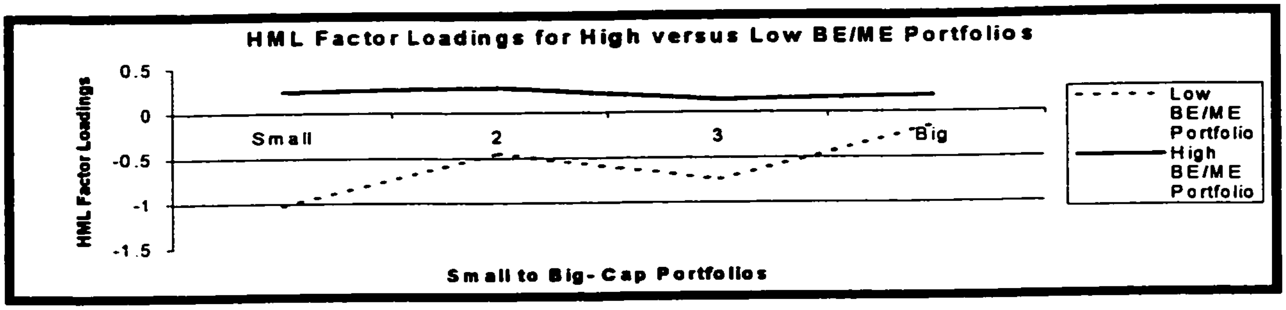
**Table 6.1.5**

**Three-Factor CAPM Time-Series Regression Estimates**

$E(R_t) - R_{f,t} = a + c[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + e_t$

| Size \ BE/ME | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME |
|---|---|---|---|---|---|---|---|---|
| | **a** | | | | **p-values** | | | |
| **Small** Mkt. Cap. | -1.64 | -0.60 | -0.29 | 0.43 | 0.00 | 0.06 | 0.56 | 0.31 |
| **2** | -1.26 | -0.99 | -1.10 | -1.39 | 0.01 | 0.10 | 0.01 | 0.00 |
| **3** | -1.07 | -0.34 | -0.82 | -0.94 | 0.00 | 0.66 | 0.08 | 0.00 |
| **Big** Mkt. Cap | 0.18 | -0.23 | -0.68 | -1.24 | 0.65 | 0.57 | 0.00 | 0.00 |
| | **e** | | | | **p-values** | | | |
| **Small** Mkt. Cap. | 0.95 | 3.08 | -1.94 | -1.59 | 0.67 | 0.07 | 0.47 | 0.49 |
| **2** | -1.32 | -2.89 | -1.10 | -1.08 | 0.62 | 0.39 | 0.66 | 0.58 |
| **3** | 0.42 | -6.17 | -1.83 | -0.43 | 0.82 | 0.16 | 0.48 | 0.75 |
| **Big** Mkt. Cap | 1.87 | 0.62 | -0.35 | -0.53 | 0.44 | 0.78 | 0.77 | 0.65 |
| | **b** | | | | **p-values** | | | |
| **Small** Mkt. Cap. | 0.77 | 0.94 | 0.95 | 1.09 | 0.00 | 0.00 | 0.00 | 0.00 |
| **2** | 0.85 | 0.84 | 0.84 | 0.71 | 0.00 | 0.00 | 0.00 | 0.00 |
| **3** | 0.82 | 1.04 | 0.92 | 0.84 | 0.00 | 0.00 | 0.00 | 0.00 |
| **Big** Mkt. Cap | 1.04 | 1.05 | 0.88 | 0.75 | 0.00 | 0.00 | 0.00 | 0.00 |

| Table 6.1.5 Continued | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| BE/ME / Size | Low BE/ME | 2 | 3 | High BE/ME | | Low BE/ME | 2 | 3 | High BE/ME |
| | s | | | | | p-values | | | |
| Small Mkt. Cap. | 1.48 | 0.99 | 0.53 | 0.78 | | 0.00 | 0.00 | 0.00 | 0.00 |
| 2 | 0.88 | 0.66 | 0.66 | 0.96 | | 0.00 | 0.00 | 0.00 | 0.00 |
| 3 | 0.08 | 0.41 | -0.29 | 0.02 | | 0.41 | 0.09 | 0.04 | 0.84 |
| Big Mkt. Cap | -0.47 | -0.02 | -0.14 | -0.10 | | 0.00 | 0.85 | 0.04 | 0.14 |
| | h | | | | | p-values | | | |
| Small Mkt. Cap. | -1.03 | -0.29 | -0.11 | 0.24 | | 0.00 | 0.00 | 0.34 | 0.01 |
| 2 | -0.45 | -0.39 | -0.04 | 0.28 | | 0.00 | 0.01 | 0.71 | 0.00 |
| 3 | -0.75 | -0.23 | 0.20 | 0.14 | | 0.00 | 0.19 | 0.06 | 0.01 |
| Big Mkt. Cap | -0.15 | -0.23 | 0.04 | 0.18 | | 0.20 | 0.01 | 0.45 | 0.00 |




Eight of the sixteen intercepts are significant at the 5 percent level of significance. This shows that generally the models are not being able to capture the pattern of returns of the portfolios or are not being able to capture all the risk factors associated with the returns. The market betas range from 0.71 to 1.05; the biggest firms with the lowest BE/ME ratios and the smallest firms with the biggest BE/ME ratios are more volatile than the market, whereas the smallest firms with the lowest BE/ME ratios and the biggest firms with the highest BE/ME ratios are less volatile than the market.

We also see that the small firms have positive coefficients on the SMB portfolios, whereas big firms have a low and negative coefficient on the SMB portfolio. Thus small firms do receive a small-firm risk premium. We see that high BE/ME (value) stocks have a positive coefficient on the HML portfolio, whereas the lower the BE/ME the more negative the coefficient is on the HML portfolio. This shows that value stocks are given the value risk premium.

Table 6.1.6 shows the regression estimates of the Multi-Factor CAPM along with their corresponding p-values.

**Table 6.1.6**

**Multi-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{ft} = a + e[PCER_t] + b[E(R_{m,t}) - R_{ft}] + sE[SMB_t] + hE[HML_t] + \delta\sqrt{(h_t)} + -\phi_1 v_{t-1} - \phi_2 v_{t-2} - \ldots - \phi_{53} v_{t-53} + \sqrt{(h_t)}\, e_t$$

$$h_t = \kappa + \alpha\varepsilon^2_{t-1} + \gamma h_{t-1} \qquad \kappa > 0$$

$$\alpha + \gamma = 1$$

| BE/ME / Size | Low BE/ME | 2 | 3 | High BE/ME | | Low BE/ME | 2 | 3 | High BE/ME |
|---|---|---|---|---|---|---|---|---|---|
| | **a** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | -2.08 | -0.68 | -1.24 | 0.43 | | 0.00 | 0.56 | 0.06 | 0.52 |
| **2** | -1.77 | -1.04 | -1.70 | 0.34 | | 0.01 | 0.02 | 0.03 | 0.78 |
| **3** | -0.57 | -0.89 | 1.82 | 2.96 | | 0.40 | 0.44 | 0.22 | 0.51 |
| **Big** Mkt. Cap | -0.63 | -0.04 | -0.89 | 6.64 | | 0.48 | 0.95 | 0.10 | 0.39 |
| | **e** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | -0.75 | 1.76 | 0.76 | -1.54 | | 0.47 | 0.27 | 0.61 | 0.39 |
| **2** | -0.03 | -2.74 | -0.54 | -1.12 | | 0.97 | 0.01 | 0.71 | 0.42 |
| **3** | 0.60 | -0.35 | -0.04 | 0.67 | | 0.69 | 0.74 | 0.98 | 0.50 |
| **Big** Mkt. Cap | 0.82 | 0.90 | -0.64 | -0.10 | | 0.61 | 0.33 | 0.47 | 0.92 |
| | **b** | | | | | **p-values** | | | |
| **Small** Mkt. Cap. | 0.82 | 0.95 | 0.87 | 1.09 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **2** | 0.88 | 0.80 | 0.69 | 0.77 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **3** | 0.88 | 0.91 | 0.88 | 0.73 | | 0.00 | 0.00 | 0.00 | 0.00 |
| **Big** Mkt. Cap | 1.08 | 0.98 | 0.87 | 0.73 | | 0.00 | 0.00 | 0.00 | 0.00 |

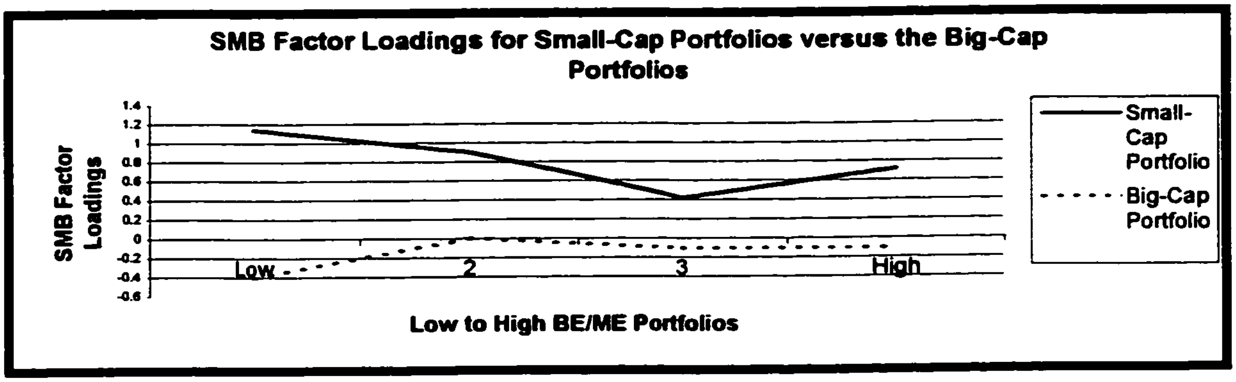
**Table 6.1.6 Continued**

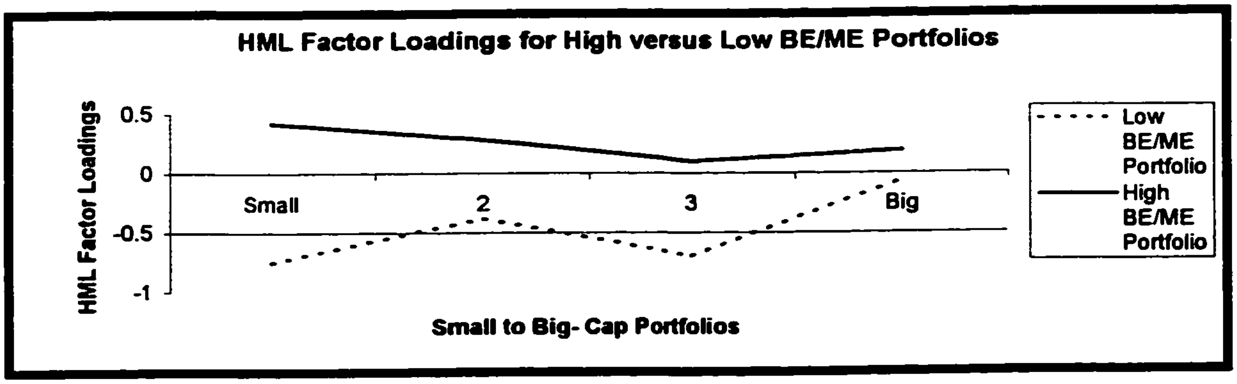
| BE/ME \ Size | Low BE/ME | 2 | 3 | High BE/ME | | Low BE/ME | 2 | 3 | High BE/ME |
|---|---|---|---|---|---|---|---|---|---|
| | s | | | | | p-values | | | |
| Small Mkt. Cap. | 1.14 | 0.90 | 0.41 | 0.71 | | 0.00 | 0.00 | 0.00 | 0.00 |
| 2 | 0.61 | 0.54 | 0.49 | 0.70 | | 0.00 | 0.00 | 0.00 | 0.00 |
| 3 | -0.01 | 0.45 | 0.15 | 0.04 | | 0.87 | 0.00 | 0.17 | 0.54 |
| Big Mkt. Cap | -0.41 | 0.00 | -0.11 | -0.11 | | 0.00 | 0.95 | 0.03 | 0.06 |
| | h | | | | | p-values | | | |
| Small Mkt. Cap. | -0.75 | -0.26 | -0.07 | 0.42 | | 0.00 | 0.00 | 0.44 | 0.00 |
| 2 | -0.38 | -0.19 | -0.11 | 0.28 | | 0.00 | 0.00 | 0.16 | 0.00 |
| 3 | -0.70 | -0.27 | 0.00 | 0.10 | | 0.00 | 0.00 | 0.96 | 0.05 |
| Big Mkt. Cap | -0.06 | -0.21 | -0.01 | 0.19 | | 0.51 | 0.00 | 0.78 | 0.00 |
| | delta | | | | | p-values | | | |
| Small Mkt. Cap. | 0.05 | 0.03 | 0.11 | -0.04 | | 0.08 | 0.93 | 0.47 | 0.80 |
| 2 | 0.14 | -0.01 | -0.02 | -0.20 | | 0.28 | 0.93 | 0.88 | 0.25 |
| 3 | -0.10 | 0.01 | -0.48 | -1.69 | | 0.65 | 0.83 | 0.00 | 0.39 |
| Big Mkt. Cap | 0.20 | -0.06 | 0.09 | -3.66 | | 0.35 | 0.63 | 0.65 | 0.35 |
| | k | | | | | p-values | | | |
| Small Mkt. Cap. | 341.34 | 0.15 | 1.54 | 0.86 | | 0.25 | 0.47 | 0.11 | 0.13 |
| 2 | 9.02 | 16.43 | 22.70 | 31.23 | | 0.23 | 0.10 | 0.09 | 0.17 |
| 3 | 0.21 | 706.52 | 11.39 | 0.02 | | 0.16 | 0.16 | 0.21 | 0.47 |
| Big Mkt. Cap | 4.01 | 23.26 | 2.09 | 0.01 | | 0.14 | 0.20 | 0.32 | 0.48 |

| Table 6.1.6 Continued | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| BE/ME Size | Low BE/ME | 2 | 3 | High BE/ME | | Low BE/ME | 2 | 3 | High BE/ME |
| | alpha | | | | | p-values | | | |
| Small Mkt. Cap. | 1.00 | 0.10 | 0.32 | 0.25 | | 0.00 | 0.28 | 0.00 | 0.00 |
| 2 | 0.74 | 1.00 | 1.00 | 0.90 | | 0.00 | 0.00 | 0.00 | 0.00 |
| 3 | 0.15 | 1.00 | 0.49 | 0.00 | | 0.00 | 0.00 | 0.00 | 0.32 |
| Big Mkt. Cap | 0.49 | 1.00 | 0.45 | 0.00 | | 0.02 | 0.00 | 0.10 | 0.39 |
| | gamma | | | | | p-values | | | |
| Small Mkt. Cap. | 0.00 | 0.90 | 0.68 | 0.75 | | 0.00 | 0.00 | 0.00 | 0.00 |
| 2 | 0.26 | 0.00 | 0.00 | 0.10 | | 0.16 | 0.00 | 0.00 | 0.60 |
| 3 | 0.85 | 0.00 | 0.51 | 1.00 | | 0.00 | 0.00 | 0.00 | 0.00 |
| Big Mkt. Cap | 0.51 | 0.00 | 0.55 | 1.00 | | 0.01 | 0.00 | 0.04 | 0.00 |

**Durbin Watson to check for Autocorrelation**

| | Durbin Watson | | | | p-value for negative autocorrelation | | | | p-value for positive autocorrelation | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME | Low BE/ME | 2 | 3 | High BE/ME |
| Small Mkt. Cap. | 2.08 | 2.19 | 1.87 | 1.85 | 0.26 | 0.06 | 0.86 | 0.89 | 0.74 | 0.94 | 0.14 | 0.11 |
| 2 | 1.75 | 1.97 | 1.97 | 2.12 | 0.98 | 0.59 | 0.58 | 0.16 | 0.02 | 0.41 | 0.42 | 0.84 |
| 3 | 1.93 | 2.07 | 1.98 | 2.25 | 0.72 | 0.29 | 0.57 | 0.02 | 0.28 | 0.71 | 0.43 | 0.98 |
| Big Mkt. Cap. | 2.02 | 2.00 | 2.02 | 1.99 | 0.46 | 0.51 | 0.43 | 0.54 | 0.54 | 0.49 | 0.57 | 0.46 |




Only four of the sixteen portfolio models are significantly different from zero at the 5 percent level of significance. This shows that in general risk factors are adequately priced leaving no abnormal return to the portfolios. The market betas range from 0.69 to 1.09; the biggest firms with the lowest BE/ME ratios and the smallest firms with the biggest BE/ME ratios are more volatile than the market, whereas the smallest firms with the lowest BE/ME ratios and the biggest firms with the highest BE/ME ratios are less volatile than the market.

We see that the small stocks are given its small stock risk premium (i.e. positive loadings on the SMB risk factors). We also see that the high BE/ME (value) stocks were given its value risk premium (i.e. positive loadings on the HML risk factors). The alpha and gamma coefficients are significantly different from zero at the 5 percent level of significance, which shows that there was time varying conditional variance in the stock returns. However, we see that the coefficients for delta are all not significantly different from zero; this may be either because the risk associated with a changing variance is not compensated for, or because this risk is somehow captured by and compensated for in a higher premium to some of the other risk factors.

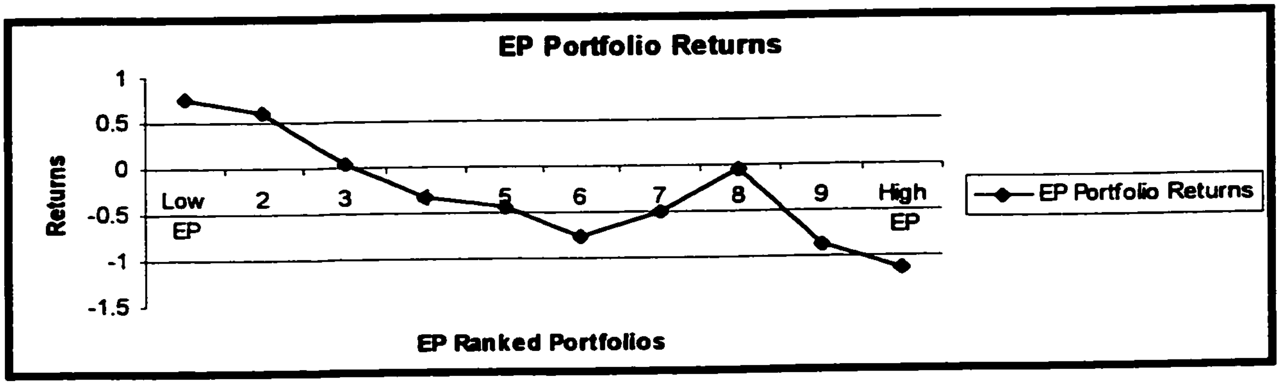
None of the sixteen portfolios showed significant negative autocorrelation when measured at the one-percent level of significance. This shows that in general autocorrelation did not pose a problem.

## 2. Tests on the 10 EP Portfolios

Table 6.2.1 shows the average out-of-sample returns to the 10 portfolios along with their corresponding p-values.

**Table 6.2.1**

| Summary Statistics | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
| Returns | 0.76 | 0.61 | 0.05 | -0.33 | -0.43 | -0.75 | -0.51 | -0.04 | -0.86 | -1.14 |
| p-value | 0.22 | 0.32 | 0.95 | 0.62 | 0.57 | 0.26 | 0.50 | 0.95 | 0.22 | 0.16 |




The average out-of-sample returns on the portfolios formed based on the EP ratio, do show a clear decreasing trend with low EP portfolios having positive returns and vice versa. This trend is contrary to what the theory suggests. However, the p-values indicate that the returns are not significantly different from zero at the 5 percent level of significance.

Table 6.2.2 presents the Akaike Information Criterion and the Schwarz Criterion, two goodness of fit measures of the estimated models.

**Table 6.2.2**

| Goodness-of-Fit | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
| **Akaike Information Criterion** | | | | | | | | | | |
| One-Factor | 1259 | 1101 | 1098 | 1049 | 1140 | 1138 | 1185 | 1179 | 1242 | 1392 |
| Three-Factor | 1166 | 1047 | 1080 | 1011 | 1128 | 1107 | 1107 | 1013 | 1101 | 1171 |
| Multi-Facor | 865 | 719 | 737 | 698 | 746 | 777 | 783 | 712 | 750 | 854 |
| **Schwarz Criterion** | | | | | | | | | | |
| One-Factor | 1269 | 1112 | 1108 | 1059 | 1151 | 1149 | 1196 | 1190 | 1252 | 1403 |
| Three-Factor | 1184 | 1065 | 1098 | 1029 | 1146 | 1125 | 1124 | 1031 | 1119 | 1189 |
| Multi-Facor | 894 | 755 | 787 | 737 | 786 | 816 | 815 | 740 | 786 | 889 |

A study of the tables shows that the Multi-Factor model has the best fit. The Three-Factor CAPM generally has a better fit than the One-Factor CAPM. On average, the AIC for the Three-factor model is 7 percent smaller than that for One-factor models, whereas the AIC for the Multi-factor models is 35 percent smaller than that for the One-factor models. . On average, the SC for the Three-factor model is 7 percent smaller than that for

One-factor models, whereas the SC for the Multi-factor models is 33 percent smaller than that for the One-factor models.

Table 6.2.3 presents the adjusted R-Square of the regression models.

**Table 6.2.3**

| Adjusted R-Square | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Low EP** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High EP** |
| **One-Factor** | 0.64 | 0.75 | 0.71 | 0.75 | 0.71 | 0.73 | 0.72 | 0.72 | 0.70 | 0.55 |
| **Three-Factor** | 0.75 | 0.80 | 0.73 | 0.79 | 0.73 | 0.76 | 0.79 | 0.85 | 0.83 | 0.81 |
| **Multi-Facor** | 0.75 | 0.80 | 0.74 | 0.80 | 0.74 | 0.78 | 0.79 | 0.85 | 0.83 | 0.81 |

The Adjusted R-Squares of the Multi-Factor CAPM regressions averages 0.79 that of the Three-Factor CAPM regressions averages 0.78, whereas the Adjusted R-Square of the One-Factor CAPM regressions average 0.70. This shows that both the Multi-Factor CAPMs and the Three-Factor CAPMs have better explanatory power than the One-Factor CAPMs.

Table 6.2.4 shows the regression estimates of the One-Factor CAPM along with their corresponding p-values.

**Table 6.2.4**

**One-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + e_t$$

| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
|---|---|---|---|---|---|---|---|---|---|---|
| a | -0.22 | -0.28 | -0.85 | -0.97 | -0.66 | -0.54 | -0.07 | -0.08 | -0.01 | -0.10 |
| p-value | 0.44 | 0.17 | 0.00 | 0.00 | 0.00 | 0.02 | 0.78 | 0.74 | 0.98 | 0.79 |
| | | | | | | | | | | |
| e | -0.76 | 0.16 | -1.66 | 1.18 | -0.56 | -0.13 | -2.18 | -1.88 | -0.35 | -0.62 |
| p-value | 0.63 | 0.89 | 0.15 | 0.26 | 0.66 | 0.92 | 0.11 | 0.16 | 0.82 | 0.76 |
| | | | | | | | | | | |
| b | 0.97 | 0.95 | 0.82 | 0.86 | 0.92 | 0.95 | 1.01 | 1.01 | 1.08 | 1.04 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Four of the ten intercepts of the regression models of all the portfolios are significant at the 5 percent level of significance and negative. The intercepts do not show any trend across portfolios. The market betas of the stocks do show a clear trend with the first six portfolios having a market beta less than one and the last four portfolios having a market beta greater than one. This shows that stocks with low EP ratios are less volatile than the market whereas stocks with high EP ratios are more volatile than the market. However we will later see that this trend is just an artifact of not bringing in all the common risk factors.

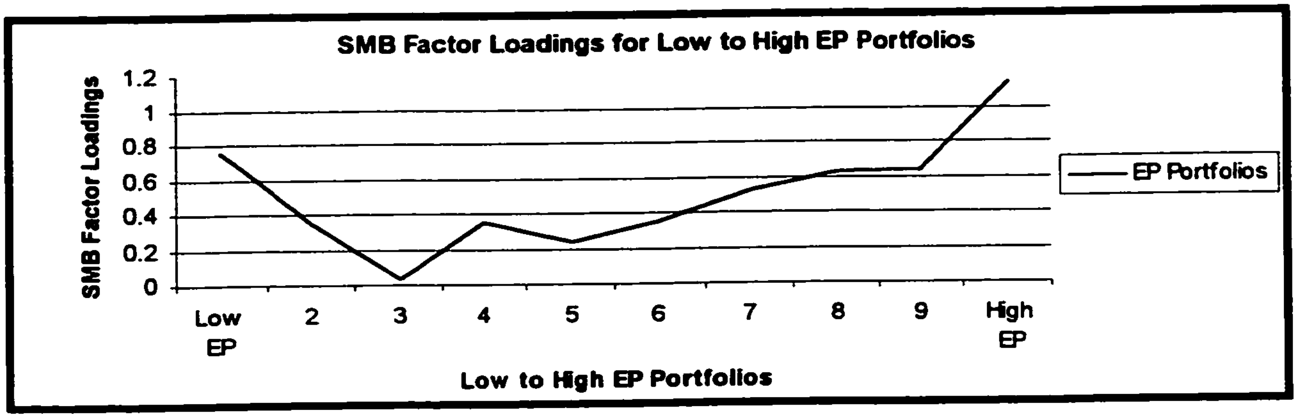
Table 6.2.5 shows the regression estimates of the Three-Factor CAPM along with their corresponding p-values.

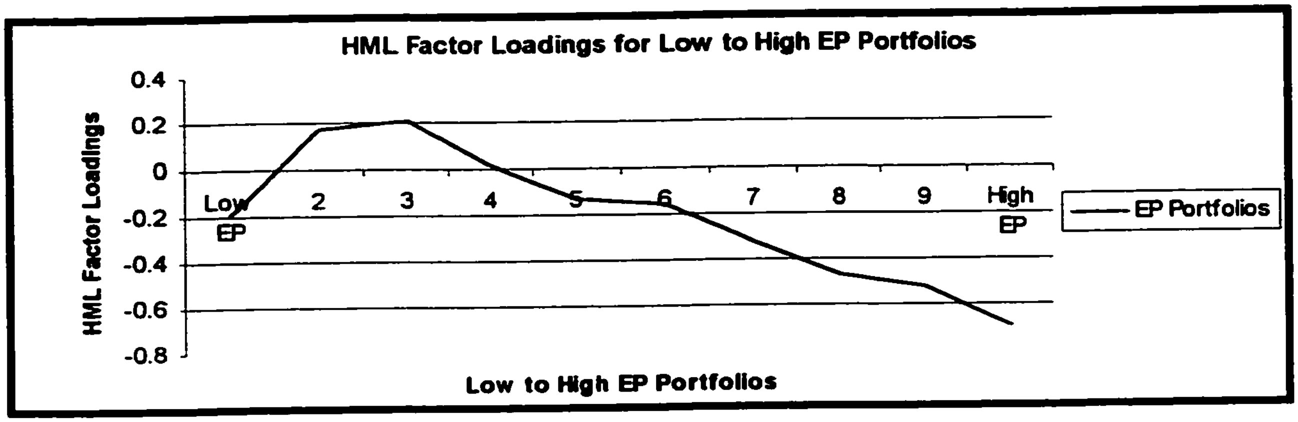
**Table 6.2.5**

| Three-Factor CAPM Time-Series Regression Estimates | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| $E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + e_t$ | | | | | | | | | | |
| | **Low EP** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High EP** |
| **a** | -0.25 | -0.06 | -0.66 | -0.89 | -0.73 | -0.62 | -0.26 | -0.39 | -0.36 | -0.52 |
| **p-value** | 0.29 | 0.74 | 0.00 | 0.00 | 0.00 | 0.00 | 0.23 | 0.03 | 0.09 | 0.03 |
| | | | | | | | | | | |
| **e** | -0.09 | 0.64 | -1.49 | 1.55 | -0.39 | 0.14 | -1.82 | -1.53 | -0.01 | 0.12 |
| **p-value** | 0.95 | 0.54 | 0.18 | 0.11 | 0.75 | 0.90 | 0.12 | 0.12 | 0.99 | 0.93 |
| | | | | | | | | | | |
| **b** | 0.94 | 0.99 | 0.87 | 0.87 | 0.89 | 0.92 | 0.95 | 0.91 | 0.98 | 0.90 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **s** | 0.76 | 0.36 | 0.04 | 0.35 | 0.24 | 0.36 | 0.53 | 0.63 | 0.64 | 1.14 |
| **p-value** | 0.00 | 0.00 | 0.51 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 6.2.5 Continued**

| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
|---|---|---|---|---|---|---|---|---|---|---|
| h | -0.19 | 0.17 | 0.21 | 0.02 | -0.13 | -0.16 | -0.32 | -0.47 | -0.52 | -0.70 |
| p-value | 0.00 | 0.00 | 0.00 | 0.70 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |




We see that six out of the ten portfolios are significantly different from zero at the 5 percent level of significance and negative. The market betas are all less than one and do show a trend with the high and the low EP ratios stocks having a higher beta (i.e. more volatility) than the middle EP ratios stocks.

The low and high EP portfolios earn a higher small-firm risk premium (i.e. positive loadings on the SMB risk factors) than the middle EP portfolios. Thus, low and high EP portfolios seem to consist of smaller firms than the middle EP portfolios. The low EP portfolios endure a lower low-distress penalty (i.e. negative loadings on the HML risk factors) than the high EP portfolios; thus, low EP portfolios seem to consist of higher BE/ME stocks i.e. value stocks, than the high EP portfolios.

Table 6.2.6 shows the regression estimates of the Multi-Factor CAPM along with their corresponding p-values.

**Table 6.2.6**

**Multi-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + \delta\sqrt{(h_t)} + -\phi_1 v_{t-1} - \phi_2 v_{t-2} - \ldots - \phi_{53} v_{t-53} + \sqrt{(h_t)}\, e$$

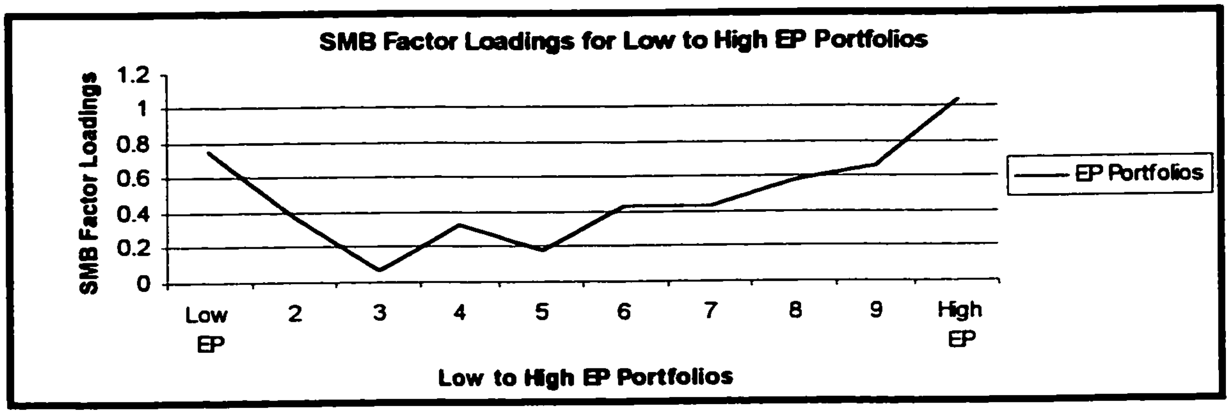
$$h_t = \kappa + \alpha\varepsilon_{t-1}^2 + \gamma h_{t-1} \qquad \kappa > 0$$

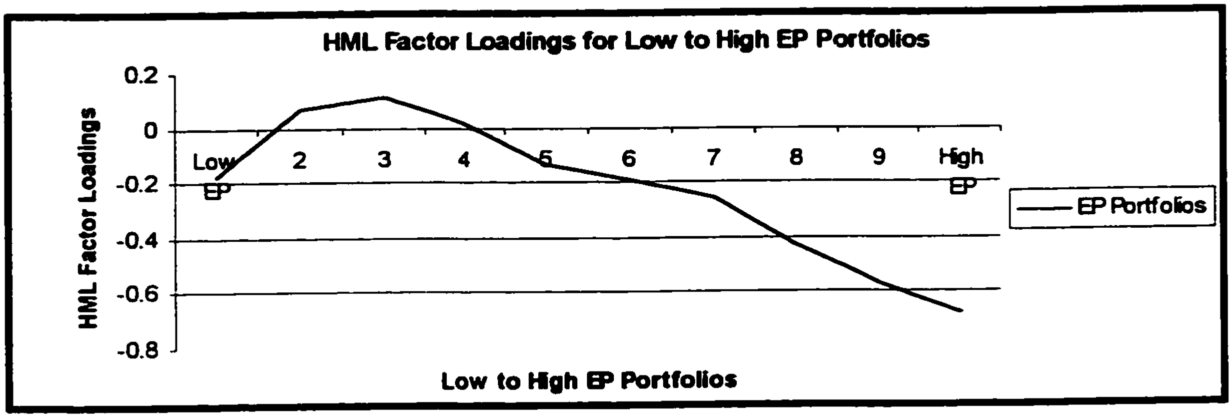
$$\alpha + \gamma = 1$$

| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
|---|---|---|---|---|---|---|---|---|---|---|
| a | -0.06 | -1.15 | -2.61 | -1.91 | -1.89 | 8.34 | 0.34 | 0.14 | -1.06 | -0.26 |
| p-value | 0.00 | 0.07 | 0.01 | 0.01 | 0.00 | 0.22 | 0.60 | 0.85 | 0.01 | 0.76 |
| | | | | | | | | | | |
| e | -0.04 | 0.60 | -0.98 | 1.49 | -0.88 | 1.57 | -0.18 | -1.09 | 1.11 | -0.49 |
| p-value | 0.97 | 0.39 | 0.25 | 0.09 | 0.32 | 0.13 | 0.86 | 0.24 | 0.16 | 0.65 |
| | | | | | | | | | | |
| b | 0.94 | 0.94 | 0.86 | 0.89 | 0.82 | 0.87 | 0.97 | 0.90 | 0.95 | 0.93 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| s | 0.75 | 0.38 | 0.07 | 0.33 | 0.18 | 0.43 | 0.44 | 0.58 | 0.66 | 1.04 |
| p-value | 0.00 | 0.00 | 0.21 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| h | -0.18 | 0.07 | 0.11 | 0.02 | -0.13 | -0.19 | -0.26 | -0.43 | -0.57 | -0.68 |
| p-value | 0.00 | 0.05 | 0.00 | 0.56 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 6.2.6 Continued**

| | Low EP | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High EP |
|---|---|---|---|---|---|---|---|---|---|---|
| **delta** | -0.07 | 0.36 | 0.50 | 0.68 | 0.38 | -4.27 | -0.33 | -0.37 | 0.29 | -0.07 |
| **p-value** | 0.00 | 0.16 | 0.01 | 0.12 | 0.03 | 0.22 | 0.33 | 0.41 | 0.12 | 0.84 |
| | | | | | | | | | | |
| **k** | 0.00 | 0.73 | 1.77 | 0.03 | 1.70 | 0.01 | 0.05 | 0.01 | 0.71 | 0.29 |
| **p-value** | | 0.31 | 0.39 | 0.45 | 0.02 | 0.29 | 0.33 | 0.30 | 0.30 | 0.45 |
| | | | | | | | | | | |
| **alpha** | 0.00 | 0.21 | 0.15 | 0.05 | 0.77 | 0.00 | 0.05 | 0.04 | 0.38 | 0.16 |
| **p-value** | 0.00 | 0.06 | 0.02 | 0.12 | 0.00 | 0.51 | 0.11 | 0.09 | 0.04 | 0.18 |
| | | | | | | | | | | |
| **gamma** | 1.00 | 0.79 | 0.85 | 0.95 | 0.23 | 1.00 | 0.95 | 0.96 | 0.62 | 0.84 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.20 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **Durbin Watson to test for Autocorrelation** | | | | | | | | | | |
| **d** | 2.16 | 2.03 | 2.31 | 1.87 | 1.63 | 1.99 | 2.09 | 2.05 | 1.80 | 2.16 |
| **p-value (for - corr)** | 0.09 | 0.40 | 0.01 | 0.86 | 1.00 | 0.54 | 0.23 | 0.35 | 0.95 | 0.09 |
| **p-value (for + corr)** | 0.91 | 0.60 | 0.99 | 0.14 | 0.00 | 0.46 | 0.77 | 0.65 | 0.05 | 0.91 |




Five of the ten intercepts are significantly different from zero at the 5 percent level of significance and negative. The market betas are all less than one and do show a trend with the high and the low EP ratios stocks having a higher beta (i.e. more volatility) than the middle EP ratios stocks.

The low and high EP portfolios earn a higher small-firm risk premium (i.e. positive loadings on the SMB risk factors) than the middle EP portfolios. Thus, low and high EP portfolios seem to consist of smaller firms than the middle EP portfolios. The low EP portfolios endure a lower low-distress penalty (i.e. negative loadings on the HML risk factors) than the high EP portfolios. Thus, low EP portfolios seem to consist of higher BE/ME stocks (i.e. value stocks) than the high EP portfolios.

The alpha coefficients are not always significantly different from zero at the 5 percent level of significance but the gamma coefficients are always significantly different from zero at the 5 percent level of significance. However, we see that the coefficients for delta are not significantly different from zero at the 5 percent level of significance. This may be either because the risk associated with a changing variance is not compensated for, or because this risk is somehow captured by and compensated for in a higher premium to some of the other risk factors. We see that the gamma is always given a higher weight than the alpha. This implies that in predicting the current residual variance, more importance is given to the one period past estimate of the residual variance than what is given to the one period past squared residual. We see that in general autocorrelation did not pose a problem.

Thus the low EP portfolios seem to consist of smaller, healthier, but more volatile stocks than the big EP portfolios, with a significant conditionally heteroskedastic error term.

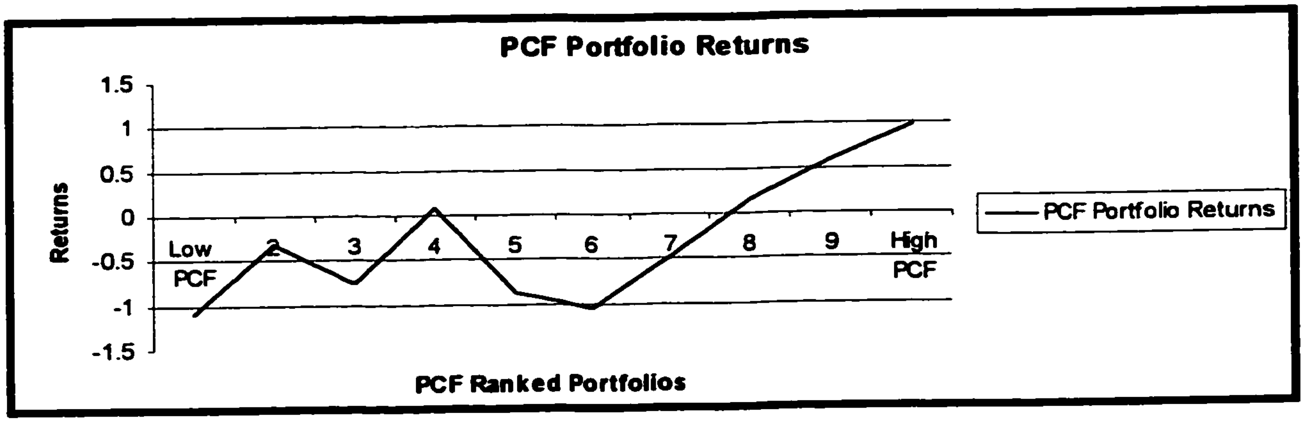
### 3. Tests on the 10 PCF Portfolios

Table 6.3.1 shows the average out-of-sample returns to the 10 portfolios along with their corresponding p-values.

**Table 6.3.1**

**Summary Statistics**

| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
|---|---|---|---|---|---|---|---|---|---|---|
| **Returns** | -1.10 | -0.32 | -0.75 | 0.08 | -0.88 | -1.05 | -0.46 | 0.15 | 0.60 | 0.99 |
| **p-value** | 0.20 | 0.64 | 0.30 | 0.91 | 0.18 | 0.19 | 0.53 | 0.83 | 0.34 | 0.10 |




The average out-of-sample returns on the portfolios formed based on the P/CF ratio, do show a clear upward trend with the low PCF portfolios having negative returns and the high PCF portfolios having positive returns. This is not consistent with what the theory suggests. However, the p-values indicate that these returns are not significantly different from zero at the 5 percent level of significance.

Table 6.3.2 presents the Akaike Information Criterion and the Schwarz Criterion, two goodness of fit measures of the estimated models.

**Table 6.3.2**

| Goodness-of-Fit | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
| **Akaike Information Criterion** | | | | | | | | | | |
| One-Factor | 1431 | 1283 | 1173 | 1161 | 1142 | 1128 | 1028 | 1032 | 1085 | 1155 |
| Three-Factor | 1191 | 1099 | 1075 | 1058 | 1082 | 1102 | 1009 | 1011 | 1034 | 1093 |
| Multi-Facor | 874 | 747 | 729 | 741 | 737 | 757 | 694 | 671 | 703 | 784 |
| **Schwarz Criterion** | | | | | | | | | | |
| One-Factor | 1442 | 1294 | 1184 | 1172 | 1153 | 1139 | 1038 | 1043 | 1095 | 1166 |
| Three-Factor | 1209 | 1117 | 1093 | 1076 | 1099 | 1120 | 1027 | 1029 | 1052 | 1111 |
| Multi-Facor | 909 | 790 | 768 | 780 | 769 | 807 | 726 | 707 | 739 | 816 |

A study of the tables shows that the Multi-Factor model has the best fit. The Three-Factor CAPM generally has a better fit than the One-Factor CAPM. On average, the AIC for the Three-factor model is 7 percent smaller than that for One-factor models, whereas the AIC for the Multi-factor models is 36 percent smaller than that for the One-factor models. . On average, the SC for the Three-factor model is 7 percent smaller than that for

One-factor models, whereas the SC for the Multi-factor models is 33 percent smaller than that for the One-factor models.

Table 6.3.3 presents the adjusted R-Square of the regression models.

**Table 6.3.3**

| Adjusted R-Square | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
| One-Factor | 0.50 | 0.67 | 0.73 | 0.74 | 0.73 | 0.73 | 0.78 | 0.79 | 0.72 | 0.70 |
| Three-Factor | 0.80 | 0.83 | 0.82 | 0.82 | 0.79 | 0.76 | 0.80 | 0.81 | 0.77 | 0.76 |
| Multi-Facor | 0.80 | 0.84 | 0.83 | 0.83 | 0.79 | 0.78 | 0.81 | 0.81 | 0.77 | 0.76 |

The Adjusted R-Squares of the Multi-Factor CAPM regressions and that of the Three-Factor CAPM regressions average 0.80, whereas the Adjusted R-Square of the One-Factor CAPM regressions average 0.70. This shows that both the Multi-Factor CAPMs and the Three-Factor CAPMs have better explanatory power than the One-Factor CAPMs.

Table 6.3.4 shows the regression estimates of the One-Factor CAPM along with their corresponding p-values.

**Table 6.3.4**

**One-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + e_t$$

| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
|---|---|---|---|---|---|---|---|---|---|---|
| a | -0.16 | 0.02 | -0.13 | -0.11 | -0.36 | -0.68 | -0.56 | -0.52 | -0.78 | -0.54 |
| p-value | 0.68 | 0.94 | 0.58 | 0.64 | 0.11 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 |
| | | | | | | | | | | |
| e | -1.55 | -0.02 | -1.01 | -2.11 | -1.55 | 0.43 | -0.62 | 0.32 | 0.07 | -1.04 |
| p-value | 0.48 | 0.99 | 0.45 | 0.11 | 0.22 | 0.72 | 0.54 | 0.75 | 0.95 | 0.42 |
| | | | | | | | | | | |
| b | 1.01 | 1.09 | 1.03 | 1.01 | 0.96 | 0.95 | 0.89 | 0.93 | 0.84 | 0.90 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

The intercepts of the regression models for the five of the ten portfolios with the highest PCF ratio stocks are all significant at the 5 percent level of significance and negative. Thus, the portfolios with the highest PCF ratio stocks earned returns less than what is expected given just the market risk. The market betas of the portfolios with the highest PCF ratio stocks are less than one, whereas the market betas of the portfolios with the lowest PCF ratio stocks are greater than one. Thus, stocks with a low PCF ratio are more volatile than the stocks with a high PCF ratio. Thus, portfolios built on a sort of stocks based on the PCF ratio all show less volatility than the market portfolio.

Table 6.3.5 shows the regression estimates of the Three-Factor CAPM along with their corresponding p-values.

**Table 6.3.5**

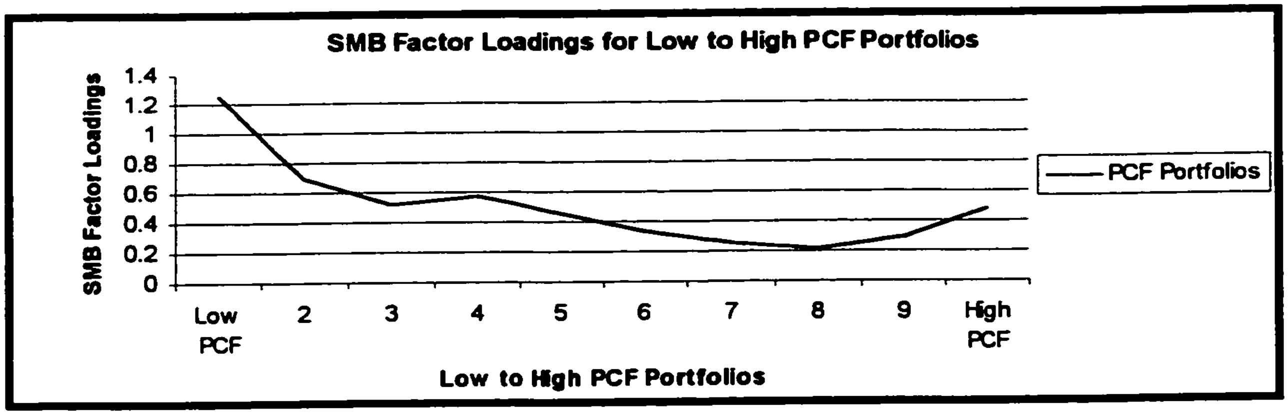
**Three-Factor CAPM Time-Series Regression Estimates**

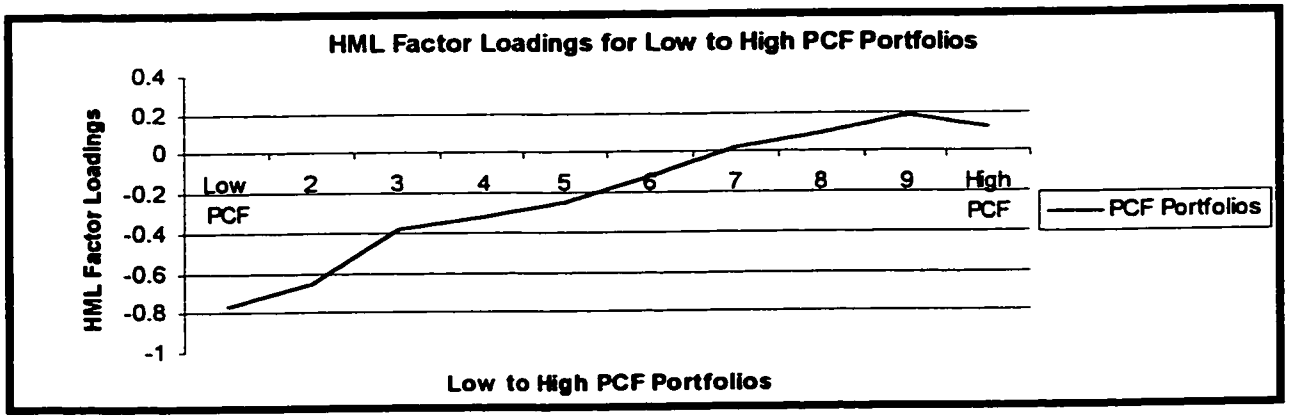
$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + e_t$$

| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
|---|---|---|---|---|---|---|---|---|---|---|
| **a** | -0.63 | -0.45 | -0.38 | -0.30 | -0.50 | -0.72 | -0.49 | -0.39 | -0.56 | -0.34 |
| **p-value** | 0.01 | 0.03 | 0.06 | 0.13 | 0.01 | 0.00 | 0.01 | 0.03 | 0.00 | 0.10 |
| | | | | | | | | | | |
| **e** | -0.74 | 0.28 | -0.72 | -1.72 | -1.24 | 0.71 | -0.35 | 0.61 | 0.51 | -0.47 |
| **p-value** | 0.59 | 0.81 | 0.51 | 0.11 | 0.27 | 0.54 | 0.72 | 0.54 | 0.62 | 0.68 |
| | | | | | | | | | | |
| **b** | 0.86 | 0.95 | 0.95 | 0.95 | 0.91 | 0.93 | 0.90 | 0.96 | 0.89 | 0.94 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **s** | 1.26 | 0.69 | 0.52 | 0.58 | 0.45 | 0.34 | 0.25 | 0.22 | 0.30 | 0.48 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 6.3.5 Continued**

| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
|---|---|---|---|---|---|---|---|---|---|---|
| h | -0.77 | -0.66 | -0.38 | -0.32 | -0.25 | -0.12 | 0.02 | 0.10 | 0.19 | 0.13 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.55 | 0.02 | 0.00 | 0.01 |




We see that seven of the ten portfolios are significantly different from zero at the 5 percent level of significance. This shows that generally the models are not being able to capture the pattern of returns of the portfolios or are not being able to capture all the risk factors associated with the returns. The market betas are all less than one. There does not seem to be any trend across market betas.

All ten portfolios are given a small-firm risk premium (i.e. positive loadings on the SMB risk factors). The portfolios with the lower PCF ratio stocks are given a higher small-firm risk premium (i.e. positive loadings on the HML risk factors) than the portfolios with the higher PCF ratio firms. The portfolios with low PCF ratios stocks endure a low-distress penalty whereas the portfolios with high PCF ratios firms are given a high-distress premium. Thus, the firms with the highest ratio consist of higher BE/ME ratios than what the firms with the lowest ratios do.

Table 6.3.6 shows the regression estimates of the Multi-Factor CAPM along with their corresponding p-values.

**Table 6.3.6**

**Multi-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{ft} = a + e[PCER_t] + b[E(R_{mt}) - R_{ft}] + sE[SMB_t] + hE[HML_t] + \delta\sqrt{(h_t)} + -\phi_1 v_{t-1} - \phi_2 v_{t-2} - \ldots - \phi_{53} v_{t-53} + \sqrt{(h_t)}\,e$$

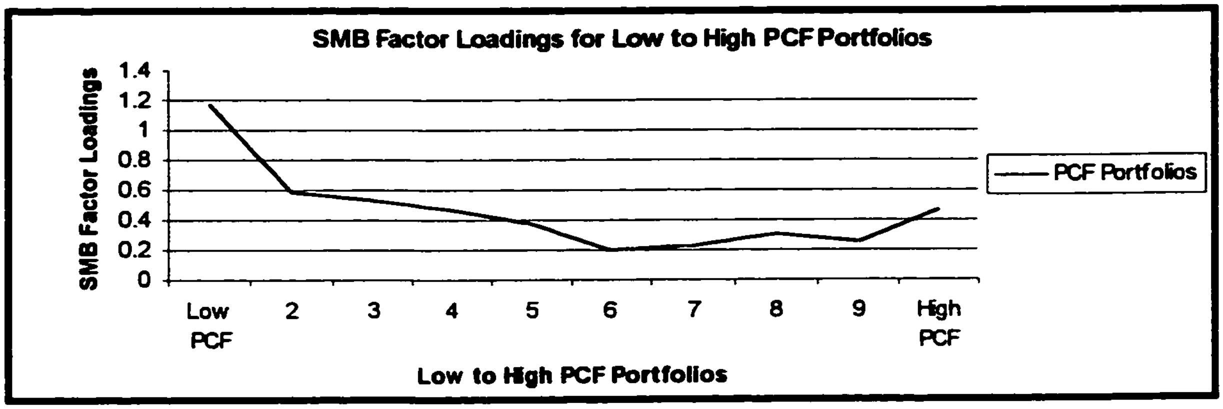
$$h_t = \kappa + \alpha\varepsilon^2_{t-1} + \gamma h_{t-1} \qquad \kappa > 0$$

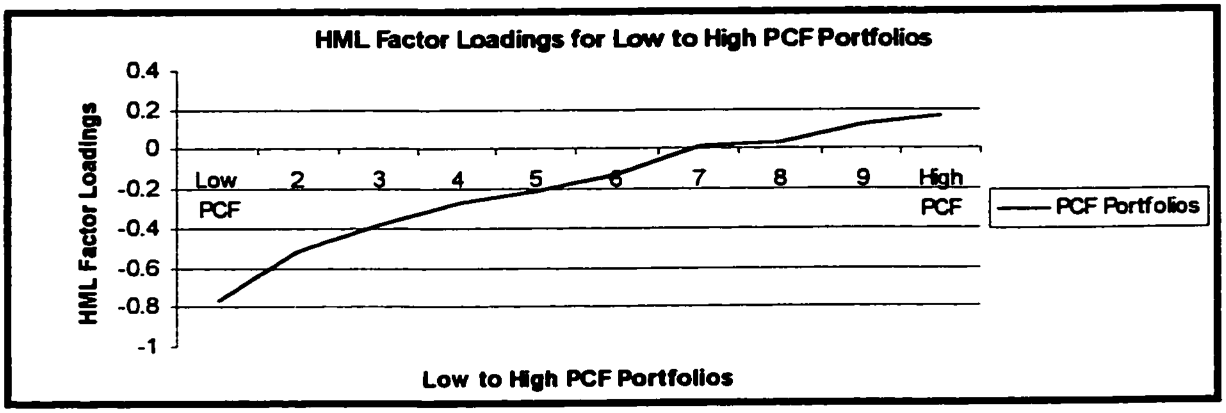
$$\alpha + \gamma = 1$$

| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
|---|---|---|---|---|---|---|---|---|---|---|
| a | -1.68 | -0.36 | 9.65 | 0.18 | -2.65 | -1.29 | -0.74 | 9.00 | -1.92 | 0.32 |
| p-value | 0.03 | 0.35 | 0.30 | 0.77 | 0.01 | 0.02 | 0.00 | 0.68 | 0.00 | 0.62 |
| e | -0.92 | 0.55 | -0.02 | -0.24 | -2.93 | 0.31 | -1.17 | 1.41 | 0.28 | -0.27 |
| p-value | 0.44 | 0.43 | 0.99 | 0.77 | 0.00 | 0.74 | 0.16 | 0.08 | 0.70 | 0.77 |
| b | 0.85 | 1.00 | 0.94 | 0.95 | 0.90 | 0.88 | 0.88 | 0.93 | 0.86 | 0.95 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| s | 1.17 | 0.59 | 0.53 | 0.47 | 0.37 | 0.20 | 0.23 | 0.31 | 0.26 | 0.47 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| h | -0.77 | -0.51 | -0.38 | -0.27 | -0.21 | -0.13 | 0.01 | 0.03 | 0.13 | 0.17 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.78 | 0.32 | 0.00 | 0.00 |

**Table 6.3.6 Continued**

| | Low PCF | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High PCF |
|---|---|---|---|---|---|---|---|---|---|---|
| **delta** | 0.43 | -0.01 | -5.24 | -0.32 | 0.69 | 0.19 | 0.18 | -5.64 | 0.56 | -0.27 |
| **p-value** | 0.19 | 0.94 | 0.31 | 0.35 | 0.00 | 0.47 | 0.00 | 0.67 | 0.06 | 0.37 |
| | | | | | | | | | | |
| **k** | 0.20 | 0.16 | 0.00 | 0.02 | 2.39 | 0.24 | 0.00 | 0.00 | 0.51 | 0.09 |
| **p-value** | 0.12 | 0.41 | 0.42 | 0.33 | 0.21 | 0.42 | NA | 0.72 | 0.46 | 0.41 |
| | | | | | | | | | | |
| **alpha** | 0.17 | 0.14 | 0.00 | 0.04 | 0.32 | 0.14 | 0.00 | 0.00 | 0.18 | 0.10 |
| **p-value** | 0.00 | 0.15 | 0.28 | 0.04 | 0.00 | 0.17 | 0.00 | 0.70 | 0.10 | 0.15 |
| | | | | | | | | | | |
| **gamma** | 0.83 | 0.86 | 1.00 | 0.96 | 0.68 | 0.86 | 1.00 | 1.00 | 0.82 | 0.90 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **Durbin Watson to test for Autocorrelation** | | | | | | | | | | |
| **d** | 2.15 | 2.31 | 2.03 | 2.00 | 1.86 | 1.74 | 2.05 | 2.15 | 2.03 | 2.01 |
| **p-value (for - corr)** | 0.12 | 0.01 | 0.39 | 0.52 | 0.87 | 0.98 | 0.34 | 0.11 | 0.40 | 0.47 |
| **p-value (for + corr)** | 0.88 | 0.99 | 0.61 | 0.48 | 0.13 | 0.02 | 0.66 | 0.89 | 0.60 | 0.53 |




Five of the ten intercepts are significantly different from zero and negative. This shows that generally the models are not being able to capture the pattern of returns of the portfolios or are not being able to capture all the risk factors associated with the returns. The market betas of the portfolios are less than or equal to one.

All ten portfolios are given a small-firm risk premium (i.e. positive loadings on the SMB risk factors). The portfolios with the lower PCF ratio stocks are given a higher small-firm risk premium than the portfolios with the higher PCF ratio firms. The portfolios with low PCF ratios stocks endure a low-distress penalty (i.e. negative loadings on the HML risk factors) whereas the portfolios with high PCF ratios firms are given a high-distress premium. Thus, the firms with the highest ratio consist of higher BE/ME ratios than what the firms with the lowest ratios do.

The alpha and the gamma coefficients are significantly different from zero at the 5 percent level of significance. However, we see that nine out of the ten coefficients for delta are not significantly different from zero at the 5 percent level of significance. This may be either because the risk associated with a changing variance is not compensated for, or because this risk is somehow captured by and compensated for in a higher premium to some of the other risk factors. We see that the gamma is always given a higher weight than the alpha. This implies that in predicting the current residual variance, more importance is given to the one period past estimate of the residual variance than what is given to the one period past squared residual.

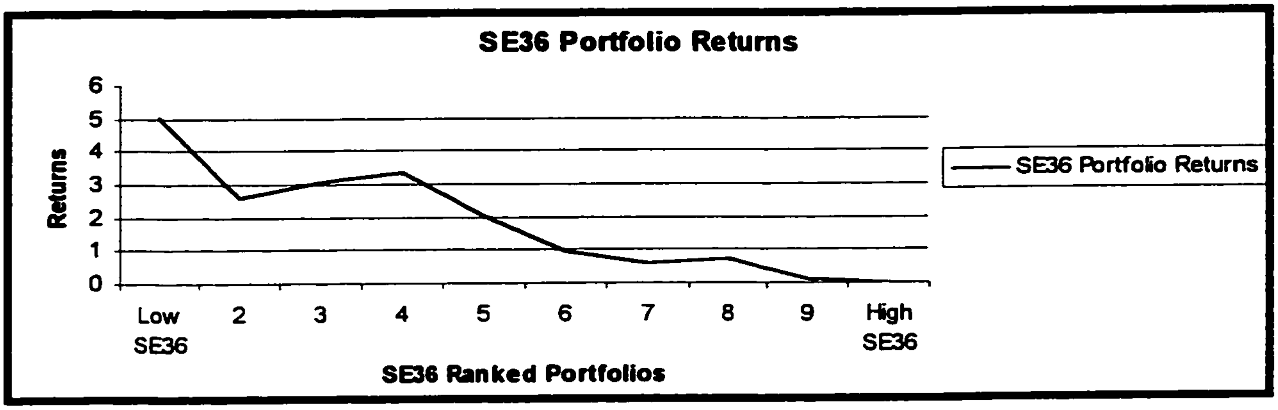
The portfolios were not faced with any issues of autocorrelation.

**4. Tests on the 10 SE36 Portfolios**

Table 6.4.1 shows the average out-of-sample returns to the 10 portfolios along with their corresponding p-values.

**Table 6.4.1**

| Summary Statistics | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
| Returns | 5.04 | 2.57 | 3.06 | 3.37 | 2.04 | 0.97 | 0.61 | 0.72 | 0.12 | 0.03 |
| p-value | 0.02 | 0.23 | 0.11 | 0.07 | 0.30 | 0.50 | 0.63 | 0.59 | 0.93 | 0.98 |




The average out-of-sample returns on the portfolios formed based on the 36 months prior returns show a very clear trend with long-term losers coming back to earn much higher returns than long-term winners. Thus there is a strong reversal in average long-term returns. The average return to all ten portfolios is 1.85 percent.

Table 6.4.2 presents the Akaike Information Criterion and the Schwarz Criterion, two goodness of fit measures of the estimated models.

**Table 6.4.2**

| Goodness-of-Fit | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
| **Akaike Information Criterion** | | | | | | | | | | |
| One-Factor | 2063 | 1985 | 1879 | 1858 | 1918 | 1891 | 1906 | 1871 | 1829 | 1884 |
| Three-Factor | 2051 | 1967 | 1876 | 1855 | 1914 | 1891 | 1903 | 1869 | 1831 | 1887 |
| Multi-Facor | 1636 | 1574 | 1476 | 1491 | 1505 | 1465 | 1479 | 1464 | 1430 | 1425 |
| **Schwarz Criterion** | | | | | | | | | | |
| One-Factor | 2074 | 1995 | 1889 | 1869 | 1928 | 1902 | 1916 | 1882 | 1840 | 1895 |
| Three-Factor | 2069 | 1984 | 1894 | 1872 | 1932 | 1909 | 1921 | 1887 | 1849 | 1905 |
| Multi-Facor | 1679 | 1616 | 1522 | 1538 | 1551 | 1511 | 1529 | 1510 | 1473 | 1461 |

A study of the tables shows that the Multi-Factor model has the best fit. The Three-Factor CAPM generally has a better fit than the One-Factor CAPM. On average, the AIC for the Three-factor model is 0.2 percent smaller than that for One-factor models, whereas the AIC for the Multi-factor models is 21.7 percent smaller than that for the One-factor models. . On average, the SC for the Three-factor model is 0.2 percent smaller than that for One-factor models, whereas the SC for the Multi-factor models is 19.8 percent smaller than that for the One-factor models.

Table 6.4.3 presents the adjusted R-Square of the regression models.

**Table 6.4.3**

| Adjusted R-Square | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Low SE36** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High SE36** |
| **One-Factor** | 0.12 | 0.19 | 0.16 | 0.20 | 0.17 | 0.18 | 0.17 | 0.22 | 0.17 | 0.18 |
| **Three-Factor** | 0.18 | 0.25 | 0.18 | 0.23 | 0.19 | 0.19 | 0.19 | 0.24 | 0.17 | 0.18 |
| **Multi-Facor** | 0.23 | 0.33 | 0.29 | 0.30 | 0.26 | 0.29 | 0.30 | 0.27 | 0.25 | 0.18 |

The Adjusted R-Squares of all three categories of portfolios is very low. The Adjusted R-Squares of the Multi-Factor CAPM regressions average 0.27 and that of the Three-Factor CAPM regressions average 0.20, whereas the Adjusted R-Square of the One-Factor CAPM regressions average0.18. This shows that both the Multi-Factor CAPMs and the Three-Factor CAPMs have better explanatory power than the One-Factor CAPMs.

Table 6.4.4 shows the regression estimates of the One-Factor CAPM along with their corresponding p-values.

**Table 6.4.4**

**One-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + e_t$$

| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
|---|---|---|---|---|---|---|---|---|---|---|
| **a** | 3.50 | 3.77 | 1.40 | 1.52 | 1.04 | 1.05 | 0.59 | 0.80 | -0.95 | -1.02 |
| **p-value** | 0.01 | 0.00 | 0.13 | 0.09 | 0.29 | 0.26 | 0.54 | 0.38 | 0.26 | 0.27 |
| | | | | | | | | | | |
| **e** | 5.89 | 2.94 | -0.75 | -0.79 | 1.91 | 2.44 | -1.05 | -1.50 | 0.72 | -0.43 |
| **p-value** | 0.42 | 0.64 | 0.88 | 0.87 | 0.73 | 0.64 | 0.85 | 0.77 | 0.88 | 0.93 |
| | | | | | | | | | | |
| **b** | 1.32 | 1.45 | 1.07 | 1.17 | 1.19 | 1.18 | 1.16 | 1.27 | 0.99 | 1.14 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

The intercepts of only two of the ten regression models are significant at the 5 percent level of significance and positive. The intercepts do show a clear trend with the low SE36 portfolios having significant and positive intercepts while the high SE36 portfolios having an intercept that is not significantly different from zero at the 5 percent level of significance. Thus stocks with a very low long-terms returns in the past seem to be overpriced. All but one of the market betas of all the portfolios is greater than one. Thus the portfolios seem to show more volatility than the market portfolio.

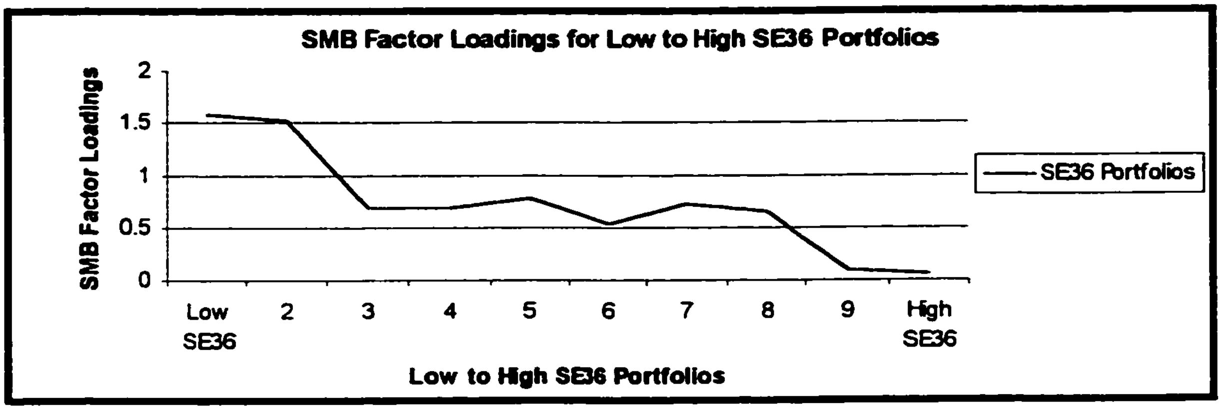
Table 6.4.5 shows the regression estimates of the Three-Factor CAPM along with their corresponding p-values.

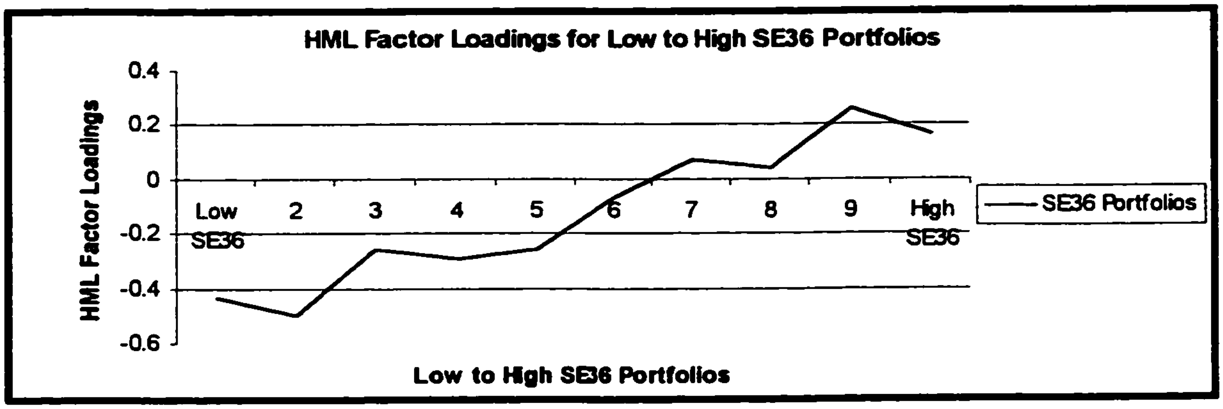
**Table 6.4.5**

**Three-Factor CAPM Time-Series Regression Estimates**

$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + e_t$

| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
|---|---|---|---|---|---|---|---|---|---|---|
| a | 3.40 | 3.59 | 1.29 | 1.38 | 0.95 | 1.08 | 0.78 | 0.95 | -0.70 | -0.86 |
| p-value | 0.01 | 0.00 | 0.17 | 0.12 | 0.34 | 0.26 | 0.43 | 0.30 | 0.41 | 0.36 |
| | | | | | | | | | | |
| e | 7.26 | 4.21 | -0.21 | -0.26 | 2.56 | 2.96 | -0.26 | -0.81 | 0.99 | -0.26 |
| p-value | 0.31 | 0.49 | 0.97 | 0.96 | 0.64 | 0.58 | 0.96 | 0.87 | 0.83 | 0.96 |
| | | | | | | | | | | |
| b | 1.25 | 1.36 | 1.02 | 1.12 | 1.15 | 1.18 | 1.19 | 1.29 | 1.05 | 1.18 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| s | 1.58 | 1.53 | 0.68 | 0.69 | 0.79 | 0.54 | 0.72 | 0.65 | 0.10 | 0.06 |
| p-value | 0.00 | 0.00 | 0.02 | 0.01 | 0.01 | 0.07 | 0.02 | 0.02 | 0.71 | 0.83 |
| | | | | | | | | | | |
| h | -0.43 | -0.50 | -0.26 | -0.29 | -0.26 | -0.07 | 0.07 | 0.04 | 0.26 | 0.17 |
| p-value | 0.15 | 0.05 | 0.21 | 0.15 | 0.26 | 0.75 | 0.74 | 0.86 | 0.18 | 0.44 |




The intercepts of only two of the ten regression models are significant at the 5 percent level of significance and positive. This shows that generally the models are being able to capture the pattern of returns of the portfolios or are being able to capture all the risk factors associated with the returns. The intercepts do show a clear trend with the low SE36 portfolios having significant and positive intercepts while the high SE36 portfolios having an intercept that is not different from zero. Thus stocks with a very low long-terms returns in the past seem to be overpriced. All the market betas are greater than one. Thus the portfolios seem to show more volatility than the market portfolio.

All ten portfolios were given a small-firm risk premium (i.e. positive loadings on the SMB risk factors), with the low SE36 portfolios receiving a higher premium than the high SE36 portfolios. Thus the low SE36 portfolios consist of smaller stocks relative to the high SE36 portfolios. The high SE36 portfolios earn a high-distress premium (i.e. positive loadings on the HML risk factors) whereas the low SE36 portfolios endure a low-distress penalty. Thus high SE36 portfolios consists of higher BE/ME ratios stocks relative to low SE36 portfolios and are thus compensated for it. Thus the low SE36 stocks are smaller stocks with lower-distress than the larger SE36 stocks.

Table 6.4.6 shows the regression estimates of the Multi-Factor CAPM along with their corresponding p-values.

**Table 6.4.6**

**Multi-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{ft} = a + e[PCER_t] + b[E(R_{m,t}) - R_{ft}] + sE[SMB_t] + hE[HML_t] + \delta\sqrt{(h_t)} + -\phi_1 v_{t-1} - \phi_2 v_{t-2} - \ldots - \phi_{53} v_{t-53} + \sqrt{(h_t)}\, e$$

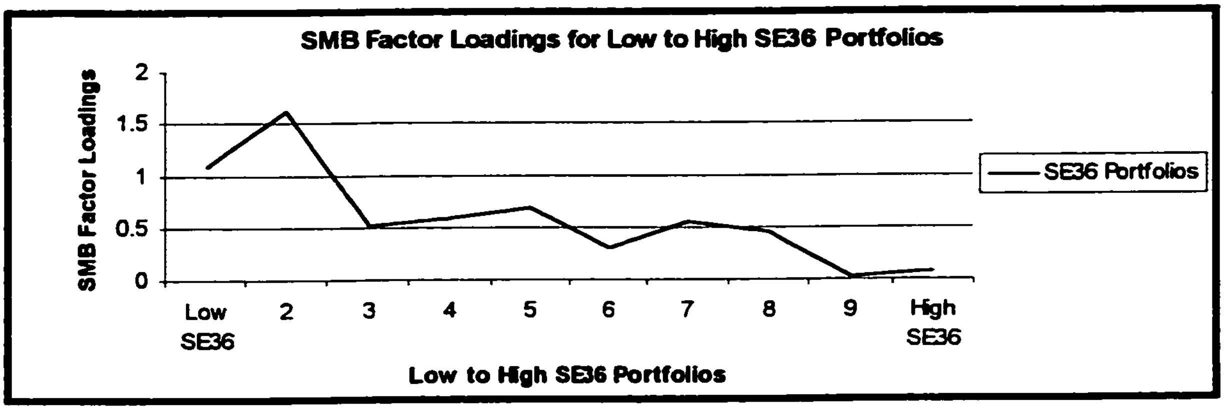
$$h_t = \kappa + \alpha\varepsilon^2_{t-1} + \gamma h_{t-1} \qquad \kappa > 0$$

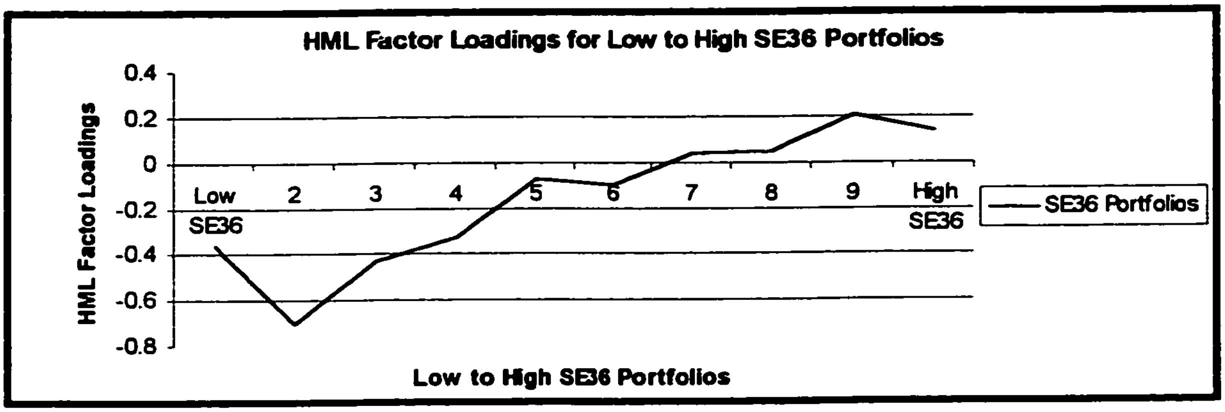
$$\alpha + \gamma = 1$$

| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
|---|---|---|---|---|---|---|---|---|---|---|
| **a** | -1.82 | 0.64 | -1.23 | -1.29 | -1.06 | -0.57 | 0.33 | 0.67 | 0.05 | 0.13 |
| **p-value** | 0.11 | 0.55 | 0.15 | 0.23 | 0.26 | 0.52 | 0.71 | 0.30 | 0.95 | 0.83 |
| | | | | | | | | | | |
| **e** | 9.83 | 4.71 | 5.09 | 0.55 | 4.18 | 2.91 | 4.06 | 1.03 | 0.29 | 1.56 |
| **p-value** | 0.00 | 0.12 | 0.08 | 0.86 | 0.14 | 0.31 | 0.09 | 0.66 | 0.91 | 0.40 |
| | | | | | | | | | | |
| **b** | 1.25 | 1.26 | 1.06 | 0.95 | 0.98 | 1.16 | 1.09 | 1.03 | 0.91 | 0.98 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **s** | 1.09 | 1.62 | 0.52 | 0.59 | 0.69 | 0.31 | 0.56 | 0.45 | 0.01 | 0.08 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 | 0.00 | 0.00 | 0.93 | 0.38 |
| | | | | | | | | | | |
| **h** | -0.36 | -0.70 | -0.43 | -0.33 | -0.07 | -0.10 | 0.04 | 0.05 | 0.21 | 0.14 |
| **p-value** | 0.01 | 0.00 | 0.00 | 0.01 | 0.55 | 0.30 | 0.67 | 0.60 | 0.01 | 0.05 |

**Table 6.4.6 Continued**

| | Low SE36 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE36 |
|---|---|---|---|---|---|---|---|---|---|---|
| **delta** | 0.31 | 0.29 | 0.28 | 0.16 | 0.15 | 0.20 | -0.04 | -0.15 | -0.12 | -0.17 |
| **p-value** | 0.01 | 0.01 | 0.01 | 0.23 | 0.25 | 0.14 | 0.76 | 0.14 | 0.36 | 0.08 |
| | | | | | | | | | | |
| **k** | 6.68 | 4.66 | 3.32 | 4.57 | 4.37 | 3.92 | 4.73 | 2.79 | 3.03 | 2.60 |
| **p-value** | 0.09 | 0.06 | 0.05 | 0.09 | 0.04 | 0.06 | 0.03 | 0.03 | 0.04 | 0.05 |
| | | | | | | | | | | |
| **alpha** | 0.33 | 0.33 | 0.34 | 0.32 | 0.44 | 0.38 | 0.46 | 0.40 | 0.36 | 0.43 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **gamma** | 0.67 | 0.67 | 0.66 | 0.68 | 0.56 | 0.62 | 0.54 | 0.60 | 0.64 | 0.57 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **Durbin Watson to test for Autocorrelation** | | | | | | | | | | |
| **d** | 1.67 | 1.84 | 1.68 | 1.71 | 1.72 | 1.74 | 1.62 | 1.77 | 1.56 | 1.75 |
| **p-value (for - corr)** | 1.00 | 0.90 | 1.00 | 0.99 | 0.99 | 0.98 | 1.00 | 0.97 | 1.00 | 0.98 |
| **p-value (for + corr)** | 0.00 | 0.10 | 0.00 | 0.01 | 0.01 | 0.02 | 0.00 | 0.03 | 0.00 | 0.02 |




The intercepts of only two of the ten regression models are significant at the 5 percent level of significance and positive. The intercepts do show a clear trend with the low SE36 portfolios having significant and positive intercepts while the high SE36 portfolios having an intercept that is not different from zero at the 5 percent level of significance. Thus stocks with a very low long-terms returns in the past seem to be overpriced. All the market betas are greater than one. Thus the portfolios seem to show more volatility than the market portfolio.

All ten portfolios are given a small-firm risk premium (i.e. positive loadings on the SMB risk factors), with the low SE36 portfolios receiving a higher premium than the high SE36 portfolios. Thus the low SE36 portfolios consist of smaller stocks relative to the high SE36 portfolios. The high SE36 portfolios earn a high-distress premium (i.e. positive loadings on the HML risk factors) whereas the low SE36 portfolios endure a low-distress penalty. Thus high SE36 portfolios consists of higher BE/ME ratios stocks relative to low SE36 portfolios and are thus compensated for it. Thus the low SE36 stocks are smaller stocks with lower-distress than the larger SE36 stocks.

The alpha and the gamma coefficients are significantly different from zero at the 5 percent level of significance. However, we see that seven out of the ten coefficients for delta are not significantly different from zero at the 5 percent level of significance. This may be either because the risk associated with a changing variance is not compensated for, or because this risk is somehow captured by and compensated for in a higher premium to some of the other risk factors. We see that the gamma is always given a slightly higher weight than the alpha. This implies that in predicting the current residual variance, more importance was given to the one period past estimate of the residual variance than what is given to the one period past squared residual.

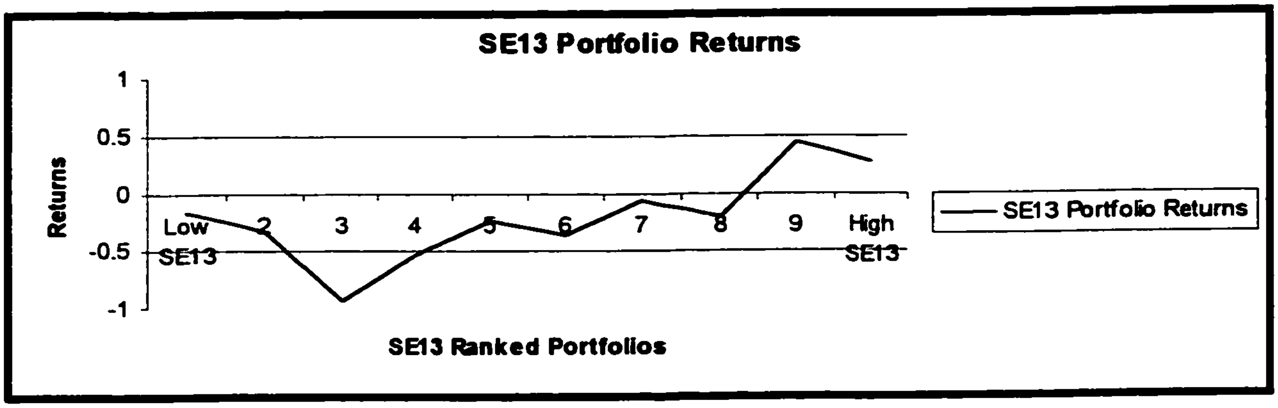
Nine of the ten portfolios show significant positive autocorrelation. This shows that autocorrelation was a problem. A positive return on average was followed by a positive return, whereas a negative return on average was followed by a negative return.

## 5. Tests on the 10 SE12 Portfolios

Table 6.5.1 shows the average out-of-sample returns to the 10 portfolios along with their corresponding p-values.

**Table 6.5.1**

| Summary Statistics | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low SE12 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE12 |
| Returns | -0.17 | -0.33 | -0.93 | -0.53 | -0.23 | -0.35 | -0.06 | -0.20 | 0.44 | 0.27 |
| p-value | 0.82 | 0.61 | 0.22 | 0.43 | 0.71 | 0.63 | 0.92 | 0.77 | 0.50 | 0.70 |




The average out-of-sample returns on the portfolios formed on the basis of the 12 months prior returns show a very clear trend with short-term losers continuing to lose in the short-run than short-term winners and vice versa. Thus there is a strong continuation in average short-term returns.

Table 6.5.2 presents the Akaike Information Criterion and the Schwarz Criterion, two goodness of fit measures of the estimated models.

**Table 6.5.2**

| Goodness-of-Fit | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low SE12 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE12 |
| Akaike Information Criterion | | | | | | | | | | |
| One-Factor | 1367 | 1374 | 1346 | 1152 | 1156 | 1030 | 1095 | 1042 | 1078 | 1123 |
| Three-Factor | 1234 | 1166 | 1196 | 1066 | 1096 | 1009 | 1077 | 1028 | 1050 | 1126 |
| Multi-Facor | 921 | 850 | 867 | 753 | 777 | 707 | 721 | 716 | 693 | 768 |
| Schwarz Criterion | | | | | | | | | | |
| One-Factor | 1377 | 1385 | 1357 | 1163 | 1166 | 1041 | 1106 | 1053 | 1089 | 1134 |
| Three-Factor | 1252 | 1184 | 1214 | 1084 | 1114 | 1027 | 1095 | 1046 | 1068 | 1143 |
| Multi-Facor | 957 | 885 | 903 | 785 | 812 | 746 | 760 | 755 | 732 | 796 |

A study of the tables shows that the Multi-Factor model has the best fit. The Three-Factor CAPM generally has a better fit than the One-Factor CAPM. On average, the AIC for the Three-factor model is 6 percent smaller than that for One-factor models, whereas the AIC for the Multi-factor models is 34 percent smaller than that for the One-factor models. . On average, the SC for the Three-factor model is 5 percent smaller than that for

One-factor models, whereas the SC for the Multi-factor models is 32 percent smaller than that for the One-factor models.

Table 6.5.3 presents the adjusted R-Square of the regression models.

**Table 6.5.3**

| Adjusted R-Square | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Low SE12** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **High SE12** |
| **One-Factor** | 0.57 | 0.56 | 0.57 | 0.74 | 0.71 | 0.80 | 0.76 | 0.78 | 0.74 | 0.74 |
| **Three-Factor** | 0.74 | 0.80 | 0.76 | 0.82 | 0.77 | 0.82 | 0.78 | 0.80 | 0.77 | 0.74 |
| **Multi-Facor** | 0.75 | 0.80 | 0.75 | 0.82 | 0.77 | 0.83 | 0.79 | 0.81 | 0.78 | 0.74 |

The Adjusted R-Squares of the Multi-Factor CAPM and the Three-Factor CAPM regressions average 0.78, whereas the Adjusted R-Square of the One-Factor CAPM regressions averages 0.70. This shows that both the Multi-Factor CAPMs and the Three-Factor CAPMs have better explanatory power than the One-Factor CAPMs.

Table 6.5.4 shows the regression estimates of the One-Factor CAPM along with their corresponding p-values.

**Table 6.5.4**

**One-Factor CAPM Time-Series Regression Estimates**

$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + e_t$$

| | Low SE12 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE12 |
|---|---|---|---|---|---|---|---|---|---|---|
| **a** | -0.32 | -0.15 | -0.50 | -0.11 | -0.57 | -0.41 | -0.19 | -0.49 | -0.61 | -0.37 |
| **p-value** | 0.36 | 0.67 | 0.13 | 0.62 | 0.01 | 0.02 | 0.36 | 0.01 | 0.00 | 0.09 |
| | | | | | | | | | | |
| **e** | 1.26 | -1.27 | -0.02 | -1.63 | 0.04 | -0.11 | -1.19 | -0.79 | -1.87 | -0.56 |
| **p-value** | 0.51 | 0.52 | 0.99 | 0.20 | 0.98 | 0.91 | 0.30 | 0.45 | 0.09 | 0.65 |
| | | | | | | | | | | |
| **b** | 1.05 | 1.03 | 0.99 | 1.01 | 0.94 | 0.95 | 0.95 | 0.92 | 0.87 | 0.94 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

The intercepts of the regression do show a clear trend with the lower SE12 portfolios having not significantly different from zero intercepts (at the 5 percent level of significance) whereas the higher SE12 portfolios have significantly negative intercepts (at the 5 percent level of significance). Thus stocks that have high short-term past returns are being under-priced. The market betas of the low SE12 portfolios are greater than one, whereas the market betas of the high SE12 portfolios are less than one. Thus, the short-term losers show more volatility in their returns than the short-term winners.

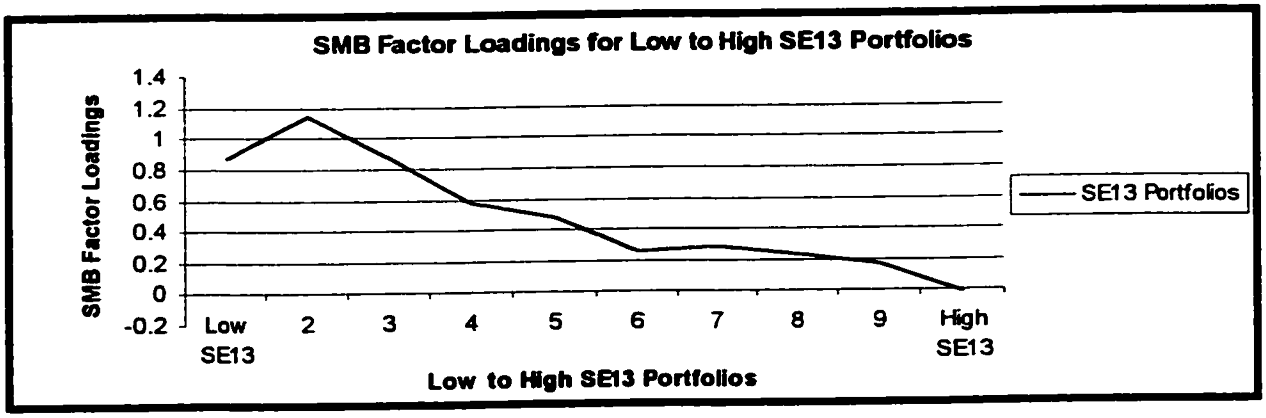
Table 6.5.5 shows the regression estimates of the Three-Factor CAPM along with their corresponding p-values.

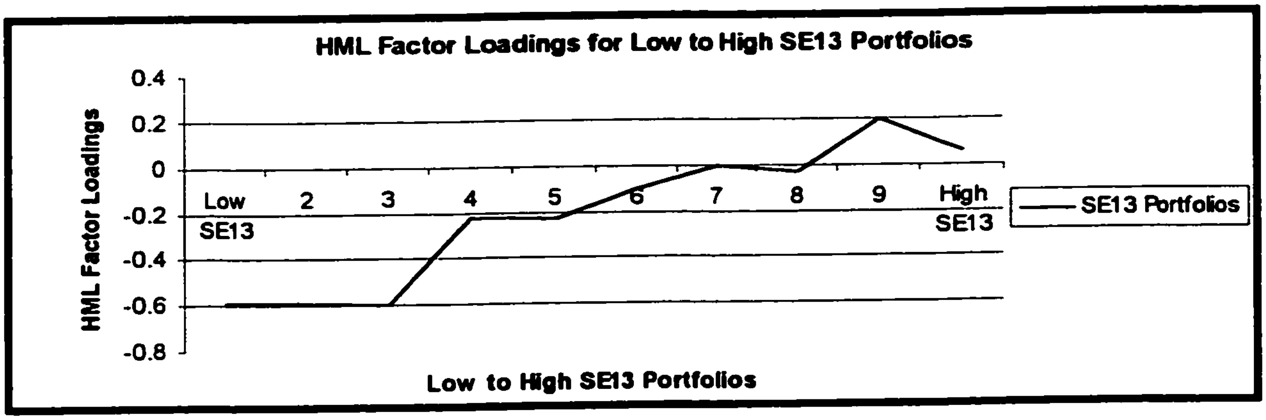
**Table 6.5.5**

**Three-Factor CAPM Time-Series Regression Estimates**

$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + e_t$

| | Low SE12 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE12 |
|---|---|---|---|---|---|---|---|---|---|---|
| **a** | -0.69 | -0.47 | -0.88 | -0.21 | -0.70 | -0.46 | -0.13 | -0.47 | -0.40 | -0.31 |
| **p-value** | 0.01 | 0.05 | 0.00 | 0.29 | 0.00 | 0.01 | 0.50 | 0.01 | 0.03 | 0.15 |
| | | | | | | | | | | |
| **e** | 1.80 | -0.45 | 0.52 | -1.17 | 0.38 | 0.09 | -0.90 | -0.55 | -1.57 | -0.53 |
| **p-value** | 0.23 | 0.73 | 0.71 | 0.28 | 0.74 | 0.93 | 0.42 | 0.58 | 0.14 | 0.66 |
| | | | | | | | | | | |
| **b** | 0.93 | 0.92 | 0.87 | 0.97 | 0.89 | 0.93 | 0.96 | 0.92 | 0.92 | 0.96 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **s** | 0.88 | 1.15 | 0.88 | 0.58 | 0.48 | 0.26 | 0.29 | 0.24 | 0.17 | -0.01 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.85 |
| | | | | | | | | | | |
| **h** | -0.59 | -0.59 | -0.60 | -0.22 | -0.23 | -0.10 | 0.00 | -0.03 | 0.20 | 0.06 |
| **p-value** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.94 | 0.54 | 0.00 | 0.22 |




Seven of the ten portfolios have intercepts that are significant at the 5 percent level of significance and negative. The intercepts do not show any clear trend. The market betas of all ten portfolios are less than one. Thus all ten portfolios have a returns volatility that is less than the volatility of the market portfolio.

All ten portfolios were given a small-firm risk premium (i.e. positive loadings on the SMB risk factors), with the low SE12 portfolios receiving a higher premium than the high SE12 portfolios. Thus the low SE12 portfolios consist of smaller stocks relative to the high SE12 portfolios. The high SE12 portfolios earn a high-distress premium (i.e. positive loadings on the HML risk factors) whereas the low SE12 portfolios endure a low-distress penalty. Thus high SE12 portfolios consists of higher BE/ME ratios stocks relative to low SE12 portfolios and are thus compensated for it. Thus the low SE12 stocks are smaller and have lower distress than the high SE12 stocks.

Table 6.5.6 shows the regression estimates of the Multi-Factor CAPM along with their corresponding p-values.

**Table 6.5.6**

**Multi-Factor CAPM Time-Series Regression Estimates**

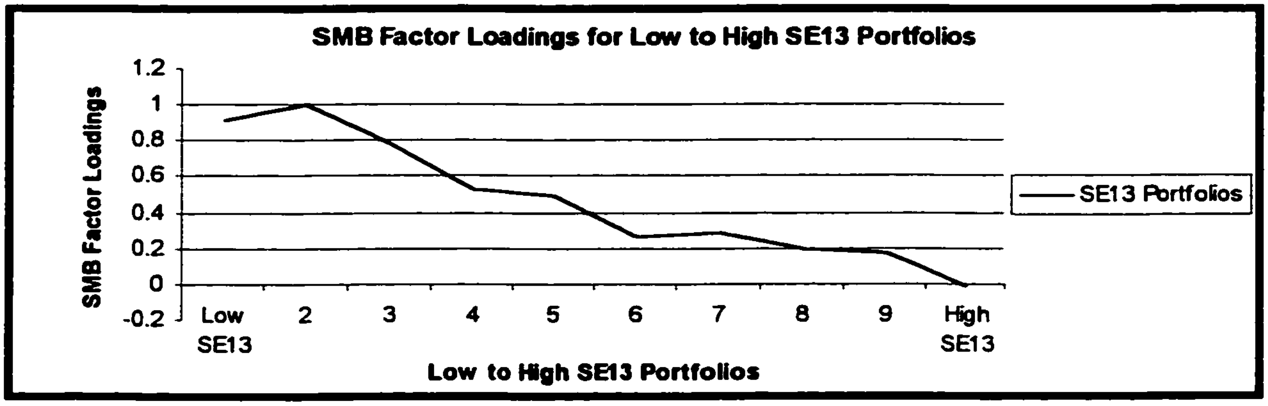
$$E(R_t) - R_{f,t} = a + e[PCER_t] + b[E(R_{m,t}) - R_{f,t}] + sE[SMB_t] + hE[HML_t] + \delta\sqrt{(h_t)} + -\phi_1 v_{t-1} - \phi_2 v_{t-2} - \dots - \phi_{53} v_{t-53} + \sqrt{(h_t)}\, e$$

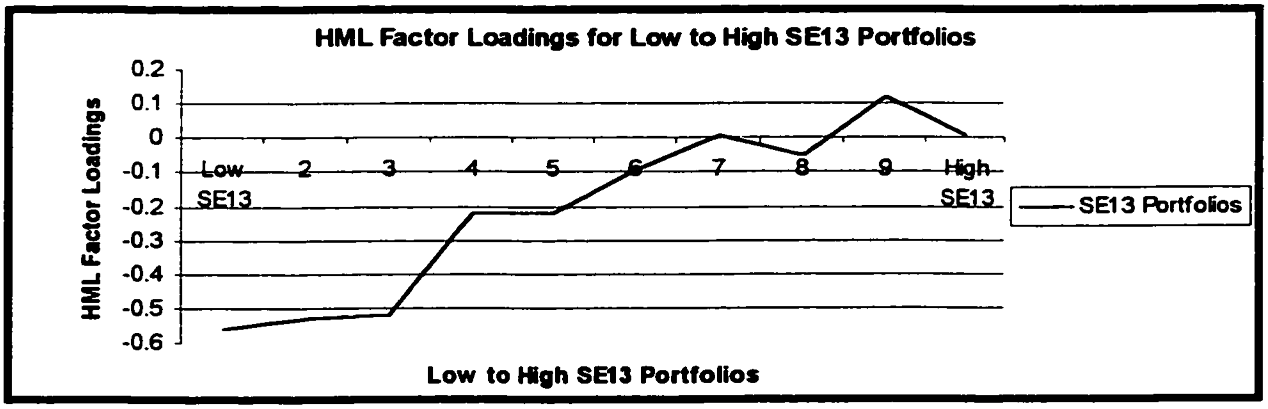
$$h_t = \kappa + \alpha\varepsilon^2_{t-1} + \gamma h_{t-1} \qquad \kappa > 0$$

$$\alpha + \gamma = 1$$

| | Low SE12 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE12 |
|---|---|---|---|---|---|---|---|---|---|---|
| a | 1.11 | -0.05 | -0.98 | -0.51 | -1.49 | -0.39 | 0.35 | -2.78 | -0.92 | 0.88 |
| p-value | 0.08 | 0.96 | 0.20 | 0.54 | 0.06 | 0.27 | 0.59 | 0.00 | 0.05 | 0.51 |
| | | | | | | | | | | |
| e | 2.10 | -0.96 | -1.99 | -0.52 | 0.02 | -0.15 | -0.27 | 0.02 | -0.72 | 1.37 |
| p-value | 0.07 | 0.32 | 0.07 | 0.58 | 0.98 | 0.85 | 0.71 | 0.98 | 0.32 | 0.10 |
| | | | | | | | | | | |
| b | 0.94 | 0.93 | 0.75 | 0.96 | 0.86 | 0.92 | 0.95 | 0.90 | 0.93 | 0.96 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| s | 0.91 | 1.00 | 0.78 | 0.53 | 0.49 | 0.26 | 0.28 | 0.20 | 0.17 | -0.01 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.90 |

| Table 6.5.6 Continued | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Low SE12 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | High SE12 |
| h | -0.56 | -0.53 | -0.52 | -0.22 | -0.22 | -0.09 | 0.01 | -0.05 | 0.12 | 0.01 |
| p-value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.87 | 0.19 | 0.00 | 0.88 |
| | | | | | | | | | | |
| delta | -0.65 | -0.18 | -0.11 | 0.14 | 0.20 | -0.08 | -0.22 | 0.83 | 0.27 | -0.26 |
| p-value | 0.00 | 0.66 | 0.62 | 0.74 | 0.37 | 0.62 | 0.30 | 0.00 | 0.20 | 0.25 |
| | | | | | | | | | | |
| k | 0.36 | 0.23 | 3.72 | 0.02 | 3.29 | 1.34 | 2.60 | 1.61 | 0.29 | 19.82 |
| p-value | 0.27 | 0.51 | 0.41 | 0.57 | 0.42 | 0.00 | 0.23 | 0.36 | 0.17 | 0.24 |
| | | | | | | | | | | |
| alpha | 0.18 | 0.13 | 0.63 | 0.04 | 0.40 | 0.87 | 0.49 | 0.29 | 0.20 | 1.00 |
| p-value | 0.05 | 0.30 | 0.13 | 0.17 | 0.03 | 0.00 | 0.05 | 0.04 | 0.01 | 0.00 |
| | | | | | | | | | | |
| gamma | 0.82 | 0.87 | 0.37 | 0.96 | 0.60 | 0.13 | 0.51 | 0.71 | 0.80 | 0.00 |
| p-value | 0.00 | 0.00 | 0.38 | 0.00 | 0.00 | 0.45 | 0.04 | 0.00 | 0.00 | 0.00 |
| | | | | | | | | | | |
| **Durbin Watson to test for Autocorrelation** | | | | | | | | | | |
| d | 2.25 | 2.00 | 2.13 | 2.15 | 1.85 | 1.95 | 1.98 | 2.08 | 2.15 | 2.14 |
| p-value (for - corr) | 0.02 | 0.49 | 0.15 | 0.11 | 0.89 | 0.65 | 0.58 | 0.27 | 0.11 | 0.13 |
| p-value (for + corr) | 0.98 | 0.51 | 0.85 | 0.89 | 0.11 | 0.36 | 0.42 | 0.73 | 0.89 | 0.87 |




Only two of the ten portfolios have intercepts that are significant and negative. This shows that generally the models are being able to capture the pattern of returns of the portfolios or are being able to capture all the risk factors associated with the returns. The intercepts do not show any clear trend. The market betas of all ten portfolios are less than one. Thus all ten portfolios have a returns volatility that is less than the volatility of the market portfolio.

All ten portfolios are given a small-firm risk premium (i.e. positive loadings on the SMB risk factors), with the low SE36 portfolios receiving a higher premium than the high SE36 portfolios. Thus the low SE36 portfolios consist of smaller stocks relative to the high SE36 portfolios. The high SE36 portfolios earn a high-distress premium (i.e.

positive loadings on the HML risk factors) whereas the low SE36 portfolios endure a low-distress penalty. Thus high SE36 portfolios consists of higher BE/ME ratios stocks relative to low SE36 portfolios and are thus compensated for it. Thus the low SE36 stocks are smaller and have lower distress than the high SE36 stocks.

The alpha and the gamma coefficients are significantly different from zero at the 5 percent level of significance. However, we see that eight out of ten coefficients for delta are not significantly different from zero at the 5 percent level of significance. This may be either because the risk associated with a changing variance is not compensated for, or because this risk is somehow captured by and compensated for in a higher premium to some of the other risk factors. We see that the gamma is generally given a higher weight than the alpha. This implies that more importance is given to the one period past estimate of the residual variance than what is given to the one period past squared residual, in predicting the current residual variance. The results show that autocorrelation did not pose a problem.

# Chapter 7 - Conclusions

We had five broad objectives for our study. Objective A was to test if the intercepts of our model for a certain country were consistently leaving a large unexplained return, implying that the common risks were not being adequately priced and thus the stock markets were not informationally efficient. Objective B was to test for the presence of serial correlation in the stock market returns, implying that the returns were predictable and thus the stocks markets were not informationally efficient. Objective C was to test if time-varying conditional variance if present was not adequately compensated for, implying that the stock markets were not adequately pricing this common risk and thus the stock markets were not informationally efficient. Objectives D1, D2, D3, and D4 were to test if low Price-to-Cash Flow (PCF), high Book Value-to-Market Value ratio (BE/ME), high Earnings-to-Price ration (EP) and low market capitalization respectively are typical of distressed firms and vice versa; and if our model is able to capture the pattern of returns in a meaningful manner. Objective E1 was to test for cyclical patterns in long-term returns and if our model is able to capture these patterns in a meaningful way. Objective E2 was to test for continuation patterns in short-term returns and if our model is able to capture these patterns in a meaningful way.

## 1. Conclusions from the South Korean Stock Market

The two Goodness-of-fit measures i.e. the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC) indicates that Multi-factor CAPM in general has a better fit than the Fama-French Three-factor CAPM. Both these categories of models have a much better fit than the One-factor CAPM. The Three-factor model has on average an 11 percent better fit than the One-factor model, whereas the Multi-factor model has on average a 35 percent better fit than the One-factor model.

The average Adjusted R-Squares indicates the Multi-factor, Three-factor, and One-factor categories of models are .90, 0.89, and 0.80 respectively. We see that in general all the categories of models have very good explanatory powers. We also see that the Multi-factor and Three-factor CAPM have about 10 percent greater explanatory power than the One-factor CAPM.

Objective A was to test for the presence of significant intercepts in the models. The disproportionate presence of significant intercepts in the Multi-factor CAPM and the Three-factor CAPM would imply the inadequacy in the pricing of common risks. The disproportionate presence of significant intercepts in the One-factor CAPM could mean either that the common risks were not being adequately priced if the same returns also showed significant intercepts in the Multi-factor and Three-factor CAPM, or that the model was not sufficient enough to adequately price all the common risks if the same returns showed non-significant intercepts in the Multi-factor and Three-factor CAPM. In general, the One-factor models were not able to capture the patterns of returns. Fortythree of the fifty-six models in this category had intercepts that were significantly different from zero at the 5 percent level of significance. In general, the Three-factor and the Multi-factor models were able to capture the pattern of returns. Only 3 out of fifty-six of the Three-factor models and 4 out of fifty-six of the Multi-factor models had intercepts that were significantly different from zero at the 5 percent level of significance. Thus, the stock market seemed to be informationally efficient.

Objective B was to test for the presence of serial correlation in the models. The presence of serial correlation in the stock market would indicate the predictability of the stock prices and thus the informational inefficiency of the stock markets. Our test for serial correlation in the Multi-factor categories of models indicates that serial correlation was not a significant issue. Only eleven of the fifty-six models had a significant Durbin-Watson (10 of the Durbin-Watsons indicated the presence of negative serial correlation). Thus, the stock market seemed to be informationally efficient.

Objective C of this study was to test for the presence of time-varying conditional variance (i.e. GARCH effects) in the returns of the portfolios and see if this variance is compensated for, in the average returns to the portfolios. We do find the presence of GARCH effects in every one of the fifty-six portfolios. However we see that in fifty-three of the fifty-six portfolios this time-varying conditional variance is not given a returns premium. Thus the stock market is to a certain extent not efficient.

Objective D1 is test if low PCF is typical of firms that are small and distressed and vice versa. From the PCF category of portfolios we do not see any clear trend in the out-of-sample returns to the portfolios formed on ranks of the P/CF ratio. The theory suggests high positive loadings to the SMB and HML risk factors for low PCF portfolios and vice versa. From the PCF category of portfolios we see that the loadings on the SMB risk factors are positive for all ranks of PCF portfolios. The loadings on the HML risk factors are negative for all ranks of PCF portfolios and are in fact more negative for high PCF portfolios than they are for low PCF portfolios, suggesting that high PCF portfolios consists of stocks of relatively stronger firms; this is in line with what the theory suggests.

Objective D2 was to test if high BE/ME is typical of firms that are distressed and vice versa. From the SZDT category of portfolios we see that the average out-of-sample returns to low BE/ME stocks are higher than the average out-of-sample returns to the high BE/ME stocks; this is not in line with what the theory suggests. The Three-factor and our Multi-factor models are able to capture the pattern of returns to portfolios formed on ranks of BE/ME in a meaningful way. From the SZDT category of portfolios we do see that the HML risk factors of the high BE/ME stocks are given significantly positive loadings and vice versa. Thus we conclusively see that high BE/ME stocks are given a value risk premium.

Objective D3 was to test if high EP is typical of firms that are small and distressed and vice versa. From the EP category of portfolios we do not see any clear trend in the out-of-sample returns to the portfolios formed on ranks of the EP ratio. The theory suggests high positive loadings to the SMB and HML risk factors for high EP portfolios and vice versa. From the EP category of portfolios we see that the loadings on the SMB risk factors are positive for all ranks of EP portfolios and are in fact greater for low EP portfolios than they are for high EP portfolios, suggesting that low EP portfolios consist of stocks of relatively smaller firms; this is not in line with what the theory suggests. The loadings on the HML risk factors are negative for all ranks of EP portfolios. The loadings on the HML risk factors are to a certain degree in line with what the theory suggests; the low EP portfolios have more negative loadings than the high EP portfolios, suggesting that the low EP portfolios consists of stocks of relatively stronger firms.

Objective D4 was to test whether low market capitalization is typical of distressed firms and vice versa. From the SZDT category of portfolios we do see that the average out-of-sample returns to small-cap stocks is in fact higher than the average out-of-sample returns to large-cap stocks. This suggests that small-cap stocks are in fact distressed stocks and are thus given a higher return to compensate for the distress. The Three-factor and our Multi-factor models are able to capture the pattern of returns to portfolios formed on ranks of market capitalization in a meaningful way. From the SZDT category of portfolios we do see that the SMB risk factors of the small-cap stocks are given significantly positive loadings and vice versa. Thus we conclusively see that small-cap stocks are given a small-cap stock risk premium.

Objective E1 was to test if there were any abnormal cyclical patterns in long-term returns and if our model would be able to capture it in a meaningful manner. The theory is that portfolios that were long-term winners (had the highest average return in the past thirty-six months) were strong stocks and so were expected to provide low returns in the following year and vice versa. The Three-factor and our Multi-factor models are able to capture the pattern of returns, and the two categories of models do so in an identical manner. From the SE36 category of portfolios we see that the winners only provided a 5 percent out-of-sample average return, whereas the losers provided a fourteen percent out-of-sample average return. The loadings on the SMB risk factor are positive for all ranks of SE36 portfolios but are greater for low SE36 portfolios than they are for high SE36 portfolios, suggesting that low SE36 portfolios consists stocks of smaller firms; this is in line with what the theory suggests. The loadings on the HML risk factor, however, are not in line with what the theory suggests. The loadings of this risk factor are positive for high SE36 portfolios (i.e. the winners) and negative for low SE36 portfolios (i.e. the losers), suggesting that the high SE36 portfolios consists of stocks of relatively distressed firms.

Objective E2 was to test if there were any continuation patterns in short-term returns and if our model would be able to capture it in a meaningful manner. The theory is that portfolios that were short-term winners (had the highest average return in the past twelve months) were weak stocks and so were expected to provide high returns in the following year and vice versa. The Three-factor and our Multi-factor models are able to capture the pattern of returns, and the two categories of models do so in an identical manner. From the SE12 category of portfolios we see that the winners only provided a 2 percent out-of-sample average return, whereas the losers provided a 5 percent out-of-sample average return. Thus we do not see a continuation pattern in short-term returns but rather a cyclical pattern. The loadings on the SMB risk factor are positive for all ranks of SE12 portfolios but are greater for low SE12 portfolios than they are for high SE12 portfolios, suggesting that low SE12 portfolios consists of stocks of relatively small firms; this is not in line with what the theory suggests. The loadings on the HML risk factor, however, are in line with what the theory suggests. The loadings of this risk factor are positive for the highest SE12 portfolio (i.e. the winner) and negative for low SE12 portfolios (i.e. the losers), suggesting that the highest SE12 portfolios consists of stocks of relatively distressed firms.

## 2. Conclusions from the Indian Stock Market

The two Goodness-of-fit measures i.e. the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC) indicates that Multi-factor CAPM in general has a better fit than the Fama-French Three-factor CAPM. Both these categories of models have a much better fit than the One-factor CAPM. The Three-factor model has on average a 4 percent better fit than the One-factor model, whereas the Multi-factor model has on average a 30 percent better fit than the One-factor model.

The Adjusted R-Squares indicates that the Multi-factor, Three-factor, and One-factor CAPM are on average 0.63, 0.61, and 0.54 respectively. In particular, the regressions on portfolios formed on the basis of long-term past returns do not have very good explanatory power with the Adjusted R-Squares for the Multi-factor, Three-factor, and One-factor CAPM being an average of 0.27, 0.20, and 0.18 respectively.

Objective A was to test for the presence of significant intercepts in the models. Objective A was to test for the presence of significant intercepts in the models. The disproportionate presence of significant intercepts in the Multi-factor CAPM and the Three-factor CAPM would imply the inadequacy in the pricing of common risks. The disproportionate presence of significant intercepts in the One-factor CAPM could mean either that the common risks were not being adequately priced if the same returns also showed significant intercepts in the Multi-factor and Three-factor CAPM, or that the model was not sufficient enough to adequately price all the common risks if the same returns showed non-significant intercepts in the Multi-factor and Three-factor CAPM. In general, the One-factor models were not able to capture the patterns of returns. The One-factor models did leave significant intercepts measured at the 5 percent level of significance. Twenty-three out of fifty-six models in the One-factor category of models left significant intercepts. The Three-factor category of models fared worse with twenty-nine out of fifty-six models in this category having significant intercepts. The Multi-factor category did relatively better than the other two categories of models with only fifteen out of fifty-six models in this category having significant intercepts. Given this evidence of significant intercepts in Multi-factor category of models, we conclude that the stock market in India is not informationally efficient.

Objective B was to test for the presence of serial correlation in the models. The presence of serial correlation in the stock market would indicate that stock prices could be predicted and thus the market was not informationally efficient. Our test for serial correlation in the Multi-factor categories of models indicates that serial correlation was an issue especially in the SE36 category of portfolios. In general, fifteen of the fifty-six models had a significant Durbin-Watsons. In the SE36 category of portfolios nine out of ten of the models had significant positive serial correlation. Thus, once again we are lead to conclude that the stock market in India is not informationally efficient.

Objective C was to test for the presence of time-varying conditional variance (i.e. GARCH effects) in the returns of the portfolios and see if this variance is compensated for, in the average returns to the portfolios. We do find the presence of GARCH effects in fifty-five of the fifty-six portfolios. However, we see that in forty-five of the fifty-six portfolios this time-varying conditional variance is not compensated for by a risk premium. Thus the stock market is not efficient, as this risk factor is not compensated for.

Objective D1 was to test if low PCF is typical of firms that are small and distressed and vice versa. From the PCF category of portfolios we see that the average out-of-sample returns for ranks of PCF portfolios are not significantly different from zero at the 5 percent level of significance. From the PCF category of portfolios we see that the loadings on the SMB risk factors are positive for all ranks of PCF portfolios but are greater for low PCF portfolios than they are for high PCF portfolios, suggesting that low

PCF portfolios consists of stocks of relatively smaller firms; this is in line with what the theory suggests. The loadings on the HML risk factors are negative for low PCF portfolios and positive for high PCF portfolios, suggesting that low PCF portfolio consists of stocks of stronger firms; this is not in line with what the theory suggests.

Objective D2 was to test if high BE/ME is typical of firms that are distressed and vice versa. From the SZDT category of portfolios we see that the average out-of-sample returns to high BE/ME stocks are greater than the average out-of-sample returns to the high BE/ME stocks; this is in line with what the theory suggests. The Three-factor and our Multi-factor models are able to capture the pattern of returns to portfolios formed on ranks of BE/ME in a meaningful way and in line with what the theory suggest. From the SZDT category of portfolios we do see that the HML risk factors of the high BE/ME stocks are given significantly positive loadings and vice versa. Thus we conclusively see that high BE/ME stocks are given a value risk premium.

Objective D3 was to test if high EP is typical of firms that are smaller and distressed and vice versa. From the EP category of portfolios we see that out-of-sample returns to the EP portfolios are not significantly different from zero at the 5 percent level of significance for all ranks of EP portfolios. From the EP category of portfolios we see that the loadings on the SMB risk factors are positive for all ranks of EP portfolios but are greater for high EP portfolios than they are for low EP portfolios, suggesting that high EP portfolios consists of stocks of relatively smaller firms; this is in line with what the theory suggests. The loadings on the HML risk factors are positive for low EP portfolios and negative for high EP portfolios, suggesting that low EP portfolios consists of stocks of distressed firms; this is not in line with what the theory suggests.

Objective D4 was to test whether low market capitalization is typical of distressed firms and vice versa. From the SZDT category of portfolios we do see that the average out-of-sample returns to small-cap stocks is in fact higher than the average out-of-sample returns to large-cap stocks. This suggests that small-cap stocks are in fact distressed stocks and are thus given a higher return to compensate for the distress. The Three-factor and our Multi-factor models are able to capture the pattern of returns to portfolios formed on ranks of market capitalization in a meaningful way. From the SZDT category of portfolios we do see that the SMB risk factors of the small-cap stocks are given significantly positive loadings and vice versa. Thus we conclusively see that small-cap stocks are given a small-cap stock risk premium.

Objective E1 was to test if there were any abnormal cyclical patterns in long-term returns and if our model would be able to capture it in a meaningful manner. The theory is that portfolios that were long-term winners (had the highest average return in the past thirty-six months) were strong and big firms and so were expected to provide low returns in the following year and vice versa. The Three-factor and our Multi-factor models are able to capture the pattern of returns, and the two categories of models do so in an identical manner. From the SE36 category of portfolios we see that the winners only provided a .03 percent out-of-sample average return, whereas the losers provided a 5.04 percent out-of-sample average return. The loadings on the SMB risk factor are positive for all ranks of SE36 portfolios but are greater for low SE36 portfolios than they are for high SE36 portfolios, suggesting that low SE36 portfolios consists of stocks of smaller firms; this is in line with what the theory suggests. The loadings on the HML risk factor, however, are not in line with what the theory suggests. The loadings of this risk factor are positive for high SE36 portfolios (i.e. the winners) and negative for low SE36 portfolios (i.e. the losers), suggesting that high SE36 portfolio consists of stocks of distressed firms.

Objective E2 was to test if there were any continuation patterns in short-term returns and if our model would be able to capture it in a meaningful manner. The theory is that portfolios that were short-term winners (had the highest average return in the past twelve months) were small and distressed firms and so were expected to provide high returns in the following year and vice versa. The Three-factor and our Multi-factor models are able to capture the pattern of returns, and the two categories of models do so in an identical manner. From the SE12 category of portfolios we see that the winners only provided a positive out-of-sample average return, whereas the losers provided a negative out-of-sample average return. Thus we do see a continuation pattern in short-term returns. The loadings on the SMB risk factor are positive for all ranks of SE12 portfolios but are greater for low SE12 portfolios than they are for high SE12 portfolios, suggesting that low SE12 portfolios consists of stocks of relatively distressed; this is not in line with what the theory suggests. The loadings on the HML risk factor, however, are in line with what the theory suggests. The loadings of this risk factor are positive for the highest SE12 portfolio (i.e. the winner) and negative for low SE12 portfolios (i.e. the losers), suggesting that the highest SE12 portfolio consisted of stocks of distressed firms.

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# Definitions

- Adjusted R-Square is the R-Square that has been adjusted for the number of independent variables in the model. AdjRSq = 1 – [(1 – RSq)(n-1)/(n-k-1)]
- AIC stands for Aikaike Information Criterion
- alpha is the coefficient of one period past squared residual
- AR stands for Autoregressive
- b is market beta
- BE/ME is ratio of the book value of common (shareholders') equity per stock of a firm and the market value of common equity per stock. (Refer to "Corporate Finance" by Ross, et al, pp. 367-369)
- C/P is the ratio of the cash flow per stock of a firm and the price of its stock.
- delta is the coefficient that measures the pricing of time-varying conditional variance
- Distressed stocks are stocks of firms whose earnings per share are low
- e is white noise
- E/P is the ratio of the earning per stock of firm and the price of its stock
- EMDB stands for Emerging Market Database
- EP portfolios are portfolios formed on ranks of stocks ranked on the E/P ratio criterion
- gamma is the coefficient of the one period past estimate of the residual variance
- GARCH stands for Generalized Autoregressive Conditional Heteroskedasticity
- GARCH-M stands for GARCH-in-mean

- h is the coefficient of the HML portfolio
- HML (High minus Low) returns are the average returns from stocks with a high BE/ME ratio minus the average returns from stocks with a low BE/ME ratio
- IFC stands for International Finance Corporation
- IGARCH stands for Integrated GARCH
- k is the constant in the GARCH expression
- MLE stands for Maximum Likelihood Estimation
- OLS stands for Ordinary Least Squares
- PCER stands for percentage change in the exchange rate from one week to the next
- PCF portfolios are portfolios formed on ranks of stocks ranked on the P/CF ratio criterion
- p-value of a coefficient has this meaning; given the null hypothesis that the coefficient is zero, the p-value gives us the probability of getting a value greater in absolute terms than that coefficient
- Rf,t is the weekly three-month US Treasury-Bill rate
- Rm,t is the IFCG market index weekly returns of the country under study
- s is the coefficient of the SMB portfolio
- SC stands for Schwarz Criterion
- SE12 portfolios are portfolios formed on ranks of stocks ranked on the basis of the average of returns over the past twelve months
- SE36 portfolios are portfolios formed on ranks of stocks ranked on the basis of the average of returns over the past thirty-six months
- Size is the market capitalization of a firm

- SMB (Small minus Big) returns are the average returns from the small-capitalization stocks minus the average returns from the big-capitalization stocks
- SZDT (SZ means Size and DT means Distress) portfolios are sixteen portfolios formed in this way; four size ranked portfolios and four BE/ME ranked portfolios lead to sixteen cells in a two-by-two classification table.

## Abstract

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*Emerging Countries Stock Markets: An analysis using an extension of the three-factor CAPM*

Dissertation directed by Dr. H. Vinod, PH.D.

The stock markets of India and South Korea became partially liberalized in 1992. Has this liberalization led to stock market efficiency? The overall goal of this paper is to test if the stock markets in these two countries have become truly informationally efficient in the Fama sense. A subordinate goal is to see if the patterns of returns seen in the US and what the theory suggests should be, is seen in the stock markets of South Korea and India. In order to meet these goals we use an extended version of the Fama and French three-factor CAPM. The Fama and French model has three factors to price the common risks associated with common stocks. The three risks which these factors price are the market risk, the common risk associated with the market capitalization of the firms, and the common risk associated with the Book Value to Market Value ratio of the firm. Our model introduces a fourth factor, which capture the risk associated with the time-varying conditional variance of the stock returns. We introduce this fourth factor because there is growing evidence that the stock returns typically exhibit phases of relative tranquillity followed by periods of high volatility. The results show that the stock market in South Korea was informationally efficient but the stock market in India was not. The results

were mixed as far as patterns of returns were concerned for both South Korea and India; that is, some of the patterns of returns were what the theory suggested while some were not.

# VITA

Mario I D'Souza, son of Reginald and Gertrude D'Souza, was born on December 28, 1967, in Calcutta, India. After graduating in 1988 from St. Xavier's High School in Calcutta, he entered St. Xavier's College in Calcutta. In 1991, he received the Bachelor of Science degree in Economics. He then entered Calcutta University in 1991. In 1993, he received the Masters degree in Economics.

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