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碩士論文

系統風險、公司規模、帳面市值比、風險值和股票報酬的關係：

以台灣股票市場為例

A reexamination of Market Beta, Firm Size, Book-to-Market,

Value-at-Risk in Stock Returns:

Evidence from the Taiwan Stock Market

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中華民國九十五年六月

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本研究利用橫斷面時間序列分析法探討台灣股票市場上:市場因素、規模效應、股價淨值比效應和風險值因素對股票市場報酬的解釋力，主要目的是要加入新的風險指標—風險值，形成四因子模型，利用時間序列分析此因子對台灣股市報酬的解釋力及影響方向，對模型的總解釋力影響為何。實證結果發現，利用歷史模擬法所算出的風險值，在橫斷面分析時，1%和 5%顯著水準之下，具有解釋能力，而在時間序列分析方面，若分成 25 投資組合來看，對大規模公司而言，風險值因子對投資組合期望報酬率較具有解釋力。

關鍵字: 資本資產定價模式; 系統風險; 異常現象; 台灣股票市場; 風險值

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This paper investigates the explanatory power of the market beta, firm size, and the book-to-market ratio, as well as Value-at-Risk regarding the cross-sectional expected stock returns in the Taiwan stock market. Our primary objective is to determine whether the Value-at-Risk factor has marginal explanatory power that is related to the Fama-French three-factor model. This study finds that Value-at-Risk can explain average stock returns at the 1% and 5% significance levels based on cross-sectional regression analysis. In addition, from the perspective of the time series regression, the HVARL factor can also help explain the variation in the stock market, especially for the larger companies in Taiwan's stock market.

Keywords: CAPM; Market beta; Anomalies; Taiwan Stock Market; Value-at-Risk

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1. Introduction

The validity of modern portfolio theory has been and will continue to be an important research issue. The tradeoff between risk and expected return, which can be viewed as a “No free lunch” principle, asserts that over the long run it is not possible to achieve exceptional returns without accepting commensurably substantial risks. Any standard equilibrium model of asset pricing justifies this relationship. The well-known capital asset pricing model (CAPM) of Sharpe (1964), Linter (1965), and Black (1972) has, for decades, been the major framework for analyzing the cross sectional variation in expected asset returns. The main implication of the theory is that: (a) the expected return on a security is a positive linear function of its market β and (b) the market β itself suffices to describe the cross-section of expected returns.

Unfortunately, theory and practice do not always match. Fama and French (1992) drew two negative conclusions regarding CAPM, namely: (a) when one allows for variations in CAPM market β s that are unrelated to size, the univariate relationship between β and the average return for 1941-1990 is weak, and (b) β does not suffice to explain the average return. Fama and French further find no cross-sectional mean-beta relationship after controlling for size and the ratio of book-to-market equity. The evidence shows that the market return should not be the only relevant risk factor in the economy, and additional factors are required to explain the expected returns.

Several alternative risk factors have consequently been employed in the literature, for example, the size effect of Banz (1981). He finds that the market value of equity (ME) provides a prominent explanation of the cross-section of average returns provided by market beta. Variables such as the book-to-market equity ratio (BE/ME) (Fama and French, 1992, 1993, 1995, 1996; Stattman, 1980; Rosenberg, Reid, and Lanstein, 1985), the price/earnings ratio (Basu, 1977), leverage (Bhandari, 1998), and

Value-at-Risk (Bali and Cakici, 2004) all have significant explanatory power for explaining average expected returns.

In particular, the concept and use of Value-at-Risk (henceforth VaR) is relatively recent and is designed to summarize the predicted maximum loss (or worst loss) over a target horizon within a given confidence interval (Jorion, 2000). Extreme price movements are rare, but they can bring serious results to some corporations, leading to disastrous consequences for a country's financial markets. For instance, the New York stock market crashed in October 1987, and then, one decade later, the Asian stock market crashed in 1997. Besides, the Enron scandal has also caused the Dow Jones Industrial Average (DJIA) to drop sharply. These crises have harmed thousands of companies and much of the value of their stocks has been wiped out within a short period of time. Therefore, to a risk manager, a good measure of market risk is more than necessary. VaR was first used by major financial firms in the late 1980's to measure the risks of their trading portfolios. Since then, the use of VaR has exploded, with J.P. Morgan's attempt to establish a market standard through its release of the RiskMetricsTM system in 1994.

VaR is now not only widely used by financial institutions, non-financial corporations, and institutional investors, but has also become a common language for communication with regard to aggregate risk taking, both within an organization and outside it (for example, with analysts, regulators, and shareholders). Even regulators have become interested in VaR. For example, the Basle Committee on Banking Supervision (Basle Committee, 1996) permits banks to calculate their capital requirements for market risk using their own proprietary VaR models, while the Securities and Exchange Commission (SEC, 1997) requires that U.S. companies disclose quantitative measures of market risks, with VaR listed as one of three possible market risk disclosure measures.

In a normal world, the standard deviation of the portfolio returns is a good risk measure, and efficient portfolios are the ones generating the best mean-variance profiles. Modeling portfolio risk with traditional standard deviation measures implies that investors are concerned only with the average variation in individual stock returns, and they are not allowed to treat the negative and positive tails of the return distribution separately. However, statistical data exhibit fat-tailed and asymmetric distributions for market returns. The fat tail represents the extent to which the portfolio's value can be affected by large jumps in market prices. The empirical evidence also indicates that the minimum-variance portfolios are far from being the most efficient ones with respect to the relevant risk measures. During the last few decades we can see that the most popular and traditional measure of risk has been volatility. The main problem with volatility, however, is that it does not take into consideration the direction of an investment's movement — a stock can be volatile because it suddenly jumps higher. However, investors are not distressed by gains! By assuming that investors care about the likelihood of a really big loss, VaR answers the question, "What is my worst-case scenario?"

Traditional models treat all uncertainty as risk, regardless of the direction it takes. As many people have shown, that is a problem if returns are not symmetrical — investors worry about their losses "to the left" of the average, but they do not worry about their gains "to the right" of the average. If investors are more averse to the risk of losses on the downside than to the gains on the upside, investors ought to demand greater compensation for holding stocks with greater downside risk. In particular, many authors, including Campbell, et al. (2001), find that market volatility increases in bear markets and recessions. Moreover, Duffee (1995) finds that idiosyncratic volatility decreases in down-markets. Both of these effects cause the conditional beta to have little asymmetry across the downside and the upside. To

sum up, this paper measures VaR in terms of a company's market value at risk. Hence the VaR is related to the company's stock price and it thus reflects the shareholders' perception of risk. The reason for considering VaR is that it is an easy-to-understand summary measure of downside risk. The downside focus separates the loss from the upside potential — only the former truly constitutes risk and only negative surprises to the stock market represent potential litigation threats. Furthermore, the concept of VaR is easily grasped and hence easily communicated.

Surprisingly, despite its wide acceptance among practitioners, academics, and regulators, VaR has so far only been considered to be a risk factor in Bali and Cakici's (2004) study. Therefore, this research aims to supplement our understanding of the measurement of risk and to provide some emerging market evidence while the only related study focuses mainly on mature markets. The Taiwan stock market is also unique for its tight short-sale constraints and a 7% daily price change limit.

An important contribution of this paper is that it tests whether the maximum likely loss measured by VaR plays a key role in explaining expected returns in Taiwan. The central motivation behind this paper is that it also provides an analysis in terms of examining the cross-sectional variation among beta, firm size, the book-to-market ratio (BE/ME) and Value-at-Risk (VaR) at the firm level. The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 describes the dataset and variable definitions. Section 4 contains the methodology and models. Section 5 presents the empirical results of our analysis. Section 6 summarizes and concludes our findings.

2. Literature Review

Empirical research has provided several pieces of evidence that reject the validity of the Sharpe-Linter capital asset pricing model (CAPM). The existence of market

frictions, the presence of irrational investors and inefficient markets may distort the cross-sectional relationship between expected stock returns and market return. This research will discuss the related evidence that has been reported in empirical studies.

2.1 Systematic Risk (Beta)

Beta, or the sensitivity of asset returns to underlying sources of risk, is central to modern finance. Beta has been used by academics and practitioners to model and measure systematic risk. Sharpe (1964) and Linter (1965) found a positive and a linear function between the expected returns on securities and their betas. Miller and Scholes (1972), Black, Jensen, and Scholes (1972), and Fama and MacBeth (1973) all empirically confirmed a positive relationship between mean returns and betas across firms.

Subsequently, Reinganum (1981) found that estimated betas were not systematically related to average returns across New York Stock Exchange and American Stock Exchange securities. In the 1990s, however, much controversy was stirred in the finance literature as if beta completely lacked predictive power for expected returns. For instance, Fama and French (1992) also found evidence that the relationship between the average return and beta for common stocks was even flatter after the sample periods used in the early empirical work on the CAPM, and that the relationship between beta and the average return was flat, even when beta was the only explanatory variable. Kothari, Shanken, and Sloan (1995) tried to resuscitate the Sharpe-Lintner CAPM by arguing that the weak relationship between the average return and beta came about just by chance. However, the strong evidence that other variables captured the variation in expected return missed by beta made this argument irrelevant. By investigating international findings, Heston, Rouwenhorst, and Wessels (1999) examined the ability of beta and size to explain cross-sectional variation in average returns in 12 European countries. They found that average stock

returns were positively related to beta and negatively related to firm size. The beta premium was in part due to the fact that high beta countries outperformed low beta countries. Within countries, high beta stocks outperformed low beta stocks only in January, but not in other months. The differences in the average returns of the size- and beta-sorted portfolios could not be explained by market risk and exposure to the excess return of small over large stocks (SMB)¹.

2.2 Size Effect

The size effect is the most well-known empirical inconsistency of the CAPM. The size premium for small-cap firms is one of the market anomalies and was originally discovered by Banz (1981). The evidence showed that the stock returns of firms with small-cap market capital (size) had statistically higher returns than firms with large-cap market capital and the CAPM beta could not justify this effect. In the meantime, Reinganum (1981) also found that the size of the firm (as measured by the market value of firm equity) was inversely related to mean returns across firms over the 1963-1977 period, after controlling for the beta. After that, there were several discussions regarding the size effect, and studies such as Chan, Chen and Hsieh (1985) among others argued that small firms had higher returns than large firms because they fluctuated more with economic expansions and contractions. Later, Fama and French (1992) concluded that, in their U.S. sample, the univariate relationship between beta and the average return for the 1941-1990 period was weak and beta did not explain the average return. It was size that captured the differences in the average stock returns.

Berk (1995) provided an explanation for the size effect and argued that firm size

¹ SMB, which stands for Small Minus Big, is designed to measure the additional return that investors have historically received by investing in the stocks of companies with relatively small market capitalization. This additional return is often referred to as the “size premium.” A further definition can be seen in Section 4.2 in this paper.

would in general explain the part of the cross-section of expected returns left unexplained by an incorrectly specified asset pricing model. Chen and Zhang (1998) found that returns were higher for small firms in the Taiwan stock market. Besides, further research on the size effect using data from international markets has also been examined. For example, Heston, Rouwenhorst, and Wessels (1995) found evidence of a size effect in European markets by showing that equally-weighted stock portfolios tended to have higher average returns than value-weighted portfolios. Chui and Wei (1998) showed that the size effect was significant in Pacific-Basin emerging markets apart from Taiwan. Rouwenhorst (1999) showed that the return factors in 20 almost emerging markets were qualitatively similar to those documented in many developed markets: small stocks outperformed large stocks.

2.3 Book-to-Market Equity (BE/ME)

Research since the 1980s has generally found that BE/ME has significant explanatory power to predict the cross-sectional stock returns and that BE/ME has better explanatory ability than firm size. Stattman (1980) documented an association between expected returns and BE/ME, which remained significant after controlling for beta, size, and other firm characteristics (Fama and French, 1992; Lakonishok, Shleifer, and Vishny, 1994). Rosenberg, Reid, and Lanstein (1985) also found a positive and significant relationship between BE/ME and mean returns across firms. Penman (1991) and Fama and French (1995) found similar evidence of high BE/ME firms being more profitable than high BE/ME firms.

There have also been many international studies examining the explanatory ability of BE/ME. Chan and Chen (1991) also found that BE/ME played an important role in explaining the cross-section of average returns on Japanese stocks. Miles and Timmerman (1996) reported that BE/ME appeared to be a main factor driving the cross-sectional company returns in the U.K. Roll (1995) analyzed

Indonesian stocks and reported that the value portfolios (high BE/ME) consistently out-performed the growth portfolios (low BE/ME). Chen and Zhang (1998) observed that the difference in returns between high BE/ME firms (risky firms) and low BE/ME firms (low-risk firms) was larger in mature markets than the difference in high-growth markets. Jansen and Verschoor (2004) discovered that the relationship between market returns and the BE/ME ratio was strong in the Czech Republic, Hungary, Poland, Russia, and Hong Kong. As a whole, the evidence provides considerable support for the cross-sectional explanatory power of BE/ME.

A positive relationship between BE/ME and risk is expected for several reasons. Chan and Chen (1991) and Fama and French (1993) suggested that a distinct “distress factor” helped explain the common variation in stock returns. Poorly performing, or distressed, firms are likely to have high BE/ME ratios. These firms are especially sensitive to economic conditions, and their returns might be driven by many of the same macroeconomic factors (such as variation over time in bankruptcy costs and access to credit markets). In addition, based on the arguments of Ball (1978) and Berk (1995), a firm’s BE/ME might proxy for risk because of the inverse relationship between market value and discount rates. By holding book value constant in the numerator, a firm’s BE/ME ratio increases as expected return, and consequently risk, increases. Alternatively, the BE/ME ratio might provide information about security mis-pricing. The mis-pricing view takes the perspective of a contrarian investor. A firm with poor stock price performance tends to be under-priced and to have a low market value relative to book value. As a result, a high BE/ME is indicative of high future returns as the under-pricing is eliminated. Lakonishok, Shleifer, and Vishny (1994) offered a rationale for the association between past performance and mis-pricing. They disputed the view that investors truthfully extrapolated past growth when evaluating a firm’s prospects. For example, investors tended to be

overly pessimistic about a firm that has had low or negative earnings.

2.4 Value-at-Risk (VaR)

The VaR analysis originated with the variance-covariance model introduced by RiskMetrics that was developed by J.P. Morgan in 1993. However, the variance-covariance approach to calculating risk can be traced back to the early days of modern portfolio theory starting with Markowitz (1959), with which most of today's risk managers are conversant. This is why this type of VaR model had a lot of applications in the early days. Engle and Manganelli (1999) extended the quantile regression to model the VaR directly instead of modeling the underlying volatility generating process and also introduced the conditional autoregressive Value-at-Risk (CAViaR) model.

More recently, one thing that particularly deserves to be mentioned is that VaR has been found to be an important risk factor for explaining cross-sectional stock returns. Bali and Cakici (2004) found that the maximum likely losses measured by VaR could capture the cross-sectional differences in expected stock returns on the NYSE, AMEX, and Nasdaq stocks for the period from January 1963 through December 2001, while the market beta and total volatility had almost no power whatsoever to explain average stock returns at the firm level. Bali and Cakici (2004) argued that VaR had so far not been regarded as an alternative risk factor that added to the explanation of stock returns. This study has been largely motivated by their strong findings and will follow a similar methodology by applying data from Taiwan that will compare the relative predictive ability (in terms of the R^2 value) of beta, size, BE/ME, and VaR to see if they can help explain the cross-sectional variation in portfolio returns.

3. Data and Variable Definitions

3.1 Data

Following Bali and Cakici (2004), this paper investigates the market factor (beta), firm size, BE/ME, and VaR to test whether the various company characteristics have significant explanatory power in relation to the average stock returns in Taiwan. The data set includes all stocks listed on the Taiwan stock exchange obtained from the Taiwan Economic Journal (TEJ) for the period from January 1990 through December 2004. This 15-year period is further divided by an estimation period and a test period. The estimation period extends from January 1990 through December 1994, while the test period extends from January 1995 to December 2004.

To be included in the sample, for a given month, a stock must satisfy certain criteria. First, its return over the previous 60 months must be available from the TEJ, and sufficient data must be available to calculate our variables, i.e. VaR and beta. Second, data must be available from the TEJ to calculate the book-to-market ratio as of December of the previous year. Finally, we include only securities defined by the TEJ as ordinary common shares. This screening process yields averages of 133 stocks per month. Therefore the returns for companies that are calculated are listed throughout the whole period. Figure 1 characterizes the industry distributions and gives a brief overview of the overall sample.

[Insert Figure 1 here]

3.2 Variable Definitions

For each stock and for each month, the following control variables are calculated.

3.2.1 Systematic risk (Beta)

Beta measures a stock's volatility, i.e. the degree to which its price fluctuates in relation to the overall market. Beta is a key component of the capital asset pricing model (CAPM) and it expresses the fundamental tradeoff between minimizing risk and maximizing return. Follow Fama and French (1992), this paper first sorts all the stocks by size (i.e. the market value of equity) to determine the stocks' quintile breakpoints. The reason why portfolios are formed according to their size is based on the evidence of Chan and Chen (1998) and others, who found that size differences may be attributed to a wide range of average returns and β s. Next, based on the stocks' quintile breakpoints, this paper subdivides each size quintile into five portfolios on the basis of pre-ranking betas for all the stocks. This paper estimates the pre-ranking betas for five years of monthly returns ending in December of year t-1. After assigning each stock in the sample to one of five size quintiles and one of the pre-ranking beta quintiles, we then calculate the equally-weighted monthly returns of the resulting 25 portfolios² for the next 12 months, from January of year t through December of year t. This procedure yields 108 post-ranking monthly returns for each of 25 portfolios from January 1996 to December 2004. Finally, this paper estimates the post-ranking betas by using a full sample of 108 post-ranking returns for each of the 25 portfolios, with the Taiwan stock value-weighted index serving as a proxy for the market. Following Allen and Cleary (1998), we estimate beta as the sum of the slopes in the regression of the returns on portfolios:

$$R_{i,t} = \alpha_i + \beta_{1,i}R_{m,t} + \beta_{2,i}R_{m,t-1} + \varepsilon_{i,t}, \quad (1)$$

2 The choice of using portfolios instead of individual shares is dictated by the evidence of Griffin (2002) that this is the way the sampling error is reduced. Additionally, using portfolios also facilitates a comparison with past studies in the field, as the majority of these studies use portfolios instead of individual stocks. Further advantages of using portfolios instead of individual firms in the regressions include the following: (1) A pooled sample of individual firms used in CSR analysis allows us to eliminate the potential threat posed by temporal and firm-specific effects in terms of biasing the results. (2) There is significantly less computational effort in using portfolios instead of individual stocks in the regression analysis.

where $R_{i,t}$ is the monthly return on stock i in period t , α_i is the intercept term, $R_{m,t}$ is the monthly return on the TEJ value-weighted index in period t , $\beta_{1,i}$ is the synchronous covariance coefficient, $\beta_{2,i}$ is the lagged one-period coefficient, and $\varepsilon_{i,t}$ is the residual series from the cross-sectional regression.

The beta estimate used to rank stocks (the pre-ranking β) is calculated as follows:

$$\beta_i = \beta_{1,i} + \beta_{2,i}, \quad (2)$$

where $\beta_{1,i}$ is the contemporaneous beta and $\beta_{2,i}$ is the lagged one-period beta. The lag term allows for a delay in the information process, which may be prevalent for small stocks or those that are infrequently traded (Scholes and Williams, 1977).

3.2.2 Size

Size refers to the value of a company, that is, the market value of its outstanding shares. This figure is found by the natural logarithm of the market value of equity (by taking the stock price and multiplying it by the total number of shares outstanding).

3.2.3 Book-to-Market Equity (BE/ME)

Book-to-market equity (BE/ME) is the natural logarithm of the ratio of the book value of equity plus deferred taxes over the market value of equity, which involves accounting- and market-based variables. The book value of equity, in turn, is the value of a company's assets expressed on the balance sheet. This number is defined as the difference between the book value of assets and the book value of liabilities. This paper uses a firm's market equity at the end of December of the previous year to compute its BE/ME.

3.2.4 Value-at-Risk (VaR)

Value-at-Risk (VaR) has been widely promoted by the Bank for International Settlements (BIS) as well as central banks of all countries as a way of monitoring and managing market risk and as a basis for setting regulatory minimum capital standards.

The revised Basle Accord, implemented in January 1998, makes it mandatory for banks to use VaR as a basis for determining the amount of regulatory capital adequate for covering market risk. VaR measures the worst expected loss under normal market conditions over a specific time interval at a given confidence level. One of its definitions states: “VaR answers the question: How much can I lose with x% probability over a pre-set horizon?” Another way of expressing this is to state that VaR is the lowest quantile of the potential losses that can occur within a given portfolio during a specified time period.

There are three major decision variables required to estimate VaR: the confidence level, a target horizon, and an estimation model. In this paper, we use three confidence levels (90%, 95%, and 99%) to check the robustness of VaR as an explanatory variable for expected stock returns. The time horizon is 1 month and the estimation model is based on the historical simulation method.³ The estimation model is also based on the lower tail of the actual empirical distribution. We use 60 monthly returns to estimate the mean, and the cut-off return at the 90%, 95%, and 99% confidence levels from the empirical distribution. The 1%, 5%, and 10% VaRs are measured by the first-lowest, third-lowest, and sixth-lowest observations from the 60 monthly returns.

Once we have the VaR measures for each stock, we rank and place them into 5 quintile portfolios. Portfolio 1 has the lowest VaR and portfolio 5 has the highest VaR. The portfolio formation procedure is very similar to Fama and French (1992), except that they update their portfolios annually, whereas we update ours on a monthly basis. The estimation period for VaR starts in January 1990 and extends through December 1995 and the test period extends from January 1996 to December

³ We also use EWMA and the Monte Carlo method to check the performance of our model. The results are similar and are not reported here.

2004. For example, in January 1996 we estimate VaR for each stock based on the return history from January 1990 to December 1995 and rank all the stocks according to the estimated VaRs. Then five equally-weighted portfolios are formed based on the VaR rank. We then calculate the one-month-ahead portfolio returns in January 1996. For the next month, by rolling over one month ahead, we re-estimate VaR for each stock, rank them based on the updated VaR, and form new portfolios. This procedure is repeated until December 2004 when we have no more data left. Therefore, we have 108 time series for the 5 equally-weighted portfolios based on their VaRs. In Figure 2-4, we graph the relationship between the 1%, 5% and 10% VaR levels and the average returns for the quintile portfolios. It is clear that the portfolios for the higher VaR tend to produce rates of return that are greater than the returns from the portfolios of lower VaR companies.



[Insert Figure 2-4 here]

4. Methodology and Models

4.1 Cross-Sectional Regression

This section tests whether the beta, size, BE/ME, 1% VaR, 5% VaR and 10% VaR can produce large and statistically significant cross-sectional variation in expected stock returns. This paper uses time series averages of the slopes from the month-by-month Fama-MacBeth (1973) (FM) regressions of the cross-section of realized average returns on Beta, Size, BE/ME, 1% VaR, 5% VaR, and 10% VaR. The average slopes provide standard FM tests for determining which explanatory variables on average have non-zero expected premiums during the January 1996 to

December 2004 period. Monthly cross-sectional regressions⁴ are run for the following econometric specifications:

$$R_{j,t} = \omega_t + \gamma_t BETA_{j,t} + \varepsilon_{j,t}, \quad (3)$$

$$R_{j,t} = \omega_t + \gamma_t \ln(ME)_{j,t} + \varepsilon_{j,t}, \quad (4)$$

$$R_{j,t} = \omega_t + \gamma_t \ln(BE / ME)_{j,t} + \varepsilon_{j,t}, \quad (5)$$

$$R_{j,t} = \omega_t + \gamma_t VaR_{j,t}^{1\%} + \varepsilon_{j,t}, \quad (6)$$

$$R_{j,t} = \omega_t + \gamma_t VaR_{j,t}^{5\%} + \varepsilon_{j,t}, \quad (7)$$

$$R_{j,t} = \omega_t + \gamma_t VaR_{j,t}^{10\%} + \varepsilon_{j,t}, \quad (8)$$

where $j=1,2,\dots,t$ (the number of firms in month t), $R_{j,t}$ is the realized average return on stock j in month t , $BETA_{j,t}$ is the full-sample pre-ranking beta for firm j in month t , and $\ln(ME)_{j,t}$ is the natural logarithm of market equity for firm j in month t . $VaR(\alpha)_{j,t}$ is -1 times the maximum likely loss (VaR) for firm j in month t with the loss probability level $\alpha=1\%$, 5% , and 10% , and $\varepsilon_{j,t}$ is the residual series from the cross-sectional regressions. The null hypothesis is the time series average of the monthly regression slopes, γ_t is zero, and statistical significance is established using a standard t-test.

4.2 Inputs to the Time Series Regression

4.2.1 The Size – Book-to-Market Portfolios⁵

Following Fama and French (1993), this study forms six portfolios in order to

⁴ Cross-sectional regression analysis – a regression analysis where observations are measured at the same point in time or over the same time period, but which differ along another dimension. For example, an analyst may regress stock returns for different companies measured over the same period against differences in the companies' fundamental variables for that period.

⁵ Portfolio analysis – a research method that ranks all stocks based on a certain variable, in order to consequently divide them into a given number of portfolios. For each portfolio an average value of the variable, on which the stocks were ranked and consequently divided into portfolios (the sorting variable), is calculated. The relationship between the average value of the sorting variable and the average portfolio returns (investigated in this study) is consequently examined.

examine the common risk factors in stock returns. The portfolios are formed yearly from a simple sorting of firms into two groups based on size and three groups based on the BE/ME. First, at the end of each year from 1996 to 2004, this study ranks all stocks in terms of size in order to allocate stocks into two groups, namely, small firms or big firms (S or B) according to the data for December of each previous year. The median size is used to split the stocks. Second, the stocks are also assigned to three BE/ME groups based on breakpoints for the bottom 30 percent (low, or L), the middle 40 percent (medium, or M), and the top 30 percent (high, or H) of the ranked values of the BE/ME for all stocks. Thus, six portfolios (S/L, S/M, S/H, B/L, B/M, and B/H) are finally constructed from the intersection of the two sizes and three BE/ME groups.

In a series of papers, Fama and French (1993, 1995, and 1996) documented the importance of RMRF, SMB, and HML. Fama and French used the excess return of the market over a risk-free return, i.e. RMRF, as a proxy for the market factor. RM was calculated as the return on the value-weighted portfolio of the stocks in the six size-BE/ME portfolios plus the negative-BE stocks that were excluded from the portfolios. The risk-free rate, RF, was the one-month CD deposit rate from the Bank of Taiwan. The SMB was meant to mimic the risk factor in returns related to size, which is the difference, for each month, between the simple average of the returns on the three small-stock portfolios (S/L, S/M, and S/H) and the simple average of the returns on the three big-stock portfolios (B/L, B/M, and B/H). Thus, SMB (small minus big) is the difference between the returns on small- and big-stock portfolios with about the same weighted-average book-to-market equity. This difference should be largely free of the influence of BE/ME, focusing instead on the different return behaviors of small and big stocks

$$SMB = ((S/L + S/M + S/H) - (B/L + B/M + B/H)) / 3. \quad (9)$$

Similarly, HML (high minus low) is defined similarly and calculated based on the difference between the return on a portfolio of high-BE/ME stocks and the return on a portfolio of low-BE/ME stocks

$$HML = ((S/H+B/H)-(S/L+B/L))/2. \quad (10)$$

HVARL, similar to SMB, is defined as the equal-weighted average of the returns on the high-VaR stock portfolios minus the returns on the low-VaR stock portfolios.

4.2.2 The VaR - BE/ME Portfolios

In order to test the performance of VaR based on the 25 portfolios of Fama and French (1993), this study devises a factor, HVARL (high VaR minus low VaR), that is designed to mimic the risk factor in returns related to Value-at-Risk and is defined as the difference between the simple average returns on the high-VaR and low-VaR portfolios. The construction of a 5 percent VaR portfolio is similar to the construction of Fama and French's size portfolios. In December of each year t from 1995 to 2004, this study ranks all stocks according to a 5 percent VaR. The median 5 percent VaR figure is used to divide the stocks into two groups — the high VaR and low VaR groups.

4.3 Main Model

This study performs a four-step analysis of the various factors (RMRF, HVARL, SMB, and HML) in explaining stock returns, and gradually examines the one- to four-factor models.

4.3.1 One-Factor Model

The one-factor regressions utilize RMRF, HVARL, SMB, and HML as explanatory variables to explain expected returns. They are in the following forms:

$$R(t) - RF(t) = a + b \times [RM(t) - RF(t)] + u(t), \quad (11)$$

$$R(t) - RF(t) = a + b \times HVARL + u(t), \quad (12)$$

$$R(t) - RF(t) = a + b \times SMB + u(t), \quad (13)$$

$$R(t) - RF(t) = a + b \times HML + u(t), \quad (14)$$

where RM is the value-weighted monthly percentage return on all the stocks in the 25 size-BE/ME portfolios, plus the negative $-BE/ME$ stocks excluded from the 25 portfolios. RF is the one-month CD deposit rate from the Bank of Taiwan. SMB (small minus big), the return on the mimicking portfolio⁶ for the size factor in the stock returns, is the difference between the average of the returns on the three small-stock portfolios (S/L, S/M, and S/H) and the average of the returns on the three big-stock portfolios (B/L, B/M, and B/H). HML , the return on the mimicking portfolio for the size factor in the stock returns, is the difference between the average of the returns on the two high-BE/ME portfolios (S/H and B/H) and the two low-BE/ME portfolios (S/L and B/L). $HVARL$ (high VaR minus low VaR) is the difference between the average of the returns on the high 5% VaR and low 5% VaR portfolios. Finally, $u(t)$ is the error term of these 108 month-by-month cross-sectional regressions.

4.3.2 Two-Factor Model

The two-factor regressions employ $RM-RF$ along with either $HVARL$, SMB , or HML as explanatory variables to explain expected returns. They are in the following forms:

$$R(t) - RF(t) = a + b \times [RM(t) - RF(t)] + c \times HVARL + u(t), \quad (15)$$

$$R(t) - RF(t) = a + b \times [RM(t) - RF(t)] + c \times SMB + u(t), \quad (16)$$

$$R(t) - RF(t) = a + b \times [RM(t) - RF(t)] + c \times HML + u(t). \quad (17)$$

4.3.3 Three-Factor Model

⁶ Mimicking portfolios – zero-investment portfolios that are sensitive to a potential risk factor, proxied by the variable on which they were created. More specifically, a mimicking portfolio is constructed by buying assets with a high value of the sorting variable (size or BE/ME in our case) and selling assets with a low value of the factor at the same time, which in effect maximizes the portfolio risk with respect to the factor proxied by the sorting variable.

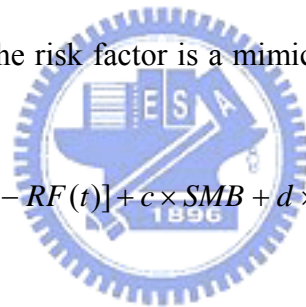
The three-factor model suggested by Fama and French (1993) provides an alternative to the CAPM for the estimation of expected returns. In this model, two additional factors are included to explain excess return; size and the book-to-market ratio.⁷ The Fama and French model is of primary interest to us as one of the objectives of the paper is to assess its implications for the investor's investment decision. The explanatory variables in the time series regressions include not only the returns on a market portfolio of stocks but also the mimicking portfolio returns for size and book-to-market:

$$R(t) - RF(t) = a + b \times [RM(t) - R(t)] + c \times SMB + d \times HML + u(t). \quad (18)$$

4.3.4 Four-Factor Model

The fourth model, the four-factor model, adds another risk factor, i.e. HVARL, to the three-factor model. The risk factor is a mimicking portfolio that follows Bali and Cakici (2004):

$$R(t) - RF(t) = a + b \times [RM(t) - RF(t)] + c \times SMB + d \times HML + e \times HVARL + u(t). \quad (19)$$



⁷ Markowitz (1999) argues that the existence of these anomalies can be due to several sources but can broadly be grouped into three categories. He states, "The first possibility is that these anomalies arise because the asset-pricing model is not capturing a component of systematic risk, which these firm characteristics may be correlated with. The second set of explanations are behavioral, suggesting that these anomalies arise because investors care about certain firm attributes, or that investors act irrationally to information, or have psychological biases in their interpretation of information, all of which may induce an apparent relation between average returns and these firm characteristics. Finally, the third set of explanations arises from flawed methodology, such as biases in computing returns from firm survivorship or microstructure effects, as well as other statistical errors." (p.1)

5. Empirical Results

5.1 VaR and Cross-Sectional Regression

To begin our analysis, we present the results of the Fama and MacBeth regressions of excess returns on characteristics that are best known to be associated with expected returns, namely, the beta, firm size, BE/ME, and VaR (1%, 5%, and 10%) variables.

[Insert Table 1 here]

Table 1 presents the time series average value of γ_t , the t-statistics, and the time series averages of the determination coefficient (R^2) over the 108 months in the sample. The t-statistics shown in the parentheses are the time series average values of γ_t divided by the corresponding time-series standard errors. As can be seen from the estimated slopes of beta, $\ln(\text{ME})$ and $\ln(\text{BE}/\text{ME})$ are both highly significant at the 1% level. The average slopes provide standard FM tests for determining which explanatory variables had, on average, nonzero expected return premiums during the January 1996 to December 2004 period. As expected, there is a strong relationship between the realized stock returns and beta. The empirical evidence shows that, the greater the sensitivity of the asset return, the greater the realized return. However, the average slope for the monthly regressions of the realized returns and size, $\ln(\text{Size})$, is positive and about 0.49, with a t-statistic of 34.81. We think that size may be related to profitability. On average, the profitability of larger-cap stocks in the Taiwan stock market is better than that of smaller-cap stocks. This result also shows that, for a firm with larger capitalization, the performance seems much better than for the small firm from the viewpoint of the cross-sectional regressions. The average slope based on the univariate regressions of the monthly return on $\ln(\text{BE}/\text{ME})$

is about 0.94, with a t-statistic of 17.36. This positive relationship indicates that it is possible that the risk captured by BE/ME is the relatively distressed factor of Chan and Chen (1991). They postulate that the earning prospects of firms are associated with a risk factor in the returns. Firms that the market judges to have poor prospects, signaled here by low stock prices and high BE/ME ratios, have higher expected returns (they are penalized with higher costs of capital) than firms with strong prospects. It is also possible that BE/ME only captures the unraveling of irrational market whims regarding the prospects of firms. This accords with the view put forward by Fama and French (1992) that BE/ME has a stronger role in explaining average stock returns than size. Furthermore, as we move to a lower significance level (higher confidence level), the VaR estimation becomes more important in explaining the cross-sectional average stock returns. We can see that the $\text{Var}(\alpha)$ are significant when the α are 1% and 5%. The results of the positive coefficients of VaR indicate that the greater a stock's potential fall in value, the higher the expected return should be.

5.2 VaR and Time-Series Variation of Expected Returns

In time-series regressions, the slopes and R^2 values are direct evidence as to whether different risk factors capture a common variation in stock returns. This study examines the explanatory power of stock market factors.

[Insert Table 2 here]

Table 2 of Panel A shows the simple statistics of RMRF, SMB, HML and HVARL. The average value of the market risk premium is 1.28% per month. This study also calculates the correlations between RMRF, SMB, HML and HVARL. Table 2 of Panel B presents the correlation coefficients for the factors used. The last

row shows that HVARL is positively correlated with RMRF and SMB, whereas it is negatively correlated with HML. A notable point is that the positive relationship between HVARL and SMB is much stronger than the negative relationship between HVARL and HML.

To compare the relative performances of HVARL, RMRF, SMB and HML, this study calculates the correlations between the returns for the 25 portfolios of Fama and French (1993) and the various factors:

[Insert Table 3 here]

Table 3 shows that, not surprisingly, the excess return on the market portfolio of stocks, RMRF, captures more common variation in stock returns, on average, than HVARL, HML and SMB. The average correlation between the returns for the 25 portfolios and RMRF is 0.7655, whereas the average correlation between HVARL and the monthly returns on the 25 portfolios is 0.4807. Furthermore, the average correlation is 0.2990 for SMB, and -0.3826 for HML. Clearly, HVARL, as a single factor, is superior to SMB and HML in explaining the time-series variation in stock returns.

5.3 Properties of Portfolios Formed Based on Size and Pre-ranking β

Fama and French (1992) found that after controlling for the size and book-to-market effects, beta seemed to have no power to explain the average returns on a security. This finding is an important challenge to the notion of a rational market, since it seems to imply that a factor that should affect return, namely, systematic risk, does not seem to matter.

[Insert Table 4 here]

The average row of Panel B of Table 4 shows that the portfolio beta of each beta group averaged across the 5 different-sized portfolios steadily increases from 0.81 to 1.21. The average row in Panel C shows that the average portfolio size within each beta group is almost identical, ranging from 8.63 to 8.81. This allows us to interpret Panel A as a test of the net effect of beta on average returns holding size fixed. Panel A of Table 4 clearly shows that, for the period 1996-2004, average returns are not positively related to beta. The highest-beta portfolios do not have the highest returns, and it occurs in the fourth-beta portfolios. The results do not support the central prediction of the CAPM, because average stock returns are not positively related to the market beta at the portfolio level. The CAPM insight is that volatility arising from specific events (called specific or idiosyncratic risk) can be eliminated in a diversified portfolio, and that investors will not be paid for bearing these risks with extra returns. This result will support us as we continue to further discuss the three- and four-factor models. We should note that average monthly post-formation returns seem to be negatively correlated with firm size. The smallest size quintile, on average, has the highest average return (1.31% per month) and the biggest size quintile has the lowest average return (0.22% per month).

5.4 Properties of Portfolios Formed on VaR and Pre-ranking β

[Insert Table 5 here]

Table 5 of Panel A reports that when common stock portfolios are formed on 5% VaR, the average stock returns are positively related to VaR. Going from the lowest 5% VaR quintile to the highest 5% VaR quintile, the average stock returns from VaR portfolios increase from 0.55% per month to 1.27% per month monotonically. This result supports our argument to the effect that if investors are more averse to the risk

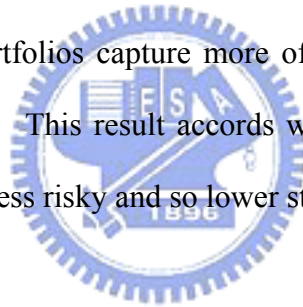
of losses on the downside than of gains on the upside, i.e. a higher VaR, investors ought to demand greater compensation. Furthermore, we can see that the greatest average monthly post-formation return is about 1.92% and not surprisingly is apparent in the highest VaR-BE/ME group. However, the average monthly post-formation returns are not similar within the same β quintile. For the smallest 5% VaR quintile, the highest β does not have the largest stock returns. Beta seems to have much less power to explain the average stock returns after controlling for the 5% VaR and book-to-market effects. These results inform us that the more a stock can potentially fall in value, the higher should be the expected return.

5.5 Main Model Results: Factor Models

[Insert Table 6 here]

Table 6 shows, not surprisingly, the excess return on the market portfolio of stocks. RMRF captures a more common variation in stock returns than SMB, HML, and HVARL. As presented in Panel A of Table 6, the coefficients of RMRF are in the range of 0.78 to 1.17, and the t statistics are in the range of 8.77 to 19.46. The \bar{R}^2 values are extremely high, but the important fact is that the market leaves much variation in stock returns that might be explained by other factors. The only \bar{R}^2 value near 0.8 is related to the big-stock high-BE/ME portfolios. For small-stock and low-BE/ME portfolios, the \bar{R}^2 are less than 0.6 or 0.5, respectively. Panel B of Table 6 indicates that HVARL, even if used alone, captures substantial time-series variation in stock returns. The slopes on HVARL range from 0.45 to 1.38, and their t-statistics are in the range of 2.81 to 7.69. We should note that 20 of the 25 \bar{R}^2 values are above 0.20. Panel C of Table 6 shows that SMB, the mimicking return for the size factor, has less power than HVARL in terms of explaining stock returns.

The \bar{R}^2 values in Panel B are greater than those in Panel C. It should be noted that both HVARL and SMB have little power for the portfolios in the big-size quintile. Specifically, the \bar{R}^2 values for HVARL are in the range of 0.08 to 0.23, whereas the corresponding figures for SMB range from 0.00 to 0.11. As expected, on average, the slopes for SMB are related to size. In every BE/ME quintile in Panel C, the slopes for SMB decrease monotonically from smaller- to bigger-size quintiles. We can see an interesting result in that smaller-size quintiles seem to capture more variations in terms of \bar{R}^2 values. Panel D of Table 6 points out that for HML, when used alone, the slopes in relation to HML increase monotonically from the strong negative values for the smaller- to bigger-size quintiles. Not surprisingly, the slopes for HML are systematically related to BE/ME. The \bar{R}^2 values for the small-stock small-BE/ME portfolios capture more of the variations in stock returns and range from 0.22 to 0.38. This result accords with the intuition that the stocks with lower BE/ME ratios are less risky and so lower stock returns are required.



[Insert Table 7 here]

Table 7 shows two-factor models in which monthly returns on 25 portfolios are regressed on RMRF along with SMB, HML and HVARL. Panel A of Table 7 displays the slope coefficients for RMRF and HVARL, their t-statistics, \bar{R}^2 values and the standard error values of estimates (SEE). All of the slopes of RMRF are statistically significant at the 5% level. The \bar{R}^2 values are in the range of 0.50 to 0.78. Panel B of Table 7 presents very similar results for RMRF and SMB. The market β s for stocks are all significant according to the t-statistics. On average, 22 of the 25 slope coefficients for HVARL are statistically different from 0. The \bar{R}^2 values fall within the range of 0.66 to 0.85. Interestingly, SMB and HML, when used

along with RMRF, capture substantial time-series variation in stock returns. Panel C of Table 7 indicates that only 3 of the 25 coefficients for HML are statistically insignificant, and the \bar{R}^2 values range from 0.54 to 0.90. Similar to Table 6, the slope coefficients for SMB and HML are related to the size and BE/ME factors, respectively. In every BE/ME quintile, on average, the SMB slopes decrease monotonically from small- to big-size quintiles. For every size quintile for stocks, the HML slopes increase monotonically from strong negative values for the lowest-BE/ME quintile to strong positive values for the highest-BE/ME quintile.

[Insert Table 8 here]

Table 8 presents estimates from the three-factor model in which the excess returns on 25 portfolios are regressed on RMRF, SMB and HML. Table 8 demonstrates that most of the coefficients for the three Fama-French factors (RMRF, SMB and HML) are highly significant. The lower BE/ME quintile and bigger size quintile portfolios capture between 70% and 90% of the variations in terms of the \bar{R}^2 values. However, the higher BE/ME quintile and smaller size quintile seem to leave 30%-40% of variations that cannot be explained by Fama and French's three-factor model. Furthermore, the results indicate that, when controlling for the BE/ME effect, the SMB factor loading is highly significant. What is initially surprising, however, is the fact that SMB seems to work in a reverse manner than what would be expected, i.e. small firms have on average higher returns than big firms. This can be seen by looking at the coefficients for SMB, which go from positive to negative when moving from small stock portfolios to big stock portfolios and after taking into account the fact that the size premium is negative during our sample period. On the other hand, when controlling for size, the HML factor clearly captures the higher returns for the

high BE/ME portfolios as compared to the low BE/ME stocks. Subsequently, we will continue to see if another factor — the VaR — can enhance and capture the variations.

[Insert Table 9 here]

Table 9 presents the parameter estimates, t-statistics, \bar{R}^2 values, and standard errors of estimate (S.E.E) from the time series regressions of excess stock returns on RMRF, SMB, HML and HVARL. As shown in Table 9, the slope coefficients for the market factor, RMRF, are highly significant. Most of the slope coefficients for SMB and HML factor are also significant. A notable point is that, for the lowest size-quintile, none of HVARL slopes are significant. Only 8 of 25 HVARL slopes are significant. The \bar{R}^2 values of the four-factor model are greater than those of the three-factor model. When viewed at the portfolio level, these empirical results show that the VaR factor plays an important role in firms especially with larger capitalization. This could be the reason why either the concept of VaR is not very familiar to individual investors since they are the major participants in Taiwan's stock market or else larger companies always pay much attention to VaR in order to control for downside risk. However, the New Basle II Accord will be implemented at the end of 2006, and so we think VaR will play an increasingly important role in the future. Therefore, this could perhaps be tested and verified by further research.

6. Conclusions and Comments

By focusing on downside risk as an alternative measure of risk measured by VaR, this paper investigates whether the new VaR factor plays an important role in explaining Taiwan's stock returns from January 1996 to December 2004. The empirical results

do not support the central prediction of the CAPM because average stock returns are not positively related to the market beta at the portfolio level. From the cross-sectional regressions in a Fama and French (1992) asset pricing framework, we can find that, in addition to market betas, idiosyncratic factors, such as firm size, book value of equity to market value of equity, 1% VaR and 5% VaR, are related to the return at the individual stock level. In particular, the BE/ME factor captures most of the variations in average realized stock returns in terms of \bar{R}^2 . From the time series regressions we investigate models with factors ranging from one to four to test the empirical performance at the portfolio level. From the results, which are based on 25 size/book-to-market portfolios of Fama and French (1993) and follow Bali and Cakici (2004), we find that the HVARL factor can also help to explain the variation in the stock market, especially for the larger companies in Taiwan's stock market. One direction for future research could explore whether expected returns are related to a stock's sensitivities to fluctuations in other aspects of VaR. Another point is that since expected average returns seem to be explained by the four-factor risk return relationship, it would be interesting to analyze whether it is the time variation in expected premiums or the time variation in the factor sensitivities that capture most of the predicted variation in the expected returns.

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Table 1: Cross-Sectional Regressions of Stock Returns on Beta, Size, BE/ME, and VaR

This table reports the time-series average of the month-by-month regression slopes from January 1996 to December 2004. The dependent variables are the monthly average returns on individual stocks. The independent variables include beta, firm size, the book-to-market ratio (BE/ME), and VaR(α), where $\alpha=1\%$, 5% , and 10% . The betas that correspond to the portfolio they belong to are assigned to individual stocks. The size is the natural log of the market value. The BE/ME is the natural log of the book-to-market value. The VaR is calculated using the historical simulation method. The t-statistic reported in the parentheses is the average slope divided by its time-series standard error.

Monthly Regression (n=108)	Average value of ω_t	Average value of γ_t	Average value of R^2
$R_{j,t} = \omega_t + \gamma_t BETA_{j,t} + \varepsilon_{j,t}$	-0.7599 ^{***} (-10.94)	1.2601 ^{***} (16.2)	0.1284
$R_{j,t} = \omega_t + \gamma_t \ln(ME)_{j,t} + \varepsilon_{j,t}$	-3.9079 ^{***} (-26.13)	0.4868 ^{***} (34.81)	0.2517
$R_{j,t} = \omega_t + \gamma_t \ln(BE/ME)_{j,t} + \varepsilon_{j,t}$	-0.7979 ^{***} (-9.82)	0.9434 ^{***} (17.36)	0.4181
$R_{j,t} = \omega_t + \gamma_t VaR_{j,t}^{1\%} + \varepsilon_{j,t}$	0.1973 ^{***} (4.3)	0.0071 ^{**} (3.08)	0.0325
$R_{j,t} = \omega_t + \gamma_t VaR_{j,t}^{5\%} + \varepsilon_{j,t}$	0.1560 ^{**} (2.66)	0.0135 ^{**} (3.01)	0.0205
$R_{j,t} = \omega_t + \gamma_t VaR_{j,t}^{10\%} + \varepsilon_{j,t}$	0.4251 ^{***} (7.24)	-0.0020 (0.35)	0.0190

Note: ***, **, * denotes significantly different from zero at the 0.01, 0.05, and 0.10-levels, respectively.

Table 2: Time Series Regressions -- Simple Statistics

This table presents simple summary statistics for the stocks in the sample. The six size-PB portfolios (S/L, S/M, S/H, B/L, B/M, and B/H) are formed in December of each year t-1 and value-weighted monthly returns are calculated from January to December of year t. Panel A presents the basic statistics of the four factors. Panel B presents the Pearson correlation coefficients that are calculated based on monthly returns for each of the factors: RMRF, SMB, HML and HVARL. The sample period extends from January 1996 to December 2004, there being 108 monthly observations.

Panel A: Simple Statistics						
Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
RMRF	108	1.2801	9.0447	138.251	-20.345	24.2122
SMB	108	-0.6058	4.6631	-65.431	-14.162	10.5153
HML	108	3.0023	6.2115	324.246	-19.486	21.4384
HVARL	108	0.4437	5.6877	47.9199	-16.046	20.1611

Panel B Pearson Correlation Coefficients, N = 108				
Prob > r under H0: Rho=0				
	RMRF	SMB	HML	HVARL
RMRF	1			
SMB	-0.0624			
HML	-0.074	-0.5955*	1	
HVARL	0.5066*	0.336*	-0.2758*	1

Note: This table gives the correlation coefficients calculated from the sample. An asterisk indicates that the correlation coefficient is significant (i.e. the p-value is less than 0.05).

Table 3: Correlations of 25 Portfolio Returns with RMRF, SMB, HML and HVARL

Correlations	RMRF	SMB	HML	HVARL
S1B1	0.6720	0.5045	-0.5785	0.5319
S1B2	0.7308	0.4740	-0.5268	0.5445
S1B3	0.6921	0.5509	-0.5088	0.5662
S1B4	0.6485	0.4840	-0.5115	0.5005
S1B5	0.6949	0.4243	-0.3128	0.4982
S2B1	0.7486	0.4834	-0.5887	0.5985
S2B2	0.7446	0.4344	-0.5218	0.4912
S2B3	0.7574	0.4624	-0.4791	0.5669
S2B4	0.6924	0.4122	-0.4994	0.4480
S2B5	0.7434	0.3502	-0.1908	0.4613
S3B1	0.7485	0.4520	-0.6137	0.5626
S3B2	0.7982	0.4131	-0.5313	0.5376
S3B3	0.7321	0.3779	-0.4187	0.4742
S3B4	0.7650	0.3576	-0.3484	0.4452
S3B5	0.7701	0.2133	-0.1495	0.4589
S4B1	0.7634	0.3700	-0.6180	0.5845
S4B2	0.7711	0.3215	-0.5371	0.5410
S4B3	0.7913	0.3034	-0.4563	0.4607
S4B4	0.8079	0.2035	-0.3390	0.3994
S4B5	0.8115	0.0823	-0.0692	0.5459
S5B1	0.8282	0.1693	-0.4647	0.4519
S5B2	0.8526	0.0552	-0.2845	0.3205
S5B3	0.8288	0.0112	-0.2246	0.2636
S5B4	0.8602	-0.1077	-0.0284	0.2860
S5B5	0.8839	-0.3281	0.2362	0.4774
Average	0.7655	0.2990	-0.3826	0.4807

Note: S1B1 (S5B5) denotes a size-BE/ME portfolio that belongs to the smallest (largest) size quintile and lowest (highest) BE/ME quintile.

Table 4: Properties of Portfolios Formed on Size and Pre-ranking β : Stocks Sorted by Size (Down) then Pre-ranking β (Across), 1996-2004

At the end of year t-1, the stocks obtained from the TEJ are assigned to 5 size portfolios. Each size quintile is subdivided into 5 β portfolios using the pre-ranking β of individual stocks estimated with 60 monthly returns ending in December of year t-1. The equal-weighted monthly returns on the resulting 25 portfolios are then calculated for year t. The average returns are the time-series average of the monthly returns, in percent. The post-ranking β s use the full 1996-2004 sample of post-ranking returns for each portfolio. The pre- and post-ranking β s are the sum of the slopes from a regression of monthly returns for the current and prior month's value-weighted market return. The average size of a portfolio is the time-series average of each month's average value of $\ln(\text{Size})$ for stock within the portfolio. Size is dominated in millions of TWD. There are, on average, about 5 stocks in each size- β portfolio in each month.

	Low - β	2	3	4	High- β	Average
Panel A: Average Monthly Post-formation Returns (in percent)						
Small-size	1.0293	1.3052	0.6207	1.0251	2.5847	1.3130
2	0.4303	0.7127	1.2314	0.6835	1.2962	0.8708
3	0.8353	0.2684	0.2441	1.2928	1.1026	0.7486
4	0.4469	0.6885	0.0076	1.2041	0.6368	0.5968
Big-size	-0.1541	0.5779	1.0680	-0.2209	-0.1574	0.2227
Average	0.5175	0.7106	0.6344	0.7969	1.0926	
Panel B: Post-ranking β						
Small-size	0.7941	0.9160	0.9644	1.2843	1.4599	1.0837
2	0.8132	0.8710	1.0172	1.1230	1.1833	1.0015
3	0.8458	0.9948	1.0100	1.3498	1.3091	1.1019
4	0.8124	1.0384	1.0222	1.4002	1.2299	1.1006
Big-size	0.7715	0.8263	0.8643	1.0182	0.8916	0.8744
Average	0.8074	0.9293	0.9756	1.2351	1.2148	
Panel C: Average $\ln(\text{Size})$						
Small-size	7.1450	7.2802	7.2981	7.2590	7.4390	7.2842
2	7.9950	8.0069	8.0009	7.9556	8.0679	8.0053
3	8.5667	8.5161	8.5679	8.6229	8.5625	8.5672
4	9.1994	9.2539	9.2348	9.2685	9.2632	9.2440
Big-size	10.2412	10.7327	10.6171	10.4087	10.7113	10.5422
Average	8.6295	8.7579	8.7438	8.7030	8.8088	

Table 5: Properties of Portfolios Formed on VaR and Pre-ranking β : Stocks Sorted by VaR (Down) then Pre-ranking β (Across), 1996-2004

The formation of the VaR-beta portfolios is similar to that of the size- β portfolios. At the end of year $t-1$, stocks are sorted by their 5% VaR and assigned to 5 portfolios. Each VaR quintile is subdivided into 5 β portfolios using the pre-ranking β ending in December of year $t-1$. The equal-weighted monthly returns on the resulting 25 portfolios are then calculated for year t . The average returns are the time-series average of the monthly returns, in percent. The post-ranking β s use the full 1996-2004 sample of post-ranking returns for each portfolio. The pre- and post-ranking β s are the sum of the slopes from a regression of monthly returns on the current and prior month's value-weighted market return. The average 5% VaR of a portfolio is the time-series average of each month's average value of 5% VaR for stock in the portfolio. There are, on average, about 5 stocks in each VaR- β portfolio each month.

Panel A: Average Monthly Post-formation Returns (in percent)						
	Low - β	2	3	4	High- β	Average
Small-VaR	-0.1722	0.8005	0.9174	0.4467	0.7515	0.5488
2	0.5899	0.6460	0.9079	0.8104	0.1219	0.6152
3	0.9873	0.5480	0.7447	1.0340	0.2751	0.7178
4	0.6689	0.3862	1.5197	0.0331	0.6422	0.6500
Big-VaR	0.7067	1.2596	1.2077	1.2487	1.9213	1.2688
Average	0.5561	0.7280	1.0595	0.7146	0.7424	
Panel B: Post-ranking β						
Small-VaR	0.4900	0.7738	0.5932	0.8779	0.8600	0.7190
2	0.9007	0.9186	0.9306	0.8939	0.8637	0.9015
3	0.9327	0.9686	1.1463	1.1416	1.1855	1.0750
4	0.9866	0.9977	1.4168	1.0077	1.2284	1.1274
Big-VaR	1.1235	1.4283	1.3407	1.3202	1.5012	1.3428
Average	0.8867	1.0174	1.0855	1.0483	1.1278	
Panel C: Average VaR						
Small-VaR	13.6133	14.0500	14.0540	14.5902	14.9116	14.2438
2	16.7515	17.0488	16.7265	16.8485	16.7665	16.8284
3	18.9336	18.8091	18.7304	19.2716	19.5507	19.0591
4	20.9608	21.4593	22.0351	21.5672	21.8481	21.5741
Big-VaR	25.8988	25.6252	25.6738	25.8725	27.3475	26.0836
Average	19.2316	19.3985	19.4440	19.6300	20.0849	

Table 6: One-Factor Model: Regression of Excess Stock Returns on the Excess Stock-Market Return, HVARL, SMB and HML (January 1996 to December 2004, n=108)

The formation of the 25 size and BE/ME-sorted portfolios and the slope coefficients b , the t -statistics, \bar{R}^2 values, and the standard errors of estimate (S.E.E) are described in this table. The construction of the SMB (Small-Minus-Big) factor portfolio (R_{SMB}), the HML and HVARL (High-Minus-Low) factor portfolios, and the $RM(t)$ (market factor) portfolio is as follows. We first exclude from the sample all firms with book values of less than zero. We take all TSE stocks in the sample and rank them according to their size and BE/ME, using a 50 percent breakpoint for size. Firms above the 50 percent size breakpoint are designated as B, and the remaining 50 percent as S. The stocks above the 70 percent BE/ME breakpoint are designated as H, the middle 40 percent of firms are designated as M, and the firms below the 30 percent BE/ME breakpoint are designated as L. These two sets of rankings allow us to form the six value-weighted portfolios L/S, M/S, H/S, L/B, M/B, and H/B. From these six portfolio returns, we calculate the SMB and HML factor portfolio returns, which are defined as $SMB = (R_{HB} + R_{HS} - R_{LB} - R_{LS}) / 2$, and the HML factor portfolio returns, which are defined as $HML = (R_{HS} + R_{MS} + R_{LS} - R_{HB} - R_{MB} - R_{LB}) / 3$. The HVARL calculation is the same as that of the SML. The estimation model uses ordinary least squares (OLS).

Panel A: $R(t) - RF(t) = a + b \times [RM(t) - RF(t)] + u(t)$

		BE/ME Quintile										
Size Quintiles	Low	2	3	4	High	Low	2	3	4	High		
		Slope Coefficient (a)					t-statistic(a)					
Small	-4.1851	-2.2994	-1.5159	-1.4129	-0.0130	-3.9171	-2.8971	-1.8968	-1.7369	-0.0178		
2	-3.0201	-1.4946	-0.9216	-0.1979	2.0933	-3.7263	-1.9612	-1.3726	-0.2695	2.8481		
3	-2.6750	-1.7270	-0.6195	-0.2426	2.3138	-3.0486	-2.3604	-0.7499	-0.3336	3.0810		
4	-2.6597	-1.1091	0.1683	-0.4765	1.8310	-3.3412	-1.5192	0.2324	-0.7999	2.4531		
Big	-2.0606	-1.0047	0.3085	-0.3497	0.8765	-3.5353	-2.0161	0.5779	-0.7663	1.6166		
		Slope Coefficient (b)					t-statistic(b)					
Small	1.0977	0.9620	0.8676	0.7846	0.8001	9.3426	11.0219	9.8720	8.7709	9.9499		
2	1.0360	0.9623	0.8818	0.7977	0.9250	11.6231	11.4829	11.9419	9.8795	11.4444		
3	1.1214	1.0976	1.0051	0.9782	1.0266	11.6216	13.6407	11.0640	12.2297	12.4304		
4	1.0652	1.0008	1.0610	0.9247	1.1736	12.1682	12.4667	13.3263	14.1146	14.2975		
Big	0.9754	0.9205	0.8953	0.8716	1.1602	15.2168	16.7963	15.2482	17.3700	19.4592		
		\bar{R}^2					S.E.E					
Small	0.4474	0.5304	0.4750	0.4161	0.4790	120.839	66.6843	67.6122	70.0459	56.6047		
2	0.5569	0.5510	0.5703	0.4754	0.5493	69.5378	61.4784	47.7262	57.0728	57.1882		
3	0.5569	0.6343	0.5324	0.5820	0.5900	81.5043	56.6699	72.2352	55.9961	59.705		
4	0.5796	0.5914	0.6233	0.6500	0.6559	67.0823	56.4153	55.4844	37.5687	58.9743		
Big	0.6836	0.7248	0.6845	0.7380	0.7796	35.9635	26.2887	30.1744	22.0412	31.1176		

(Continued)

Panel B: $R(t) - RF(t) = a + b \times HVARL + u(t)$

	Slope Coefficient (a)					t-statistic(a)				
Small	-3.1918	-1.3674	-0.7304	-0.6801	0.7827	-2.9103	-1.4553	-0.8861	-0.7826	0.8998
2	-2.0724	-0.5463	-0.0877	0.5892	3.0404	-2.3820	-0.5820	-0.1126	0.6825	3.1919
3	-1.6366	-0.6521	0.3883	0.7403	3.3709	-1.6902	-0.6844	0.3774	0.7834	3.3158
4	-1.6688	-0.1444	1.2435	0.4912	3.0467	-1.8625	-0.1621	1.2560	0.5590	2.7871
Big	-1.0498	0.0266	1.3512	0.6735	2.1546	-1.1872	0.0300	1.4734	0.7808	2.0476
	Slope Coefficient (b)					t-statistic(b)				
Small	1.3816	1.1399	1.1288	0.9629	0.9123	6.4667	6.6839	7.073	5.9521	5.9165
2	1.3171	1.0095	1.0496	0.8208	0.9127	7.6908	5.8052	7.0856	5.159	5.3522
3	1.3403	1.1755	1.0353	0.9052	0.9727	7.0058	6.5635	5.5456	5.1185	5.317
4	1.297	1.1166	0.9822	0.727	1.2555	7.4164	6.6219	5.344	4.4859	6.7089
Big	0.8463	0.5503	0.4528	0.4608	0.9965	5.2158	3.4836	2.8136	3.0728	5.5939
	\bar{R}^2					S.E.E				
Small	0.2774	0.2911	0.3154	0.2448	0.2426	158.007	100.677	88.1646	90.6003	82.2953
2	0.3533	0.2354	0.3162	0.1946	0.2068	101.517	104.675	75.9589	87.6242	100.650
3	0.3113	0.2836	0.2190	0.1921	0.2045	126.692	111.025	120.651	108.251	115.841
4	0.3366	0.2872	0.2062	0.1532	0.2927	105.857	98.4182	116.937	90.9179	121.229
Big	0.1981	0.0959	0.0624	0.0748	0.2220	91.1343	86.3676	89.6643	77.8451	109.850

Panel C: $R(t) - RF(t) = a + b \times SMB + u(t)$

	Slope Coefficient (a)					t-statistic(a)				
Small	-1.8114	-0.3346	0.4063	0.2796	1.5852	-3.9171	-2.8971	-1.8968	-1.7369	-0.0178
2	-0.9078	0.3971	0.8398	1.3813	3.7896	-3.7263	-1.9612	-1.3726	-0.2695	2.8481
3	-0.4437	0.3456	1.2768	1.5468	3.9622	-3.0486	-2.3604	-0.7499	-0.3336	3.0810
4	-0.6895	0.6625	2.0044	0.9808	3.4731	-3.3412	-1.5192	0.2324	-0.7999	2.4531
Big	-0.5777	0.2437	1.4688	0.6379	1.8557	-3.5353	-2.0161	0.5779	-0.7663	1.6166
	Slope Coefficient (b)					t-statistic(b)				
Small	1.5985	1.2104	1.3396	1.1358	0.9475	6.0163	5.5429	6.7965	5.6943	4.8237
2	1.2976	1.089	1.0442	0.9211	0.8452	5.6852	4.9654	5.3688	4.6576	3.8495
3	1.3136	1.1019	1.0063	0.8869	0.5516	5.2173	4.6706	4.2020	3.9423	2.2482
4	1.0013	0.8095	0.7889	0.4517	0.2309	4.1000	3.4960	3.2779	2.1395	0.8503
Big	0.3867	0.1156	0.0236	-0.2117	-0.8353	1.7683	0.5693	0.1158	-1.1155	-3.5755

(Continued)

	\bar{R}^2					S.E.E				
Small	0.2488	0.2188	0.2982	0.2284	0.1737	164.255	110.950	90.3864	92.5655	89.7672
2	0.2279	0.1825	0.2078	0.1636	0.1159	121.206	111.925	88.0048	91.0021	112.170
3	0.1982	0.1644	0.1363	0.1212	0.0382	147.482	129.496	133.429	117.743	140.058
4	0.1303	0.0966	0.0851	0.0341	-0.0008	138.778	124.748	134.780	103.700	171.534
Big	0.0213	-0.0046	-0.0075	0.0041	0.1008	111.242	95.9618	96.3487	83.7954	126.965

Panel D: $R(t) - RF(t) = a + b \times HML + u(t)$

	Slope Coefficient (a)					t-statistic(a)				
Small	1.3514	1.9636	2.3829	2.2969	2.5858	1.0434	1.8052	2.2714	2.2728	2.4325
2	1.8681	2.6855	2.6459	3.3389	4.3155	1.7179	2.5055	2.6635	3.4411	3.6347
3	2.7798	2.8721	3.1804	2.9572	4.4990	2.4175	2.5364	2.6242	2.5383	3.5115
4	2.4736	3.2201	4.2007	2.4035	3.7709	2.3196	3.0255	3.6221	2.2963	2.6889
Big	1.5803	1.5166	2.5152	0.8920	1.0064	1.5590	1.5074	2.4581	0.9060	0.8117
	Slope Coefficient (b)					t-statistic(b)				
Small	-1.3760	-1.0097	-0.9287	-0.9011	-0.5245	-7.3022	-6.3802	-6.0842	-6.1284	-3.391
2	-1.1865	-0.982	-0.8123	-0.8379	-0.3457	-7.499	-6.2968	-5.6201	-5.9352	-2.0014
3	-1.3388	-1.0639	-0.8371	-0.6487	-0.2901	-8.0021	-6.4574	-4.7475	-3.8272	-1.5564
4	-1.2556	-1.0152	-0.8907	-0.5650	-0.1458	-8.0927	-6.5561	-5.2789	-3.71	-0.7145
Big	-0.7968	-0.4473	-0.3533	-0.0419	0.4514	-5.4029	-3.0558	-2.3729	-0.2927	2.5023
	\bar{R}^2					S.E.E				
Small	0.3296	0.2720	0.2531	0.2560	0.0910	146.598	103.400	96.185	89.2556	98.7588
2	0.3416	0.2666	0.2237	0.2437	0.0290	103.340	100.399	86.2387	82.2813	123.195
3	0.3718	0.2768	0.1690	0.1147	0.0148	115.551	112.063	128.362	118.616	143.458
4	0.3772	0.2831	0.2022	0.1081	-0.0028	99.3824	98.9915	117.541	95.7451	171.877
Big	0.2099	0.0740	0.0432	-0.0068	0.0486	89.7947	88.4625	91.5003	84.7106	134.342

Table 7: Two-Factor Model: Regression of Excess Stock Returns on the Excess Stock-Market Return and HVARL/ SMB / HML (January 1996 to December 2004, n=108)

Panel A: $R(t) - RF(t) = a + b \times [RM(t) - RF(t)] + c \times HVARL + u(t)$

Size Quintiles	BE/ME Quintile									
	Low	2	3	4	High	Low	2	3	4	High
	Slope Coefficient (a)					t-statistic(a)				
Small	-4.0373	-2.2140	-1.3993	-1.3235	0.0433	-4.3214	-3.0052	-2.0392	-1.7591	0.0612
2	-2.8880	-1.4206	-0.8287	-0.1373	2.1390	-4.3560	-1.9767	-1.4116	-0.1947	2.9689
3	-2.5410	-1.6378	-0.5547	-0.1811	2.3601	-3.4346	-2.4726	-0.6958	-0.2598	3.2050
4	-2.5357	-1.0166	0.2285	-0.4460	1.8787	-3.8110	-1.5526	0.3287	-0.7575	2.5717
Big	-2.0212	-1.0230	0.2623	-0.4005	0.8690	-3.5547	-2.0603	0.5138	-0.9512	1.5965
	Slope Coefficient (b)					t-statistic(b)				
Small	0.7738	0.7748	0.6122	0.5889	0.6768	6.6218	8.4082	7.1326	6.2570	7.6551
2	0.7465	0.8003	0.6781	0.6650	0.8251	9.0010	8.9020	9.2354	7.5367	9.1552
3	0.8278	0.9022	0.8632	0.8433	0.9251	8.9450	10.8883	8.6559	9.6727	10.0435
4	0.7934	0.7983	0.9290	0.8578	1.0691	9.5333	9.7468	10.6871	11.6485	11.6997
Big	0.8890	0.9607	0.9966	0.9829	1.1767	12.5000	15.4673	15.6104	18.6656	17.2832
	Slope Coefficient (c)					t-statistic(c)				
Small	1.1127	0.6431	0.8775	0.6726	0.4238	5.8080	4.2567	6.2360	4.3592	2.9243
2	0.9947	0.5569	0.6998	0.4561	0.3435	7.3165	3.7787	5.8131	3.1533	2.3249
3	1.0088	0.6714	0.4876	0.4634	0.3486	6.6492	4.9426	2.9828	3.2420	2.3085
4	0.9339	0.6958	0.4533	0.2299	0.3589	6.8445	5.1818	3.1808	1.9041	2.3960
Big	0.2966	-0.1382	-0.3483	-0.3824	-0.0566	2.5436	-1.3575	-3.3275	-4.4298	-0.5071
	\bar{R}^2					S.E.E				
Small	0.5785	0.5965	0.6140	0.5018	0.5145	92.3287	57.4119	49.8089	59.8769	52.8405
2	0.7043	0.6017	0.6725	0.5171	0.5680	46.4958	54.6343	36.4502	52.6321	54.9064
3	0.6858	0.7010	0.5656	0.6172	0.6068	57.9004	46.4115	67.2269	51.3857	57.3623
4	0.7071	0.6721	0.6538	0.6591	0.6712	46.8280	45.3543	51.0901	36.6607	56.4495
Big	0.6996	0.7275	0.7124	0.7776	0.7785	34.1988	26.0814	27.5561	18.7475	31.3372

(Continued)

Panel B: $R(t) - RF(t) = a + b \times [RM(t) - R(t)] + c \times SMB + u(t)$

	Slope Coefficient (a)					t-statistic(a)				
Small	-3.2036	-1.5472	-0.6970	-0.7152	0.5790	-4.4004	-2.9786	-1.5238	-1.2007	1.0313
2	-2.2135	-0.8112	-0.2692	0.3790	2.6359	-4.5082	-1.5196	-0.6356	0.6583	4.4057
3	-1.8535	-1.0271	0.0199	0.3272	2.6970	-3.1752	-2.1738	0.0304	0.5728	3.8916
4	-2.0190	-0.5815	0.6883	-0.1570	2.0424	-3.2897	-0.9676	1.1513	-0.2887	2.7770
Big	-1.7744	-0.8760	0.3833	-0.4098	0.4826	-3.2746	-1.7756	0.7140	-0.8925	1.0842
	Slope Coefficient (b)					t-statistic(b)				
Small	1.1536	1.0049	0.9143	0.8244	0.8339	14.4857	17.6842	18.2722	12.6521	13.5788
2	1.0819	1.0013	0.919	0.8306	0.956	20.1443	17.1464	19.8362	13.1904	14.6061
3	1.1682	1.1374	1.0415	1.0106	1.0484	18.2951	22.007	14.5593	16.1726	13.8297
4	1.1017	1.0309	1.0906	0.9429	1.1856	16.4103	15.6812	16.6768	15.8493	14.736
Big	0.9917	0.9278	0.8995	0.8682	1.1378	16.7291	17.1929	15.3163	17.284	23.365
	Slope Coefficient (c)					t-statistic(c)				
Small	1.7382	1.3321	1.4503	1.2356	1.0485	11.2525	12.0859	14.943	9.7769	8.8022
2	1.4286	1.2103	1.1554	1.0217	0.961	13.7131	10.685	12.8581	8.3647	7.5697
3	1.455	1.2396	1.1324	1.0092	0.6785	11.7474	12.3649	8.1609	8.3262	4.6144
4	1.1347	0.9343	0.921	0.5658	0.3744	8.7137	7.3272	7.2605	4.9036	2.3993
Big	0.5067	0.228	0.1325	-0.1066	-0.6975	4.4071	2.1778	1.1628	-1.0939	-7.3847
	\bar{R}^2					S.E				
Small	0.7476	0.8021	0.8308	0.6920	0.6979	55.3022	28.1537	21.8308	37.0156	32.8812
2	0.8401	0.7832	0.8319	0.6828	0.7061	25.1527	29.7337	18.7141	34.5761	37.3502
3	0.8071	0.8499	0.7116	0.7464	0.6565	35.5532	23.2928	44.6206	34.0489	50.1116
4	0.7542	0.7276	0.7474	0.7131	0.6713	39.3014	37.6841	37.291	30.8596	56.4416
Big	0.7309	0.7347	0.6860	0.7389	0.8539	30.6386	25.3921	30.0745	22.0004	20.6756

(Continued)

Panel C: $R(t) - RF(t) = a + b \times [RM(t) - R(t)] + c \times HML + u(t)$

	Slope Coefficient (a)					t-statistic(a)				
Small	-0.3058	0.4952	1.0601	1.1057	1.3387	-0.3661	0.7741	1.5341	1.5324	1.7553
2	0.2949	1.2142	1.2906	2.1213	2.8523	0.5496	1.9947	2.2577	3.2973	3.5390
3	1.0813	1.1896	1.6284	1.4332	2.8675	2.0529	2.3487	2.0859	1.9751	3.4458
4	0.8589	1.6895	2.5629	0.9588	1.8907	1.9658	3.1568	4.1701	1.6331	2.2619
Big	0.0729	0.0691	1.1006	-0.5100	-0.9013	0.1615	0.1367	1.9248	-1.0003	-1.9457
	Slope Coefficient (b)					t-statistic(b)				
Small	1.0334	0.9157	0.825	0.7429	0.7777	12.5058	14.4703	12.0682	10.4078	10.3087
2	0.9811	0.9175	0.8451	0.7593	0.9125	18.4826	15.2356	14.9446	11.9309	11.4445
3	1.0592	1.0492	0.9678	0.9504	1.0174	20.3272	20.9407	12.5321	13.2397	12.3588
4	1.0069	0.9545	1.0213	0.9009	1.1726	23.2953	18.0279	16.7982	15.5119	14.1807
Big	0.94	0.9027	0.8821	0.8743	1.1897	21.0332	18.0604	15.595	17.3347	25.9623
	Slope Coefficient (c)					t-statistic(c)				
Small	-1.2647	-0.9111	-0.8398	-0.8211	-0.4407	-10.51	-9.8872	-8.4372	-7.9	-4.0114
2	-1.0808	-0.8831	-0.7212	-0.7561	-0.2474	-13.983	-10.071	-8.7585	-8.1588	-2.1312
3	-1.2247	-0.9509	-0.7329	-0.5463	-0.1805	-16.14	-13.033	-6.5168	-5.2268	-1.5058
4	-1.1471	-0.9124	-0.7807	-0.4679	-0.0195	-18.226	-11.835	-8.8185	-5.5331	-0.1616
Big	-0.6956	-0.3501	-0.2582	0.0523	0.5796	-10.688	-4.8099	-3.1351	0.7116	8.6861
	\bar{R}^2					S.E.E				
Small	0.72859	0.75499	0.68472	0.63101	0.5447	59.4476	34.8623	40.678	44.3513	49.55
2	0.84404	0.76981	0.74981	0.6765	0.5646	24.5274	31.568	27.8408	35.2616	55.339
3	0.87176	0.85927	0.66452	0.66584	0.59557	23.6367	21.8555	51.9222	44.858	58.9995
4	0.89826	0.82363	0.782	0.72696	0.65335	16.2653	24.4024	32.1798	29.3645	59.5211
Big	0.84729	0.77276	0.7093	0.73732	0.87074	17.3882	21.7474	27.8544	22.1443	18.2792

Table 8: Three-Factor Model: Regression of Excess Stock Returns on the Excess Stock-Market Return, SMB, and HML (January 1996 to December 2004, n=108)

Panel A: $R(t) - RF(t) = a + b \times [RM(t) - RF(t)] + c \times SMB + d \times HML + u(t)$										
BE/ME Quintile										
Size Quintiles	Low	2	3	4	High	Low	2	3	4	High
Slope Coefficient (a)						t-statistic(a)				
Small	-1.2431	-0.2835	0.0541	0.3584	0.4384	-1.7428	-0.5406	0.1096	0.5637	0.6896
2	-0.4324	0.5643	0.5434	1.5836	1.8644	-1.0566	1.0639	1.2125	2.6366	2.8322
3	0.4694	0.5721	0.9231	0.6936	2.1760	1.0606	1.3787	1.2889	1.0788	2.7975
4	0.5814	1.4275	2.1814	0.7122	1.4257	1.3676	2.6830	3.6391	1.2104	1.7314
Big	0.1396	0.1377	1.1975	-0.4262	-0.6001	0.3025	0.2667	2.0516	-0.8188	-1.3350
Slope Coefficient (b)						t-statistic(b)				
Small	1.0962	0.9678	0.8923	0.7929	0.8380	15.6973	18.8463	18.4660	12.7380	13.4644
2	1.0297	0.9610	0.8952	0.7953	0.9786	25.6974	18.5043	20.3999	13.5244	15.1839
3	1.1001	1.0906	1.0150	0.9999	1.0637	25.3901	26.8443	14.4753	15.8851	13.9678
4	1.0255	0.9720	1.0469	0.9174	1.2037	24.6380	18.6593	17.8380	15.9257	14.9298
Big	0.9356	0.8981	0.8757	0.8687	1.1695	20.7034	17.7639	15.3233	17.0451	26.5736
Slope Coefficient (c)						t-statistic(c)				
Small	1.1364	0.9442	1.2197	0.9061	1.0916	6.7589	7.6361	10.4841	6.0455	7.2846
2	0.8819	0.7880	0.9060	0.6519	1.1978	9.1406	6.3024	8.5752	4.6042	7.7191
3	0.7420	0.7487	0.8551	0.8968	0.8384	7.1119	7.6545	5.0648	5.9170	4.5726
4	0.3365	0.3176	0.4627	0.2990	0.5637	3.3575	2.5325	3.2743	2.1560	2.9040
Big	-0.0808	-0.0832	-0.1175	-0.1016	-0.3651	-0.7428	-0.6835	-0.8536	-0.8277	-3.4458
Slope Coefficient (d)						t-statistic(d)				
Small	-0.7499	-0.4834	-0.2873	-0.4107	0.0538	-5.9367	-5.2035	-3.2869	-3.6471	0.4777
2	-0.6813	-0.5262	-0.3108	-0.4608	0.2951	-9.3986	-5.6008	-3.9160	-4.3319	2.5316
3	-0.8886	-0.6117	-0.3455	-0.1401	0.1993	-11.3363	-8.3237	-2.7238	-1.2307	1.4465
4	-0.9947	-0.7685	-0.5711	-0.3325	0.2359	-13.2110	-8.1553	-5.3798	-3.1906	1.6175
Big	-0.7322	-0.3877	-0.3114	0.0063	0.4142	-8.9568	-4.2397	-3.0127	0.0679	5.2024
\bar{R}^2						S.E				
Small	0.8114	0.8430	0.8467	0.7270	0.6985	41.7016	22.5528	19.9666	33.1337	33.1247
2	0.9135	0.8335	0.8535	0.7312	0.7232	13.7316	23.0631	16.4661	29.5727	35.5204
3	0.9137	0.9099	0.7308	0.7500	0.6633	16.0555	14.1141	42.0498	33.8829	49.5956
4	0.9082	0.8339	0.8023	0.7386	0.6793	14.8157	23.2060	29.4529	28.3786	55.5860
Big	0.8481	0.7738	0.7113	0.7390	0.8840	17.4627	21.8583	27.9265	22.2109	16.5639

Table 9: Four-Factor Model: Regression of Excess Stock Returns on the Excess Stock-Market Return, SMB, HML, and HVARL (January 1996 to December 2004, n=108)

Panel A:

$$R(t) - RF(t) = a + b \times [RM(t) - RF(t)] + c \times SMB + d \times HML + e \times HVARL + u(t)$$

Size Quintiles	BE/ME Quintile									
	Low	2	3	4	High	Low	2	3	4	High
	Slope Coefficient (a)					t-statistic(a)				
Small	-1.2804	-0.1465	0.0281	0.4176	0.5671	-1.7750	-0.2822	0.0563	0.6507	0.8933
2	-0.5232	0.7215	0.5312	1.7299	1.9928	-1.2835	1.3837	1.1713	2.9017	3.0285
3	0.4022	0.6564	1.0819	0.7923	2.1788	0.9046	1.5843	1.5168	1.2269	2.7672
4	0.4391	1.3661	2.2951	0.8208	1.2736	1.0596	2.5475	3.8276	1.3937	1.5451
Big	0.2090	0.4032	1.5860	-0.1560	-0.9247	0.4507	0.8476	3.1810	-0.3260	-2.4988
	Slope Coefficient (b)					t-statistic(b)				
Small	1.0754	1.0440	0.8778	0.8258	0.9095	12.6257	17.0331	14.8941	10.8969	12.1325
2	0.9793	1.0482	0.8884	0.8765	1.0499	20.3462	17.0258	16.5872	12.4511	13.5120
3	1.0628	1.1374	1.1032	1.0547	1.0653	20.2436	23.2467	13.0975	13.8315	11.4576
4	0.9465	0.9379	1.1100	0.9777	1.1192	19.3430	14.8114	15.6773	14.0590	11.4989
Big	0.9741	1.0455	1.0914	1.0187	0.9893	17.7875	18.6122	18.5377	18.0263	22.6405
	Slope Coefficient (c)					t-statistic(c)				
Small	1.1017	1.0715	1.1956	0.9610	1.2112	5.8859	7.9553	9.2310	5.7709	7.3523
2	0.7977	0.9340	0.8947	0.7877	1.3171	7.5409	6.9032	7.6016	5.0918	7.7135
3	0.6796	0.8271	1.0026	0.9885	0.8410	5.8900	7.6921	5.4163	5.8987	4.1163
4	0.2043	0.2606	0.5683	0.3999	0.4225	1.9001	1.8725	3.6525	2.6167	1.9751
Big	-0.0164	0.1633	0.2433	0.1493	-0.6665	-0.1362	1.3231	1.8807	1.2024	-6.9413
	Slope Coefficient (d)					t-statistic(d)				
Small	-0.7412	-0.5156	-0.2812	-0.4246	0.0235	-5.7695	-5.5781	-3.1634	-3.7150	0.2080
2	-0.6600	-0.5631	-0.3080	-0.4952	0.2649	-9.0909	-6.0643	-3.8128	-4.6640	2.2609
3	-0.8728	-0.6315	-0.3828	-0.1633	0.1986	-11.0223	-8.5584	-3.0136	-1.4203	1.4165
4	-0.9613	-0.7541	-0.5979	-0.3580	0.2717	-13.0260	-7.8959	-5.5988	-3.4134	1.8506
Big	-0.7485	-0.4502	-0.4028	-0.0572	0.4905	-9.0624	-5.3134	-4.5358	-0.6717	7.4425

(Continued)

	Slope Coefficient (e)					t-statistic(e)				
Small	0.0689	-0.2531	0.0480	-0.1093	-0.2378	0.4285	-2.1868	0.4313	-0.7638	-1.6795
2	0.1675	-0.2902	0.0225	-0.2700	-0.2372	1.8431	-2.4958	0.2222	-2.0312	-1.6166
3	0.1241	-0.1558	-0.2932	-0.1824	-0.0051	1.2517	-1.6858	-1.8432	-1.2664	-0.0292
4	0.2628	0.1135	-0.2101	-0.2006	0.2809	2.8443	0.9490	-1.5710	-1.5274	1.5282
Big	-0.1281	-0.4902	-0.7174	-0.4989	0.5993	-1.2389	-4.6210	-6.4524	-4.6746	7.2625
	\bar{R}^2					S.E.E				
Small	0.8103	0.8488	0.8458	0.7264	0.7043	42.0315	21.7615	20.1241	33.2670	32.5548
2	0.9156	0.8417	0.8524	0.7396	0.7280	13.4222	21.9590	16.6180	28.7097	34.9778
3	0.9143	0.9117	0.7374	0.7519	0.6607	15.9685	13.8685	41.1023	33.6873	50.0767
4	0.9142	0.8340	0.8055	0.7425	0.6840	13.8701	23.2281	29.0430	28.0194	54.8814
Big	0.8492	0.8112	0.7928	0.7830	0.9227	17.3734	18.2806	20.0809	18.5015	11.0607



Figure 1: The Industry Distributions of the Total Sample (N=133)

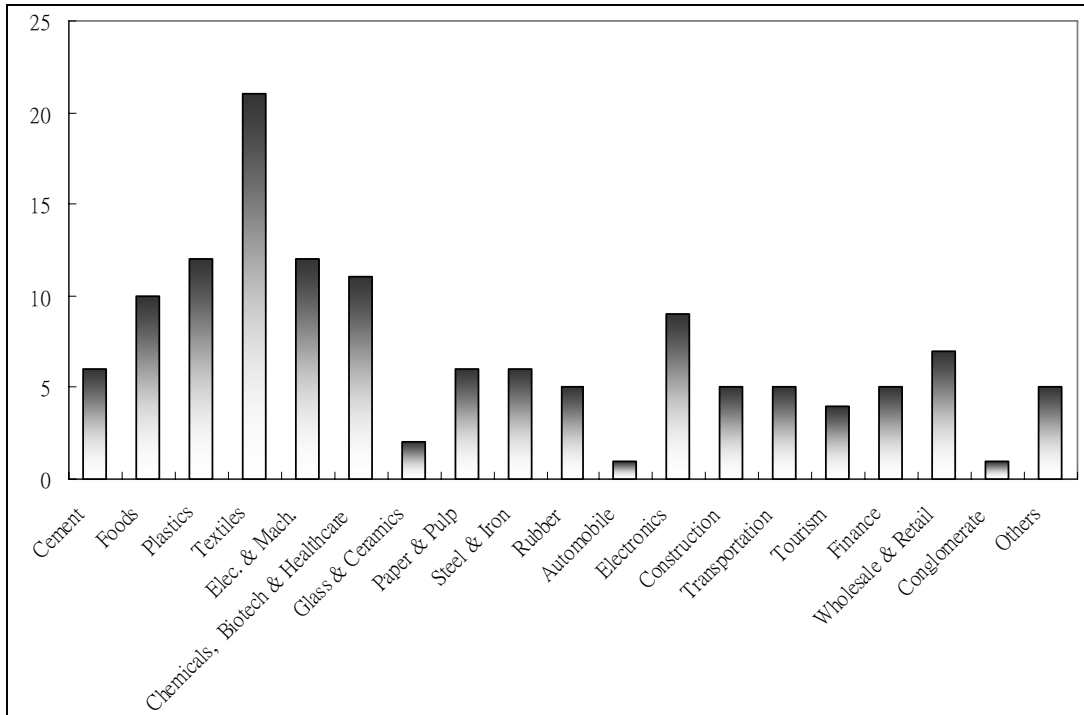


Figure 2: Average Return of the Portfolios Sorted on 1% VaR (January 1996 to December 2004)

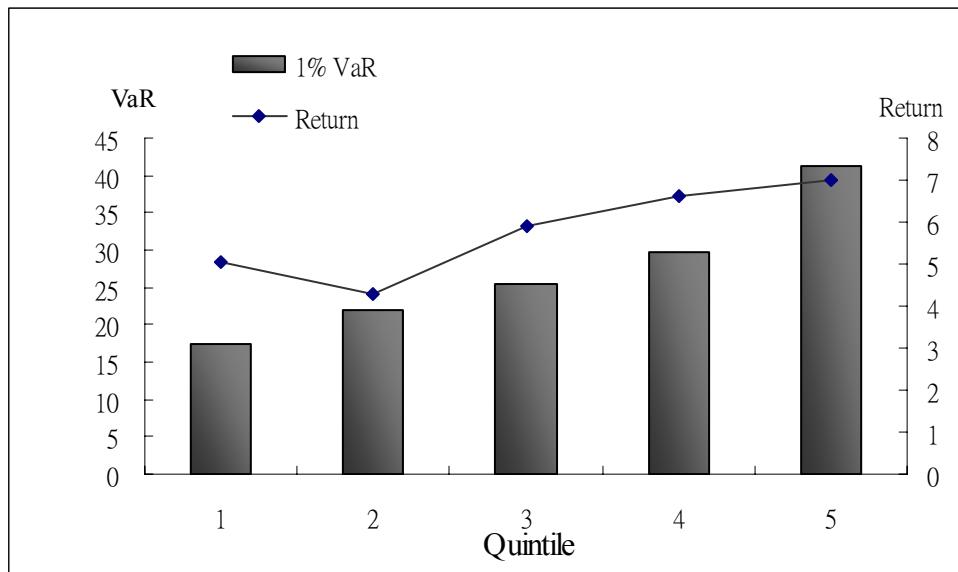


Figure 3: Average Return of the Portfolios Sorted on 5% VaR (January 1996 to December 2004)

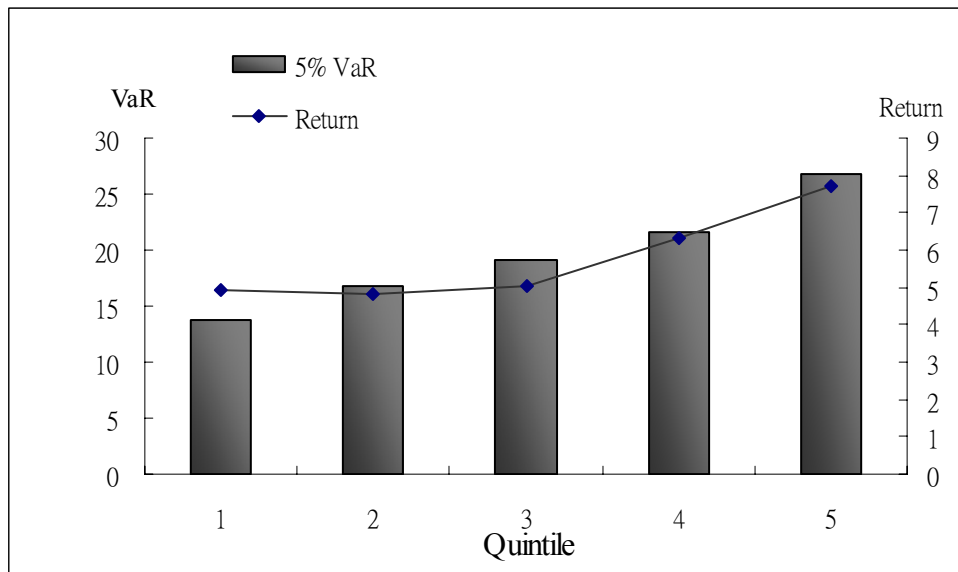


Figure 4: Average Return of the Portfolios Sorted on 10% VaR (January 1996 to December 2004)

