An Examination of Conditional Effect on Cross-Sectional Returns: Singapore Evidence

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Abstract

This paper examines the application of conditional effect across up and down markets based on the sign of market excess return to market beta and to some firm-specific factors of firm size, book-to-market equity ratio (B/M), and earnings-to-price ratio (E/P). Consistent with previous studies, though beta plays no role under unconditional framework, there is evidence of a significantly positive (negative) risk premium on beta during periods of up (down) markets, supporting for the continuous use of beta as a risk measure. Interestingly, our results show that firm size is the only significant variable in explaining average returns but loses its capability to do so under the unconditional and conditional frameworks respectively. Moreover, significant conditional effect of E/P is found. Although B/M alone is not significantly conditionally related to returns, in various combinations with beta, it becomes significant and the joint role of beta and B/M has an "amplified" gain in the explanatory power. We also find evidence that investors in the Singapore stock market react virtually the same to these firm-specific factors and to beta during up and down markets.

***JEL Classification**: G12; G15*

***Keywords:** Beta; firm size; book-to-market equity ratio; earnings-to-price ratio; up and down markets*

1. Introduction

The trade-off between risk and return is the most fundamental tenet in the financial theory and practice. Markowitz (1959) laid the groundwork for the quantification of such risk-return relationship. He formalized the principles of portfolio selection by mean-variance analysis, i.e. investors would optimally hold a mean-variance efficient portfolio. Thereafter, the mean-variance analysis with various modifications and additions has been made for the theoretically correct method of capital asset pricing.

First proposed by Sharpe (1964) and subsequently completed by Lintner (1965) and Black (1972), the capital asset pricing model (hereafter the SLB model) has long been widely used for valuing risky assets and as a benchmark for performance evaluation. The SLB model states that (a) expected return on a risky asset is positively related to its systematic risk or market beta, and (b) no variable other than market beta can explain the cross-sectional variation of expected returns.

Since then, a large body of research has been devoted to evaluate the reliability of the SLB model in a real world setting and a majority of the initial empirical tests seems to support (or better to say not to refute) the model (e.g., Black, Jensen, and Scholes, 1972; Blume and Friend, 1973; Fama and MacBeth, 1973). However, beginning in the late 1970s there has been a growing body of literature, which raises doubts as to the validity of the model. According to this literature, many firm-specific characteristics besides the market beta have been found to have significant explanatory power for stock returns, for example, earnings-to-price ratio (E/P) (e.g., Basu, 1977, 1983; Ball, 1978; Jaffe, Keim, and Westerfield, 1989), firm size (e.g., Banz, 1981; Reinganum, 1981, 1983; Jegadeesh, 1992; Herrera and Lockwood, 1994), and book-to-market equity ratio (B/M) (e.g., Rosembery, Reid, and Lanstein, 1985;

Chan, Hamao, and Lakonishok, 1991; Fama and French, 1992).[1] Since these non-beta variables are not consistent with the SLB model, they are widely considered as asset pricing anomalies.

In comprehensive tests over different time frames and with the inclusion of all major anomalous variables, Fama and French (1992) in their well-quoted study, reach two powerful conclusions. First, beta when used alone has little ability to explain the cross-section of average returns on the U.S. stocks between 1941 and 1990 and none between 1963 and 1990. They argue that beta is not positively related to returns; a result which violates the main prediction of the SLB model. Second, a model including firm size and B/M does well in explaining return variation. Not surprisingly, these conclusions are highly provocative and controversial, and a number of criticisms has come out to defend the market beta or the SLB model.

As argued by Pettengill, Sundaram, and Mahur (1995), however, one cannot use ex-post data to make inferences about ex-ante expectations and the relationship between beta and realized returns varies from the relationship between beta and expected return. After accounting for the fact that it is of non-zero probability that the risk-free return may be higher than the realized market return, Pettengill et al. propose a conditional version of the SLB model, in which a conditional relationship between beta and return should exist. During periods of "up" markets where the realized market return exceeds the risk-free return, there should be a positive relationship between beta and return; whereas during periods of "down" markets where the risk-free return exceeds the realized market return, an inverse relationship, that is, negative relationship, should be exhibited. Hence, according to Pettengill et al., the SLB model should be modified to account for the dependency of the beta-return relationship

[1] This paper does not include every anomaly found in the literature but the most important and well documented ones.

upon the sign of realized market excess return by introducing a dummy variable for up and down markets:

$$R_i = \gamma_0 + \gamma_{1\text{up}} \cdot \delta \cdot \beta_i + \gamma_{1\text{down}} \cdot (1 - \delta) \cdot \beta_i + \varepsilon_i \tag{1}$$

where R_i is the excess return on asset i over the risk-free rate, β_i is the measure of market (or systematic) risk on asset i, and ε_i is a random error term. $\gamma_{1\text{up}}$ and $\gamma_{1\text{down}}$ are the regression coefficient estimates of the conditional beta on positive and negative realized market excess returns respectively, and δ is a dummy variable which takes 1 and 0 for up (i.e. positive realized market excess return) and down (i.e. negative realized market excess return) markets respectively. By adding a dummy variable to identify the negative market risk premium in the cross-sectional regression, the market risk premium can be separated into positive and negative parts in order to recognize a systematic conditional relationship between beta and realized returns, if $\gamma_{1\text{up}}$ coefficient is significantly positive whereas $\gamma_{1\text{down}}$ coefficient is significantly negative. As pointed out by Pettengill et al., however, the existence of the conditional relationship does not guarantee a positive relationship between beta and return. Two conditions are necessary for such positive risk-return tradeoff. The beta effects in up and down markets should be symmetrical, that is, of equal magnitude but opposite signs ($\gamma_{1\text{up}} = -\gamma_{1\text{down}}$) and the realized market excess return should be positive on average.

Recognizing the problem of measuring expected returns with realized returns such that market may experience a significant number of periods when the realized market return is less than the risk-free rate, this paper further investigates the switching logic between up and down markets of Pettengill et al. At this point in the literature, limited studies have documented this switching logic in non-U.S. stock markets. Fletcher (1997) examines the conditional relationship between beta and return in the U.K. between 1975 and 1994 and finds significant conditional risk-return relationship. However this relationship is not symmetric across up and down markets due to the stronger relationship in down market. Lilti and Montagner (1998) test whether or not beta has been a determinant of realized stock returns in the French market using 43 stock over the period from 1990 to 1995. After taking account of the possibility of observing negative risk premiums, they find no relationship at all between beta and realized returns on the data.

For Asian stock markets, Hodoshima, Garza-Gómex, and Kunimura (2000) investigate the unconditional as well as conditional relationship between return and beta using monthly returns for stocks listed on the first section of the Tokyo Stock Exchange from 1952 to 1995. The relationship between beta and return in the Japanese stock market is found to become significantly conditional after taking into account the difference between positive and negative market excess returns. In addition, they report that the conditional relationship is in general better fit in the down market than in the up market in terms of the goodness of fit measures such as R^2 and the standard error of the regression equation. Lam (2001) examines the risk-return relationship in the Hong Kong stock market using daily returns of 132 continuously listed stocks from 1980 to 1995. The test results show that there is a strong relationship between beta and return during both up and down markets. However, the estimated risk premiums for the two markets are found to be not symmetric; the magnitude of the down market is much larger than that of the up market.

A more recent paper by Tang and Shum (2004) extends the idea of systematic conditional relationship to a number of statistical measures of stock characteristics in the Singapore stock market for the period from April 1986 to December 1998. Tang and Shum input the five statistical measures, namely, beta-squared, unsystematic risk, skewness, total risk, and kurtosis separately, in addition to market beta, into the conditional SLB model of Pettengill et al. (1995). The results show that, no matter whether being alone or in combination with any extra statistical measure of stock characteristics, beta is found to be significantly related to realized returns across up and down markets; however, the symmetry of the risk-return relation in up and down markets is weak. In combination with beta, only three of the five statistical measures are partially related to realized returns[2] and the remaining two statistical measures are even irrelevant in pricing returns[3].

In summary, the previous test results show that the relationship between beta and return is significantly positive in up markets, significantly negative in down markets, and non-existent in mixed markets. And the "down"-market effect is stronger than the "up"-market effect. The significant role of conditional beta in asset pricing, however, does not rule out the possibility that anomalous variables also exist conditionally. Hence, inspired by Tang and Shum (2004), this paper extends to include some firm-specific characteristics in addition to beta in investigating the conditional effect across up and down markets of Pettengill et al. (1995).

In the past 10 to 15 years, international investing has come up as a rapidly growing phenomenon. The surge in international capital flows has given energy to some markets especially those in Asia. With this growing relevance, theoretical and empirical research on these markets is important. With no ambition to test the validity of the SLB model (or CAPM) nor develop a new asset pricing model, the purpose of this study is to provide more empirical evidence on the relationship between returns and beta, firm size, book-to-market equity ratio, and earnings-to-price ratio for the stocks listed on the Stock Exchange of Singapore (SES), which is a relatively developed stock market in the Asia Pacific region where its current activities are considered comparable to markets such as those in Australia and Hong Kong. The selection of these explanatory variables is due to their popularity among researchers and practitioners. It is interesting to examine whether the concept of conditional effect on the basis of up and down markets can also be applied to these firm-specific variables in the

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[2] Three statistical measures, unsystematic risk, total risk, and kurtosis, are significantly, with expected signs, related to realized returns in up market only and they are found to be asymmetric during up and down markets.

[3] The remaining two statistical measures, beta-squared and skewness, are insignificantly related to realized returns in both up and down markets and also asymmetrical across up and down markets.

Singapore stock market. This paper can fill the gap and examine whether other risk factors besides beta are also determinants of the cross-sectional variation in realized returns if market is split into up and down periods.

The remainder of this paper is organized as follows. In the following section, we describe the data and discuss the methodology to be used in this study. Section 3 reports the main empirical results obtained under both unconditional and conditional markets. The final section concludes with a brief summary.

2. Data and Methodology

All of the data used in this study are collected from the Pacific-Basin Capital Markets (PACAP) Databases. Basically, the database can furnish all the relevant information on the Singapore stock market. The study period extends from January 1987 to December 1998. This 12-year period is selected for two reasons. As the latest data provided by PACAP are up to the year of 1998 only, more recent data are not available. Also, our preliminary analysis reveals that in the early years the database contains a lot of missing data. In order to insure that there is a sufficient number of stocks qualified in our analysis, years prior to 1987 are excluded as these years have less than 100 stocks used in the calculation of the proxies of market returns. The number of stocks in our initial sample ranges from the lowest of 100 (in February 1987) to the highest of 243 (in December 1998). Of course, the use of relatively short period is sometimes subject to the criticism that an "abnormal" period in the history of stock exchange might be selected. However, the analysis of longer period does not in any case answer the question of how risk factors and realized return are related under the conditional framework based on up and down markets. Rather, it depends on whether there is a substantial number of months of down market (i.e. negative market excess return) over the study period. In addition, one may believe that understanding the latest behavior of the stock returns would be more relevant to any investors in the drastic and continuously changing environment.

Monthly return data with appropriate adjustments for capital changes is used in our tests. Both equally weighted (EW) and value-weighted (VW) market returns with cash dividends reinvested of all stocks with non-missing returns and non-missing markets values for the previous month are employed to serve as a proxy for the market index. Owing to data unavailability, Chui and Wei (1998) use different return rates as the risk-free rate during their sample period; for example, they use overnight interbank offer rate during 07/1977–12/1978 period, 1-month fixed deposit rate during 01/1979-12/1982, and 1-month interbank offer rate during 01/1983-06/1993 for the Malaysia market. Similarly, due to discontinuity of the Singapore Interbank Offer Rate (SIBOR) as well as the 3-month Treasury bill rate over our whole sample period, the risk-free rate used in this study is the average savings deposits rate compiled from that quoted by ten leading banks on the last working day of the final week of the month.[4] Of the 96 monthly returns examined in the test period from January 1991 to December 1998, the EW market excess return takes 52 positive values and 44 negative values while the VW market excess return takes 54 positive values and 42 negative values. It shows that the market excess return is negative in substantial proportions of the sample. The two percentages of down markets for the EW and VW market proxies respectively are 45.83% and 43.75%, which are very close to 42.42%, 280 out of 660 months, of down markets that was used by Pettengill et al. (1995).

Firm size is measured by market capitalization or market value of equity. A firm's monthly market equity is in turn defined as the product of market price per share and the number of common shares outstanding at the end of that month. Book-to-market equity (B/M) is computed as the ratio between the book equity of a firm at fiscal year-end and the firm's

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[4] According to major similar studies, the empirical results are not materially affected by the choice of risk-free proxy.

market equity at the end of each of the following 12 months which lead the month of fiscal year-end by six to 18 months. Earnings-to-price ratio (E/P) is defined as the earning per share at fiscal year-end to the market price per share at the end of each of the following 12 months leading the fiscal year-end by six to 18 months. By using this matching method, the gap for all firms spreads between six and 18 months consistently. The shortest six-month gap is to make certain that the annual reports compiled by the listed firms are publicly available to all investors before the relevant accounting data (book value of equity and earnings) are used to explain the stock returns. And any gap longer than 18 months is certainly an unrealistic match. It is worth to note that these three firm-specific explanatory variables are updated monthly as stock price changes every month. If a variable, such as market equity, is kept as a constant throughout 12 months, there may be concern that this matching will potentially bias the statistical power of the related variables such as firm size, B/M, and E/P and therefore their explanatory role in the cross-section of returns may be either enhanced or diluted spuriously. Under these circumstances, we relate the most recent publicly available information to stock returns in this study.

We apply several criteria for the selection of sample stocks to be used in the test period. First, to be included during any month t in the test period, a stock should have valid monthly return in month t and have 48 valid consecutive monthly returns preceding month t. The first 24 returns are used for the estimation of betas of individual stocks while the following 24 returns for the estimation of portfolios betas. A stock does not need records throughout the study period, thus reducing problems associated with survivorship bias. Second, a stock should have valid accounting data in the last month of the portfolio formation period and also in month t. Any stock with financial statements covering not exactly 12 months is disregarded. Third, in line with previous international studies, all financial firms are excluded since they have unique regulatory characteristics and their accounting information may not have the same interpretation as those of non-financial firms. In addition, we only include stocks with positive book values and earnings. As a result, during the test period, the number of stocks which can satisfy the requirements is between 45 and 107.

Our analysis of the conditional relationship with realized returns is conducted at the portfolio level.[5] Portfolios are formed on the basis of the two explanatory variables, beta and firm size. To form portfolios, four sorting procedures are employed: a univariate sort by beta alone and three bivariate sorts by the two variables, consisting of (1) within-group sorting by beta and then size, (2) within-group sorting by size and then beta, and (3) independent-group sorting by beta and size simultaneously. For beta sorted portfolios, it is well-known that it is difficult to distinguish between the role of beta and size in average returns; statistical inferences lack power to separate size from beta effects in average returns when portfolios are sorted by beta alone. Bivariate sorting procedure is used to allow beta to vary in a way that is independent of size, so that beta and size effect can be disentangled. In fact, from Table 1, which reveals the correlations between realized excess return, *BETA* and other hypothesized explanatory variables of *SIZE*, *BM* and *EP* during the test period from January 1991 to December 1998 for portfolios formed by different sorting procedures and different market proxies, we can observe that the results support our bivariate analysis. In Panel A of using EW market return as market proxy, the correlation coefficients between *BETA* and *SIZE* have the negative sign which is consistent with major international findings. Also, the objective of diminishing the association between *BETA* and *SIZE* is met as their correlation coefficient of –0.3838 in the univariate sort is reduced by approximately half to –0.1730, –0.1929, and –0.1725 in the three aforementioned bivariate sorts respectively. This implies that it is of value to form portfolios by bivariate sorting procedures as they can reduce the moderate correlation between *BETA* and *SIZE* to low correlation. Except for the correlation coefficients

[5] The purposes of using portfolios instead of individual stocks are: (1) to reduce the errors-in-variables problem [see Blume (1970) for details] and (2) to mitigate the impact of large informational surprises [see Elton (1999) for details], in order to increase the stability of beta estimates.

between *BETA* and *SIZE*, the remaining coefficients are quite consistent in the four sorting procedures. Moreover, all correlation coefficients have the expected signs except for those between *BETA* and *EP*.

In Panel B of using VW market return as market proxy, there appear two puzzling results. First, the correlation between *BETA* and *SIZE* is low at –0.1496 even in the univariate sort. Although their correlation is also reduced by approximately one-third, the correlation coefficients have the unexpected positive sign in all bivariate sorts (+0.0948, +0.1055, and +0.0852). Second, the correlation coefficients between *BETA* and *BM* are all negative and opposite to those in Panel A of using EW market excess return as market proxy. Besides, their correlations are also much lower than those in Panel A. Except for these two puzzling results, the results are consistent in the four sorting procedures and with those in Panel A. Because of the points discussed above, portfolios formed by univariate sort are not studied here. Also, the analysis of bivariate independent-group sorted portfolios is not presented and discussed because of significant variation in the number of stocks in each of the portfolios and too few stocks in some portfolios. As a result, we report here only the results obtained from the analysis using the two bivariate within-group sorting procedures for comparison purpose.[6] On the other hand, caution should be exercised since the results in Table 1 show that the correlation coefficients between *BM* and *EP* range from 0.7257 to 0.7986, thus, indicating the presence of multicollinearity problem. The high intercorrelation between *BM* and *EP* may lead to incorrect conclusions about which of the two independent variables is statistically significant and which is not as it is very difficult to obtain reliable estimates of the separate effect.[7]

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[6] Indeed, upon testing portfolios formed by univariate sort and bivariate independent-group sort, the results using independent-group sort are of no material difference to those using the two within-group sorts, while those using univariate and bivariate sorts are quite similar and significantly different in some cases only.

[7] Fortunately, the estimates are still valid and multicollinearity causes no special problem for statistical inferences associated with the overall regression model.

Beginning with January 1987, the first 24 consecutive months are used for individual stock beta estimation. Using the time-series Ordinary Least Squares (OLS) regression, betas are estimated for each individual stock in the sample by regressing individual stock excess returns on the market excess returns. Then portfolio formation is done by using the two bivariate within-group sorting procedures. For the procedure of bivariate within-group sort by beta (primary) and then size (secondary), all stocks are sorted into three groups of approximately equal number of stocks according to their beta estimates from low to high. Each beta group is then divided into three subgroups of approximately equal number of stocks, on the basis of firm size at the end of the last month in the individual stock betas estimation period from small to large. Thus, a total of nine 3×3 beta-size sorted portfolios are formed and each stock receives the same weight in its portfolio.[8] For each of these portfolios formed in the first 24 consecutive months, portfolio beta estimation will be done by using the following 24 consecutive months. Lastly, monthly portfolio excess returns for the nine portfolios for every 49th month t are calculated. Dropping the earliest month and adding a new month, the whole process is repeated every month using the most recent 49 months from $t - 48$ to t. Hence, there are totally 96 months in the test period from January 1991 to December 1998 for analysis. For each month, the composition of beta-size sorted portfolios may change because betas and firm sizes may change.[9] The process matching monthly portfolio excess returns with betas and other firm-specific explanatory variables is conducted in each month of the test period. Similarly, the procedure of bivariate within-group sort by size (primary) and then beta (secondary) will first sort all stocks into three groups of approximately equal number of stocks based on their sizes, measured at the end of the last month in the individual stock betas estimation period, from small to large. Then, each size

[8] In deciding on the number of portfolios formed, we have to insure that there are sufficient stocks in each portfolio during the entire test period. The number of stocks in the tested sample is between 45 and 107 only. Therefore, this portfolio formation can enable us to avoid too few stocks in some portfolios.

[9] Klein and Bawa (1977) suggest that portfolios rebalanced monthly on the basis of firm size reduce estimation risk.

group is divided into three subgroups of approximately equal number of stocks, according to their beta estimates from low to high, resulting in a total of nine size-beta sorted portfolios. The following steps then remain the same as those for beta-size sorted portfolios.

The commonly used method of time-series *t*-test of monthly cross-sectional regressions is not used in this study. In fact, running monthly cross-sectional regressions based on portfolios may encounter the statistical problem of too small degrees of freedom.[10] There are only 10 portfolios in univariate sort (decile-sorting) and 9 portfolios in bivariate sort (3×3-sorting) and therefore the degrees of freedom are 8 and 7 for the two sorts respectively when there is only one explanatory variable and the degrees of freedom are even smaller when all four explanatory variables are simultaneously included in the multivariate regressions: 5 and 4 for the two sorts respectively. As a result, the coefficient estimates obtained from the monthly cross-sectional regressions may be unreliable. In order to solve this problem, another method of time-series pooling cross-sectional regression is employed in our analysis. Once the matching process is completed, we pool all 96 months' data together and the monthly portfolio excess returns are then regressed cross-sectionally with the hypothesized explanatory variables. That is, we run a single time-series pooling cross-sectional regression using all monthly portfolio excess returns in the test period simultaneously in order to get a set of regression coefficient estimates for the corresponding hypothesized explanatory variables. By using this statistical method based on portfolios, there are totally 960 observations (10 decile-portfolios × 96 months) for univariate sort and 864 observations (9 3×3-portfolios × 96 months) for bivariate sorts. Therefore, the degrees of freedom will not be

[10] One may suggest that running monthly cross-sectional regression based on individual stocks can solve the problem of too small degrees of freedom. However, using data in individual stocks instead of portfolios may encounter another statistical problem. Market beta is first computed on the basis of portfolio and then subsequently assigned to individual stocks within each portfolio. There is concern that this process may dilute the statistical power of beta. At the same time, assigning the precisely measured firm size and accounting data to individual stocks may enhance their role in capturing the cross-sectional variation in returns. Therefore, this study keeps the data in portfolios for analysis.

so small that the coefficient estimates obtained from the time-series pooling cross-sectional regressions will not be unreliable.

As the basic unit of analysis throughout this study is portfolio, the empirical model used for testing the unconditional relationship between returns and beta as well as other firm-specific explanatory variables is as follows:

$$R_{p,t} = \gamma_0 + \sum_{j=1}^{k} (\gamma_{j\,\text{full}} \cdot X_{j\,p,t-1}) + \varepsilon_p \tag{2a}$$

where $R_{p,t}$ is the excess return on portfolio p in month t, k is the number of hypothesized explanatory variables, $X_{j\,p,t-1}$ is the jth hypothesized explanatory variable of return on portfolio p in month $t-1$, $\gamma_{j\,\text{full}}$ is the regression coefficient estimate of the jth hypothesized explanatory variable without splitting the test period into two periods of up and down markets, and ε_p is the error term. To test the conditional effect on beta as well as the other explanatory variables based on the sign of the market excess return, the expanded model of Equation (1) is employed:

$$R_{p,t} = \gamma_0 + \sum_{j=1}^{k} [\gamma_{j\,\text{up}} \cdot \delta_t \cdot X_{j\,p,t-1} + \gamma_{j\,\text{down}} \cdot (1 - \delta_t) \cdot X_{j\,p,t-1}] + \varepsilon_p \tag{2b}$$

where δ_t is a dummy variable taking 1 and 0 for the periods of up and down markets respectively in month t. In this study, we include beta (*BETA*) as well as three firm-specific explanatory variables: firm size (*SIZE*), book-to-market equity (*BM*), and earnings-to-price (*EP*). The *SIZE* (in natural logarithm), *BM* (in natural logarithm), and *EP* are the averages of the associated variables of the stocks in the portfolio.

Using Equation (2b) to examine the conditional relationship with returns, the following hypotheses are formulated and tested:

Hypothesis		Null : H_o	Alternative : H_a
1	Intercept	$\gamma_0 = 0$	$\gamma_0 \neq 0$
2	$X_j = BETA$	$\gamma_{j\,\text{up, down}} = 0$	$\gamma_{j\,\text{up}} > 0$, $\gamma_{j\,\text{down}} < 0$
3	$X_j = SIZE$	$\gamma_{j\,\text{up, down}} = 0$	$\gamma_{j\,\text{up}} < 0$, $\gamma_{j\,\text{down}} > 0$

4	$X_j = BM$	$\gamma_{j\text{up},\text{down}} = 0$	$\gamma_{j\text{up}} > 0$, $\gamma_{j\text{down}} < 0$
5	$X_j = EP$	$\gamma_{j\text{up},\text{down}} = 0$	$\gamma_{j\text{up}} > 0$, $\gamma_{j\text{down}} < 0$
6	Symmetry with Opposite Signs for X_j = *BETA, SIZE, BM, & EP*	$\gamma_{j\text{up}} + \gamma_{j\text{down}} = 0$	$\gamma_{j\text{up}} + \gamma_{j\text{down}} \neq 0$
7	Average Market Excess Return	$\overline{r_m - r_f} = 0$	$\overline{r_m - r_f} > 0$

By inputting various combinations of the four hypothesized explanatory variables to Equation (2b), statistical inferences of explanatory variables and regression equations as well as comparisons of different conditional relationships with returns can be made. Main statistical inferences include the t test on the significance of the regression coefficients of every variable and the Wald test on the equality of every pair of regression coefficients ($\gamma_{j\text{up}}$ and $\gamma_{j\text{down}}$). In addition, the summary measure of adjusted coefficient of determination (or adjusted R^2), *adj.* R^2, is used to compare the goodness of fit (or the predictive power) across different regression models.

Running time-series pooling cross-sectional regressions, the OLS standard errors of the regression coefficient estimates may be underestimated due to the possible presence of autocorrelation in the portfolio returns. Thus, the usual OLS standard errors may be unreliable and should not be used for statistical inference. Indeed, the problem of autocorrelation does exist in our statistical results as the Durbin-Watson d-statistic values are all less than 1, which indicates that, as the rule of thumb, there is a strong positive correlation.[11] In order to adjust for the downward bias in the OLS standard errors, the heteroskedasticity- and autocorrelation-consistent (HAC) standard error, developed by Newey and West (1987), is employed. Using the HAC standard error instead of the OLS standard error in the presence of heteroskedasticity as well as autocorrelation of unknown form does not change the point estimates of the regression coefficients, but only the inferences of the significance of variables. However, HAC standard error is strictly speaking valid in large

[11] To save space, these Durbin-Watson results are not reported here but available from the authors upon request.

samples and may not be appropriate in small samples. Our samples of 864 observations are large enough.

Table 2 provides the summary statistics of the nine bivariate within-group sorted portfolios over the test period. The statistics include the average monthly portfolio excess returns in percentage, the average values of *BETA*, *SIZE* (in natural logarithm), *BM* (in natural logarithm), *EP*, and the average numbers of stocks in portfolios. In Panel A, it is observed that there are great dispersions in the monthly average excess returns of the nine portfolios. For example, in the first matrix of beta-size sorted portfolios using EW market proxy, the average return on the low-beta/small-size portfolios is 1.393% which is about 620 times of the average return of 0.002% on the low-beta/large-size portfolios. Even in the last matrix of size-beta sorted portfolios using VW market proxy, the average return on the small-size/high-beta portfolios is 1.419% which is about five times of the average return of 0.273% on the large-size/medium-beta portfolios. Within each size-group, average return appears to be independent of beta. This finding indicates that there may be no market beta effect on Singapore stocks. In nearly all beta-groups, average returns have a tendency to decrease with increasing size and small-size portfolios have a higher average return than the large-size ones. This preliminary finding suggests that a negative size effect may exist in Singapore stocks and is consistent with that found by Wong and Lye (1990).

In Panel B, post-ranking betas appear to be dependent of pre-ranking betas within each size-group. In each size-group, the post-ranking betas closely reproduce the order of the pre-ranking betas. Therefore, it is evidenced that the post-ranking beta estimates are informative about the order of the true betas. Similarly, in Panel C, it shows that there is a strong relationship between the post-ranking sizes and the pre-ranking sizes. In each beta-group, the post-ranking sizes closely follow the order of the pre-ranking sizes. In addition, as illustrated in Panels B and C, our bivariate within-group sorts provide fairly good separation of beta and size effects. Panel B shows that *BETAs* are reasonably stable across size-groups within beta-groups. Also, it is observed that, in Panel C, *SIZEs* are reasonably stable across beta-groups within size-groups. These indicate that our bivariate sorts can achieve their goal of distinguishing the role of beta and size in average returns by controlling either size or beta. Lastly, it is noted that, in Panel F, the average numbers of stocks in portfolios are not necessarily whole numbers as the numbers of stocks in portfolios change every month.

3. Empirical Results

3.1. Results from Unconditional Regression Analysis

Table 3 presents the results of preliminary examination of the relationship between each of the variables, beta, size, B/M and E/P, and the returns of the nine portfolios formed by the two different bivariate within-group sorting procedures (beta-size and size-beta) and two different market proxies (EW and VW market excess returns) in the Singapore stock market without differentiating positive and negative market excess returns during January 1991 to December 1998.[12] The statistical results of the univariate regressions indicate that when used alone, the explanatory variables of *BETA*, *BM*, and *EP* are not statistically significant at all conventional significance levels. None of the *t*-statistic values is significant for their regression coefficients ($\gamma_{j\,\mathrm{full}}$). The results are robust for both bivariate sorting procedures and for both market proxies. Evidence from the table also indicates that in the univariate regressions with *SIZE* as the only explanatory variable, a significantly negative size effect exists in the Singapore stock market. The negative monthly risk premiums on *SIZE* are about 0.72%, 0.79%, 0.72%, and 0.76% for Panels A, B, C, and D respectively. The finding of significant size effect is consistent with that found for U.S. stocks by Fama and French (1992)

[12] For the sake of brevity, we only report the results from all univariate regression models and the bivariate regression models where variable *BETA* is included.

and for Mexican stocks by Herrera and Lockwood (1994) although ours is not as strong as theirs.

From Table 3, it is found that, even in combination with the variable *BETA*, the significantly negative relationship between average returns and firm size still persists in all bivariate regressions. All the *t*-statistic values for the coefficient estimates on *SIZE* are negatively significant at the 5% level. This result further confirms that, without splitting markets into up and down, firm size shows power to explain the cross-sectional variation of average returns for Singapore stocks. Nevertheless, the magnitude of significance in the relationship between average returns and firm size seems diminishing from beta-size sorted portfolios (Panels A and C) to size-beta sorted portfolios (Panels B and D) for both market proxies. For example, for EW market proxy, the absolute *t*-statistic values of *SIZE* in univariate and bivariate regressions in Panel A are 2.468 and 2.481 respectively while the corresponding values from Panel B are 1.785 and 1.658; for VW market proxy, the absolute *t*-statistic values of *SIZE* in the univariate and bivariate regressions in Panel C are 2.628 and 2.815 respectively while the corresponding values from Panel D are 1.691 and 1.835. The decrease of about one-third in firm size effect from beta-size sorted portfolios to size-beta sorted portfolios is noticeable.

The evidence of the bivariate regressions reveals that, in combination with the variable *BETA*, the coefficient estimates on *BM* and *EP* are still not significant. Their insignificance is consistent under both bivariate sorting procedures and also under both market proxies. However, although the variable *BETA* is not statistically significant at the 5% level in all regressions, *BETA* seems to have little role in explaining the cross-sectional returns for Singapore stocks as it is significantly positive at the 10% level in some bivariate regressions. Our result of marginally significant beta effect is consistent with the evidence reported by Tang and Shum (2004) that the positive relationship between beta and return is rather weak under an unconditional framework in the Singapore stock market. Besides, in line with previous major international findings, the coefficient estimates on *BETA*, *BM*, and *EP* are all found to be positive in all regressions.

Intercept estimates take positive values as well as negative values and, as expected, they are not significant in most of the regressions presented in Table 3. However, interestingly, those marginally significant intercept estimates are always found in the regressions using *SIZE* as the explanatory variable no matter whether being used alone or in combination with *BETA*. The adjusted R^2s in the univariate regressions running by *BETA* are the lowest of nearly 0. The highest adjusted R^2s of around 0.03 are found in the regressions running by *BETA* and *EP* together and by *EP* alone.

The above findings suggest that there is no significant risk premium on market beta, B/M and E/P and that firm size is the only factor to explain the cross-sectional returns for Singapore stocks. However, these results may be biased due to the aggregation of positive and negative market excess returns. Therefore, we take account of the difference between positive and negative market excess returns and then test the seven hypotheses given in the last section.

3.2. Results from Conditional Regression Analysis

The time-series pooling cross-sectional regression results for the conditional relationship with returns are obtained by using two different bivariate within-group sorting procedures and two different market proxies. At first glance, there is no material difference across the four results. The only two appreciable differences are that, for both market proxies, size effect seems again diminishing from beta-size sorted portfolios to size-beta sorted portfolios and that, as expected, the magnitude of significance of beta in explaining the cross-sectional returns is decreasing from using EW market proxy to VW market proxy under both bivariate sorting procedures. The second difference is caused by the beta estimates using EW market proxy which are, in general, larger than those using VW market proxy. As the results do not change materially and thus the basic findings are essentially unaltered, we here report only findings obtained from size-beta sorted portfolios with EW market proxy, which is the methodology used in a majority of similar studies.[13] Table 4 summarizes the intercept and coefficient estimates with corresponding *t*-statistics and also the *F*-statistics as well as adjusted R^2s of the regression models. The table also presents the χ^2-statistics of the Wald test which tests the equality of every pair of regression coefficients ($\gamma_{j\,\mathrm{up}}$ and $\gamma_{j\,\mathrm{down}}$).

Consistent with previous studies for Singapore market by Tang and Shum (2004) and also for major international markets such as the U.S. by Pettengill et al. (1995), the U.K. by Fletcher (1997), and Japan by Hodoshima et al. (2000), although beta-return relationship is "flat" in unconditional market, after taking into account the difference between positive and negative market excess returns, significant conditional relationship between return and beta is found. The results in Table 4 show that the relationship between return and beta is significantly positive when market excess return is positive whereas their relationship is significantly negative when market excess return is negative. Used alone, the two coefficient estimates ($\gamma_{j\,\mathrm{up}}$ and $\gamma_{j\,\mathrm{down}}$) for the variable *BETA* have their expected opposite signs of positive and negative in up and down markets respectively and their associated *t*-statistic values of +4.676 and –5.964 are highly statistically significant. This indicates that when compared with low-beta ones, high-beta portfolios earn higher returns in up markets and incur larger losses in down markets. Besides, the monthly risk premiums on *BETA* are +6.2414% and –6.0360% which are very close to the corresponding average market excess returns of +6.2935% and –5.4912% in up and down markets respectively. In addition to these univariate results, looking down the column for *BETA* further confirms that the conditional relationship between return

[13] The other three results are omitted for the sake of brevity but available from the authors upon request.

and beta is reliable. Even in combination with the other explanatory variables, *BETA* is still significantly conditionally related to portfolio returns at the 5% level in all regressions except in the regression running by *BETA* and *EP* together. Furthermore, the coefficient estimates for the various combinations of *BETA* consistently take positive values in up markets as well as negative values in down markets. These results provide sufficient evidence to reject our Hypothesis (2) significantly and support the view that market beta still plays a significant role in pricing returns after taking into account the difference between positive and negative market excess returns.

The variable *SIZE* is not consistently significant in all regressions and, on the contrary, the signs of the coefficient estimates on *SIZE* in most regressions are opposite to those hypothesized under the conditional framework based on up and down markets. Evidence in Table 4 shows that during up markets, the size effect is significant in few regressions only and the coefficient estimates on *SIZE* are also vague as different signs have been shown in different regressions; during down markets, although the coefficient estimates are significant in most regressions using various combinations of *SIZE*, their signs are opposite to what we expect in nearly all regressions. These findings may indicate that the switching logic between up and down markets does not exist in size effect. Thus, we suggest that our Hypothesis (3) is not rejected in this study.

The results of the univariate regressions in Table 4 reveal that variable *BM* alone has no significance in either market whereas variable *EP* alone is highly significant in both markets. The pair of coefficient estimates for *BM* alone is +0.0671 and –0.0179, corresponding to the *t*-statistic values of +1.456 and –0.665; the coefficient estimates are not significant at the 5% level but of the expected signs. During up markets, the coefficient estimate on *EP* alone is +1.4253, corresponding to a *t*-statistic value of +4.719. This impressive value indicates that the E/P effect is significant at even 1% level and positive. During down markets, the coefficient estimate on *EP*, –0.6533, remains highly significant with *t*-statistic value of –3.148 and retains its expected negative sign. Looking down the columns for *BM* and *EP*, interestingly, contrary to the results of unconditional regressions reported in Table 3, both variables are highly significant in most regressions during up and down markets. Variable *BM* becomes significant in nearly all regressions except in the regression where *EP* is added and the significance of the coefficient estimates on *EP* persists across the various regressions except the last three multivariate regressions for down markets only. In these two columns, both *BM* and *EP* have consistent signs of the conditional relationship with portfolio excess returns in both up and down markets: positive during up markets and negative during down markets. These results suggest that B/M and E/P, after taking account of the conditional relationships with returns, are likely to be factors that should be priced by the conditional market. And it is likely that Hypotheses (4) and (5) are both rejected in the Singapore stock market. It is important to note that these two variables are highly correlated as their correlation coefficients shown in Table 1 are all above 0.7.

As Pettengill et al. (1995) pointed out, the existence of a systematic conditional relationship does not guarantee a positive risk-return tradeoff and two more conditions are necessary for a positive tradeoff between risk and return, that is, the average market excess return should be positive and the risk premiums should be symmetric across up and down markets. To test Hypothesis (7) that average market excess return is not significantly different from zero, 96 monthly returns are used. Using EW market returns, the average monthly market excess return is 0.8912% and on an annualized basis, the average excess return is 11.25%; the associated *t*-statistic value and *p*-value are 0.965 and 0.1684 respectively. Unexpectedly, these results provide insufficient evidence to reject Hypothesis (7) of zero average market excess return, but coincide with the findings of Tang and Shum (2004). On the contrary, using VW market returns, the average monthly and annualized market excess returns are 0.9605% and 12.15% respectively and the associated t-statistic value of 1.476 with p-value of 0.0716 is marginally significant at the 10% level. This indicates a marginally significant positive reward for holding risk during the test period.

The second condition required for a positive tradeoff is a symmetrical relationship between risk and return in up and down markets. We further extends this idea to the other explanatory variables hypothesized in this study, that is, the risk premiums on these explanatory variables are of equal magnitude but opposite signs if such symmetrical relationship exists among them during up and down markets. Evidence from Table 4 indicates that the χ^2-statistic values of the Wald test on every pair of coefficient estimates are all not significant at the 5% level. Given the expected difference in signs, the χ^2-statistic values for *BETA* in all regressions range from 0.010 to 0.610 only and thus are highly insignificant. This result provides significant evidence to support the symmetrical relationship between market beta and return during up and down markets. For the two significant conditional variables *BM* and *EP*, their pairs of coefficient estimates, with expected opposite signs, are not significantly different at the 5% level in all regressions. Note that although the risk premiums on *EP* across up and down markets are not significantly different, the E/P effect seems to be stronger in up markets than in down markets as the associated absolute values of t-statistic are larger in up markets consistently. Interestingly, although most coefficient estimates on variable *SIZE* in up and down markets have the wrong signs, they are not significantly different at the 5% level in all regressions. Hence, our findings suggest that the risk premiums on *BETA*, *SIZE*, *BM*, and *EP* are all symmetric across up and down markets. Hypothesis (6) of symmetrical relationship with returns during up and down markets is not statistically rejected at the 5% significance level. The results imply that investors in the Singapore stock market respond identically to these explanatory variables in the two periods of up and down markets.

As shown in Table 4, the intercept estimates (γ_0) are not significant at the 5% level in all regressions. This suggests that the return rate used in this study is the same as the risk-free rate. Thus, Hypothesis (1) is not rejected statistically. The table also reports that the 15 *F*-statistic values of the various combinations of pooling cross-sectional regressions are all highly significant at the 1% level. All 15 regressions are useful to explain the cross-sectional variation of returns. However, it can be observed that the regression running by *BM* alone has a relatively low *F*-statistic value of 23.098 whereas the next lower value is already 122.300 in the last multivariate regression. Indeed, the univariate regression running by *BM* also has an extremely low adjusted R^2 of 0.049, which means that the conditional variable *BM* alone has little explanatory power of 4.9% for portfolio returns.

The adjusted R^2s of the regression models are of great difference between the unconditional and conditional relationships with returns. For the unconditional relationship with returns, the adjusted R^2s are much lower than those under the conditional framework based on up and down markets. For example, from Panel B of Table 3, evidence shows that without taking account of the difference between up and down markets, the adjusted R^2 of the relationship between return and beta alone is nearly zero while as shown in Table 4, the adjusted R^2 of the conditional relationship between return and beta alone is 0.374. Our result is close to those reported by Tang and Shum (2004); the corresponding values are 0.003 and 0.321. This dramatic increase of explanatory power of beta for the cross-sectional returns provides evidence to support the statement that beta is still alive and well when the conditional beta-return relationship is considered.

Results from the tables also reveal that the adjusted R^2 of using *EP* as the only regressor is the highest among the four univariate regressions under unconditional market as well as conditional market. Furthermore, the conditional E/P effect seems to dominate the conditional effects of the other factors; *EP* is found to be significant whereas the other explanatory variables become insignificant in the bivariate regression using various combinations of *EP* and the other variables. Besides, it is also found that of the six bivariate regressions, only one includes two significant independent variables simultaneously; it is the regression running by *BETA* and *BM* together. Surprisingly, we find that the adjusted R^2 of using both *BETA* and *BM* as the only regressors is unusually higher than the sum of the two adjusted R^2 of using *BETA* alone and *BM* alone as regressor; the corresponding adjusted R^2 of the three regressions are 0.504, 0.374, and 0.049. It is because both *BETA* and *BM* are dummy variables under conditional market and thus there may be interaction between them. Consequently, their effect on the dependent variable, portfolio return, may not be simply additive but multiplicative as well. This would imply that an interaction dummy, which is defined as the product of two dummy variables, is needed in our regression model in order to modify the effect of the two factors considered individually (i.e. additively). In our further analysis of introducing the multiplicative dummy, the product of variables *BETA* and *BM*, into the regression model, the additive dummies are still statistically significant whereas the multiplicative dummy is not. Hence, as space does not permit a detailed examination of the role of such multiplicative dummy, we do not highlight here the results of the modified regression models including the multiplicative dummy. Anyway, these findings indicate that there exists an "amplified" effect between beta and B/M. In other words, it is suggested that beta and B/M share a joint role in explaining the cross-sectional variation of returns under conditional market and this joint role has a significant gain in explanatory power for the cross-sectional returns.

In the remaining multivariate regressions, it can be observed that their adjusted R^2s are between 0.507 and 0.529 and have no much difference. However, the significant conditional E/P effect seems to be intervened by the significant conditional joint effect of beta and B/M as the coefficient estimates on *EP* become insignificant in the various regressions where *BETA* and *BM* are simultaneously included during down markets. On the other hand, this significant conditional joint effect persists across the regressions using various combinations of *BETA* and *BM*. Therefore, these results suggest that both beta and B/M together may be more important in explaining the cross-sectional returns than E/P alone.

4. Summary and Conclusion

Fama and French (1992) find that the traditional measure of market risk, beta, fails to capture the variation in cross-sectional returns and thus ask the question "Can β be saved?" (p.438). Pettengill et al. (1995) argue that these results are biased due to the conditional relationship between beta and realized returns. This paper attempts to examine the application of conditional effect across up and down markets based on the sign of market excess return not only to beta but also to other firm-specific variables, namely, firm size, B/M, and E/P, in the Singapore stock market from January 1987 to December 1998. Using a single time-series pooling cross-sectional regression, we find that although no evidence supports any significant unconditional relationship between beta and return, beta revives when conditional relationship with return is considered; after distinguishing the signs of market excess returns, there is evidence of a significantly positive risk premium on beta during periods of up markets as well as a significantly negative risk premium on beta during periods of down markets. The results are robust for both within-group sorting procedures including beta-size and size-beta and for both proxies of the market return including equally and value-weighted indexes. Therefore, our study provides support for the continuous use of beta as a measure of market risk.

Mixing markets of positive and negative market excess returns, firm size is significant in the relationship with realized returns whereas both B/M and E/P have no explanatory power for returns. Splitting markets into up and down periods, on the contrary, firm size seems incapable of explaining the cross-section of returns and thus should not be priced by the conditional market whereas the effect of E/P is significant; although B/M alone is not significantly related to realized returns, in various combinations with beta, B/M becomes significant and the joint role of beta and B/M has an "amplified" gain in explanatory power for the cross-sectional returns as their joint effect is not simply additive but multiplicative as well. Hence, our study suggests that beta does not suffice to explain the cross-sectional variation of returns, but it is possible that the joint effect of beta and B/M may be a surrogate as an underlying and more fundamental factor that is missing in the conditional SLB model.

Our results also show that the average monthly market excess return is not significantly different from zero using EW market return and is marginally significantly different from zero using VW market return. Besides, we find evidence that the risk premiums associated with beta, size, B/M and E/P are all symmetric across up and down markets. The results imply that investors in the Singapore stock market react virtually the same to these factors during up and down markets.

The paper is far from closed on the concept of conditional relationship with returns. Questions remain and require additional research. Nevertheless, results in this study provide insights into what additional research is to be conducted. The evidence on the joint effect as well as the multiplicative effect of beta and B/M is important. If such an effect exists, what is the theoretical motivation behind or economic interpretation on it? Is it also present in other less developed and/or even developing stock markets especially those in the Asia Pacific region? All these are left for future research.

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Table 1
Correlations among Variables of *BETA*, *SIZE*, *BM*, *EP*, and *Return* (on the basis of Portfolios) during the Test Period from January 1991 to December 1998

Panel A: Equally Weighted Market Proxy

Univariate Sorting by Beta Alone

	BETA	*SIZE*	*BM*	*EP*	*Return*
BETA	1				
SIZE	−0.3838	1			
BM	0.1265	−0.3640	1		
EP	−0.0770	−0.2404	0.7986	1	
Return	0.0174	−0.0829	0.1013	0.1610	1

Bivariate Within-Group Sorting by Beta and then Size

	BETA	*SIZE*	*BM*	*EP*	*Return*
BETA	1				
SIZE	−0.1730	1			
BM	0.1273	−0.3220	1		
EP	−0.0081	−0.2222	0.7467	1	
Return	0.0296	−0.0822	0.1133	0.1618	1

Bivariate Within-Group Sorting by Size and then Beta

	BETA	*SIZE*	*BM*	*EP*	*Return*
BETA	1				
SIZE	−0.1929	1			
BM	0.1446	−0.3018	1		
EP	−0.0128	−0.2304	0.7758	1	
Return	0.0334	−0.0890	0.1118	0.1679	1

Bivariate Independent-Group Sorting by Beta and Size

	BETA	*SIZE*	*BM*	*EP*	*Return*
BETA	1				
SIZE	−0.1725	1			
BM	0.1333	−0.2857	1		
EP	−0.0555	−0.1931	0.7257	1	
Return	0.0259	−0.0963	0.1165	0.1673	1

Panel B: Value-Weighted Market Proxy

Univariate Sorting by Beta Alone

	BETA	*SIZE*	*BM*	*EP*	*Return*
BETA	1				
SIZE	−0.1496	1			
BM	−0.0755	−0.2670	1		
EP	−0.1877	−0.1654	0.7954	1	
Return	0.0423	−0.0685	0.0974	0.1596	1

Bivariate Within-Group Sorting by Beta and then Size

	BETA	*SIZE*	*BM*	*EP*	*Return*
BETA	1				
SIZE	0.0948	1			
BM	−0.0678	−0.2971	1		
EP	−0.1978	−0.2207	0.7759	1	
Return	0.0460	−0.0831	0.1155	0.1753	1

Bivariate Within-Group Sorting by Size and then Beta

	BETA	*SIZE*	*BM*	*EP*	*Return*
BETA	1				
SIZE	0.1055	1			
BM	−0.0791	−0.2917	1		
EP	−0.1890	−0.2284	0.7909	1	
Return	0.0459	−0.0857	0.1164	0.1739	1

Bivariate Independent-Group Sorting by Beta and Size

	BETA	*SIZE*	*BM*	*EP*	*Return*
BETA	1				
SIZE	0.0852	1			
BM	−0.0791	−0.2909	1		
EP	−0.2363	−0.2173	0.7514	1	
Return	0.0396	−0.0853	0.1061	0.1713	1

Table 2

Summary Statistics for the Nine (3×3) Bivariate Within-Group Sorted Portfolios during the Test Period from January 1991 to December 1998

		Beta-Size Sorted Portfolios						Size-Beta Sorted Portfolios					
		EW Market Proxy			VW Market Proxy			EW Market Proxy			VW Market Proxy		
Panel A: Average Excess Return (%)		beta			beta			beta			beta		
		low	medium	high	low	medium	high	low	medium	high	low	medium	high
size	small	1.393	1.073	1.027	1.248	1.384	1.209	1.549	1.152	1.014	1.206	1.127	1.419
	medium	0.944	0.532	0.806	1.049	0.385	0.795	0.683	0.947	0.637	0.734	0.490	1.067
	large	0.002	0.662	0.580	0.002	0.282	0.632	0.261	0.529	0.473	0.305	0.273	0.683
Panel B: Average *BETA*		low	medium	high	low	medium	high	low	medium	high	low	medium	high
size	small	0.763	1.026	1.263	0.857	1.177	1.382	0.767	1.038	1.248	0.863	1.136	1.374
	medium	0.695	1.033	1.192	0.886	1.219	1.416	0.708	1.057	1.211	0.864	1.217	1.419
	large	0.716	1.011	1.109	0.862	1.305	1.360	0.725	1.012	1.080	0.918	1.330	1.381
Panel C: Average *SIZE* (in natural logarithm)		low	medium	high	low	medium	high	low	medium	high	low	medium	high
size	small	4.750	5.089	4.878	4.693	5.073	4.979	4.795	4.988	4.884	4.823	4.961	4.910
	medium	5.949	6.085	5.726	5.741	6.012	5.947	5.928	5.762	5.831	5.910	5.760	5.854
	large	7.866	7.560	6.914	7.727	7.608	7.160	7.843	7.442	7.123	7.816	7.487	7.139
Panel D: Average *BM* (in natural logarithm)		low	medium	high	low	medium	high	low	medium	high	low	medium	high
size	small	0.015	−0.155	−0.107	0.003	−0.123	−0.104	−0.018	−0.175	−0.105	−0.028	−0.169	−0.094
	medium	−0.138	−0.035	−0.113	−0.161	−0.038	−0.066	−0.104	−0.011	−0.109	−0.115	−0.010	−0.106
	large	−0.426	−0.079	−0.066	−0.388	−0.149	−0.073	−0.413	−0.123	−0.020	−0.409	−0.122	−0.026
Panel E: Average *EP*		low	medium	high	low	medium	high	low	medium	high	low	medium	high
size	small	0.067	0.060	0.061	0.063	0.059	0.061	0.068	0.057	0.060	0.063	0.060	0.062
	medium	0.068	0.057	0.046	0.068	0.056	0.059	0.068	0.059	0.051	0.069	0.056	0.054
	large	0.060	0.050	0.066	0.063	0.048	0.056	0.058	0.049	0.062	0.058	0.049	0.063
Panel F: Average Number of Stocks		low	medium	high	low	medium	high	low	medium	high	low	medium	high
size	small	9.7	9.6	9.5	9.7	9.6	9.5	9.7	9.4	9.0	9.7	9.4	9.0
	medium	9.4	9.3	9.2	9.4	9.3	9.2	9.6	9.3	8.9	9.6	9.3	8.9
	large	9.0	8.9	8.8	9.0	8.9	8.8	9.5	9.2	8.8	9.5	9.2	8.8

Table 3
Results of Unconditional Time-Series Pooling Cross-Sectional Regressions: Coefficient Estimates, t-Statistics and Adjusted R^2s

Panel A: Beta-Size Sorted Portfolios/EW Market Proxy

	Intercept	*BETA*	*SIZE*	*BM*	*EP*	*adj. R^2*
$\gamma_{j\,\text{full}}$	−0.003276	0.011570				−0.000
t-statistic	−0.266	0.752				
$\gamma_{j\,\text{full}}$	0.051943		−0.007207			0.006
t-statistic	2.280**		−2.468***			
$\gamma_{j\,\text{full}}$	0.011120			0.025040		0.012
t-statistic	1.043			0.764		
$\gamma_{j\,\text{full}}$	−0.022384				0.513423	0.025
t-statistic	−1.038				1.188	
$\gamma_{j\,\text{full}}$	0.044423	0.006191	−0.006967			0.005
t-statistic	1.954*	0.411	−2.481***			
$\gamma_{j\,\text{full}}$	0.005169	0.006026		0.024606		0.011
t-statistic	0.340	0.449		0.750		
$\gamma_{j\,\text{full}}$	−0.034256	0.012082			0.514214	0.025
t-statistic	−1.130	0.790			1.192	

Panel B: Size-Beta Sorted Portfolios/EW Market Proxy

	Intercept	*BETA*	*SIZE*	*BM*	*EP*	*adj. R^2*
$\gamma_{j\,\text{full}}$	−0.005490	0.013775				−0.000
t-statistic	−0.565	1.041				
$\gamma_{j\,\text{full}}$	0.055830		−0.007876			0.007
t-statistic	1.827*		−1.785**			
$\gamma_{j\,\text{full}}$	0.011047			0.025033		0.011
t-statistic	1.046			0.764		
$\gamma_{j\,\text{full}}$	−0.024103				0.542413	0.027
t-statistic	−1.037				1.174	
$\gamma_{j\,\text{full}}$	0.047241	0.006959	−0.007588			0.006
t-statistic	1.314	0.497	−1.658**			
$\gamma_{j\,\text{full}}$	0.003842	0.007262		0.024463		0.011
t-statistic	0.271	0.654		0.744		
$\gamma_{j\,\text{full}}$	−0.038598	0.014660			0.543878	0.027
t-statistic	−1.206	1.094			1.178	

Panel C: Beta-Size Sorted Portfolios/VW Market Proxy

	Intercept	*BETA*	*SIZE*	*BM*	*EP*	*adj.* R^2
$\gamma_{j\ \mathrm{full}}$	−0.008765	0.014398				0.001
t-statistic	−0.502	0.992				
$\gamma_{j\ \mathrm{full}}$	0.052230		−0.007249			0.006
t-statistic	2.416**		−2.628***			
$\gamma_{j\ \mathrm{full}}$	0.011117			0.025714		0.012
t-statistic	1.038			0.770		
$\gamma_{j\ \mathrm{full}}$	−0.025888				0.571369	0.030
t-statistic	−1.037				1.163	
$\gamma_{j\ \mathrm{full}}$	0.035193	0.017016	−0.007699			0.008
t-statistic	1.310	1.176	−2.815***			
$\gamma_{j\ \mathrm{full}}$	−0.008462	0.016924		0.026531		0.014
t-statistic	−0.490	1.150		0.792		
$\gamma_{j\ \mathrm{full}}$	−0.059647	0.026273			0.625528	0.035
t-statistic	−1.431	1.481*			1.234	

Panel D: Size-Beta Sorted Portfolios/VW Market Proxy

	Intercept	*BETA*	*SIZE*	*BM*	*EP*	*adj.* R^2
$\gamma_{j\ \mathrm{full}}$	−0.009042	0.014704				0.001
t-statistic	−0.533	1.086				
$\gamma_{j\ \mathrm{full}}$	0.054136		−0.007577			0.006
t-statistic	1.765*		−1.691**			
$\gamma_{j\ \mathrm{full}}$	0.011235			0.026023		0.012
t-statistic	1.061			0.792		
$\gamma_{j\ \mathrm{full}}$	−0.025712				0.570166	0.029
t-statistic	−1.059				1.191	
$\gamma_{j\ \mathrm{full}}$	0.036513	0.017799	−0.008096			0.008
t-statistic	1.026	1.352*	−1.835**			
$\gamma_{j\ \mathrm{full}}$	−0.009378	0.017766		0.027004		0.014
t-statistic	−0.565	1.293*		0.819		
$\gamma_{j\ \mathrm{full}}$	−0.059247	0.026165			0.620776	0.034
t-statistic	−1.505	1.598*			1.264	

$R_{p,t} = \gamma_0 + \sum_{j=1}^{k} (\gamma_{j\ \mathrm{full}} \cdot X_{j\ p,t-1}) + \varepsilon_p$. Without splitting markets into up and down, monthly portfolio excess returns are regressed on the portfolios' *BETA*, *SIZE* (in natural logarithm), *BM* (in natural logarithm), and *EP* using data of all 96 months in the test period simultaneously. $\gamma_{j\ \mathrm{full}}$ is the regression coefficient estimated by OLS and the associated *t*-statistic is computed by dividing the OLS coefficient estimate by the HAC (Heteroskedasticity- and Autocorrelation-Consistent) standard error. *Adj.* R^2 is the adjusted coefficient of determination of the regression model.

* Statistically significant at 10%.

** Statistically significant at 5%.

*** Statistically significant at 1%.

Table 4

Results of Conditional Time-Series Pooling Cross-Sectional Regressions for Size-Beta Sorted Portfolios using EW Market Proxy: Coefficient Estimates, t-Statistics, F-Statistics, Adjusted R^2s and χ^2-Statistics

	Intercept	*BETA*		*SIZE*		*BM*		*EP*		F-statistic	*adj.* R^2
		Up	Down	Up	Down	Up	Down	Up	Down		
$\gamma_{j\,\text{up, down}}$	0.001617	0.062414	−0.060360							259.028	0.374
t-statistic	0.191	4.676***	−5.964***							***	
χ^2-statistic		0.010									
$\gamma_{j\,\text{up, down}}$	0.047862			0.002127	−0.016735					219.298	0.336
t-statistic	1.799*			0.571	−3.892***					***	
χ^2-statistic				3.449*							
$\gamma_{j\,\text{up, down}}$	0.012176					0.067089	−0.017918			23.098	0.049
t-statistic	1.258					1.456*	−0.665			***	
χ^2-statistic						0.783					
$\gamma_{j\,\text{up, down}}$	−0.018911							1.425335	−0.653258	428.797	0.498
t-statistic	−1.439							4.719***	−3.148***	***	
χ^2-statistic								2.523			
$\gamma_{j\,\text{up, down}}$	0.045125	0.058838	−0.068499	−0.006647	−0.005798					131.921	0.378
t-statistic	1.474	3.620***	−4.946***	−1.558*	−1.674**					***	
χ^2-statistic		0.179		2.781*							
$\gamma_{j\,\text{up, down}}$	0.013675	0.063221	−0.075321			0.105218	−0.042778			220.133	0.504
t-statistic	1.348	5.683***	−7.303***			3.246***	−3.534***			***	
χ^2-statistic		0.441				3.143*					
$\gamma_{j\,\text{up, down}}$	−0.029387	0.018872	−0.002443					1.319954	−0.480162	216.883	0.500
t-statistic	−1.524	1.621*	−0.160					3.640***	−2.331**	***	
χ^2-statistic		0.610						3.187*			
$\gamma_{j\,\text{up, down}}$	0.026112			0.008658	−0.014474	0.117418	−0.059618			217.075	0.500
t-statistic	1.291			2.336***	−4.209***	3.476***	−4.664***			***	
χ^2-statistic				0.714		2.489					
$\gamma_{j\,\text{up, down}}$	0.003814			−0.003675	−0.003145			1.411428	−0.706509	215.163	0.498
t-statistic	0.131			−1.039	−0.822			3.779***	−3.599***	***	
χ^2-statistic				1.013				2.204			
$\gamma_{j\,\text{up, down}}$	−0.006865					0.035017	−0.010212	1.243877	−0.804832	223.737	0.508
t-statistic	−0.440					1.262	−0.709	4.973***	−3.420***	***	
χ^2-statistic						0.493		0.918			

$\gamma_{j\text{ up, down}}$	0.025180	0.034646	−0.041798	0.003222	−0.007768	0.111335	−0.052064			153.064	0.514
t-statistic	0.926	2.822***	−3.635***	0.783	−2.298**	3.285***	−4.053***			***	
χ^2-statistic		0.132		0.413		2.629					
$\gamma_{j\text{ up, down}}$	−0.006335	0.034815	−0.028349	−0.006878	0.001646			1.342812	−0.582219	148.805	0.507
t-statistic	−0.156	2.612***	−2.049**	−1.701**	0.418			3.541***	−2.806***	***	
χ^2-statistic		0.076		0.491				2.476			
$\gamma_{j\text{ up, down}}$	−0.018871	0.041153	−0.033665			0.057331	−0.039350	0.857437	−0.171172	162.666	0.529
t-statistic	−0.830	3.520***	−2.550***			1.980**	−3.047***	3.185***	−0.795	***	
χ^2-statistic		0.124				0.260		2.388			
$\gamma_{j\text{ up, down}}$	0.004877			0.002848	−0.008584	0.062409	−0.044657	0.854226	−0.238266	157.115	0.520
t-statistic	0.167			0.812	−2.307**	2.039**	−3.416***	3.259***	−1.162	***	
χ^2-statistic				0.731		0.277		2.255			
$\gamma_{j\text{ up, down}}$	−0.005807	0.034867	−0.028674	−0.000415	−0.003887	0.061229	−0.046372	0.797273	−0.093206	122.300	0.529
t-statistic	−0.139	2.552***	−2.013**	−0.104	−1.035	1.983**	−3.425***	2.888***	−0.415	***	
χ^2-statistic		0.065		0.359		0.184		2.490			

$R_{p,t} = \gamma_0 + \sum_{j=1}^{k} [\gamma_{j\text{ up}} \cdot \delta_t \cdot X_{j\,p,t-1} + \gamma_{j\text{ down}} \cdot (1-\delta_t) \cdot X_{j\,p,t-1}] + \varepsilon_p$. Splitting markets into up and down, monthly portfolio excess returns are regressed on the portfolios' *BETA*, SIZE (in natural logarithm), *BM* (in natural logarithm), and *EP* using data of all 96 months in the test period simultaneously. $\gamma_{j\text{ up, down}}$ are the conditional regression coefficients, on the basis of up and down markets respectively, estimated by OLS and the associated t-statistic is computed by dividing the OLS coefficient estimate by the HAC (Heteroskedasticity- and Autocorrelation-Consistent) standard error. F-statistic is for testing the overall significance and *adj.* R^2 is the adjusted coefficient of determination of the regression model. χ^2-statistic (in grey) of the Wald test is for testing the equality of the pair of regression coefficients, $\gamma_{j\text{ up}}$ and $\gamma_{j\text{ down}}$.

* Statistically significant at 10%.

** Statistically significant at 5%.

*** Statistically significant at 1%.