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THE EFFECT OF COMMON STOCK BETA VARIABILITY ON THE VARIABILITY OF THE PORTFOLIO BETA

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Abstract

The relationship between the variability of individual stock betas and the variability of small portfolio betas is tested. Stocks are combined into small portfolios using two measures of beta variability, the standard deviation of beta and the coefficient of variation of beta. The following results are of particular interest to managers of small portfolios: (1) minimization of portfolio beta variability cannot be achieved by combining stocks which, individually, have low beta variability, and (2) stocks with low betas have greater relative beta variability.

INTRODUCTION

Theory suggests portfolio managers effectively control the risk of their portfolio by determining and varying the weighted average beta of the securities they hold. However, it is well established that individual stock betas can change dramatically over two successive time periods (see Blume [1], Levy [10], Hawawini, Michel, and Corhay [7]). Also, Rosenberg (14) argues that the historical beta, estimated through ordinary least squares, is not the true beta. He contends the value of the estimated beta over any period is actually the average of the changing beta for that period and not the true, fixed beta.

Since this beta variability indicates uncertain systematic risk exposure, portfolio managers should consider it a form of risk to be controlled. Tole (16) suggests beta variability can be eliminated by randomly assembling a very large (100 to 500) number of stocks. Since movements of the individual betas are not perfectly correlated, beta variability is effectively diversified. To minimize beta variability in small portfolios, however, a different strategy is required.

Previous studies have not examined the effect of the variability of individual common stock betas on the variability of the portfolio beta. The primary focus has been on the difference in the value of individual and portfolio betas in two successive periods. This research differs in that it focuses upon the variability of individual stock and portfolio betas *during* the measurement period.

Stocks are combined into small portfolios using two measures of individual stock beta variability. These measures are beta standard deviation, a measure of absolute variability, and beta coefficient of variation, a measure of relative variability. In each case the relationship between individual stock and portfolio beta variability is tested. Results indicate beta variability is considerable and subject to change. They also suggest the variability of portfolio betas is an inverse function of the value of beta.

LITERATURE REVIEW

Beta coefficients must be stable to be good estimates of systematic risk exposure in subsequent periods. Roenfeldt, Grienpentrop, and Pflaum (13) find a four year estimation period optimal for predicting beta for the subsequent 4, 3, 2, or 1 year period. They suggest a one year estimation period is not adequate for estimating the

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subsequent one year beta. Blume (1) and Levy (10) find single asset betas are poor estimates of betas in subsequent periods, but the quality of the estimate improves as the number of stocks in the portfolio increases. Hawawini, Michel, and Corhay (7) find similar results. Using five year base and test periods, Tole (16) shows the difference between predicted and actual (OLS estimated) beta for the subsequent five year period decreases as the number of stocks in the portfolio increases.

King (8), Campanella (3), Livingston (11), Farrell (6), Klemkosky and Martin (9), Martin and Keown (12), and Chen (4) show beta nonstationarity is related across groups of firms. That is, the nonstationarity of beta across securities might be related according to some source of covariation other than the market. Certain industry factors, common sensitivity to interest rates, common cyclical natures, rates of growth, etc., are shared factors that can make the returns of groups of stocks covary with each other as well as with the overall market.

DATA AND METHODOLOGY

A sample of 600 common stocks was generated from the Center for Research in Security Price (CRSP) NYSE/ASE daily returns tape. To be included the stock must have traded continuously from January, 1975, to December, 1990.

A sequence of 30, 180 day betas was generated for each stock in the sample. Beginning with the first trading day of 1975, 180 daily returns were regressed on the returns for the CRSP Equal Weighted Index. This generated the first beta of the sequence. Each successive beta was computed by adding the next 60 daily returns while dropping the first 60.

From the 30 betas generated, the mean beta, beta standard deviation, and beta coefficient of variation were computed for all 600 stocks. The stocks were then ranked by beta standard deviation and coefficient of variation. The 60 stocks with the highest beta standard deviations were placed in portfolio one. The 60 next highest were placed in portfolio two, and so on, until ten portfolios were formed. In the same fashion, twenty portfolios of 30 stocks each and forty of 15 stocks each were also assembled yielding a total of 70 portfolios of varying size. Using the same technique, 70 portfolios were formed using beta coefficient of variation to rank and divide the 600 stocks.

Next, using the same 180 day sequential procedure beginning in November, 1982, a series of 30 betas was calculated for each portfolio. This established nonoverlapping base and test periods of approximately 7.7 years each.

If, within a portfolio, the movements of individual stock betas have perfect positive correlation, the standard deviation and coefficient of variation of the portfolio beta will be simple weighted averages. If less than perfect positive correlation exists, they will be lower than their corresponding weighted averages. The difference between the portfolio measure and the corresponding weighted average indicates the degree of diversification of beta variability that has occurred. Using a technique similar to that employed by Solnik (15), the degree of diversification achieved was estimated as below:

Equation 1

$$DOD_{SD} = 1 - SD/ASD$$

and

Equation 2

$$DOD_{CV} = 1 - CV/ACV$$

where:

DOD = the degree of diversification, measured as the percentage of beta variability removed through portfolio formation
SD = the standard deviation of the portfolio beta over the test period
ASD = the weighted average beta standard deviation of the individual stocks within the portfolio

CV = the coefficient of variation of the portfolio beta over the test period
ACV = the weighted average beta coefficient of variation of the individual stocks within the portfolio

To approximate a normal distribution of tested sample variables, thirty-five random portfolios of 60, 30, and 15 stocks each were generated from the 600 stock sample. The DOD_{SD} and DOD_{CV} were determined for each random portfolio, and the mean DOD_{SD} and DOD_{CV} and their standard deviations were estimated for each set of 35 random portfolios. T-tests were employed to determine if the degree of diversification achieved with the formed portfolios was significantly different from what can be achieved randomly.

RESULTS

No portfolio in either category, beta standard deviation or coefficient of variation rankings, showed a greater degree of diversification than can be achieved randomly. However, several of the portfolios showed less diversification. At the 5 percent significance level, 17 of the 70 standard deviation based portfolios and 24 of the 70 coefficient of variation based portfolios showed less diversification.

Spearman coefficients and regression analysis were used to test and quantify the relationship between the variability of the portfolio beta and the standard deviation and coefficient of variation of individual betas in the portfolio. First, portfolios in each size category were ranked by weighted average beta standard deviation (ASD) and by degree of diversification (DOD). The portfolio in each size category with the highest ASD was assigned a rank of 1, the next highest 2, etc. The same ranking scheme was used with DOD. Spearman coefficients were computed to test the correlation between the ASD and DOD rankings for each size category. The same technique was used to compare weighted average coefficient of variation, ACV, and DOD. Results are shown in Table 1.

TABLE 1
A Spearman Rank Test Of The Correlation Of Portfolio Weighted Average Standard Deviation, ASD, And Weighted Average Coefficient Of Variation, ACV, With Degree Of Diversification, DOD.
(t-Statistics In Parentheses)

Portfolio Size	Correlation with DOD	
	ASD	ACV
60	.61 (1.83)	-.50 (-1.51)
30	.50 (2.19)	-.31 (-1.37)
15	.37 (2.32)	-.42 (-2.60)

A direct relationship between weighted average standard deviation and DOD is shown by the significant positive correlations. Portfolios containing stocks with the highest beta standard deviations tend to have the greatest degree of diversification. This indicates a tendency for portfolios of stocks with lower beta standard deviations to experience less diversification. It also indicates that more stable individual stock betas do not change in random fashion with respect to one another. Rather, their movements must be positively correlated. These results agree with those of Martin and Keown (12) who found that low betas have a high degree of extra market covariation. As stated by Chen and Martin (5, p. 270),

> ". . . should the betas covary positively with one another, then the nonstationarity (variability) . . . will not be diversifiable."

The relationship between DOD and portfolio weighted average coefficient of variation is generally weaker and less significant. However, the generally negative correlations indicate an inverse relationship between the portfolio weighted average beta coefficient of variation and diversification.

Results of the regression of DOD on ASD are presented in Table 2. The significant positive coefficients provide further evidence that the diversification of beta variability lessens as the weighted average beta standard deviation of the portfolio decreases. Both the Spearman rank and regression tests indicate the relationship is stronger as the size of the portfolio is increased. (The regression of DOD on portfolio weighted average coefficient of variation showed no significant results.)

TABLE 2
A Regression Of Degree Of Diversification, DOD, On Portfolio Weighted Average Standard Deviation, ASD.
(t-Statistics In Parentheses)

Portfolio Size	R^2	Coefficient
60	.72	.40 (4.50)
30	.44	.34 (3.75)
15	.09	.17 (1.96)

This evidence suggests when stocks with relatively stable betas are combined, there is a tendency for the portfolio to have a relatively unstable beta. This could only occur if the movements of the betas of these stocks have significant positive correlation. Therefore, attempting to stabilize the portfolio beta by combining stocks with low beta variability is counterproductive. However, combining stocks whose individual betas are relatively unstable leads to significant reduction of portfolio beta variability. Hence, the movements of these betas must be relatively uncorrelated.

To quantify the relationship between beta variability and the value of beta, portfolio beta was regressed on portfolio weighted average standard deviation, ASD, and coefficient of variation, ACV. The results are presented in Table 3. The R^2 and highly significant positive coefficients for the ASD regression indicate a strong positive relationship between the level of beta and its variability.

The highly significant inverse relationship between beta and its coefficient of variation is opposite to that found between beta and its standard deviation. This suggests low beta stocks have greater relative beta variability, which helps explain the conclusion of Bowlin and Dukes (2) that beta values of less than one are poorer predictors of portfolio returns than betas greater than one.

TABLE 3
Regression Of Portfolio Beta On Portfolio Weighted Average Standard Deviation, ASD, And Coefficient Of Variation, ACV.
(t-Statistics In Parentheses)

Portfolio Saize	ASD		ACV	
	R^2	Coefficient	R^2	Coefficient
60	.84	.388 (6.38)	.87	-.570 (-7.24)
30	.75	.371 (7.32)	.77	-.554 (-7.72)
15	.68	.351 (8.99)	.66	-.529 (-8.55)

CONCLUSION

This study has examined the effect of the variability of individual common stock betas on the variability of small portfolio betas. Portfolios were formed based on the variability of individual stock betas, using both standard deviation and coefficient of variation as measures.

The following results are of particular interest to managers of small portfolios:

1. Minimization of portfolio beta variability cannot be achieved by combining stocks which, individually, have low beta variability. This strategy, although intuitively appealing, produces portfolio betas that are more variable than those produced through random combination.

2. Low beta stocks have greater relative beta variability. This and previous studies have shown a direct relationship between the level of beta and standard deviation. However, coefficient of variation reveals an inverse relationship between the level of beta and relative variability. This explains results of previous research that betas less than 1.00 are poor predictors of future returns.

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