

WILEY

Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence

Author(s): Laxmi Chand Bhandari

Source: *The Journal of Finance*, Jun., 1988, Vol. 43, No. 2 (Jun., 1988), pp. 507-528

Published by: Wiley for the American Finance Association

Stable URL: <https://www.jstor.org/stable/2328473>

JSTOR is a not-for-profit service that helps scholars, researchers, and students discover, use, and build upon a wide range of content in a trusted digital archive. We use information technology and tools to increase productivity and facilitate new forms of scholarship. For more information about JSTOR, please contact support@jstor.org.

Your use of the JSTOR archive indicates your acceptance of the Terms & Conditions of Use, available at <https://about.jstor.org/terms>



and Wiley are collaborating with JSTOR to digitize, preserve and extend access to *The Journal of Finance*

JSTOR

Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence

LAXMI CHAND BHANDARI*

ABSTRACT

The expected common stock returns are positively related to the ratio of debt (non-common equity liabilities) to equity, controlling for the beta and firm size and including as well as excluding January, though the relation is much larger in January. This relationship is not sensitive to variations in the market proxy, estimation technique, etc. The evidence suggests that the "premium" associated with the debt/equity ratio is not likely to be just some kind of "risk premium".

BETA, THE RISK MEASURE suggested by the mean-variance equilibrium models, has been found to be inadequate in explaining the expected common stock returns. For example, the common stocks with higher earnings/price ratios (Basu [2]), smaller market values outstanding (Banz [1]), and lower share prices (Stoll and Whaley [15]) earn higher average returns controlling for beta, though there seems to be an agreement that all of these variables represent the same underlying influence (Reinganum [12], Basu [3], and Stoll and Whaley [15]). These studies conclude either that beta may be an inadequate measure of risk or that we need to account for the market imperfections such as transaction costs. A natural proxy for the risk of common equity of a firm is that firm's debt/equity ratio (*DER*). Therefore, we propose to use *DER* as an additional variable to explain the expected common stock returns.

An increase in the *DER* of a firm increases the risk of its common equity, measuring risk in any reasonable way.¹ Though it does not follow that, cross-sectionally, the common equity of a higher *DER* firm always has higher risk since the firm-level risk may vary, *DER* is expected to be positively correlated to the risk of common equity across firms.² Thus, *DER* can be used as a proxy for the risk of common equity when an adequate measure of risk is not known or cannot be calculated from available information.

Generally, an estimate of beta, which we term *BETA*, is used to control for beta. *BETA* is based on a market proxy and calculated from a period termed the

* Faculty of Business, University of Alberta. Currently with the Capital Markets Group, Chemical Bank. This paper builds on a part of my Ph.D. thesis at the Graduate School of Business, University of Chicago (1984). I would like to thank Eugene Fama, Arnold Zellner and other members of my thesis committee, Gordon Sick, Giovanni Barone-Adesi, and anonymous referees for their comments at various stages of this research. Computer support from the Graduate School of Business, University of Chicago, and the Faculty of Business, University of Alberta, is gratefully acknowledged.

¹ We assume that the common equity has more risk than the debt in a firm. Thus, the unlikely possibility of a negative common-equity beta, for example, is excluded.

² We assume that the cross-sectional correlation between *DER* and the firm-level risk is not so highly negative as to negate this conclusion.

BETA calculation period, which does not overlap with the corresponding test period. The above argument, in conjunction with the estimation errors in *BETA*, use of a proxy for the market portfolio, and possible changes in beta over time, suggests that *BETA* alone may not be as good a proxy for beta *during* the test period as *BETA* and *DER* together. For example, to the extent that the firm beta is relatively stable, a higher *DER* during the test period relative to that during the *BETA* calculation period will indicate a higher-than-estimated common-equity beta during the test period. Since *DER* is available on a more current basis, it can be used as a proxy for beta during the test period in addition to *BETA*. Also, usually the data requirements are such that the *BETA* calculation period for a firm excludes the period surrounding the time it drops out of the data set. Then the combination of low return on the market proxy and low “residual” return for a firm is more likely to be excluded from *BETA* calculation since such a combination is more likely to cause that firm to go bankrupt and drop out. This sample-selection bias will bias *BETA* downward in all practical cases. Since the probability of bankruptcy increases as *DER* increases, a higher *DER* may indicate more downward bias in *BETA*.

Subject to the limitations on their applicability across firms, the above arguments suggest that *DER* may be a useful proxy for risk in addition to *BETA* even when beta is an adequate measure of risk. Of course, *DER* is likely to be more useful as a proxy for risk if beta is not an adequate measure of risk. Furthermore, to the extent that *DER* is likely to be a better proxy for risk cross-sectionally than firm size (and the other variables mentioned above), its inclusion as an explanatory variable will take us a step closer to understanding the nature of the “size premium”.

With risk-averse investors, we expect a positive correlation between *DER* and the expected common stock returns when the other explanatory variables used are inadequate to control for risk. In this paper, we test whether the expected common stock returns are positively related to *DER* controlling for *BETA* and size and find that they are. Since we control for an estimated beta, it is interesting to know whether this result is due to *DER* acting as a proxy for beta. We find that that is not the case. Actually, the evidence suggests that the “premium” associated with *DER* is not likely to be just some kind of “risk premium”.

Section I describes the model, data, and test design used. Section II provides the empirical results that show that the expected common stock returns are positively related to *DER* and that this result is not due to *DER* acting as a proxy for beta. A summary of the empirical results and the conclusions are presented in Section III.

I. Model, Data, and Test Design

The following equation forms the basis of our tests:

$$E(\tilde{r}_i) = E(\tilde{\gamma}_0) + E(\tilde{\gamma}_1)LTEQ_i + E(\tilde{\gamma}_2)BETA_i + E(\tilde{\gamma}_3)DER_i, \quad i = 1, \dots, N, \quad (1)$$

where E is the expectation operator and \sim denotes a random variable. Subscript i represents the common stock i , and $E(\tilde{\gamma})$'s are assumed to be fixed within a

test subperiod. (Henceforth, the word “test” is omitted where the context is clear.) However, $\tilde{\gamma}$ ’s can be stochastic within a subperiod. Noting that our tests are not conditional on the return on the market proxy, $\tilde{\gamma}_2$ is clearly stochastic.

The monthly real rate of return [i.e., return adjusted for changes in the Consumer Price Index (CPI)] on stock i is denoted r_i . In a cross-sectional equation like (1), the use of real rather than nominal returns only changes the scale. However, since the rate of inflation varied considerably over the time period across which we average our results, the use of real returns seems preferable. For the same reason, we express our size variable in constant dollars. In any case, the results are virtually identical when nominal returns are used in place of the real returns, except that the estimated intercept term goes up approximately by the average amount of inflation.

LTEQ is the natural logarithm of total common equity, where total common equity is the number of shares outstanding times (month-end) price per share, expressed in millions of December 31, 1925 dollars using the CPI to deflate them. *BETA* is the ordinary least squares (OLS) estimate of the slope coefficient in the regression of (real) returns on a market proxy. The (real) returns on the equally weighted portfolio of all stocks traded on the New York Stock Exchange (NYSE) are used as the market proxy. *DER* is the ratio:

$$\frac{\text{book value of total assets} - \text{book value of common equity}}{\text{market value of common equity}},$$

measured at the accounting year-ends. The mean-variance equilibrium models and Banz’s [1] empirical findings, respectively, suggest that the expected common stock returns should be linearly related to *BETA* and *LTEQ*. We propose, as a first approximation, that the expected common stock returns are linearly related to *DER* as well. Our main objective is to test whether $E(\tilde{\gamma}_3)$ is positive.

The following sources of data provided by the Center for Research in Security Prices (CRSP) at the University of Chicago are used. Number of shares outstanding, price per share, and nominal returns are taken from the CRSP monthly stock returns file. Returns on the equally weighted NYSE portfolio are provided by the CRSP monthly stock index file. The COMPUSTAT files provide the book values of total assets and common equity, and the CPI is from the Ibbotson-Sinquefeld file. Our test period is essentially restricted by the COMPUSTAT files, which contain data from 1946.

A. Sample Selection and Model Estimation

We use the Fama-MacBeth [5] (henceforth FM) methodology with some improvements. While an alternative methodology proposed by Gibbons [7] and refined by other authors (e.g., Jobson and Korkie [8]) is currently more popular in this area, there are several reasons for our choice of the FM methodology. To explain these reasons in detail would require a separate paper. The following, however, are some of the major considerations.

First of all, our tests (as well as the evidence in previous studies, e.g., Banz [1]) show that the estimation errors in *BETA* have no significant effect (statistically or economically) on our results except for lowering the estimated coeffi-

cient of *BETA*. The lower estimated coefficient of *BETA* is reflected in the higher estimated intercept, but the estimated coefficients of *LTEQ* and *DER* are virtually unaffected. Furthermore, one of our modifications to the FM methodology substantially reduces the bias in the estimated coefficient of *BETA*, in some cases to a statistically (as well as economically) insignificant amount. Thus, the only limitation of the FM methodology, namely the error-in-the-variables problem, is not a serious problem in our case. Even if it were, there are ways to adjust for it. See Banz [1] for one possible approach.

Second, the Gibbons methodology is convenient only when the alternative is two-sided. For example, we would be testing $E(\tilde{\gamma}) = 0$ against $E(\tilde{\gamma}) \neq 0$. When these tests are done in subperiods and aggregated, which is always the case due to stationarity considerations, we will tend to reject the null hypothesis if $E(\tilde{\gamma})$ was varying randomly across subperiods with mean zero. Under the FM methodology, by using a one-sided alternative $E(\tilde{\gamma}) > 0$ or $E(\tilde{\gamma}) < 0$, we will tend to reject the null hypothesis only if $E(\tilde{\gamma})$ is consistently positive or negative across subperiods. We prefer the latter because in this paper we are not interested in random effects. The tests with a one-sided alternative are also more powerful.

Third, unlike the FM tests, the Gibbons tests are usually conditional on the returns on the market proxy during a subperiod disallowing any test of the hypothesis that $E(\tilde{\gamma}_2) = 0$. Modifications to permit tests of this hypothesis essentially take us back to the FM methodology. Fourth, unlike the FM methodology, the Gibbons methodology is not easily adapted to allow for nonsynchronous trading in estimation of *BETA*, to allow for autocorrelation in returns caused by nonsynchronous trading (or other reasons), etc.³

Finally, the FM tests are less sensitive to departures from the standard assumptions such as normal distribution of errors⁴ and are more easily aggregated across subperiods, and their small-sample properties are better understood. On the other hand, the Gibbons tests based on the χ^2 distribution can be misleading when small subperiods are used (see Jobson and Korkie [8]), while those based on the *F*-distribution are not as easily aggregated across subperiods. Due to the two-sided nature of the Gibbons tests, unlike the FM tests, their large-sample properties cannot be assumed after aggregation across subperiods. While the above is not a complete list of considerations for our choice, it should be clear that the advantages of the FM methodology outweigh its disadvantages.

We use two-year subperiods that go from 1948–1949 to 1980–1981. The choice of two-year subperiods reflects our desire to minimize the possible changes in the parameters during a subperiod while retaining reasonable degrees of freedom in our test statistics. The sample-selection and estimation procedures are illustrated

³ There is a significant amount of positive first-order autocorrelation in monthly portfolio returns as noted by Fisher [6]. Scholes and Williams [13] show that the measured portfolio returns will have positive first-order autocorrelation when trades in individual securities are not synchronized.

⁴ Bhandari [4] provides some evidence of departure from the normal distribution of monthly portfolio returns. One of the advantages of the Gibbons methodology is that it can be used with individual security returns, while the FM methodology requires portfolio returns to minimize the error-in-the-variables problem. In fact, the Gibbons methodology is often used with individual security returns. However, the problem of non-normally distributed returns is more serious at the individual security level, making the use of this methodology questionable.

below for the 1948–1949 subperiod. For other subperiods, these procedures are identical except that all periods are advanced by the appropriate number of years.

First, the explanatory variables are calculated for each common stock. For the 1948–1949 subperiod, *LTEQ* and *DER* are their latest available values during 1946–1947. *BETA* is calculated from the 1946–1947 and 1950–1951 return data.⁵ The *BETA* calculated from 1946–1947 and 1950–1951 is likely to better approximate the beta prevailing *during* 1948–1949 than the *BETA* calculated from, say, 1944–1947, when beta may be changing through time.⁶ The use of the former is therefore likely to reduce the bias in the estimated coefficient of beta. (See Bhandari [4].) Our empirical evidence confirms this.

Another *BETA* is calculated from the 1942–1945 return data for portfolio-formation purposes.⁷ All common stocks that have at least one nonmissing monthly return during 1948–1949 and have enough data available to calculate the explanatory variables as well as the portfolio-formation *BETA* are included in the sample. All sample stocks are first ranked on *LTEQ* and divided into three groups containing equal numbers of stocks.⁸ Within each of these groups, the stocks are ranked on the portfolio-formation *BETA* and subdivided into three equal-sized groups. They are further subdivided into three equal-sized groups each after ranking the stocks on *DER*. This procedure gives us twenty-seven groups or portfolios that are used in our tests. The individual stocks are given equal weights (that sum to one) within a portfolio, and therefore, the value of an explanatory variable for a portfolio is the simple average of the corresponding values for individual stocks in that portfolio.

Within a subperiod, the same twenty-seven portfolios are used each month, except for the stocks having missing returns for a month, which are excluded for that month. Values of explanatory variables are not updated within a subperiod. Both the portfolios and the values of explanatory variables are updated for each new subperiod.

The actual returns for month t can be written as

$$\tilde{r}_{it} = \tilde{\gamma}_{0t} + \tilde{\gamma}_{1t}LTEQ_i + \tilde{\gamma}_{2t}BETA_i + \tilde{\gamma}_{3t}DER_i + \tilde{e}_{it}, \quad i = 1, \dots, N, \quad (2)$$

⁵ Two separate calculations of *BETA* are made for 1946–1947 and 1950–1951. This allows beta and the other parameters of the return distributions to be different in 1946–1947 from in 1950–1951. To make these calculations, the returns on the stock must be available continuously from at least February of the first year (1946 or 1950, respectively) to November of the second year. The final value of *BETA* is a simple average of these two values when both are available, which is the usual case. When only one of these values is available, that is our final value of *BETA*.

⁶ Use of the period before and after the test period to estimate the input parameters is common in event studies in finance.

⁷ Separate calculations of *BETA* are made for 1942–1943, 1943–1944, and 1944–1945, with data requirements as in footnote 5. The final value of *BETA* is a simple average of the 1942–1943 and 1944–1945 values when both are available, which is the usual case. When only one of the above three values is available, that is our final value of *BETA*. When only two of the above three values are available, and they use overlapping periods, the final value of *BETA* is 0.3 times the first estimate (chronologically) plus 0.7 times the second estimate. These weights are chosen as an attempt to give at least one-third weight to the (chronologically) last year's observations.

⁸ When equal division results in fractional stocks, the cumulative number of stocks up to a group is rounded to the nearest integer.

or

$$\tilde{r}_{it} = E(\tilde{\gamma}_0) + E(\tilde{\gamma}_1)LTEQ_i + E(\tilde{\gamma}_2)BETA_i + E(\tilde{\gamma}_3)DER_i + \tilde{u}_{it}, i = 1, \dots, N, \quad (3)$$

where

$$\begin{aligned} \tilde{u}_{it} = & [\tilde{\gamma}_{0t} - E(\tilde{\gamma}_0)] + [\tilde{\gamma}_{1t} - E(\tilde{\gamma}_1)]LTEQ_i + [\tilde{\gamma}_{2t} - E(\tilde{\gamma}_2)]BETA_i \\ & + [\tilde{\gamma}_{3t} - E(\tilde{\gamma}_3)]DER_i + \tilde{e}_{it}, \quad i = 1, \dots, N, \end{aligned} \quad (4)$$

where subscript i now refers to portfolio i and \tilde{u}_{it} is the unexpected return on portfolio i for month t . The OLS estimates of $E(\tilde{\gamma})$'s are calculated for each month in our test period using (3). OLS gives the minimum-variance linear unbiased estimators for $E(\tilde{\gamma})$'s as long as the \tilde{e}_{it} 's are uncorrelated across stocks and have one common variance. (See Bhandari [4].) Note that \tilde{u}_{it} 's are, in general, correlated across stocks and have different variances. In particular, a stochastic $\tilde{\gamma}_2$, for example, allows the \tilde{r}_{it} 's to covary with the market proxy in proportion to their $BETA$ s (which, of course, they do) and, as a result, to covary with each other. Similarly, the covariances between stock returns are allowed to have a constant component as well as components proportional to $LTEQ$ s and DER s.

It should also be noted that, when using this (or similar) methodology with OLS, one should always include $BETA$ as an explanatory variable, even if $BETA$ has no effect on the expected returns and therefore $E(\tilde{\gamma}_2)$ equals zero. The reason is that the unexpected returns (\tilde{u}_{it} 's) are cross-sectionally correlated with $BETA$ s through stochastic $\tilde{\gamma}_2$, and, if $BETA$ is not included as an explanatory variable, OLS will no longer give the *minimum-variance* linear unbiased estimators for the parameters in (3).⁹ (See Bhandari [4].)

Since a large part of the unexpected returns is explained by the "market factor", especially at the portfolio level, which is already allowed for in (4), generalizing it further and using the generalized least squares (GLS) for estimation does not seem justified in view of the number of additional parameters that would need to be estimated relative to our small (twenty-four months) subperiods. When GLS is used, the estimation errors in the estimated variance-covariance matrix of \tilde{u}_{it} 's are typically ignored, which is justified only if the sample size is reasonably large. With our sample size, the estimated precision of the GLS estimates may be questionable. In any case, Banz [1], whose specification is slightly more restrictive than (4), finds virtually no gain in the precision when he uses GLS in place of OLS. Therefore, we use OLS only in this paper.

In testing hypotheses, unless stated otherwise, we assume that \tilde{u}_{it} 's are independently distributed over time, have a constant variance-covariance matrix

⁹ In fact, any variable that is cross-sectionally correlated with the unexpected returns should be included as an explanatory variable even if it does not affect the expected returns, if the gain in the precision of estimates due to the correlation of this variable with the unexpected returns outweighs the loss in the precision due to the estimation of an unnecessary parameter that will depend on the contribution of this variable to the level of multicollinearity. Given the high cross-sectional correlation of $BETA$ s with the unexpected returns, the inclusion of $BETA$ as an explanatory variable would usually result in a net gain in precision. Therefore, we do not drop $BETA$ as an explanatory variable, except for sensitivity analysis, even when its estimated effect on the expected returns is statistically and economically insignificant.

within a subperiod, and are multivariate-normally distributed. However, the evidence for our conclusions usually is so strong that, unless stated otherwise, our conclusions are not likely to change if we allow for reasonable deviations from the above assumptions.

B. Overall Estimates and Test Statistics

Two overall estimates are calculated for each $E(\tilde{\gamma})$. One is a simple average (SA) of the month-by-month estimates for the entire test period. The t -statistic for this estimate is calculated in the usual way. The other overall estimate is a weighted average (WA) of the subperiod mean estimates (simple averages of the month-by-month estimates within the respective subperiods) where weights are inversely proportional to their (usual) estimated standard errors. An appropriate t -statistic for the WA estimate turns out to be simply \sqrt{s} times the simple average of the corresponding subperiod t -statistics (calculated in the usual way) "standardized" to have standard deviation equal to one,¹⁰ where s is the number of subperiods.

In our empirical results, we reject the hypothesis that the sampling variances of the month-by-month estimates are constant across subperiods. The WA estimates, therefore, have smaller sampling variances compared with the SA estimates. Sometimes we also reject the hypothesis that a given coefficient is constant across subperiods. The standard error of an SA estimate is overestimated in such cases because we make no allowance for such nonconstancy, though it is possible to do so, to maintain some comparability with the related papers. The estimated standard error of a WA estimate does allow for such nonconstancy.¹¹ Clearly the WA estimates provide a better basis for hypothesis testing. We always refer to the t -statistics corresponding to the WA estimates, unless noted otherwise, in testing hypotheses and making statements about their *statistical* significance. However, when a given coefficient changes across subperiods, the SA estimate is economically more meaningful as it estimates the (simple) average of that coefficient across subperiods. The weights given to different subperiods in a WA estimate are economically meaningless. Therefore, we always use the SA estimates, unless noted otherwise, in discussing the magnitudes of different coefficients and their *economic* significance.

Unless noted otherwise, the distribution of all t -statistics used in this paper is approximately standard normal under the corresponding null hypotheses, and all statistical tests are done at the 0.05 significance level.

II. Empirical Results

Table I summarizes the empirical results. The results are reported including as well as excluding January because January seasonality has been found in other

¹⁰ A t -statistic with ν degrees of freedom is divided by the square root of $\nu/(\nu - 2)$ to "standardize".

¹¹ The standard errors of both the WA estimates and the SA estimates are overestimated to the extent that the coefficients in (1) change within a subperiod. Other than causing the standard errors/sampling variances to be overestimated, the assumption that these coefficients are constant within a subperiod is not critical.

Table I
Estimated Coefficients (Percent per Month) for the Expected-Return Equation
 $[E(\tilde{r}_i) = \gamma_0 + \gamma_1 LTEQ_i + \gamma_2 BETA_i + \gamma_3 DER_i]$, Their Estimated Test-Period Betas, and the
Summary Statistics for the Explanatory Variables: 1948–1979^a

All-Firms Sample				Manufacturing-Firms Sample				
	Constant	LTEQ	BETA	DER	Constant	LTEQ	BETA	DER
Panel A: Weighted (in Inverse Proportion to Estimated Standard Errors) Averages of the Subperiod Mean Estimates								
Including January <i>t</i> -Statistic	1.01	-0.10 (-3.12)	0.30 (1.23)	0.09 (3.93)	1.29	-0.11 (-3.14)	-0.05 (-0.21)	0.17 (3.91)
Excluding January <i>t</i> -Statistic	0.56	-0.01 (-0.45)	0.16 (0.60)	0.05 (2.37)	0.85	-0.02 (-0.62)	-0.19 (-0.76)	0.10 (2.24)
Panel B: Simple Averages of the Subperiod Mean Estimates								
Including January <i>t</i> -Statistic	1.01	-0.11 (-3.00)	0.17 (0.60)	0.13 (3.84)	1.45	-0.12 (-3.32)	-0.24 (-0.87)	0.18 (3.47)
Excluding January <i>t</i> -Statistic	0.52	0.00 (0.01)	0.01 (0.04)	0.09 (2.47)	1.01	-0.02 (-0.57)	-0.40 (-1.47)	0.11 (2.00)
Panel C: Estimated Test-Period Betas of the Estimated Coefficients (Including January)								
Estimated Test-Period Beta <i>t</i> -Statistic	0.07 (0.94)	-0.00 (-0.23)	0.93 (-1.00)	-0.00 (-0.08)	0.18 (2.10)	-0.01 (-0.47)	0.83 (-2.39)	0.02 (0.82)

Panel D: Summary Statistics for the Explanatory Variables at the Portfolio Level

Mean	3.97	0.96	1.38	3.94	1.02	0.97
Median	3.87	0.98	0.91	3.76	1.01	0.69
Range:						
Minimum	2.29	0.60	0.17	2.16	0.72	0.14
Maximum	6.10	1.44	4.44	6.17	1.42	2.81
Correlation with:						
BETA	-0.44			-0.47		
DER	-0.33	0.25		-0.44	0.51	

* *LTEQ*, *BETA*, and *DER* stand for the logarithm of total equity, debt/equity ratio, and estimated beta, respectively. All results are based on twenty-seven portfolios, formed by ranking the securities on the explanatory variables, for each two-year subperiod. The test-period betas and the means and correlations of the explanatory variables are simple averages of the corresponding subperiod values. The values of the explanatory variables are averaged across subperiods for each portfolio, and the medians and ranges are for these averaged values. The *t*-statistics for the average estimated coefficients are distributed as approximately standard normal under the null hypothesis that the coefficient is zero. the *t*-statistics for the estimated test-period betas are distributed as "Student's" *t* with 15 d.f. under the null hypothesis that the test-period beta is zero (one, in the case of the coefficient of *BETA*).

studies (e.g., Keim [9]). To facilitate interpretation of these results, the means, medians, ranges, and correlations of the explanatory variables at the portfolio level are provided in the bottom portion of the table. The ranges in individual subperiods tend to be wider than those shown in the table.

When all firms are used, the average correlation between *BETA* and *DER* is only 0.25. Moreover, their correlation varies from -0.10 for the subperiod 1978-1979 to 0.56 for the subperiod 1948-1949. The low average and high variability of their correlation are explained to a large extent by many finance, real estate, and insurance companies having very large *DERs*, especially in the later subperiods, but not correspondingly large common-equity *BETAs*. Utilities are, of course, another reason since they tend to have higher *DERs* and lower common-equity *BETAs*. As shown in Figure 1, the average *DER* increased substantially in the 1970's, especially for the nonmanufacturing firms.¹² In fact, many finance, real estate, and insurance companies have a *DER* well in excess of twenty-five during this period, and they dominate the average. This results in a very skewed cross-sectional distribution of *DERs*, with the mean and median *DERs* equal to 1.38 and 0.91, respectively. The results below suggest that the linear functional form for *DER* proposed in (1) is probably not adequate for the extreme *DERs*. Therefore, we also present the results for the manufacturing firms only.

When only manufacturing firms are used, the average correlation of *DER* with *BETA* increases to 0.51, and it varies only from 0.35 for the subperiod 1958-1959 to 0.69 for the subperiod 1952-1953. As reflected in the mean, median, and range for *DER*, the distribution of *DERs* is much less skewed in this sample. The average correlation between *DER* and *LTEQ* is higher in this sample as well.

The correlation between *LTEQ* and *BETA* varies substantially across subperiods in both samples. When all firms are used, it varies from -0.73 for the subperiod 1976-1977 to 0.04 for the subperiod 1954-1955. When only manufacturing firms are used, it varies from -0.77 for the subperiod 1976-1977 to 0.10 for the subperiod 1954-1955.

The number of stocks included in the sample varies between 331 (for 1948-1949) and 1241 (for 1978-1979), the average being about 728 stocks or about twenty-seven stocks in each portfolio when all firms are used. When only manufacturing firms are used, the sample includes between 259 (for 1948-1949) and 679 stocks (for 1978-1979), with an average of about 462 stocks or about seventeen stocks in each portfolio.

The hypothesis that the sampling variances of the month-by-month estimates are constant across subperiods is strongly rejected for all coefficients in both samples, including or excluding January, using a likelihood-ratio test. (See Kendall and Stuart [11], p. 252.) For example, when all firms are used and January is included, the value of the test statistic is 87.16, 70.74, and 155.66 for the coefficients of *LTEQ*, *BETA*, and *DER*, respectively. The distribution of this test statistic is approximately χ^2 with 15 degrees of freedom (d.f.). Thus, as expected, the WA estimates have noticeably lower estimated standard errors compared with the SA estimates. The estimated standard errors of the WA

¹² Manufacturing firms are those firms with SIC (Standard Industrial Classification) codes starting with 20 to 39 all through their existence on the CRSP monthly returns tape.

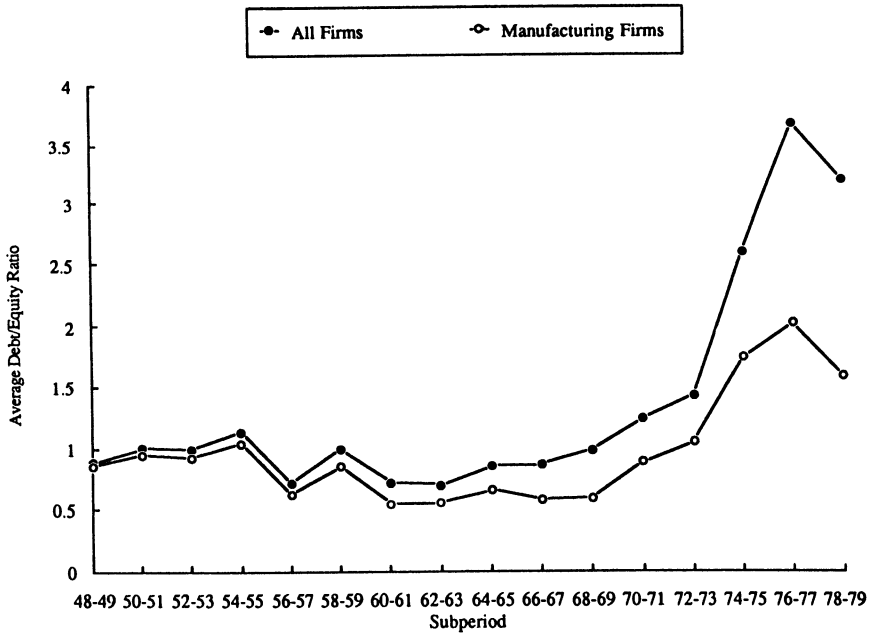


Figure 1. Average Debt/Equity Ratio by Subperiods

estimates including January are sixteen percent, fifteen percent, and thirty-five percent lower for the coefficients of *LTEQ*, *BETA*, and *DER*, respectively, in the all-firms sample. They are eleven percent, fifteen percent, and twenty percent lower, respectively, in the manufacturing-firms sample. A larger gain in precision occurs for the coefficient of *DER*, especially in the all-firms sample, partly due to the larger variation in the sampling variances of the month-by-month estimates across subperiods and partly because the standard error of the SA estimate is overestimated due to the nonconstancy of this coefficient, both of which in turn are mostly due to the extreme *DERs* as discussed below.

In the all-firms sample, the SA estimate gives a much higher coefficient for *DER* compared with the WA estimate including or excluding January. This difference indicates significant changes in this coefficient across subperiods, which in turn can be traced mainly to the extreme *DERs* discussed above. The extreme *DERs* result in smaller estimated coefficients for *DER*, indicating that the linear functional form for *DER* proposed in (1) is probably not adequate for the extreme *DERs*. They also result in lower estimated standard errors for the estimated coefficients of *DER* because they double, triple, and even quadruple the dispersion of the *DERs*. For example, for the subperiod 1958–1959, which is a typical subperiod without many extreme *DERs*, the mean estimate of the coefficient of *DER* including January is 0.16 percent, with an estimated standard error of 0.14 percent. In contrast, for the subperiod 1976–1977, which has a large number of extreme *DERs*, the mean estimate of the coefficient of *DER* including January is 0.03 percent, with an estimated standard error of 0.02 percent. We can reject the hypothesis that the coefficient of *DER* including (excluding)

January during 1948–1969, when there are fewer firms with extreme *DERs*, is the same as that during 1970–1979, with a *t*-statistic of 2.19 (1.95).¹³ Figures 2 and 3 plot the estimated coefficients of *DER* by subperiods. Since more precise subperiod estimates are given higher weights in the WA estimate, this leads to a lower estimate. As noted above, the SA estimate is a better indicator of the average magnitude of the coefficient in this case.

It is apparent from Table I that the expected common stock returns are significantly related to *DER* both including and excluding January, though the estimated coefficient of *DER* is much higher in January. Using the SA estimates, *DER* has an average coefficient of 0.13 percent and 0.18 percent per month, respectively, in the all-firms and manufacturing-firms samples including January. Excluding January, its average coefficient goes down to 0.09 percent and 0.11 percent, respectively. In January, the average coefficient is 0.64 percent and 1.00 percent in the respective samples. We can reject the hypothesis that the coefficient of *DER* in January is the same as that in the other months with a *t*-statistic of 5.31 (5.41) in the all-firms (manufacturing-firms) sample.¹⁴ Thus, *DER* has a much larger coefficient in January compared with the other months, the difference being larger in the manufacturing-firms sample (see Figure 4), and it has a larger coefficient in the manufacturing-firms sample, especially in January.

Given the wide range of *DERs*, the estimated coefficients of *DER* are economically substantial. For example, they imply a difference in the expected returns of 5.83 percent $[= (2.81 - 0.14) \times 0.182 \times 12]$ per annum (we ignore compounding in annualizing the results since we are dealing with “excess” returns) including January, 2.66 percent in January and 3.17 percent in the remaining months, between our maximum and minimum average *DER* portfolios, controlling for *LTEQ* and *BETA*, in the manufacturing-firms sample. For comparison, the implied difference in the expected returns between our minimum and maximum average *LTEQ* portfolios, controlling for *BETA* and *DER*, is 5.79 percent per annum including January, 5.00 percent in January and 0.79 percent in the remaining months, in the same sample.¹⁵ It should be remembered that, given

¹³ We allow the sampling variances of the month-by-month estimates to be different in the two periods. (See Kendall and Stuart [11], equation 21.21.)

¹⁴ The *t*-statistic reported is \sqrt{s} times the average of the subperiod *t*-statistics “standardized” to have standard deviation equal to one (see footnote 10), where *s* is the number of subperiods. Each subperiod *t*-statistic is the usual two-sample *t*-statistic, assuming that the sampling variance of the estimated coefficient in January is the same as that in the other months. Our conclusion, however, does not change when we allow the sampling variance to be much higher (say four times) or lower (say one-fourth) in January compared with the other months. The evidence on the sampling variance in January relative to that in the other months is discussed later.

¹⁵ These calculations apply *average* (across subperiods) estimated coefficients to the range of *average DERs/LTEQs*, which can be misleading if the range and the estimated coefficient of a variable are significantly correlated across subperiods. To check for this possibility, we apply the subperiod estimates to the subperiod *DERs/LTEQs* and average their products across subperiods. In this case, the implied difference in expected returns between the maximum and minimum average *DER* portfolios is 5.51 percent per annum including January, 2.54 percent in January and 2.97 percent in the remaining months, controlling for *BETA* and *LTEQ*, in the manufacturing-firms sample. Similarly, the implied difference in expected returns between the minimum and maximum average *LTEQ* portfolios is 6.05 percent per annum including January, 5.10 percent in January and 0.95 percent in the remaining months, controlling for *BETA* and *DER*, in the same sample. Clearly, the results using the *averages* are not misleading in these cases.

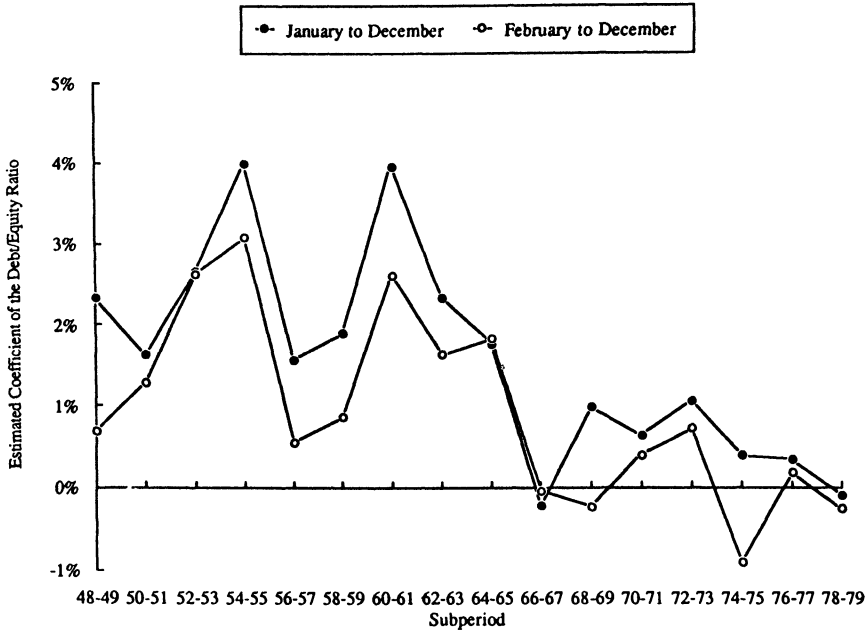


Figure 2. Estimated Coefficients of Debt/Equity Ratio by Subperiods—All Firms

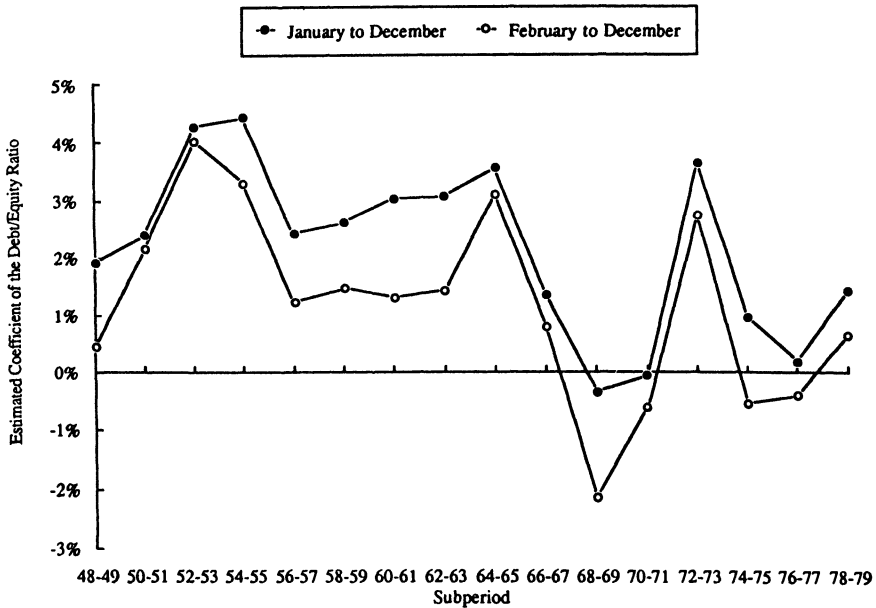


Figure 3. Estimated Coefficients of Debt/Equity Ratio by Subperiods—Manufacturing Firms

the way these portfolios are formed, the maximum (minimum) average *DER/LTEQ* portfolio usually does not contain all of the largest (smallest) *DER/LTEQ* stocks.

Figures 2 and 3 depict the estimated coefficients of *DER* by subperiods for the

all-firms and manufacturing-firms samples, respectively. The estimated coefficients are plotted for January to December (sum of the coefficients for individual months, averaged across the two years in a subperiod) and February to December. The difference between the former and the latter represents the estimated coefficient for January. The estimated coefficient of *DER* for January is positive in each one of the subperiods in the manufacturing-firms sample. It is negative in only two subperiods (out of sixteen) in the all-firms sample and, even then, only slightly negative. The estimated coefficient of *DER* for January to December is negative in only two subperiods in either sample and again only slightly negative even then. Noting that an estimated coefficient can be interpreted as the difference between returns on two particular portfolios, we can create a portfolio based on *DERs* that will give positive “excess” returns most of the time and slightly negative “excess” returns once in a while. Therefore, the “excess” return associated with *DER* is *not* likely to be just some kind of “risk premium”.

As noted above, there are more stocks with extreme *DERs* in the later subperiods, especially in the all-firms sample, resulting in lower estimated coefficients for *DER*. This partly explains the lower estimated coefficients in the second half of the subperiods in Figures 2 and 3, especially when all firms are used.

Figure 4 shows the simple averages of the estimated coefficients (across subperiods) of *DER* for each of the twenty-four subperiod months. As noted above, the two January coefficients are larger compared with the other months in both the all-firms and manufacturing-firms samples. The first January tends to have a somewhat larger coefficient than the second January. No other month consistently stands out in this figure.

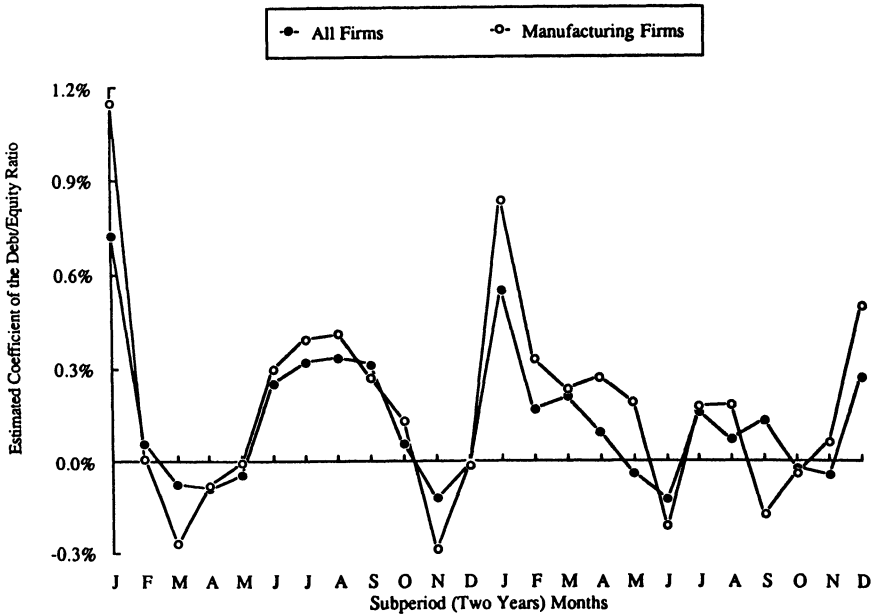


Figure 4. Estimated Coefficients of Debt/Equity Ratio by Subperiod Months—1948 to 1979

The expected common stock returns are significantly related to *LTEQ*, but only in January, in either sample. We can reject the hypothesis that the coefficient of *LTEQ* in January is the same as that in the other months with a *t*-statistic of -12.26 (-11.68) in the all-firms (manufacturing-firms) sample. (See footnote 14.) In January, using the SA estimates, *LTEQ* has an average coefficient of -1.31 percent and -1.25 percent per month, respectively, in the all-firms and manufacturing-firms samples. The economic significance of these estimates has already been indicated above. The estimated coefficient of *LTEQ* for January is negative in each one of the subperiods, in either sample. Thus, the “size premium” in January is also *not* likely to be just some kind of “risk premium”.

Excluding January, the expected common stock returns are not significantly related to *BETA* in either sample. *BETA* actually has a negative estimated coefficient including or excluding January in the manufacturing-firms sample. However, we can reject the hypothesis that the coefficient of *BETA* in January is the same as that in the other months with a *t*-statistic of 1.98 (2.01) in the all-firms (manufacturing-firms) sample.¹⁶ The expected common stock returns tend to be significantly related to *BETA* in January with a *t*-statistic of 1.86 (1.39) in the all-firms (manufacturing-firms) sample. These *t*-statistics are distributed as “Student’s” *t* with 15 d.f.¹⁷ In January, using the SA estimates, *BETA* has an average coefficient of 1.87 percent and 1.56 percent per month, respectively, in the all-firms and manufacturing-firms samples. These imply a difference in the expected returns of 1.57 percent (1.09 percent) in January between our maximum and minimum average *BETA* portfolios, controlling for *LTEQ* and *DER*, in the all-firms (manufacturing-firms) sample.¹⁸ This difference, however, is more than offset by the opposite difference in the remaining months in the manufacturing-firms sample.

To summarize, then, *DER* has a significant positive effect on the expected common stock returns, both in January and in the other months, though the effect is much larger in January. The effect of *DER* is smaller in the later subperiods, partly due to certain firms with extreme *DER*s for which the linear functional form specified in (1) is probably not adequate. *LTEQ* has a significant negative effect, but only in January. *BETA* tends to have a significant positive effect in January, which is offset by an opposite effect in the other months in the manufacturing-firms sample. We also argue that the “excess returns” or “premiums” associated with *DER* and *LTEQ* are *not* likely to be just some kind of “risk premiums”.

A. Are “January Premiums” More Uncertain?

Given the large “January premiums”, it is natural to ask whether they are partly due to higher risk. Essentially, we want to test whether January estimates

¹⁶ See footnote 14 for details of the test statistic used. When we allow the sampling variances to be 1.5 to 2.5 times larger in January compared with the other months, we can still reject this hypothesis, but at the 0.1 significance level (one-sided).

¹⁷ Because there are only two January observations in each subperiod, we use the time series of mean January estimates across subperiods to calculate this *t*-statistic.

¹⁸ Applying the procedure described in footnote 15, the implied differences are 1.66 percent and 1.16 percent, respectively, in the all-firms and manufacturing-firms samples.

have larger sampling variances. Unfortunately, tests of this hypothesis are sensitive to departures from the standard assumptions we have already made, such as normally distributed errors, and require some additional assumptions to aggregate across subperiods. The problem is made worse because of only two January observations in a subperiod. We consider three different tests, all based on the usual F -test for equality of variances, requiring different sets of additional assumptions. In these tests, we always put the estimated sampling variance of the January estimate in the numerator of the F -statistic.

In the first test, we do a separate F -test for each subperiod. Each subperiod F -statistic is distributed as $F_{1,21}$, the subscripts being the numerator and denominator d.f., respectively. We reject the hypothesis in the overall period at the 0.05 significance level if it is rejected at the 0.0032 significance level in at least one subperiod out of sixteen. (See Kendall and Stuart [10], p. 40.) In the second test, we assume that the sampling variances (though not the mean coefficients) are constant across subperiods. In this case, the F -statistic is the ratio of the sums of the subperiod estimates of the respective sampling variances and is distributed as $F_{16,336}$. The third F -test is based on the time series of mean subperiod estimates, assuming that both the mean coefficients and sampling variances are constant across subperiods. This F -statistic is distributed as $F_{15,15}$.

For *DER*, the maximum and minimum subperiod F -statistics are 4.74 and 0.026 (3.03 and 0.017), respectively, in the all-firms (manufacturing-firms) sample. The second and third F -statistics are 0.81 and 2.74 (0.81 and 1.13), respectively, in the all-firms (manufacturing-firms) sample. Only the third F -test in the all-firms sample rejects the null hypothesis. However, the value of this F -statistic seems quite unreasonable in comparison with the others and, in view of the other evidence, is probably caused by the nonconstancy of the mean coefficients across subperiods. Thus, we cannot reject the hypothesis that the "premium" associated with *DER* has the same variance in January as in the other months. Based on the second F -test, its estimated variance in January is about eighty-one percent of that in the other months in either sample.

For *LTEQ*, the maximum and minimum subperiod F -statistics are 12.13 and 0.0012 (10.30 and 0.0031), respectively, in the all-firms (manufacturing-firms) sample. The second and third F -statistics are 2.07 and 2.66 (2.52 and 1.54), respectively, in the all-firms (manufacturing-firms) sample. All three F -tests indicate a rejection of the null hypothesis in favor of the one-sided alternative that the "premium" associated with *LTEQ* has a larger variance in January compared with the other months in the all-firms sample. The evidence in the manufacturing-firms sample is mixed, where the second F -test rejects the null hypothesis strongly, the first F -test comes close to rejecting it, but the third F -test does not reject it even at the 0.1 significance level. The nonconstancy of the coefficient between the two Januaries of a subperiod, which affects the first two F -tests, is probably part of the reason for this difference. Our conclusion is that the "premium" associated with *LTEQ* has about a 1.5 to 2.5 times larger variance in January compared with the other months.

For *BETA*, the maximum and minimum subperiod F -statistics are 6.16 and 0.0013 (6.49 and 0.0129), respectively, in the all-firms (manufacturing-firms) sample. The second and third F -statistics are 1.81 and 0.84 (2.26 and 0.95),

respectively, in the all-firms (manufacturing-firms) sample. The evidence is clearly mixed because the second *F*-test rejects the null hypothesis while the others do not in either sample. Thus, the “premium” associated with *BETA* may have from about the same to about twice as large a variance in January compared with the other months.

To summarize, the larger “premium” associated with *DER* in January is not likely to be due to higher risk. There remains a possibility, however, that the “premiums” associated with *LTEQ* and *BETA* in January may be partly, but partly only in view of the other evidence, due to higher risk.

B. Effects of Estimation Errors in BETA

Since *BETA* contains estimation errors, the other variables may proxy for the true beta. We can test this by estimating the test-period betas of the estimated coefficients. The OLS estimate of the slope coefficient in the regression of the estimated coefficients on the market proxy is their estimated test-period beta. A test-period beta equal to zero for the estimated coefficients of a variable means that the variable does not proxy for beta. On the other hand, if *BETA* is a good proxy for the true beta, the test-period beta of its estimated coefficients will be close to one. (See Bhandari [4].)

The test-period betas of the estimated coefficients are estimated for each subperiod. The simple averages of these subperiod estimates are reported in Table I. The corresponding *t*-statistics are based on the time series of the subperiod estimates. The estimated test-period betas of the estimated coefficients are close to zero for *DER* and *LTEQ* in either sample. They are statistically insignificant and economically negligible. Thus, neither *DER* nor *LTEQ* seems to proxy for the true beta. *BETA* is a better proxy for the true beta in the all-firms sample than it is in the manufacturing-firms sample. As expected, the estimation errors cause the test-period beta of the estimated coefficients of *BETA* to be less than one and, correspondingly, the test-period beta of the estimated intercept terms to be greater than zero. Thus, we can conclude that the only major effect of the estimation errors in *BETA* is the underestimation of the coefficient of beta, probably by about seven percent (seventeen percent) in the all-firms (manufacturing-firms) sample. These errors have virtually no effect on the estimation of the coefficients of *DER* and *LTEQ*.

C. “Incremental” Effects of Explanatory Variables

In this subsection, we analyze the effects of inclusion or exclusion of an explanatory variable on the estimated coefficients of the other variables. Table II summarizes the results for each possible combination of explanatory variables. To keep the other things constant, the portfolios used in all of these combinations are exactly the same as those used when all of the explanatory variables are included. In this table, only the results based on the SA estimates are shown because they provide a better basis for comparison by keeping the subperiod weights constant across different combinations. Note, however, that the coefficient of *DER* excluding January is sometimes not statistically significant based on the *t*-statistics in this table, even though it is based on the *t*-statistics

Table II
Estimated Coefficients (Percent per Month) for the Expected-Return Equation
 $[E(\tilde{r}_i) = \gamma_0 + \gamma_1 LTEQ_i + \gamma_2 BETA_i + \gamma_3 DER_i]$ Using All Possible Combinations of the Explanatory
Variables: 1948–1979^a

All-Firms Sample				Manufacturing-Firms Sample				
Explanatory Variables	Constant	LTEQ	BETA	DER	Constant	LTEQ	BETA	DER
Panel A: Results Including January								
LTEQ	1.49	-0.15 (-3.29)			1.42	-0.13 (-2.87)		
BETA	0.27		0.63 (2.15)		0.30		0.57 (1.89)	
DER	0.70			0.16 (3.97)	0.68			0.22 (3.06)
LTEQ, BETA	1.15	-0.13 (-3.33)	0.25 (0.92)		1.44	-0.15 (-3.82)	0.02 (0.08)	
LTEQ, DER	1.28	-0.13 (-2.93)		0.12 (3.54)	1.13	-0.09 (-2.30)		0.14 (2.48)
BETA, DER	0.24		0.49 (1.68)	0.16 (4.02)	0.48		0.21 (0.72)	0.23 (3.70)
LTEQ, BETA, DER	1.01	-0.11 (-3.00)	0.17 (0.60)	0.13 (3.84)	1.45	-0.12 (-3.32)	-0.24 (-0.87)	0.18 (3.47)
Panel B: Results Excluding January								
LTEQ	0.68	-0.01 (-0.39)			0.60	0.01 (0.15)		
BETA	0.48		0.13 (0.47)		0.65		-0.04 (-0.16)	
DER	0.56			0.07 (1.70)	0.58			0.04 (0.54)
LTEQ, BETA	0.57	-0.01 (-0.33)	0.07 (0.27)		1.00	-0.04 (-1.06)	-0.24 (-0.91)	
LTEQ, DER	0.57	-0.00 (-0.09)		0.07 (2.17)	0.49	0.02 (0.63)		0.05 (0.93)

<i>BETA, DER</i>	0.47	0.07 (0.26)	0.08 (2.09)	0.73	-0.19 (-0.70)	0.10 (1.63)
<i>LTEQ, BETA, DER</i>	0.52	0.00 (0.01)	0.09 (2.47)	1.01	-0.02 (-0.57)	0.11 (2.00)

^a *LTEQ*, *BETA*, and *DER* stand for the logarithm of total equity, debt/equity ratio, and estimated beta, respectively. The results in all combinations are based on twenty-seven portfolios, formed by ranking the securities on all three explanatory variables, for each two-year subperiod. The estimated coefficients are simple averages of the corresponding subperiod mean estimates. Their *t*-statistics, given in parentheses, are distributed as approximately standard normal under the null hypothesis that the coefficient is zero.

corresponding to the WA estimates, because the former t -statistics are usually ten to fifteen percent lower than the latter ones in the case of *DER*.

The following effects can be seen in Table II. Including January, *DER* and *LTEQ*, when included, reduce the absolute value of each other's estimated coefficients. Excluding January, the inclusion of *DER* still makes the estimated coefficient of *LTEQ* less negative, but the inclusion of *LTEQ* increases the estimated coefficient of *DER*. The estimated coefficient of *BETA* goes down when either of the other variables is included, and the inclusion of *BETA* increases the estimated coefficient of *DER*, including or excluding January. These effects occur in both samples and are more pronounced in the manufacturing-firms sample. Inclusion of *BETA* makes the estimated coefficient of *LTEQ* less negative in the all-firms sample but more negative in the manufacturing-firms sample, including or excluding January.

The estimated coefficient of *DER* excluding January in the manufacturing-firms sample becomes small and statistically insignificant when *BETA* is not included because *DER* is positively correlated with *BETA* (see Table I), which in turn has a negative, though possibly unexpected, effect on the returns in this sample for this period. Similarly, the estimated coefficient for *BETA* including January becomes large and statistically significant, in both samples, when *LTEQ* and *DER* are not included.

Unfortunately, the usual R^2 criterion is not applicable in our case to decide which explanatory variables should be included.¹⁹ (See Bhandari [4].) Based on the above evidence, excluding any one of the explanatory variables seems undesirable.

D. Some Further Comments

The results are not sensitive to changes in the order of explanatory variables in ranking to form the portfolios used in the tests or the market proxy and estimation technique used for *BETA*.²⁰ They are also not sensitive to the use of nominal returns rather than real returns or to excluding January in calculating *BETA*.

The monthly portfolio returns used in our tests have a small but significant positive first-order autocorrelation. (See footnote 3.) As a result, the estimated coefficients have a positive first-order autocorrelation as well. The correction for such autocorrelation lowers our t -statistics somewhat, but none of our conclusions is otherwise changed.

The use of COMPUSTAT data induces a survival bias in our sample because a given edition of the COMPUSTAT tapes excludes firms that did not exist at the end of the period covered by that edition. This problem is mitigated to some extent by our use of a file provided by the CRSP that merges several editions of

¹⁹ The basic reason is the use of portfolios formed in a certain way rather than the use of individual securities. Also, the computation of the correct R^2 will require the knowledge of the variance-covariance matrix of \tilde{u}_{it} 's in (3) up to a constant scalar multiplier.

²⁰ The market proxies used are the equally weighted and value-weighted portfolios of the NYSE securities, as well as an extended market portfolio similar to that of Stambaugh [14]. The *BETA* estimation techniques used are OLS and the technique developed by Scholes and Williams [13].

the COMPUSTAT tapes. Actually, when survival bias was artificially introduced in those years when it did not exist by requiring the data to be available for the following years, the results were virtually unchanged.

When the stock price goes down, other things equal, the corresponding *DER* goes up. If down movements in the stock prices tend to be followed by up movements, then this “reversal” effect can cause the *DER* to have a significant coefficient in our regressions. To check for this, we included the average returns for the previous four years as another independent variable in our regressions.²¹ For the all-firms sample reported in Table I, this additional explanatory variable caused the estimated coefficient of *DER* to change from 0.13 percent (0.09 percent) per month to 0.11 percent (0.09 percent) per month including (excluding) January using the SA estimates, with the corresponding *t*-statistic changing from 3.84 (2.47) to 3.44 (2.75).²² Similar results are obtained for other samples. Thus, the “reversal” effect can explain only a part of the coefficient of *DER* in January.

The ratio of long-term debt to equity does not perform as well as our measure of *DER*. The major reason for this seems to be that a large number of firms have no long-term debt, especially in the earlier period. Almost half of the firms used in the subperiod 1948–1949 had no long-term debt. Thus, the ratio of long-term debt to equity is not able to differentiate between many firms that have different amounts of common equity relative to their total assets.

Finally, since debt liabilities are fixed in monetary terms, it is interesting to know whether the estimated coefficients of *DER* are related to inflation. We calculated the correlation of the estimated coefficients over time with the actual inflation and the change in inflation from the previous month, where inflation is measured as the rate of change in the CPI, for each subperiod. The change in inflation is used as a measure of the unexpected inflation. The average (across subperiods) correlation of the estimated coefficients of *DER* with both the total and the unexpected inflation rates ranges from -0.01 to 0.06 in different samples. The estimated coefficients of *LTEQ* and *BETA*, on average, have a somewhat higher correlation with the inflation than that. Thus, the coefficient of *DER* does not seem to be related to the inflation in any important way.

III. Summary and Conclusions

The expected returns on common stocks are positively related to the debt/equity ratio (*DER*), controlling for the beta and firm size, both including and excluding January. The estimated coefficient of *DER* is 0.13 percent (0.18 percent) per month including January and 0.09 percent (0.11 percent) per month excluding January when all (only manufacturing) firms are used. The estimated coefficient is 0.64 percent (1.00 percent) per month in January using all (only manufacturing)

²¹ This additional check was suggested by an associate editor and the editor of this Journal. The reason for using raw average returns, rather than “risk-adjusted” returns, is to avoid another variable with the error-in-the-variables problem, especially in view of the fact that *BETA* is already an independent variable and that the estimation error of *BETA* would be correlated with the estimation error of the “risk-adjusted” return.

²² Use of average returns from two years before and two years after the test subperiod increases the estimated coefficient of *DER* both including and excluding January.

firms. Given the wide range of *DERs*, these estimated coefficients are economically substantial. The results are not sensitive to the choice of the market proxy or estimation technique used for beta.

DER does not proxy for the true beta with respect to the market proxies used. Though it may proxy for the true beta with respect to the *true* market portfolio, the insensitivity of our results to different market proxies used suggests that this is not likely. Thus, if *DER* is just a proxy for risk, a measure of risk different from beta is required or the risk-expected return tradeoff will have to be nonlinear. Actually, considering that the "premium" associated with *LTEQ* occurs only in January, that the "premium" associated with *DER* is much larger but no more uncertain in January compared with the other months, and especially that the "premiums" associated with *DER* and *LTEQ* are very consistently positive, it is not likely that the "premiums" associated with *DER*, *LTEQ*, and probably even *BETA* are due to higher risk. In any case, the evidence presented here has clear implications for the evaluation of investment performance, for tests of capital market efficiency, and for estimating the cost of capital for firms.

REFERENCES

1. Rolf W. Banz. "The Relationship between Return and Market Value of Common Stocks." *Journal of Financial Economics* 9 (March 1981), 3–18.
2. S. Basu. "Investment Performance of Common Stocks in Relation to Their Price-Earning Ratios: A Test of the Efficient Market Hypothesis." *Journal of Finance* 32 (June 1977), 663–82.
3. ———. "The Relationship between Earnings' Yield, Market Value and Return for NYSE Common Stocks: Further Evidence." *Journal of Financial Economics* 12 (June 1983), 129–56.
4. Laxmi Chand Bhandari. "Capital Market Imperfections, Risk and Expected Returns: Empirical Evidence and Some Propositions." Ph.D. Thesis, University of Chicago, 1984.
5. Eugene F. Fama and James D. MacBeth. "Risk, Return and Equilibrium: Empirical Tests." *Journal of Political Economy* 81 (May–June 1973), 607–36.
6. Lawrence Fisher. "Some New Stock-Market Indexes." *Journal of Business* 39 (January 1966), 191–225.
7. Michael R. Gibbons. "Multivariate Tests of Financial Models: A New Approach." *Journal of Financial Economics* 10 (March 1982), 3–27.
8. J. D. Jobson and Bob Korkie. "Potential Performance and Tests of Portfolio Efficiency." *Journal of Financial Economics* 10 (December 1982), 433–66.
9. Donald B. Keim. "Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence." *Journal of Financial Economics* 12 (June 1983), 13–32.
10. Maurice G. Kendall and Allan Stuart. *The Advanced Theory of Statistics, Volume 3*, 1st ed. London: Charles Griffin, 1966.
11. ———. *The Advanced Theory of Statistics, Volume 2*, 4th ed. London: Charles Griffin, 1979.
12. Marc R. Reinganum. "Misspecification of Capital Asset Pricing: Empirical Anomalies Based on Earnings' Yields and Market Values." *Journal of Financial Economics* 9 (March 1981), 19–46.
13. Myron S. Scholes and Joseph Williams. "Estimating Betas from Non-Synchronous Data." *Journal of Financial Economics* 5 (December 1977), 309–27.
14. Robert F. Stambaugh. "On the Exclusion of Assets from Tests of the Two-Parameter Model: A Sensitivity Analysis." *Journal of Financial Economics* 10 (November 1982), 237–68.
15. Hans R. Stoll and Robert E. Whaley. "Transaction Costs and the Small Firm Effect." *Journal of Financial Economics* 12 (June 1983), 57–79.