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A FINANCIAL PROFILE OF THOSE FIRMS WITH THE LOWEST COST OF EQUITY FUNDS AND A CANONICAL RANKING OF THE RISK – RETURN FACTORS

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Abstract: *The estimation of the overall weighted average cost of capital for any firm is of paramount importance, and for good reason. An estimate that is too high can result in a firm turning down projects that it should have accepted. An estimate that is too low can result in accepting projects that should have been rejected. The cost of using borrowed funds, and the cost of using preferred stock, if it is cumulative, can be observed, but the cost of using both internal and external equity funds must be estimated. The present study is concerned with that estimate and the risk-return variables that affect that estimate. A financial profile is established for those firms that have very low costs of equity funds. As in previous studies of this nature, multiple discriminant analysis is used, and the variables that affect the cost of using equity funds are ranked canonically.*

Keywords: *financial profile, cost of equity, discriminant analysis.*

I. INTRODUCTION

It would be hard to imagine any research topic in finance that has generated more interest and more studies than the cost of capital. The determination of the overall cost of capital or weighted average cost of capital (WACC) is a primary concern for all companies, and the subject matter is covered thoroughly in all basic courses in managerial finance. The cost of using borrowed funds, given market interest rates and flotation costs, and the cost of using preferred stock, if it is cumulative, can be observed. However, the cost of using both internal and external equity funds must be estimated, and therein lies the challenge. Scholars have established, and most textbooks have included, at least three widely used models developed for the purpose of helping to make that estimate. There is first, the capital asset pricing model (CAPM) established by Sharpe (1964) and Lintner (1965). Secondly, the dividend discount model (DDM) proposed by Gordon and Shapiro was first introduced in 1956. It became the most widely used model both in research and in textbooks until the appearance of the CAPM. Third, the bond-yield plus a risk premium approach is used, but it is more subjective than the previous two models. For example, a firm's analyst may use the company's bond yield and by various subjective methods add a risk premium for the company's stock. Of the three methods, the CAPM is used most often in practice. It has been observed that the DDM lends itself to including flotation costs, but analysts now just compute the cost of equity capital using the CAPM and then add flotation costs (Brigham and Daves, 2016).

Two other models have been developed by scholars for the computing the cost of equity capital that are little used in practice, but they are intellectually appealing and theoretically logical. Thus, they deserve mention here. A major objection to the CAPM is that the model uses ex post data to estimate ex ante results. This was found to be objectionable by some scholars and two rather famous alternative models have been proposed. They are first, the Fama – French Three Factor Model (Fama and French, 1997), and secondly, the Arbitrage Pricing Theory (APT) model. The Fama – French (FFTF) three factor model considers both the size of the firm and the book to market multiple in addition to the market risk premium, whereas the CAPM only considers the market risk premium. Thus, there are three factors, in the FFTF and each factor is assigned their own sensitivity coefficient (beta). As in the case of most contributions to the literature, the FFTF has drawn criticism. Allen, Singh and Powell (2009) found that the FFTF is not necessarily linear and that it is less effective when analyzing the extremes within a distribution. Brigham and Daves (2016) simply stated that the model is less useful in computing the cost of capital because it does not establish a clear link between risk and the rate of return. It does however add measures of two important variables that impact the cost of equity capital.

Arbitrage pricing theory can contain any number of measures that may affect the cost of equity capital, each with its own sensitivity coefficient. Theoretically, this model would absolutely describe reality if the appropriate measures together with their sensitivity coefficients could be identified and empirically tested. There have been no satisfactory empirical tests of the APT. Although, there have been attempts to test the APT model with factor analysis, the results have not been definitive. Thus, the model does not provide insights to the determinants of risk (Brigham and Daves, 2016), and it is rarely used in practice.

Regardless of the all the attention and literary contributions given the subject of the cost of capital since Ezra Solomon's publication of *The Management of Corporate Capital* in 1959, there have been no studies that attempted to establish a financial profile, containing standard measures of risk, return, and market perception, for those firms that have historically experienced the lowest cost of equity capital.

The purpose of this study is to establish a financial profile for those firms identified as having the lowest costs of equity capital in a database of 2000 firms created by (Damodaran, 2014) from Bloomberg, Morningstar and Compustat. Specifically, the analysis will test for significant differences in the financial profiles of firms with the lowest costs of equity capital and to compare those profiles with companies identified as having the highest costs of equity. If the two groups of firms have unique financial profiles, and the model can be validated without bias, it suggests that the profile may be used as a tool to forecast companies that will maintain low costs of equity capital in future periods. The use of such a new tool to forecast low costs of equity capital would have implications for investors, managers, lenders, investment counselors, and academicians.

II. SELECTION OF SAMPLE AND INDEPENDENT VARIABLES

Given the all the discussion, development of models, empirical tests, and unmatched interest in financial literature, since Solomon's 1959 attempt at arriving at a synthesis, the present study should be regarded as furthering that interest, and an addition to the entire body of knowledge regarding the estimate of the cost of using equity funds. Thus, the dependent variables used here are the group of firms reporting the lowest cost of equity capital and the firms that were identified as having the highest cost of equity capital.

All data used in the analysis were gathered from Domodaran's 2014 set. The sample selected for this study consists of two groups. The LCEC group contains 709 observations, and the HCEC group contains 887 observations. This, of course, exhausted the available data in the Domodaran set that was judged suitable for this study. The sample is large enough (1596 companies) that as long as the variance covariance matrices are equal, it renders the difference in the size of the groups insignificant, and of course, the sample gathered simply exhausted Domodaran's database in the LCEC category.

Previous studies using this and other statistical methods have chosen explanatory variables by various methods and logical arguments. In this study the group of explanatory variables chosen for analysis includes two measures of return to capital, three measures of risk, one measure of value, and one measure of how the company may be perceived by investors at the margin (those willing and able to buy). An evaluation of those measures is needed to accomplish the purpose of this study. A basic tenet of this study is that all investors "trade off" indicators of risk and return to establish the value of the firms.

Following are the seven explanatory variables:

X_1 Market Capitalization is used here as a simple measure of the size of the firm. Total sales could have been used, and has been used in prior studies to measure size, but it has a greater annual fluctuation than market capitalization.

X_2 The enterprise value multiple is included here as a measure of how investors at the margin perceive the value of the firm. It has been described as how much an acquiring firm would have to pay to take over a company, and that number is divided by the company's latest earnings before interest and taxes plus depreciation and amortization (EBITDA). It is more commonly referred to as the enterprise value multiple, and it is said to be roughly analogous to the payback period. Reese (2013) offered the opinion that the significance of the enterprise value multiple (EVM) lies in its ability to compare companies with different capital structures, and that by using the EVM instead of market capitalization to look at the value of a company, investors get a more accurate sense of whether or not a company is truly valued.

X_3 One measure of return is return on equity. Return on total capital could have been used, but it includes a return to creditors as well as owners, and recognizes that value is affected by the cost of debt. However, the return on equity measure is more consistent with the stated purpose of estimating the cost of using that equity capital.

X_4 Growth may also be regarded as a return on capital, and indeed growth has been of interest to financial investors for years, and all investors as well as financial managers value expected growth more than historical growth. In this study Damodaran's (2014) expected two-year change in earnings per share (EPS) was used.

X_5 There is in any company both financial risk (financial leverage) and operating risk (operating leverage). Sharpe's beta coefficients contain the effects of both operating and financial risk. It is customary in modern research to separate the two types of risk to identify and compare the sources of risk. The separation is accomplished by using Hamada's (1972) equation to "unlever" the published betas. Damodran (2014) used that equation to unlever the "bottom up" sector betas. Those betas are used here as a measure of operating leverage (operating risk that results from fixed operating costs).

X_6 Financial leverage (financial risk resulting from fixed finance costs) is measured here by use of the long term debt to total invested capital ratio (DTC). That ratio is used here as a measure of financial leverage. There are other ratios that measure financial risk very well, but the long-term debt to total capital ratio again recognizes that the firm is financed by creditors as well as owners.

X_7 The seventh explanatory variable is the coefficient of variation in earnings before interest and taxes (EBIT). The coefficient of variation (CV) standardizes the relative variance in EBIT among companies, and allows comparison of those variances in relation to the expected value of EBIT for each company in the dataset. The greater the CV, the greater is the risk in relation to the expected EBIT. Thus, it is included here as a measure of a different type of risk than indicated by the above two leverage ratios, i.e. one that measures risk per unit of EBIT.

In sum, there are seven explanatory variables in the multiple discriminant model. They are as follows:

X1 – Market Capitalization (Size)

X2 – The Enterprise Value Multiple

X3 – Return to Equity Capital

X4 – The Expected Two Year Growth Rate

X5 – The Unlevered Sector Beta (Operating Risk)

X6 – The Long Term Debt to Total Capital Ratio (Financial Risk)

X7 – The Coefficient of Variation in Operating Income

The explanatory variable profile contains basic measures of common financial variables. They were chosen, as in any experimental design, because of their consistency with theory, adequacy in measurement, the extent to which they have been used in previous studies, and their availability from a reputable source. Other explanatory variables could have been added, however their contributions to the accomplishment of the stated purpose of the study would have been negligible. When there are a large number of potential independent variables that can be used, the general approach is to use the fewest number of explanatory variables that accounts for a sufficiently large portion of the discrimination procedure (Zaiontz 2014). The more accepted practice is to use only the variables that logically contribute to the accomplishment of the study's purpose (Suozzo 2001). This study is consistent with both references.

III. TESTS AND RESULTS

The discriminant function used has the form:

$$Z_j = C_0 + V_1X_{1j} + V_2X_{2j} + \ldots + V_nX_{nj} \quad (1)$$

Where:

C_0 is a constant

X_{ij} is the firm's value for the ith independent variable.

V_i is the discriminant coefficient for the firm's jith variable.

Z_j is the jth individual's discriminant score.

The function derived from the data in this study and substituted in equation 1 is:

$$Z_j = -5.461 - 0.053X_1 - 0.599X_2 + 0.00001_3 + 6.010X_4 + .070X_5 + 1.177X_6 - 0.232X_7 \quad (2)$$

Classification of firms is relatively simple. The values of the seven variables for each firm are substituted into equation (5). Thus, each firm in both groups receives a Z score. If a firm's Z score is greater than a critical value, the firm is classified in group one (LCEC). Conversely, a Z score less than the critical value will place the firm in group two (HCEC). Since the two groups are heterogeneous, the expectation is that LCEC firms will fall into one group and the HCEC firms will fall into the other. Interpretation of the results of discriminant analysis is usually accomplished by addressing four basic questions:

1. Is there a significant difference between the mean vectors of explanatory variables for the two groups of firms?
2. How well did the discriminant function perform?
3. How well did the independent variables perform?
4. Will this function discriminate as well on any random sample of firms as it did on the original sample?

To answer the first question, SPSS provides a Wilk's Lamda – Chi Square transformation (Sharma 1996). The calculated value of Chi-Square is 788.9. That exceeds the critical value of Chi-Square 14.067 at the five percent level of significance with 7 degrees of freedom. The null hypothesis that there is no significant difference between the financial profiles of the two groups is therefore rejected, and the first conclusion drawn from the analysis is that the two groups have significantly different financial characteristics. This result was of course, expected since one group of firms experienced very low costs of equity funds and the other group experienced high costs of those funds. The discriminant function thus has the power to separate the two groups. However, this does not mean that it will in fact separate them. The ultimate value of a discriminant model depends on the results obtained. That is what percentage of firms was classified correctly and is that percentage significant?

The firms that were classified correctly are shown on the diagonal in Table I. Of the total of 1.956 firms in the dataset 1262 or 79.1 percent were classified correctly.

TABLE 1

CLASSIFICATION RESULTS

Predicted Results

LCEC - HCEC Classification

Actual Results	LCEC	HCEC
LCEC	561	14
HCEC	186	701

To answer the second question a test of proportions is needed. Thus, to determine whether 79.1 percent is statistically significant, formal research requires the proof of a statistical test. In this case, the Press's Q test is appropriate (Hair et al. 1992, 106). Press's Q is a Chi-square random variable:

$$\text{Press's } Q = [N-(n \times k)]^2 / N(k-1) \qquad (3)$$

where:

N = Total sample size

n = Number of cases correctly classified

k = Number of groups

In this case:

$$\text{Press's } Q = [1596 - (1263 \times 2)]^2 / [1596\,(2-1)] = 541.92 > \chi^2_{.05}\ 3.84 \text{ with one d. f.} \qquad (4)$$

Thus, the null hypothesis that the percentage classified correctly is not significantly different from what would be classified correctly by chance is rejected. The evidence suggests that the discriminant function performed very well in separating the two groups. Again, given the disparity of the two groups, and the sample size, it is not surprising that the function classified 79.1 percent correctly.

The arithmetic signs of the adjusted coefficients in Table 2 are important to answer question number three. Normally, a positive sign indicates that the greater a firm's value for the variable, the more likely it will be in group one, the LCEC group. On the other hand, a negative sign for an adjusted coefficient signifies that the greater a firm's value for that variable, the more likely it will be classified in group two, the HCEC group. An examination of Table 2 reveals that the entire set of explanatory variables, with the exception of market capitalization (size) were associated with firms experiencing low costs of equity capital. That is, the firms with lower costs of equity capital had higher measures of value, return and risk than the firms with higher costs of equity capital. Conversely, they were smaller in size than the firms with high costs of equity capital.

The relative contribution of each variable to the total discriminating power of the function is indicated by the discriminant loadings, referred to by SPSS as the pooled within-groups correlations between discriminating variables and canonical function coefficients, or more simply their structure matrix. Those structure correlations are indicated by canonical correlation coefficients that measure the simple correlation between each independent variable and the Z scores calculated by the discriminant function. The value of each canonical coefficient will lie between +1 and -1. Multicollinearity has little effect on the stability of canonical correlation coefficients, in contrast to the discriminant function coefficients where it can cause the measures to become unstable. (Sharma 1996, 254). The closer the absolute value of the loading to 1, the stronger the relationship between the discriminating variable and the discriminant function These discriminant loadings are given in the output of the SPSS 21.0 program, and shown here with their ranking in Table 2.

TABLE 2

RELATIVE CONTRIBUTION OF THE VARIABLES

Discriminant Variables	Coefficient	Rank
The Two Year Expected Growth Rate	0.964	1
Long Term Debt to Total Capital (Financial Risk)	0.192	2
The Unlevered Sector Beta (Operating Risk)	0.082	3
The Coefficient of Variation in EBIT	0.08	4
Market Capitalization (Size)	-0.059	5
The Enterprise Value Multiple	0.058	6
Return on Equity Capital	0.037	7

Table 2 reveals that five year annual growth rate, made the greatest contribution to the discriminant function. That is followed respectively by the measure financial risk, the measure of operating risk, the coefficient of variation in EBIT, the enterprise value multiple, and the return on equity capital. Conversely the greater the size of the firm, the more likely it would be classified as having high costs of equity capital.

Some multicollinearity may exist between the predictive variables in the discriminant function, since both return and risk could be reflected in the costs of equity capital. Hair, et al. (1992) wrote that this consideration becomes critical in stepwise analysis and may be the factor determining whether a variable should be entered into a model. However, when all variables are entered into the model simultaneously, the discriminatory power of the model is a function of the variables evaluated as a set and multicollinearity becomes less important. More importantly, the rankings of explanatory variables in this study were made by the canonical correlation coefficients shown in Table 2. As discussed the previous paragraph, those coefficients are unaffected by multicollinearity (Sharma, 1996).

IV. VALIDATION OF THE MODEL

Before any general conclusions can be drawn, a determination must be made on whether the model will yield valid results for any group of randomly drawn firms. The procedure used here for validation is referred to as the Lachenbruch or, more informally, the "jackknife" method. In this method, the discriminant function is fitted to repeatedly drawn samples of the original sample. The procedure estimates (k – 1) samples, and eliminates one case at a time from the original sample of "k" cases (Hair et al. 1992). The expectation is that the proportion of firms classified correctly by the jackknife method would be less than that in the original sample due to the systematic bias associated with sampling errors. In this study there was a difference of only three firms. At first glance a reader might conclude that it is unusual to complete an analysis of this size and have a difference of only three firms between the two groups. However, with a very large sample such as the 1596 companies used in this study, the differences seem to diminish. The major issue is whether the proportion classified correctly by the validation test differs significantly from the 79.1 percent classified correctly in the original test. That is, is the difference in the two proportions classified correctly by the two tests due to bias, and if so is that bias significant? Of course, it may be obvious that a difference of only three cases will not be significant with a sample of 1596 companies. However, as in the aforementioned case of the Press's Q test of proportions, formal research requires the proof of a statistical test. The jackknife validation resulted in the correct classification of 78.9 percent of the firms. Since there are only two samples for analysis the binomial test is appropriate:

$$t = r - n\,p \,/\, [n\,p\,q]^{1/2} \tag{5}$$

Where:

t is the calculated t statistic

r is the number of cases classified correctly in the validation test.

n is the sample size.

p is the probability of a company being classified correctly in the original test.

q is the probability that a firm would be misclassified in the original test.

In this case: 1259 - 1596 (.791) / [1596 (.791) (.209)] ^{½} = - 0.21 is less than t_{05} 1.645. (6)

Thus, the null hypothesis that there is no significant difference between the proportion of firms classified correctly in the original test and the proportion classified correctly in the validation test cannot be rejected. Therefore, it can be concluded that while there may be some bias in the original analysis, it is not significant and it is concluded that the procedure will classify new firms as well as it did in the original analysis.

In addition to the validation procedure, researchers usually address the question of the equality of matrices. This is especially important in studies such as this where there is disparity in the size of the groups. One of the assumptions in using MDA is that the variance-covariance matrices of the two groups are equal. The SPSS program tests for equality of matrices by means of Box's M statistic. In this study Box's M transformed to the more familiar F statistic of 245.8 resulted in a zero level of significance. Thus, the null hypothesis that the two matrices are equal cannot be rejected.

V. SUMMARY AND CONCLUSION

The purpose of this study was to establish a financial profile of those firms identified as having the lowest cost of equity capital in a database of 1596 firms created by (Damodaran 2014). Specifically, the analysis tested for significant differences in the financial profiles of firms with the lowest cost of equity capital and to compare those profiles with companies that experienced the highest cost of equity capital. In this study the group of explanatory variables chosen for analysis includes two measures of return to capital, three measures of risk, one measure of value, and one measure of how the company may be perceived by investors at the margin (those willing and able to buy). Those investors "trade off" indicators of risk and return to buy and sell securities. It is the buying and selling of those investors that establish the market value of both equity and debt.

The results of the statistical analysis indicated first, that there was a significant difference in the financial profiles of the two groups of firms. The fact that the discriminant function separated two heterogeneous groups, and classified a significant proportion correctly is no surprise. In fact, the two groups of firms were so diverse in the matter of using equity funds that identification of two distinct groups based on the explanatory variables was expected.

Table 2 reveals that the expected two year annual growth rate, made the greatest contribution to the discriminant function, followed respectively by the measure financial risk, the measure of operating risk, the coefficient of variation in EBIT, the enterprise value multiple, and the return on equity capital. Conversely, the greater the size of the firm, the more likely it would be classified as having high costs of equity capital. More specifically, firms in this sample of 1259 that were classified as having the lowest cost of equity were characterized by greater returns, greater risk, and greater value. They were also are associated with one group or the other are beyond the scope of this study. However, a few comments on the findings may be in order.

Five of these results, may have been expected, one variable had no a priori expectation (The relationship was simply not known), and one was a surprise. It may have been that expected growth and the return to equity simply outweighed the three measures of risk and thus, all five of those variables may have had an a priori expectation of being characteristic of those firms with lower costs of equity. Indeed, the expected two year growth rate was the strongest of the discriminant variables. The EV/EBIT is said to be roughly analogous to the payback period. It gives the analyst an idea of how long it may take to recover the initial investment. There was no a priori expectation for this variable, but it is associated with the LCEF.

The study resulted in one surprise. Market capitalization was expected to be associated with the LCEF. That was not however, the case. Market capitalization was associated with high costs of equity. Large firms have the opportunity for greater diversity of products, greater share price liquidity, and are simply better known. No explanation of this empirical result can be offered here, and it may indeed defy logic. However, that finding as well as the other conclusions of the study is rich in content for needed further research.

This study has resulted in a contribution toward the construction of a theory that describes the value, risk-return, size and of firms that have achieved the lowest cost of using equity funds. It is further suggested that since the model was validated without bias, it can be used to predict firms that may achieve low costs of equity financing in the future. In order to make a more complete contribution to the theory, the aforementioned further research is needed. The evolution and appearance of a complete theory would aid managers, investors, academicians, and investment counselors by providing greater of knowledge on which to base financial decisions.

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