A FINANCIAL ANALYSIS OF THOSE FIRMS IN EMERGING MARKETS WITH THE GREATEST CAPITAL EXPENDITURES IN A PERIOD OF DECLINE

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ABSTRACT

Investment in capital assets for manufacturing companies in emerging markets has been declining since the year 2012. However, during the period of decline in capital spending for most all firms and governments, there were firms that greatly increased their capital spending. The risk-return characteristics (financial profile) of those companies are compared with companies from the same emerging markets that reported the lowest or no capital investments. If the statistical comparison finds that the group with the highest capital expenditures have a unique financial profile, and the test can be validated without bias, it suggests that the unique profile may be used as a tool to forecast companies that will maintain high capital expenditures in future periods of decline. **JEL Classification:** G11

INTRODUCTION

Emerging markets have various degrees of efficiency, and established markets, while not perfectly efficient, are very efficient and thus may have become somewhat saturated with investment capital. Conversely, emerging markets and the companies in those markets have a great need for investment capital, and particularly by those companies that are growing. Emerging stock markets appeal to investors, and particularly institutional investors, for several reasons, the most frequently cited being their rapid growth. Following this appeal, the strength of cash flows from investors into emerging markets observed over the last few years has been extraordinarily strong. The Emerging Markets Investable Index (MSCI) covers securities across developing nations. That index is up sixteen percent the first four months of this year compared to 7.2 percent for the Standard and Poors 500 (Veiga, 2016). The strength of cash flows from investors into emerging markets observed over the last few years can be explained by several additional factors, including higher than average returns, new sources of income, and the opportunity for global diversification (Vanguard, 2010). To maintain the strength of needed cash flows into those markets, capital investment in the form of new productive assets, research and development, and infrastructure is required.

Capital expenditures for new productive assets in those markets had been in sharp decline since the year 2012. More recent reports find that after years of declining capital expenditures, the forecasts are more optimistic for 2018-2019. (Bloomberg, 2018). In addition, Alter and Elkdag (2018) found that accommodative U.S. monetary conditions have been reliably associated with faster emerging market corporate leverage and capital spending in part by influencing domestic interest rates and by relaxing corporate borrowing constraints. Owusu (2018) offered a cautionary note regarding that optimism. He concluded that global market capital expenditures may be a victim of the U.S. tariffs levied against Chinese imports. This argument is partially evidenced by the fact that the global capex growth slowed to five percent for the first half of 2018 after growing at double that pace in 2017 (Owusu, 2018). Given the latest macroeconomic data on tariffs at the time of this study, the Owusu conclusions are logical.

The Price-Earnings Multiple is said to provide investors with a rough idea of the current value of the firm based on earnings, other ratios used by researchers in their attempts to find the intrinsic value of a firm include the market value to book value ratio, Tobin's Q, the price earnings growth ratio, and more recently the enterprise value multiple. If those tools have a common fault, it is that they value a company at one point in time (the present) Forbes (2012). The same reasoning leads to the conclusion that the Cash Flow to Capital Spending ratio (Capex), like the Research and Development to Earnings ratio provide an insight into the future value of a company, and that future value may be directly related to capital expenditures made in the past. During the aforesaid five-year period of decline in capital spending in emerging markets by both governments and companies, there were some companies that significantly increased their capital expenditures. That invites the obvious questions, who were the companies that continued to make capital investments during a period of decline for such investments, what are the financial characteristics of those firms that establish value, and finally how are those firms regarded in the present market? Those companies have become the subject of a great deal of interest and study by fundamental analysts, investors, and investment analysts that are continuously evaluating potential investments in emerging markets for the purpose of estimating the intrinsic value of firms, and thus to identify investment potential (Antonia, 2017). Regardless of the growing interest and apparent advantages of considering capital expenditures to aid in estimating the future intrinsic value of firms, there have been no studies that have determined, or established an association, between the effects of traditional measures of risk and return on capital spending.

The purpose of this study is to establish a financial profile of those firms identified as having made the highest capital investment expenditures during a five-year period when most firms and governments were decreasing or making no capital expenditures. Data were gathered from a database of over 5000 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 highest capital expenditures and to compare those profiles with companies that reported the lowest or no capital expenditures. The financial profiles simply consist of common risk-return variables, and two indicators that may reflect how the market views the intrinsic value of the firm. If differences do exist in the mean vectors of variables between firms that reported high expenditures and firms that reported low expenditures, then the two groups are valued differently and will be viewed differently by investors at the margin (those willing and able to buy). That is, investors trade off different proxies for risk and return to determine the value of the firm. If the two groups of firms have unique financial profiles, and the model can be validated without bias, it suggests that the unique profile may be used as a tool to forecast companies that will maintain high capital expenditures in future periods of declining investments. The use of such a new tool to forecast higher positions of value would have implications for investors, managers, lenders, investment counselors, and academicians.

METHODOLOGY

The issues to be resolved are first, classification or prediction, and then evaluation of the accuracy of that classification. More specifically, can firms be assigned, based on selected financial variables, to one of two groups: (1) firms that were identified as having made the highest capital expenditures during a five-year period of steep decline in all capital expenditures and simply referred to here as highest capital expenditures in emerging markets (HCEM) or, (2) firms making the lowest or no capital expenditures in the same markets and in the same period (LCEM)?

Multiple discriminant analysis (MDA) provides a procedure for assigning firms to predetermined groupings based on variables or attributes whose values may depend on the group to which the firm actually belongs, and canonical correlation ranks those variables in order of their weighted effects on the results of the analysis. If the purpose of the study were simply to establish a financial profile of each group of firms, simple ratios would be adequate. However, as early as 1968, in a seminal paper on the use of MDA in finance, Altman showed that sets of variables used in multivariate analysis were better descriptors of the nature of firms and had more predictive power than individual variables used in univariate tests. It is thus, appropriate and indeed necessary to use MDA with simultaneous evaluation to accomplish the purpose of this study.

The use of MDA in the social sciences for the purpose of classification is well known. MDA is appropriate when the dependent variables are nominally or ordinally measured and the predictive variables are metrically measured. In addition to its use in the Altman study to predict corporate bankruptcy, other early studies used MDA to predict financially distressed property-liability insurance firms (Trieschmann and Pinches, 1973), to determine value (Payne, 2010), and the failure of small businesses (Edmister, 1982). This study also employs nominally measured dependent variables and metrically measured predictive variables. The nominally measured dependent variables are the group of HCEM firms and the group of LCEM firms. The computer program used to perform the analysis is SPSS 19.0 Discriminant Analysis (SPSS Inc. 2010). Since the objective of the analysis is to determine the discriminating capabilities of the entire set of variables without regard to the impact of individual variables, all variables were entered into the model simultaneously. Again, this method is appropriate since the purpose of the study was not to identify the predictive power of any one variable, but instead the predictive power of the entire set of independent variables (Hair et al. 1992).

SELECTION OF SAMPLE AND INDEPENDENT VARIABLES

Whereas, capital expenditures in emerging markets declined over the five-year period preceding this study regardless of record amounts of capital flowing into emerging markets, and that the purpose of the study is to determine whether the financial profiles of firms that made greater capital expenditures during that period when the average was declining are significantly different from firms that made little or no capital investments. The difference if any, in the financial profiles of the two groups of firms are the subject of this study.

All data used in the analysis were gathered from Damodaran's 2018 dataset. The sample selected for this study consists of two groups. The first group was identified by Damodaran as the group in that database making the greatest capital expenditures in emerging markets and the second group was selected from the firms identified as making little or no capital expenditures. The HCEM group contains 307 observations and the LCEM group has 77 observations for a total sample of 384 firms. The sample is so large that if the variance covariance matrices are equal, it renders the differences in the size of the groups insignificant (Sharma 1996), and of course, the use of that much data exhausted that part of Domodaran's database that listed capital spending in emerging markets.

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 one measure of the size of the firm, one measure of growth, one measure of earnings three measures of risk, and one measure of how the firm may be perceived by investors at the margin. It is the buying and selling of those investors that establish the market value of both equity and debt. 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 to establish the market value of firms. Following are the seven explanatory variables:

X_1 - Market Capitalization is included as a measure of the size of the firm. The literature is mixed on whether the size of the firm is a factor in establishing value in emerging markets. Thus, it is included in the set simply to add clarity.

X_2 - Growth is often regarded as a return to capital, and indeed growth has been the single variable cited most often as appealing to emerging market investors (Kupper 2016). Damodaran (2018) measured past changes in several variables over periods of five years, and two years, and published forecasts of change two years into the future. In this study the two-year forecast of change in sales was used. Changes in revenue, cash flow, earnings and dividends are also given, but those variables are a long-term function of sales.

X_3 - One measure of return is return to all invested capital. Return to total capital includes a return to creditors as well as owners and recognizes that value is affected by the cost of debt. A measure of return to equity could be used, but it would ignore the cost of debt and the fact that debt as well as equity is used to finance assets. This is consistent with the use of the debt to total capital ratio as a measure of financial leverage.

X_4 - Long Term Debt to Total Capital (DTC) is used here as a measure of financial risk (financial leverage). 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. 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_5 - Operating Risk is measured here as using Hamada's unlevered beta resulting from Hamada's equation. Operating, or business risk is a function of fixed operating costs.

X_6 - The coefficient of variation in operating income (CVOI) is used here as a measure of risk. The variance in operating income is often used, but unlike the variance and standard deviation, the CVOI is the ratio of marginal risk to marginal income, or marginal income per unit of risk.

X_7 - The ratio of market price to earnings (P/E) has been used for years as a rough measure of how the market values a firm. Indeed, the P/E multiple, and dividend yield are the only ratios reported every day on the financial pages of newspapers, and it has been argued that in efficient markets the multiple reflects the intrinsic value of stocks, (Scripto, 1998; Payne Tyler and Daghestani, 2013). More recently, the price earnings growth ratio (PEG) has grown in popularity. The price earnings growth multiple adjusts the P/E ratio for potential growth, and it is suggested that the price earnings multiple (P/E) used without the adjustment for growth has a high potential for undervaluing a company. Damodaran, (2014) writes that the PEG ratio is a better measure of a company's potential future value, and was developed to address the shortcomings of the P/E multiple. He further writes that many analysts have abandoned the P/E ratio, not because of any perceived shortcomings, but simply because they desire more information about a stock's potential. Thus, the use of the PEG ratio is used here as a measure of a company's potential long term value.

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

X1 - Total Market Capitalization
X2 - The Two-Year Forecast Growth Rate in Sales
X3 - Return to Total Capital
X4 - Long Term Debt to Total Capital (Financial Risk)
X5 - Hamada's Unlevered Beta (Operating Risk)
X6 - Coefficient of Variation in Operating Income
X7 - The Price Earning Growth Ratio

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 such as the dividend payout ratio and free cash flows 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 independent 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 the accomplishment of the study's purpose (Suozzo, 2001). This study is consistent with both references.

The financial profiles simply consist of one measure of the size of the firm, one measure of growth, one measure of earnings three measures of risk, and one indicator that may reflect how the market views the intrinsic value of the firm. If the two groups of firms have unique financial profiles of those measures, and the model can be validated without bias, it suggests that the profile for the group characterized by HCEM may be used as a tool to forecast companies that will maintain HCEM in future periods.

TESTS AND RESULTS

The discriminant function used has the form:

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

Where:

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:

$$Z_j = 3.104 + .0001X_1 - .110X_2 + .004X_3 - .824X_4 - .214X_5 - .918X_6 + .006X_7 \qquad (2)$$

Classification of firms is relatively simple. The values of the seven variables for each firm are substituted into equation (2). 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 (HCEM). Conversely, a firm's Z score that is less than the critical value will place the firm in group two (LCEM). Since the two groups are heterogeneous, the expectation is that HCEM firms will fall into one group and the HEVM 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 Lambda – Chi Square transformation (Sharma, 1996). The calculated value of Chi-Square is 631.02. That far exceeds the critical value of Chi-Square 14.107 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 engaged in very high capital expenditures, and the other group had little or no capital investment. 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 by the test and is that percentage significant?

To answer the second question a test of proportions is needed. Of the 384 firms in the total sample 377 or 98.2 percent were classified correctly. The results are shown in Table 1. Of course, it is obvious that 98.2 percent is significant, but formal research requires the proof of a statistical test. To test whether a 98.2 percent correct classification rate is statistically significant, the Press's Q test is appropriate (Hair et al.,1992). Press's Q is a Chi-square random variable:

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

where:

N =Total sample size
n = Number of cases correctly classified
k = Number of groups

In this case:

$$\text{Press's Q} = [384 - (377 \times 2)]^2 / [384 (2-1)] = 356.51 > \chi^2_{.05}\ 3.84 \text{ with one d. f.} \quad (4)$$

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 98.2 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 HCEM 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 LCEM group. Thus, according to Table 2, the greater the level of return to total capital, the greater the size of the frim, the greater the level of financial risk, the higher the rate of growth, and finally, the greater the price earnings growth ratio the more likely the firms would have made significant capital expenditures in a period when most firms and governments were decreasing their capital investments. Conversely, the greater the measure of operating leverage (risk), and the greater the coefficient of variation for operating income, the more likely the firm will report low capital expenditures.

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, unlike the discriminant function coefficients where it can cause the measures to become unstable. (Sharma, 1996). The closer the absolute value of the loading to the integer one, the stronger the relationship between the discriminating variable and the discriminant function These discriminant loadings are given in the output of the SPSS 19.0 program and shown here with their ranking in Table 2.

Table 2 reveals that the measure for return on invested capital made the greatest contribution to the overall discriminating function. It is followed respectively by the measure Size, the measure for financial leverage, the price-earnings-growth ratio, the measure of operating risk (leverage), the measure of variance in operating income, and finally, the forecasted rate of growth.

Some multicollinearity may exist between the predictive variables in the discriminant function since growth could be reflected in the returns. 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).

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 384 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 98.2 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 384 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 97.4 percent of the firms. Since there are only two samples for analysis the binomial test is appropriate:

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

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: $374 - 384(.982) / [384\,(.982)\,(.018)]^{½} = -\,1.18$ 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 the present study 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 14.94 resulted in a zero level of significance. Thus, the null hypothesis that the two matrices are equal cannot be rejected, and we conclude that the variance-covariance matrices are equal.

SUMMARY AND CONCLUSIONS

Investment in capital assets for manufacturing companies in emerging markets has been declining since the year 2012. However, during the period of decline in capital spending for most all firms and for governments, there were firms that greatly increased their capital spending. The purpose of this study was to establish a financial profile of those firms identified as having made the highest capital investment expenditures during a five-year period when most firms and governments were decreasing or making no capital expenditures. Specifically, the analysis tested for significant differences in the financial profiles of firms with the highest capital expenditures and compared those profiles with companies that reported the lowest or no capital expenditures. The financial profiles simply consisted of common risk-return variables, one indicator of size, and one indicator that may reflect how the market views the intrinsic value of the firm.

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 investing in capital spending that it would certainly have been a surprise if the discriminant function had not been so efficient.

Table 2 reveals that the greater the level of return to total capital, the greater the size of the firm, the greater the level of financial risk, the higher the rate of growth, and finally, the greater the price-earnings- growth ratio the more likely the firms would have made significant capital expenditures in a period when most firms and governments were decreasing their capital investments. Thus, it is concluded here that those are financial characteristics of those firms in emerging markets that report high investments in capital expenditures. Conversely, the greater the measure of operating leverage (risk), and the greater the coefficient of variation for operating income, the more likely the firm will report low capital expenditures.

Five of these of these results may have been expected, one had no apriori expectation and, one was simply a surprise. Explanations as to why the variables 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.

There was no apriori expectation about the relationship between capital spending and the size of the firm. It was simply not known. The study resulted in one mild surprise. The level of financial leverage (risk) was greater for the companies that were engaged in capital spending. The fixed costs of borrowing must be paid whether there is revenue of not. Thus, financial risk and the potential of financial distress was greater in the HCEM companies. However, according to financial signaling theory, if corporations are optimistic about the future of the company, they are more likely to acquire new capital investments through borrowing than to finance with new equity. If this is indeed the case, then borrowing would be consistent with the motives for making capital investments. No concrete explanation of this empirical result can be offered here. 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 risk-return and market perception characteristics of firms that have invested heavily in capital assets in a time when other firms were decreasing such investments. It is further suggested that since the model was validated without bias, it can be used to predict firms that may again be characterized by high capital expenditures. To make a more complete contribution to the theory, the aforementioned further research is needed.

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TABLE 1
CLASSIFICATION RESULTS
Predicted Results

HCEM – LCEM Classification

Actual Results	HCEM	LCEM
HCEM	300	0
LCEM	7	77

TABLE 2
RELATIVE CONTRIBUTION OF THE VARIABLES

Discriminant Variables	Coefficient	Rank
Return on Invested Capital	0.959	1
Market Capitalization	0.050	2
Long Term Debt to Total Capital	0.047	3
The Price-Earnings-Growth Ratio	0.045	4
Operating Leverage (Risk)	-0.034	5
Coefficient of Variation in Operating Income	-0.013	6
The Two-Year Forecast Growth Rate in Sales	-0.080	7