ON THE USE OF ENTERPRISE VALUE MULTIPLES AS INDICATORS OF INTRINSIC VALUE IN EMERGING MARKETS

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ABSTRACT

Emerging stock markets appeal to investors for several reasons, the most frequently cited are rapid growth, higher than average returns, new sources of income, and the opportunity for global diversification. In recent years the strength of cash flows from investors in established markets to emerging markets has been of immense magnitude and, as a result, emerging market stocks have outperformed stocks in established markets. As in any market, potential investors constantly analyze companies in emerging markets to estimate the intrinsic value of those firms to identify investment potential. Some of the more familiar valuation ratios used to estimate that intrinsic value are the price earnings multiple, the market value to book value ratio, Tobin's Q, and the price earnings growth ratio. However, recent studies have concluded that low enterprise value multiples (market value to earnings) are the most significant financial characteristic of those firms favored by investors in emerging markets. An identification of the risk-return characteristics, or the establishment of a financial profile of those firms with very low enterprise value multiples in emerging markets would be an invaluable aid to investors, investment counselors, and financial researchers whose task it is to determine intrinsic value. Thus, the purpose of this study is to establish a profile of risk-return measures of those companies in emerging markets that have the lowest enterprise value multiples and to compare those firms with firms that have the highest enterprise value multiples. **JEL Classification:** G11

INTRODUCTION

Emerging markets have been broadly described as those that are experiencing rapid growth, expanding infrastructure, and attracting significant capital from various sources. They are also characterized as often moving to an open market economy, and having a growing working age population (Kupper 2016). Emerging stock markets appeal to investors for several reasons, the most frequently cited being their rapid growth. In recent years the strength of cash flows from investors in established markets to emerging markets has been of immense magnitude. 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. Further, \$26.17 billion flowed from U.S. funds into emerging markets during the same period. That is an increase of 20 percent from all net flows that went into emerging markets from U.S. funds in all of 2016 (Viega 2016). In addition, institutional investors alone have invested at least 50 billion dollars into emerging stock and bond markets since 2013 (Payne, Wong, and Payne 2017).

The continuing extraordinary 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). One of the results of those strong cash inflows into emerging markets is that stocks in those markets have outperformed stocks in established markets. Given that on-going performance, investment analysts are continuously evaluating potential investments in emerging markets.

BACKGROUND

As in any markets, investors and investment analysts constantly analyze companies in emerging markets to estimate the intrinsic value of those firms and to identify investment potential. Some of the more familiar valuation ratios used to estimate that intrinsic value are the price earnings multiple, the market value to book value ratio, Tobin's Q, and the price earnings growth ratio. If those tools have a common fault, it is that they value a company at one point in time, and their reliability may be questioned when comparing companies with different capital structures, or in different industries Forbes (2012). The analysts at Forbes (2012) further 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 a company is truly valued. Sadler, Daghestani, and Payne (2016) found that the (EVM) was the single most significant variable used in their study to identify value; however, that study suffered from the lack of broad based data since only U.S. companies were included. Zucchi (2013) concluded that EVM is the most encompassing and generally considered the most useful tool in analyzing the current valuation of a stock. However, the denominator in Zucchi's ratio neglected to account for earnings. O'Shaughnessy (2011) found that enterprise value has the advantage of measuring the value of the firm as an on-going entity, and the ability to compare companies with different capital structures and in different industries, and further has for the past three decades grown in use more extensively than of other measures. However, like the Zucchi study, the O'Shaughnessy study suffered from the fact that only the numerator in the enterprise value multiple was assessed, and again earnings were neglected. Thus, companies of different size, different industries, or different capital structures could not be compared. Conversely, the enterprise multiple considers a company's debt and cash levels in addition to its stock price and relates that value to the firm's cash profitability. It is defined as:

$$\text{Enterprise Value Multiple} = EV / EBITDA \tag{1}$$

Where:
EV = Market Capitalization + Debt + Preferred Stock + Minority Interest - Cash and Cash equivalents. (2)

EBITDA = Earnings Before Interest, Taxes, Depreciation and Amortization. (3)

If EBITDA are relatively stable, this measurement allows investors to assess a company on the same basis as would an acquirer or other buyer. Thus, the multiple is roughly analogous to the familiar payback period and the lower that value is the more attractive the investment. Regardless of the growing interest and apparent advantages of using the EVM to the estimate intrinsic value of firms in emerging markets, there have been no studies that have determined, or established an association, between the effects of traditional measures of risk and return on the enterprise multiple.

The purpose of this study is to establish a financial profile of those firms identified as having the lowest enterprise value multiples and to compare those firms with firms that have the highest enterprise value multiples in the database of over 1287 firms created by (Damodaran 2014) from Bloomberg, Morningstar and Compustat. Specifically, the analysis will test for significant differences in the financial profiles of firms in emerging markets with the lowest EVM's and those firms with the highest EVM's. The financial profiles consist of common risk-return variables that determine the value of the firm. If the test finds that the group with lowest EVM's have a unique financial profile, 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 EVM in future periods. The use of such a new tool to forecast higher positions of value would be an invaluable aid to investors, investment counselors, and financial researchers whose task it is to determine intrinsic value. As in previous studies of this nature those variables are analyzed using multiple discriminant analysis, and ranked with canonical correlation.

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 the lowest enterprise value multiples in their database and simply referred to here as lowest enterprise value multiples (LEVM) or, firms having the highest enterprise value multiples (LEVM)?

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 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 firms, and had more predictive power than individual variables used in univariate tests.

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 LEVM firms and the group of HEVM 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. 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

Inasmuch as the EVM has the advantage of measuring the value of the firm as an on-going entity, and the ability to compare companies with different capital structures and in different industries, and as previously stated, has for the past two decades grown in use more extensively than of other measures (O'Shaughnessy, 2011), it is used here as the subject of study.

All data used in the analysis were gathered from Domodaran's 2014 set. The sample selected for this study consists of two groups. The LEVM group contains 1034 observations and the HEVM group has 253 observations. The sample is so large that as long as the variance covariance matrices are equal, it renders the size of the groups insignificant, and of course, the use of that much data exhausted Domodaran's database. The first group was identified by Damodaran as the group in that database having the lowest EVM. The second group was selected from the remaining firms in that database.

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, three measures of risk, and two measures 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 of risk and return to establish the value of the 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 in an attempt to add clarity.

X_2 - Share Price Liquidity. Established exchanges add efficiency and liquidity to liquidity to the market. Liquidity of share prices adds to the value of equities being traded. Kemp (2014) explained clearly how share price liquidity (SPL) would be of paramount importance to traders in emerging markets. Thus, it is included here.

X_3 - 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 2014) 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_4 - 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. "The unlevered beta resulting from Hamada's equation is used as a measure of operating or business risk that results from fixed operating costs.

X_5 - Long Term Debt to Total Capital (DTC) is used here as a measure of financial risk (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_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 measures marginal risk to marginal income.

X_7 - The activity of institutional investors has long been a favored topic in financial literature. The daily trading of such investors varies between 50 and 70 percent of all daily trading on the New York Stock Exchange (Brancato and Rabimov 2008). The buying activity of institutional investors is included here simply as an indicator of how the market or at least a significant portion of the market perceives the value of firms in emerging markets. As stated above, institutional investors alone have invested at least 50 billion dollars into emerging stock and bond markets since 2013 (Payne, Wong, and Payne 2017).

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

X1 - Total Market Capitalization
X2 - Share Price Liquidity
X3 - The Two Year Growth Rate in Sales
X4 - Hamada's Unlevered Beta (Operating Risk)
X5 - Long Term Debt to Total Capital (Financial Risk)
X6 - Coefficient of Variation in Operating Income
X7 - Institutional Investor Buying Activity

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 return on investment, three measures of risk, one measure of the size of the firm, and two indicators 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 low EVM may be used as a tool to forecast companies that will maintain low EVM in future periods.

TESTS AND RESULTS

The discriminant function used has the form:

$$Z_j = V_1X_{1j}+V_2X_{2j}+\ldots\ldots+V_nX_{nj} \qquad (4)$$

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:

$$Z_j = -1.554 + .0001X_1 + 3.886X_2 - .002X_3 + .187X_4 + 3.052X_5 + 12.770X_6 - 1.188X7 \qquad (5)$$

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 less than a critical value, the firm is classified in group one (HEVM). Conversely, a firm's Z score that is greater than the critical value will place the firm in group two (LEVM). Since the two groups are heterogeneous, the expectation is that LEVM 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 Lamda – Chi Square transformation (Sharma 1996). The calculated value of Chi-Square is 342.48. 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 experienced very high enterprise value multiples and the other group had very low EVM. 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?

To answer the second question a test of proportions is needed. Of the 1287 firms in the total sample 1019 firms, or 79.2 percent were classified correctly. The results are shown in Table 1. Of course, it is obvious that 79.2 percent is significant, but formal research requires the proof of a statistical test. To test whether a 79.2 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:

$$\text{Press's Q} = [N-(n \times k)]^2 / N(k-1) \tag{6}$$

where:

N = Total sample size

n = Number of cases correctly classified

k = Number of groups

In this case:

$$\text{Press's Q} = [1287 - (1019 \times 2)]^2 / [1287 (2-1)] = - 438.23 > \chi^2_{.05}\ 3.84 \text{ with one d.f.} \tag{7}$$

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 79.2 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 two, the LEVM 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 one, the HEVM group.

Thus, according to Table 2, the greater the level of both financial and operating risk, the greater the variance in operating income, the greater the measure of share price liquidity, and the greater the two-year expected growth, the more likely the firm would have a low enterprise value multiple. Conversely, the greater the measure of the size of the firm, and the greater the level of institutional investor buying activity, the more likely the firm will experience high enterprise value multiples.

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 1, 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 of financial risk (leverage) made the greatest contribution to the overall discriminating function. It is followed respectively by the measure of operating risk financial risk (leverage), the measure of variance in operating income, institutional investors buying activity, the measure of size, share price liquidity, and finally growth.

Some multicollinearity may exist between the predictive variables in the discriminant function, since both size and financial leverage could be reflected in the EVM. 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 in 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 four 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 four firms between the two groups. However, with a very large sample such as the 1287 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 79.2 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 four cases will not be significant with a sample of 1287 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:

$$t = r - n\,p \,/\, [n\,p\,q]^{1/2} \tag{8}$$

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: $1015 - 1287(.792) / [1287\,(.792)\,(.208)]^{½} = -.003$ is less than t_{05} 1.645. (9)

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 123.37 resulted in a zero level of significance. Thus, the null hypothesis that the two matrices are equal cannot be rejected.

SUMMARY AND CONCLUSIONS

In recent years the strength of cash flows from investors in established markets to emerging markets has been of immense magnitude. As in any markets, investors and investment analysts constantly analyze companies in emerging markets to estimate the intrinsic value of those firms and to identify investment potential. It was established in previous studies that among the many tools used by analysts to value companies, the enterprise value multiple has become the tool most favored by many. The reasons most cited are that enterprise value has the advantage of measuring the value of the firm as an on-going entity, and the ability to compare companies with different capital structures and in different industries, and further has for the past three decades grown in use more extensively than of other measures.

The purpose of this study was to establish a financial profile of those firms identified as having the lowest enterprise multiples in emerging markets from the database of over 1287 firms created by (Damodaran 2014). Specifically, the analysis tested for significant differences in the financial profiles of firms with the lowest enterprise multiples and compared those profiles with companies from the same database with the highest enterprise multiples. The financial profiles simply consist of one measure of return on investment, three measures of risk, one measure of the size of the firm, and two indicators that reflect how the intrinsic value of the company may be perceived by investors at the margin. A unique set of explanatory variables was found for those firms with low enterprise value multiples, and since the model was validated without bias, it is suggested that the profile may be used to identify firms that will maintain those low multiples in the future.

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 achieving low multiples that it would certainly have been a surprise if the discriminant function had not been so efficient.

Table 2 reveals that the measure of financial risk (leverage) made the greatest contribution to the overall discriminating function. It is followed respectively by the measure of operating risk (leverage), the variance in operating income, institutional investors buying activity, size, share price liquidity, and finally the two-year rate of expected growth. The greater the values for financial leverage, operating leverage, variance in operating income, share price liquidity, and growth, the more likely the firm has a low enterprise value multiple. Conversely, the greater the values for institutional investor buying activity, and the size of the firm, less likely the firm would have a low enterprise value multiple.

Four of these of these results may have been expected, two 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.

It was expected that since heavy institutional investor buying activity, and market capitalization (size) add to the value of the numerator in the enterprise value multiple, it follows that those factors are consistent with high multiples. It may have also been expected that growth and share price liquidity would be consistent with low enterprise value multiples since growth was cited as the most important factor in attracting marginal investors to emerging markets, and share price liquidity simple follows from heavy buying activity. There were no aprori expectations for the companies experiencing greater levels of variance in operating income, and greater levels of operating leverage. It was simply not known.

The study resulted in one surprise. The long term debt to total capital ratio (financial leverage) was not characteristic of firms that achieved higher levels of enterprise value. Since long term debt is a major component of the numerator in the enterprise value multiple, this outcome is at variance with previous research. 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 risk-return and market perception characteristics of firms that have achieved the lowest enterprise value multiples in emerging markets. 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 low enterprise value multiples in the future. In order 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

LEVM - HEVM Classification

Actual Results	LEVM	HEVM
LEVM	850	184
HEVM	84	169

TABLE 2
RELATIVE CONTRIBUTION OF THE VARIABLES

Discriminant Variables	Coefficient	Rank
Total Market Capitalization	-0.217	5
Share Price Liquidity	0.073	6
The Two Year Expected Growth Rate	0.041	7
Hamada's Unlevered Beta	0.576	2
Long Term Debt to Total Capital	0.764	1
Variance in Operating Income	0.548	3
Institutional Investor Buying Activity	-0.259	4