Companies Identified as Having the Greatest Returns to Capital in Emerging Markets During a Worldwide Pandemic

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The COVID-19 pandemic of the year 2020 resulted in high unemployment, business closings, property loss and decimation of individual wealth, disruption of global supply chains, and illness and deaths everywhere, but most intensely in countries classified as emerging markets. However, during this year, cash flow from investors in established markets to emerging markets has been of immense magnitude. While many companies, in emerging markets, reported very high risk-adjusted rates of return, many others reported so low rates during this period. This study aims to establish a unique profile of risk-return characteristics of the companies in emerging markets that have constantly reported the highest risk-adjusted returns to total capital during the pandemic. The statistical results of our study suggest that such unique profile can be used as a tool to forecast which companies, in such markets and during such disturbances in the future, will maintain high returns to capital providing an invaluable tool for investors, investment counselors and financial researchers tasked to determine firm's intrinsic value in such an environment.

Keywords: pandemic returns, emerging markets, market efficiency during pandemic, return to capital

INTRODUCTION

The economic and business effects resulting from international lockdowns and illness caused by the coronavirus 19 pandemic disease have resulted in high unemployment, business closings, property loss, decimation of individual wealth, disruption of global supply chains, and high rates of human casualty in countries described as emerging markets. The shutdown measures to contain the virus caused a severe contraction in the global economy. According to World Bank forecasts, the global economy shrunk by 5.2% in 2020. That represented the deepest recession since the Second World War (Business Insider, 2020). When those initial effects end the long-term consequences may continue for long into the future, and long after the virus is eradicated. (Goldberg and Reed 2020). The literature is replete with endless stories of hardships and small business bankruptcies in emerging countries caused by the virus and those events continue to plague all countries at various degrees at the time of this writing.

Logic seems to dictate that capital flow from domestic markets to emerging markets in a pandemic environment would certainly diminish. However, the opposite has been true and continues to be true. For example, for the past three decades, the strength of cash flows from investors from established markets to emerging markets has undiminished with the onset of the virus as shown by the Emerging Markets Investable Index (MSCI) that covers securities across developing nations. During the first four months of 2020, this index has shown an increase of sixteen percent compared to 7.2 percent increase in Standard and Poor's 500 index. Further, a prolonged period of low interest rates encouraged both borrowers and lenders to take increasing risk in emerging markets. Surges in portfolio outflows into riskier asset markets contributed to the buildup of debt resulting in, in some cases, stretched valuations. (De Bock, et al. 2020). For example, institutional investors alone have invested at least 50 billion dollars into emerging stock and bond markets since 2016 (Payne, Wong, and Payne 2017). The steady and extraordinary cash flows from investors into emerging markets observed over the last few years could have been driven by several additional factors, such as new sources of income, potential growth, and the opportunity for global diversification. Another key driver among European investors could be the potential for enhanced rate of returns compared to that in developed markets (Vanguard 2019). It is expected that domestic investors will make larger allocations toward emerging markets over the next twelve months, and much larger allocations over the longer term (Taylor 2020).

As in any market, companies in emerging markets are not homogeneous with regard to many business variables including potential returns on invested capital. Regardless of the terrible consequences of the pandemic, many companies in emerging markets have reported very high risk-adjusted rates of return and there are many more companies whose returns are low enough to have caused the average of all companies to decline. Potential investors constantly analyze companies in emerging markets to estimate their intrinsic value and to determine which firms may provide a risk-adjusted return that would justify further investment.

This study aims to establish a financial profile of the firms having the highest returns to total capital in emerging markets during the pandemic period and to compare that profile with that of firms' that reported the lowest returns during the same period. More Specifically the study is focused on determining those variables that can serve as indicators of the firm's risk-return tradeoff character. If our test finds that the group with the highest returns to total capital in emerging markets have a unique financial profile, and if the test is statistically validated without bias, it would suggests that the unique profile may be used as a tool to forecast which companies in those markets would maintain high returns to capital in future periods with similar disturbances. Such a new tool would aid to the analysis of emerging financial markets and would be a net addition to the growing body of knowledge in the field. This will also be an invaluable tool for investors, investment advisors, and a financial researcher whose task is to determine firm's intrinsic value in such an environment. Previous studies of this nature used multiple discriminant analysis to analyze the variables used in this study and canonical correlation coefficient to rank firms.

METHODOLOGY[1]

In 1968, Altman in his seminal paper on the use of multiple discriminant analysis (MDA) in finance showed that sets of variables used in multivariate analysis were better descriptors of firms and had more predictive power than individual variables used in univariate tests. He further concluded that every firm was indeed a set of ratios and other measures and that the variables in that set should be evaluated simultaneously (Altman 1968). Thus, this study contains two sets of variables that measure risk, return, size, and market perception simultaneously. Here those sets are referred to as the company's financial profile. If the test finds that the group with the highest returns has a unique financial profile, and the model can be validated without bias, it would suggest that the unique profile may be used as a tool to forecast companies that will maintain high returns to total capital in future periods As in previous studies of this nature those variables are analyzed using multiple discriminant analysis and ranked with canonical correlation.

The first issue here is to resolve if firms, based on selected financial variables, can be assigned to one of two groups: (1) firms having the highest returns in emerging markets during a pandemic (HREMP) and

(2) firms having the lowest returns in emerging markets during a pandemic (LREMP). The second issue is the evaluation of the accuracy of that classification. Multiple discriminant analysis (MDA) furnishes a way to assign firms to predetermined groupings based on variables or attributes whose values may depend on the group to which the firm actually belongs. The canonical correlation coefficients then can be used to rank those variables in order of their weighted effects on the results of the analysis. If the purpose of the study were to simply establish a financial profile of each group of firms, simple ratio analysis would be adequate. However, according to aforementioned seminal study by Altman's and its conclusions the sets of variables used in multivariate analysis are better descriptors of the firms and had more predictive power than individual variables used in univariate tests. Therefore, it is appropriate to use MDA with simultaneous evaluation to accomplish the purpose of this study.

The use of MDA for the purpose of classification is well known in social science researches. It is especially appropriate in research involving dependent variables that are nominally or ordinally measured and the predictive variables are metrically measured. While Altman study used MDA to predict corporate bankruptcy other early studies used it to predict financially distressed property-liability insurance firms (Trieschmann and Pinches 1973), to determine value (Payne 2010), and to predict the failure of small businesses (Edmister 1982). We used SPSS 21.0 to perform Multiple Discriminant Analysis in this study. Since the objective of our analysis was to determine the discriminating capabilities of the entire set of variables without regard to the impact of individual variables, we entered all variables simultaneously into the model. Again we found this method appropriate as the purpose of our study was to identify the predictive power of the entire set of independent variables rather than that of any one variable (Hair et al. 1992).

SELECTION OF SAMPLE AND INDEPENDENT VARIABLES

The purpose of this study was to determine whether the financial profiles of firms that achieved the highest returns while the average returns were declining during a period are unique. The other purpose of this study was to see if difference in the financial profiles of the two groups of firms is statistically significant and to see if the variables used to establish that difference are significant.

Sample selected for this study consists of two groups: (a) the HREMP group which contains 461 observations and (b) the LREMP group which contains 257 observations with a total of 718 firms. Since the sample is so large the equality of the variance-covariance matrices would imply that the difference in the size of the groups is insignificant (Sharma 1996). The first group selected from the database is that of firms with the highest returns in emerging markets during the pandemic and the second group is that of randomly selected ones from the remaining firms in that same database. While previous studies using similar statistical methods have used various methods and logics to choose explanatory variables, explanatory variables chosen in this study includes one measure of the firm's size, one measure of the firm's value, three measures of risk, and one measure of how the firm is perceived by investors at the margin. So, literally the purpose of this study is an evaluation of those measures. A basic idea of this study is that investors trade-off the indicators of risk and return to determine a firm's market value. It is the buying and selling by investors that establish the market value of both equity and debt of a firm, which in turn determine the risk and rate of return of the firm. The six explanatory variables mentioned above are as following:

X_1 (Total Market Capitalization): It measures the size of a firm. The literature on how the size of a firm affects its value in an emerging market is mixed. However, it is included in the study to add clarity.

X_2 (EV/EBITDA): It measures a firm's value as a ratio of earnings before interest, taxes, depreciation, and amortization. One advantage of using this variable is that it is independent of capital structures and therefore enables us to directly compare companies with different levels of debt. It, thus allows one to focus on the outcome of operating decisions excluding the impacts of non-operating decisions, such as, interest expenses - a financing decision, tax rates - a government decision, or appreciation and amortization - an accounting decision (Investing Answers 2017).

X_3 (Hamada's Unlevered Beta): A firm may experience both financial risk and operating risk. So, first Sharpe's beta coefficients are estimated, which contain the effects of both operating and financial risk. Then the two sources of risk are separated using Hamada's (1972) equation. "The unlevered beta resulting from Hamada's equation is used to measure the operating risk that results from fixed operating costs.

X_4 (Long Term Debt to Total Capital Ratio, DTC): It measures the financial risk. Although other ratios are also used to measure financial risk, but this ratio also recognizes that the firm is financed by both creditors and owners.

X_5 (Coefficient of Variation in Operating Income, CVOI): It is computed as the ratio of marginal risk to marginal income and is used here as a measure of risk.

X_6 (Institutional Investor Buying Activity): It has long been a favored topic in financial literature. The daily trading of such investors varies between 50 and 70 percent of all trading on the New York Stock Exchange (Brancato and Rabimov 2008). This is included here as an indicator of how the market perceives the value of firms in emerging markets. Studies show that since 2013 institutional investors alone have invested at least 50 billion dollars into emerging stock and bond markets (Payne, Wong, and Payne 2017).

The rationale for choosing these explanatory variables is their consistency with theory, adequacy in measurement, wide use in previous studies, and the availability of data for those variables from a reputed source. While there is a large number of potential independent variables that can be used the general approach is to use the fewest number of independent variables required for discrimination procedure (Zaiontz 2014). The general practice is to use only the variables that logically contribute to the study's purpose (Suozzo 2001). This study accounts for both references. In this study, financial profiles of firm include one measure of size, one measure of value, three measures of risk, and one indicator of market perception of the intrinsic value of the firm. If the study finds that the two groups of firms have unique financial profiles of those measures and the model is validated without bias, it would enable us to use the profile for the group characterized by HREMP as a tool to forecast companies that will maintain HREMP in future distressed periods also.

TESTS AND RESULTS

The discriminant function in our study takes the following form:

$$Z_j = V_1X_{1j}+V_2X_{2j}+\ldots+V_nX_{nj} \tag{1}$$

where:

X_{ij} = the firm's value for the i^{th} independent variable.
V_i = the discriminant coefficient for the firm's i^{th} variable.
Z_j = the j^{th} individual's discriminant score.

Equation-2 below is the estimated version of Equation-1:

$$Z_j = -\,2.043 + .0001X_1 + .004X_2 + 1.608X_3 + 3.991X_4 + 2.486X_5 - 1.954_6 \tag{2}$$

In order to compute the Z-score of a firm, we simply need to substitute into Equation-2 the value of the six independent variables. If a firm's Z-score is greater than a critical value, the firm is classified in group one (HREMP), otherwise in group two (LREMP). Due to the heterogeneity of the two groups we expect the HREMP firms to fall into one group and the HEVM firms into the other. Then the results of discriminant analysis are interpreted by addressing the following four basic questions:

1. Are the mean vectors of explanatory variable for the two groups of firms significantly different?
2. Did the discriminant function perform well?
3. Are the independent variables statistically significant?

4. Will this function discriminate equally on any random sample of firms?

We use the Wilk's Lambda – a Chi-square transformation (Sharma 1996) generated by SPSS to answer the first question. The calculated Chi-Square value in our study is 339.51, which far exceeds its critical value of 14.107 at the five percent significance level with 7 degrees of freedom. So, we reject the null hypothesis that there is no significant difference between the financial profiles of the two groups, which leads us to the conclusion that the two groups have significantly different financial characteristics. This result was as expected as one group of firms experienced very high returns to invested capital while the other group had very low returns. Thus the discriminant function does have the power to separate the two groups. However, the ultimate success of the discriminant model depends on what percentage of firms it can classify correctly and if that percentage is statistically significant?

In order to answer the second question we performed a test of proportions whose result is presented in Table 1 below.

TABLE 1
HREMP – LREMP CLASSIFICATION

Actual Results	HREMP	LREMP
HREMP	336	125
LREMP	107	150

As shown in the table above, of the 716 firms in total a sample of 486 or 67.7 percent were classified correctly. To test whether a 67.7 percent correct classification rate is statistically significant, we applied the Press's Q test (Hair et al. 1992). Press's Q –statistic has a Chi-square distribution and is computed as,

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

where:

N = number of firms in the sample
n = number of firms classified correctly
k = number of groups of firms

In our study:

$$\text{Press's Q-statistic} = [716 - (461 \times 2)]^2 / [716\,(2-1)] = 59.27 \quad (4)$$

Since the above value of Press's Q-statistic is greater than the critical value of 3.84 of $\chi^2_{.05}$ with one degree of freedom, we reject the null hypothesis that the percentage classified correctly is not significantly different from what would be classified correctly by chance. Therefore, we can conclude that the discriminant function performed well in separating the two groups.

The sign of the adjusted coefficients shown in Table 2 is used to answer question three. While a positive sign indicates that the greater a firm's value for the variable, the more likely it is to fall in group one (the HREMP group), a negative sign, on the other hand, indicates that the greater a firm's value for that variable, the more likely it is to fall in group two (the LREMP group). Based on the result shown in Table 2, it can be concluded that the greater the level of both financial and operating leverage (risk), the greater the coefficient of variation in operating income, and the greater the value of EBITDA, the more likely it is that the firms would report high returns on invested capital. Conversely, the greater the size of the firm and the higher the level of institutional investors' buying activity, the more likely that the firms would report low returns to invested capital.

The relative contribution of each variable to the total discriminating power of the function is measured by the discriminant loadings, which SPSS reports as the pooled within-groups correlations between discriminating variables and canonical function coefficients known as the structure matrix. The correlations are indicated by canonical correlation coefficients that measure the simple correlation between each independent variable and the Z scores computed by the discriminant function. The value of each canonical coefficient must lie between +1 and -1. In our study, we didn't examine multicollinearity as it has little effect on the stability of canonical correlation coefficients, unlike in 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 produced by SPSS 20.0 are reported in Table 2.

TABLE 2
RELATIVE CONTRIBUTION OF THE VARIABLES

Discriminant Variables	Coefficient	Rank
Long-term Debt to Total Capital Ratio	0.680	1
Enterprise Value / EBITDA	0.485	2
Institutional Investor Buying Activity	- 0.351	3
Coefficient of Variation in Operating Income	0.139	4
Hamada's Unlevered Beta (Operating Risk)	0.115	5
Market Capitalization (Firm's Size)	-0.060	6

Table 2 shows that the measure of financial risk (long-term debt to total capital ratio) had the highest contribution to the overall discriminating function, followed by enterprise value, institutional investor buying activity, the coefficient of variation in operating income, Hamada's unlevered beta (operating risk), and market capitalization (firm's size) respectively.

Since both the variance in operating income and Hamada's unlevered beta could be reflected in the returns, some multicollinearity may exist between the predictive variables in the discriminant function. To Hair, et al. (1992) such consideration may becomes critical in stepwise analysis and may be a basis for determining whether a variable should be included in a model. But when all variables are included in a model simultaneously, the discriminatory power of the model is a function of all included variables and so, multicollinearity becomes less important. Also, since the rankings of explanatory variables in this study was based on canonical correlation coefficients shown in Table 2, those coefficients are unaffected by multicollinearity (Sharma, 1996).

VALIDATION OF THE MODEL

Before drawing any conclusion we must determine if the model works equally well for any group of randomly drawn firms. The method we used for the validation is referred to as the Lachenbruch or "jackknife" method, in which the discriminant function is fitted to k -1 number of repeatedly drawn samples from the original sample eliminating one case at a time from the original sample of "k" cases (Hair et al. 1992). This method assumes that the proportion of firms classified correctly would be less than that in the original sample due to the systematic bias associated with sampling errors. The next step is to determine if the proportion classified correctly by the validation test differs significantly from the 67.7 percent classified correctly in the original test. In other words, we must determine if the difference in the two proportions classified correctly by the two tests is due to bias, and if so is that bias significant? To that end we turn to the Press's Q test of proportions. Since there are only two samples and Q-statistic has a t-distribution, we applied the binomial test in which the t-statistic is calculated as following:

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

where:

t = calculated value of t-statistic
r = number of cases classified correctly in the validation test.
n = sample size.
p = probability of a firm being classified correctly in the original test.
q = probability of that firm being misclassified in the original test.

In our case:

$$t = 478 - 718(.677) / [718 (.667 (.333)]^{½} = - .0720 \quad (6)$$

Since the t-statistic calculated above is less than its critical value of 1.645 at 5% significance level, we cannot reject 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, which leads us to the conclusion that while there may be some bias in the original analysis, it is not significant and that the method we used will classify new firms equally well as it did in the original analysis.

Usually, in addition to the validation test, researchers also address the question of the equality of matrices, which is even more important in studies where there is a disparity in the size of the groups. The MDA analysis we used is based on the assumption that the variance-covariance matrices of the two groups are equal. The SPSS program tests for such equality using Box's M-statistic, which has an F-distribution. In this study Box's M-statistic was 85.81resulting in a zero level of significance. So, we cannot reject the null hypothesis that the two matrices are equal, which leads us to conclude that the variance-covariance matrices are equal.

SUMMARY AND CONCLUSIONS

The economic and business effects resulting from international lockdowns and illness caused by the coronavirus 19 pandemic disease resulted in high unemployment, business closings, property loss, decimation of individual wealth, disruption in global supply chains, and high rates of human casualty in countries described as emerging markets. This study aims to establish a profile of risk-return characteristics of the companies in emerging markets that have constantly reported the highest risk-adjusted returns to total capital during the pandemic and to compare such firms to those reporting the lowest returns on total capital. Results of our study indicated that there was a significant difference in the financial profiles of the two groups of firms as the discriminant function separated two heterogeneous groups and classified a significant proportion correctly.

The signs of the adjusted coefficients in Table 2 indicate the characteristics of each group. Theoretically, a positive sign for an adjusted coefficient indicates that the greater the value of the variable for a firm, the more likely it is to fall in group one (the HREMP group). To the contrary, a negative sign for an adjusted coefficient indicates that the greater the value of the variable for a firm, the more likely it is to fall in group two (the LREMP group). In terms of the results shown in Table 2, the higher the level of both financial and operating risks, the greater the coefficient of variation in operating income, and the greater the value of EBITDA for a firm, the more likely it is to report high returns on invested capital. Conversely, the greater the size of the firm, and the greater the level of institutional investors' buying, the more likely it is that the firm will report low returns to invested capital. Three of these results were as expected, two had no a priori expectation and one was a surprise. Although finding why the variables are associated with one group or the other is beyond the scope of this study, a few comments on the findings are in order. Since financial leverage, operating leverage, and the variance in operating income are all a measure of risk, they are expected to be associated with higher returns on investment. But there was no a priori consensus on which group the enterprise value and the measure of firm's size might belong.

The study resulted in one surprise. Institutional investor activity was a characteristic of those firms that reported lower returns on capital. This outcome is a surprise because as previous research and reasonable logic suggest institutions' buying are motivated high returns to capital. Although institutional buying activity may reflect the higher risk, institutional investors constantly analyze companies in emerging markets to estimate the intrinsic value of those firms. However the finding and the conclusions of this study are rich enough to invoke further research. This study makes a major contribution to the existing body of knowledge in the field by constructing a theory that identifies some risk-return and market perception characteristics of firms achieving the highest returns on invested capital in emerging markets during a pandemic. Also, since the model was validated without bias, it can also be used to predict firms that can achieve high returns to total capital in those and similar markets in the future.

ENDNOTE

1. We offer our sincere gratitude to Bruce Payne for his permission to use the multiple discriminant model and analysis he first set up in his 1977 dissertation at Louisiana State University.

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