A FINANCIAL INQUIRY INTO THOSE INDUSTRIES REPORTING THE GREATEST CONTRIBUTIONS TO ECONOMIC VALUE ADDED (EVA) IN A PERIOD OF ECONOMIC GROWTH

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ABSTRACT

Just as economic value added (EVA) is reported by companies for purposes of computing value, it is also reported by industries as a significant component of private investment for the computation of gross domestic product (GDP), and is then referred to as (GDP)-by-industry. In any economy, industries are not consistent concerning their contributions to GDP-by-industry. Many industries have a very high level of EVA contributions to GDP and there are many more industries whose contributions are low enough to have caused the average contribution of all industries to decline. Previous studies that examined the fundamental financial characteristics of those industries identified as having the greatest contributions via EVA to GDP have ignored the macroeconomic background at the time those contributions were made. The purpose of this study is to establish a financial profile of those industries identified as contributing the highest level of economic value to (GDP)-by-industry in a robust, growing economic environment and to compare those industries with the industries identified as contributing the least economic value to determine whether the industries making the greatest contributions have a unique risk-return profile. Thus, this study examines the fundamental financial characteristics of those industries that made the greatest contributions to GDP in the three years preceding the 2020 occurrence and resulting economic downturn of the coronavirus-19 pandemic. **JEL Classifications**: C38; E22; L25

INTRODUCTION

Economic Value Added (EVA) is a measure of a company's financial performance in creating wealth in excess of the weighted cost of all sources of capital. The measure was created by Stern Value Management in 1983 and quickly adopted as a primary measure of firm and management performance by many of the nation's leading companies, the U.S. Postal Service, and the Chinese Government (Stern Management, 2020). As the initial use of the measure continued to grow, industries began to collect the EVA data from all firms reporting in their industry and began reporting EVA by industry. The industry data is used to identify the sectors that have been responsible for the economy's growth as well as providing insights about who drives output from these industries (Fortune, 1993). The EVA data by industry is regarded at the time of this writing as having such significance that the Bureau of Economic Analysis (BEA) includes it as a contribution to gross domestic product (GDP) and it is there referred to as (GDP)-by-industry.

Previous studies on the contributions and value of the measure have ignored the macroeconomic background and conditions in the financial markets at the time those industry data were collected and reported. An economy characterized by rapid growth, low unemployment, and a low rate of inflation should increase the EVA by all industries and while that is generally true, during this period there were industries that made significant contributions to GDP and there were industries that impeded growth or added very little. Regardless of the consistently high level of interest and apparent advantages of using the EVA as a measure of financial performance and as an addition to GDP, there have been no studies that identified differences or established an association, between traditional financial measures of risk and return by industry and EVA by industry in that economic environment. This study examines the fundamental financial characteristics of that group of industries identified as making the greatest contributions to (GDP)-by-industry during the three years preceding this study. That period contained steady to high economic growth, record low unemployment, stable prices, and record-high equity markets. Industry EVA data collected during that period yields empirical evidence of the financial characteristics of industries during such an economic environment. Thus, the period February 2017 to January 2020 provides a workshop for the study of (GDP)-by-industry and the financial characteristics of those industries ranked highest for contributions to (GDP)-by-industry in a period of unusual economic growth.

The purpose of this study is to establish a financial profile of those firms industries identified as having the highest contributions to (GDP)-by-industry in a growing economic environment and to compare those industries that made the lowest contributions to determine whether the firms that made the greatest contributions have a unique risk-return profile. If the study can be validated to exclude any bias, the model may identify industries that will contribute significant (GDP)-by-industry future periods of high economic growth. This would have implications for financial managers, investors, investment counselors, and academic researchers.

METHODOLOGY

The issues to be resolved are first, classification or prediction, and then evaluation of the accuracy of that classification. More specifically, can diverse industries be assigned, based on selected financial variables, to one of two groups: (1) industries that were identified as making the greatest (GDP)-by-industry contributions to GDP and referred to here as high EVA or (HEVA) or, industries that made the lowest or no contributions to (GDP)-by-industry or (LEVA)?

Multiple discriminant analysis (MDA) provides a procedure for assigning industries to predetermined groupings based on variables or attributes whose values may depend on the group to which the industry 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 industries, 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 industries and had more predictive power than individual variables used in univariate tests (Altman, 1968).

The use of MDA in the social sciences for 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 & Pinches, 1973), to determine value (Payne, Wong, & Payne 2017), 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 HEVA industries firms and the group of LEVA industries. The computer program used to perform the analysis is SPSS 25.0 Discriminant Analysis (SPSS Inc. 2019). 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 industry EVA data is reported by industries as a significant component of private investment for the computation of gross domestic product (GDP) and since it has been adopted as a primary measure of management performance by many of the nation's leading companies, the U.S. Postal Service, the Chinese Government and others (Stern Management, 2020), it is used here as the subject of this study.

All Industry data used in the analysis were gathered from Damodaran's reports as of January 5, 2020, one month before the magnitude of the effects of the Covid-19 pandemic became apparent. Detailed definitions of individual items of data are contained in the industry database (Damodaran, 2020). The sample consists of 96 industries containing 7,671 companies. The first group of 48 industries was identified by Damodaran (2020) as making the greatest contributions to GDP-by-industry during the period 2017–2020. Again, they are abbreviated here as (HEVA) and a second group is a group of 48 industries described as having made the lowest contributions to GDP-by-industry during the same period, abbreviated here as (LEVA). Both the HEVA and LEVA industries are listed in appendix A.

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 simply consists of one measure of return on investment, three measures of risk, and three measures of how the intrinsic value of firms within an industry is perceived in the capital markets. A basic tenet of this study is that all investors trade off indicators of risk and return, and their perception of risk and return to establish the value of the firms and thus the industries. Following are the seven explanatory variables from 96 industries:

X_1 - Return to total capital is used as a measure of return on investment. It 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 finances assets.

X_2 - The ratio of market price to earnings (P/E) has been used for years as a rough measure of how investors at the margin (those willing and able to buy) value a firm. More recently, the price-earnings growth ratio (PEG) has grown in popularity. Damodaran (2002) writes that the PEG is a better measure of a company's potential future value, He further writes that many analysts have abandoned the P/E ratio, simply because they desire more information about a stock's potential. Thus, PEG is used here as an indicator of the market's perception of an industry.

X_3 - 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 the average of all company fixed operating costs in an industry, and the debt to total capital ratio is used as a measure of financial leverage (risk) (Van Horne, 2001, Brigham & Daves, 2019).

X_4 - Long Term Debt to Total Capital (DTC) is used 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 firms within industries are financed by creditors as well as owners.

X_5 - The standard deviation of the movements of all common equity securities held by all companies in an industry is averaged to find the standard deviation for the industry. It is used here as a measure of the volatility or risk associated with the equity values in that industry.

X_6 - 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 (Josephson, 2021. 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 within industries.

X_7 - Capital Spending is needed to maintain the annual strength of contributions to GDP-by-industry. Expenditures in the form of new productive assets, research and development, and infrastructure are required **to maintain operating assets.** EVA is calculated after the capital expenditures are deducted from operating income. Whereas capital spending is necessary to ensure the future value of companies and industries, a comparison is needed to determine if there is a difference in capital spending between the HEVA industries and the LEVA industries.

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

X1 – Return to Total Capital
X2 –The Price Earnings Growth Multiple
X3 – Hamada's Unlevered Beta (Operating Risk)
X4 – Long Term Debt to Total Capital (Financial Risk)
X5 – A Measure of Share Price Volatility
X6 – Capital Expenditures Per Share
X7 – Institutional Investor Buying

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 account for a sufficiently large portion of the discrimination procedure (Zaiontz, 2014). The more accepted practice is to use only the variables that logically contribute to the accomplishment of the study's purpose (Suozzo, 2001). The construction of this study is consistent with both references.

The financial profiles simply consist of, as previously mentioned, one measure of return on investment, three measures of risk (the unlevered beta, the volatility of share prices, and the debt/equity ratio), and three measures of how the intrinsic value of firms within an industry might be perceived in a capital market (The PEG ratio, Institutional Buying, and Capital Spending). If the two groups of industries have unique financial profiles of those measures, and the model can be validated without bias, it suggests that the profile for the industries that have the highest contributions to EVA and GDP-by-industry may be used as a tool to forecast industries that will maintain significant contributions to EVA and GDP-by-industry in a growth economy in the future.

TESTS AND RESULTS

The discriminant function used has the form:

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

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:

$$Z_j = .094 + 5.662X_1 + .037X_2 - .469X_3 - 4.764X_4 + 4.228X_5 + 4.720X_6 + .443X_7 \qquad (2)$$

The 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 less than a critical value, the firm is classified in group one (LEVA). Conversely, a firm's Z score that is greater than the critical value will place the firm in group two (HEVA). Since the two groups are heterogeneous, the expectation is that HEVA firms will fall into one group and the LEVA 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 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 in this study is 32.54. That exceeds the critical value of Chi-Square 14.07 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 industries experienced very high levels of EVA and the other group did not. 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 were classified correctly and is that percentage significant?

To answer the second question a test of proportions is needed. Of the 48 HEVA firms in the total sample, 78.1 percent were classified correctly. It may appear obvious that 78.1 percent classified correctly is significant, but formal research requires the proof of a statistical test. To test whether a 78.1 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:

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

where:

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

In this case:

$$\text{Press's Q} = [96 - (75 \text{ x } 2)]^2 / [96 (2-1)] = 30.37 > \chi^2_{.05} \ 3.84 \text{ with one d.f.} \quad (4)$$

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 78.1 percent correctly.

The arithmetic signs of the adjusted coefficients in Table 1 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 HEVA 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 LEVA group. Thus, according to Table 1, the greater the canonical coefficients of return on total capital, capital expenditures, the standard deviation in equity prices, the price-earnings multiple, the unlevered beta coefficient, and institutional buying activity, the more likely the industry would be a heavy contributor to EVA and GDP-by-industry. Conversely, the greater the use of financial leverage (financial risk) more likely the firm would be a very light contributor to EVA and GDP-by industry.

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 25.0 program and shown here with their ranking in Table 2.

Table 2 reveals that the measure of return to total capital made the greatest contribution to the overall discriminating function. That was followed respectively by the debt to total capital, capital expenditures, the volatility of equity prices, the price-earnings multiple, institutional buying, and finally Hamada's unlevered beta.

Some multicollinearity may exist between the predictive variables in the discriminant function since both return to total capital and financial leverage could be reflected in the results of the analysis. 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 seven firms between the original test and the validation test. The major issue is whether the proportion classified correctly by the validation test differs significantly from the 78.1 percent classified correctly in the original test. That is, is the difference in the two proportions classified correctly by the two tests due to bias, and if so is that bias significant? Of course, it may be obvious that a difference of only seven cases will not be significant with a sample of two groups of forty-eight firms in each group. 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 70.8 percent of the firms. Since there are only two samples for analysis the binomial test is appropriate:

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

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: 68 – 96 (.781) / [96 (.781) (.219)] ^{½} = - 1.73 is less than t_{05} 1.96. (6)

Therefore, 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. Thus, 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.

Two basic assumptions in the model are: 1.) the variables on which the classifications are based are assumed to have multivariate normal distributions, and 2.) the within-group variances are assumed to be equal. Thus, researchers usually address the question of the equality of matrices. This is especially important in studies such as this where there is a disparity in the size of the groups. However, there is no disparity in this study, both groups have 48 observations. The SPSS program tests for equality of matrices by means of Box's M statistic. Box's M is a parametric test used to compare variation in multivariate samples. More specifically, it tests if two or more covariance matrices are equal (homogeneous). In this study Box's M transformed to the more familiar F statistic of 90.92 resulted in a zero level of significance. Thus, the null hypothesis that the two matrices are equal cannot be rejected.

SUMMARY AND CONCLUSIONS

The purpose of this study was to establish a financial profile of those industries identified as contributing the highest level of economic value to (GDP)-by-industry in a robust, growing economic environment and to compare those industries with the industries identified as contributing the least economic value to determine whether the industries making the greatest contributions have unique risk-return characteristics.

The financial profiles simply consisted of one measure of return on investment, three measures of risk (the unlevered beta, the volatility of share prices, and the debt/equity ratio), and three measures of how the intrinsic value of firms within an industry might be perceived in a capital market (The PEG ratio, Institutional Buying, and Capital Spending).

A unique set of explanatory variables was found for those firms that made the highest contributions to EVA and GDP-by industry, and since the model was validated without bias, it is suggested that the profile may be used to identify industries that will maintain those high contributions in future markets characterized by high economic growth.

The results of the statistical analysis indicated first that there was a significant difference in the financial profiles of the two groups of industries. Table 2 reveals that the greater the values for return to total capital, the debt to total capital, capital expenditures, the volatility of equity prices, the price-earnings multiple, institutional buying, and Hamada's unlevered beta, the more likely the industry would make high contributions to EVA and GDP-by-industry. Conversely, the greater the degree of financial leverage (debt to total capital), the more likely the industry will make little or no significant contributions.

Four of these results may have been expected, two had no apriori expectations and, one was simply a mild 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 return to total capital, capital expenditures, the price-earnings-growth multiple, and institutional buying activity would be characteristics of those industries that made high EVA and GDP-by-industry contributions. There were no apriori expectations regarding either financial or operating leverage. That was simply not known.

The analysis of data resulted in one mild surprise. It is logical to surmise that the average rate of the volatility of equity securities in the high contributions to the EVA group would be less than that of the low contributions group. That was, however, not the case. The volatility of equity prices in the high contribution industries was greater in the high contribution group than the low contribution group. 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 financial characteristics of industries that make the greatest contributions to economic value-added, and to GDP-by-industry in a period of very strong economic growth. It is further suggested that since the model was validated without bias, it may be used to predict industries that will again make significant contributions to EVA and GDP-by-industry. The contribution is offered here as a logical and plausible explanation of observed phenomena. In order to make a more complete contribution to the theory, the aforementioned further research is needed.

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TABLE 1
RELATIVE CONTRIBUTION OF THE VARIABLES

Discriminant Variables	Canonical Coefficient	Rank
Return to Total Capital	0.641	1
Debt to Total Capital	-0.539	2
Capital Expenditures Per Share	0.303	3
Standard Deviation in Equity Prices	0.217	4
Price Earnings Growth Multiple	0.197	5
Institutional Investor Buying	0.133	6
Hamada's Unlevered Beta	0.020	7