A FINANCIAL PROFILE OF FIRMS IDENTIFIED AS INSTITUTIONAL FAVORITES IN EMERGING MARKETS

Bruce C. Payne, Barry University
Roman Wong, Barry University
John B. Payne, Valencia State College

ABSTRACT

In many developing countries, and emerging markets worldwide, there exists a growing need for investment capital. Institutional investors have been attracted to those financial markets in their search for new sources of income and greater diversification in their investment portfolios. Thus, there has been a relatively recent great flow of capital into those markets from institutional investors. The institutional investors are obviously not interested in every potential investment in emerging markets, and that raises the question of what companies have benefited from that inflow of capital and what are the financial characteristics of those companies that may have attracted the institutional investors. There has been a good deal of academic research on the financial characteristics of such "institutional favorites," but most of the work was done in long established markets and very little has been done in emerging markets.

The purpose of this study is to provide a financial analysis of firms that may be described as "institutional favorites" in emerging markets. Specifically, the analysis will test for significant differences in the financial profiles of the institutionally favored firms, and companies selected at random during the same period. A unique financial profile is established for the institutionally favored firms, and it is validated without bias. Therefore, it is suggested that the profile may be used to predict firms that may become favored in emerging markets in the future. If this is true, it will have implications for investors, investment counselors, financial managers, and scholars interested in emerging markets. **JEL Classification**: G11, G15

INTRODUCTION

Emerging financial markets are, at the time of this writing, a favored topic in investment and financial literature. There exists a great need for investment capital in those markets by companies, and particularly by companies that are growing. The building or rebuilding of infrastructure in Southeast Asia alone is expected to be a 2.8 trillion dollar industry over the next five years, creating jobs and profits around the globe (Butler 2015). Emerging stock markets appeal to institutional investors for several reasons, the most frequently cited being their rapid economic growth. The strength of cash flows from institutional investors into emerging markets observed over the last few years can be explained by a number of factors, including higher than average returns, new sources of income, and the opportunity for global diversification (Vanguard 2010). Those investors have invested at least 50 billion dollars into emerging stock and bond markets since 2013 (Rao 2015).

The significance of the flow of funds from institutional investors cannot be overestimated. Celik and Isakson (2013) reported that as late as in the mid-1960s, institutional investors held 16 percent of all publicly listed stocks in the United States. Today they hold around 60 percent. In Japan, the portion of held by institutional investors is even greater. In 2011 institutional investors held 82 percent of all public equity in that country. In the UK, the increase in institutional ownership is even more pronounced. In the last 50 years, the portion of public equity held in the UK by institutional investors increased from 46 percent to 88.7 percent (Celik and Isakson 2013). Thus, it is small wonder that many publications are exclusively devoted to institutional trading. For example, the *Institutional Investor Journal* website (www.iijournals.com/) lists nine on-line journals devoted to nothing but research on the activity of institutional investors. Moreover, the market performance and changes in the composition of those firms most favored by institutions have been reported in financial literature since the 1950's (Bogle and Tuardowski 1980). This is not to imply that institutions always move together or in the same direction. Several empirical studies have failed to find evidence of a "herd instinct" That is, they may be active simultaneously, but not necessarily on the same side of the market, and it has been suggested that they actually promote stability by providing liquidity for one another and for non-institutional investors (Reilly 1985). There has been a good deal of academic research on the financial characteristics of "institutional favorites," but most all of that the work was done in long established markets and very little has been done in emerging markets (Bogle and Tuardowski 1980, Payne 1989, Graham 1973, and Kitchen 1985).

Despite the interest in institutional investment behavior, and despite the interest in emerging markets, there have been no studies that sought to identify the financial characteristics that measure the risk-return tradeoff profile, of firms seemingly favored by institutions in the aforesaid emerging markets.

The purpose of this study is to complete a financial analysis of firms that may be described as "institutional favorites" in emerging markets from a database of 2000 firms created by (Damodaran 2014) from Bloomberg, Morningstar and Compustat. Specifically, the analysis will test for significant differences in the financial profiles of firms from emerging markets that have that have been identified as "institutional favorites," and to compare those profiles with companies selected at random from the same database. If the two groups of firms have unique financial profiles, and the model can be validated without bias, it suggests that the profile may be used as a tool to forecast companies that may become "institutional favorites" in future periods. The use of such a new tool to forecast the holdings of institutional investors in emerging markets 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, the question is asked: can firms be assigned, on the basis of selected financial variables, to one of two groups: (1) firms whose shares were most heavily held by institutional investors in Damoadan's database of emerging markets, and simply referred here as institutional favorites in emerging markets (IFEM) or, firms whose shares were least held by institutions from the same database and referred to here as firms least held by institutions (FLHI)? That is, the firms in those markets that were most heavily held by institutional investors are compared firms whose shares were least held by institutions from the same database of emerging markets to accomplish the aforementioned purpose.

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 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 IFEM firms and the group of FLHI firms. The computer program used to perform the analysis is SPSS 21.0 Discriminant Analysis (SPSS Inc. 2012). 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

Given the interest in financial literature regarding emerging markets and the interest in the behavior of institutional investors, the present study should be regarded as furthering that interest, and contributing to the entire base of knowledge of firms that are favored by institutions in emerging markets. Thus, the dependent variables used here are the group of firms whose shares are most heavily held by institutions in those markets and firms whose shares were least held by institutions in the same database.

All data used in the analysis were gathered from Domodaran's 2014 set. The sample selected for this study consists of two groups. The IFEM group contains 709 observations, and the FLHI group contains 887 observations. This, of course, exhausted the available data in the Domodaran set that was judged suitable for this study. The sample is large enough (1865 companies) that as long as the variance covariance matrices are equal, it renders the difference in the size of the groups insignificant, and of course, the sample gathered simply exhausted Domodaran's database in the IFEM category.

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

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

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

X_3 One measure of return is return to total capital. Return on equity capital could have been used, but it does not include a return to creditors and does not recognize that total value includes those assets financed by debt.

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

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

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

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

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

X1 – Market Capitalization (Size)
X2 – The Enterprise Value Multiple
X3 – Return to Total Capital
X4 – The Expected Two Year Growth Rate
X5 – The Unlevered Sector Beta (Operating Risk)
X6 – The Long Term Debt to Total Capital Ratio (Financial Risk)
X7 – The Coefficient of Variation in Operating Income

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

TESTS AND RESULTS

The discriminant function used has the form:

$$Z_j = C_0 + V_1X_{1j} + V_2X_{2j} + ... + V_nX_{nj} \tag{1}$$

Where:
C_0 is a constant

X_{ij} is the firm's value for the ith independent variable.
V_i is the discriminant coefficient for the firm's jith variable.
Z_j is the jth individual's discriminant score.

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

$$Z_j = - .482 + .0001X_1 + .003X_2 + .0001_3 + .0001X_4 + .101X_5 - .0001X_6 - .482X_7 \tag{2}$$

Classification of firms is relatively simple. The values of the seven variables for each firm are substituted into equation (1). 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 (IFEM). Conversely, a Z score less than the critical value will place the firm in group two (FLHI). Since the two groups are heterogeneous, the expectation is that IFEM firms will fall into one group and the FLHI 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 848.5. That exceeds the critical value of Chi-Square 14.067 at the five percent level of significance with 7 degrees of freedom. The null hypothesis that there is no significant difference between the financial profiles of the two groups is therefore rejected, and the first conclusion drawn from the analysis is that the two groups have significantly different financial characteristics. This result was of course, expected since one group of firms was widely held by institutional investors and the other was sparsely held. The discriminant function thus has the power to separate the two groups. However, this does not mean that it will in fact separate them. The ultimate value of a discriminant model depends on the results obtained. That is, what percentage of firms was classified correctly and is that percentage significant?

The firms that were classified correctly are shown on the diagonal in Table I. Of the total of 1865 firms in the dataset 1620 or 86.9 percent were classified correctly

To answer the second question a test of proportions is needed. Thus, to determine whether 86.9 percent is statistically significant, formal research requires the proof of a statistical test. In this case, the Press's Q test is appropriate (Hair et al 1992, 106). Press's Q is a Chi-square random variable:

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

where:

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

In this case:

$$\text{Press's } Q = [1865 - (1620 \times 2)]^2 / [1865 (2-1)] = 1013.74 > \chi^2_{.05}\ 3.84 \text{ with one d. f.} \quad (4)$$

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 86.9 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 IFEM 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 FLHI group. An examination of Table 2 reveals that institutional ownership is associated with growth, enterprise value, operating risk, and returns to total capital. Conversely, they were smaller in size, had less volatility in operating income, and less financial risk than the firms that were sparsely held.

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

Some multicollinearity may exist between the predictive variables in the discriminant function, since both return and risk could be reflected in the institutional holdings. 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 1596 companies used in this study, the differences seem to diminish. The major issue is whether the proportion classified correctly by the validation test differs significantly from the 86.9 percent classified correctly in the original test. That is, is the difference in the two proportions classified correctly by the two tests due to bias, and if so is that bias significant? Of course, it may be obvious that a difference of only three cases will not be significant with a sample of 1596 companies. However, as in the aforementioned case of the Press's Q test of proportions, formal research requires the proof of a statistical test. The jackknife validation resulted in the correct classification of 86.6 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:

$$1615 - 1865(.869) \,/\, [1865(.869)\,(.131)]^{½} = -\ 0.392 \text{ is less than } t_{05}\ 1.645. \qquad (6)$$

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

In addition to the validation procedure, researchers usually address the question of the equality of matrices. This is especially important in studies such as this where there is disparity in the size of the groups. One of the assumptions in using MDA is that the variance-covariance matrices of the two groups are equal. The SPSS program tests for equality of matrices by means of Box's M statistic. In this study Box's M transformed to the more familiar F statistic of 323.2 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 firms in emerging markets that were identified as being most widely held by institutional investors in a database of 1865 firms created by (Damodaran 2014), and to compare that profile with those companies that were identified as being the least widely held by said institutional investors. Specifically, the analysis tested for significant differences in the financial profiles of the two groups of firms.

In this study the group of explanatory variables chosen for analysis includes one measure of the size of firms, one measure of how the company may be perceived by investors at the margin (those willing and able to buy), two measures of return to total capital, and three measures of risk. Investors "trade off" indicators of risk and return to buy and sell securities. It is the buying and selling action of those investors that establish the market value of both equity and debt, and thus, the 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 institutional ownership that identification of two distinct groups based on the explanatory variables was expected. Table 2 reveals that the institutional ownership is positively associated with growth, enterprise value, operating risk, and returns to total capital. Conversely, the firms favored by institutions were smaller in size, had less volatility in operating income, and less financial risk than the firms that were sparsely held. 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.

Five of these results, may have been expected, one variable had no apriori expectation (The relationship was simply not known), and one was a surprise. It may have been that expected growth and the return to equity simply outweighed the three measures of risk and thus, all five of those variables may have had an aprori expectation of being characteristic of those firms that were favored by institutional investors. Indeed, the expected two-year growth rate was the strongest of the discriminant variables. The size of the firms, favored by institutional investors, and measured by market capitalization was simply not known beforehand. That is, there was no aprori expectation for this variable, but it is associated with the IFEM group.

The study resulted in one surprise. Operating risk (operating leverage) was expected to be associated with the FLHI group. That was not however, the case. Operating risk was associated with institutional favorites. Whereas the firms favored by institutions were smaller in size, there seems to be no explanation as to why they would have greater fixed operating costs (operating leverage). 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 a financial profile that includes a risk-return tradeoff picture, a measure of the perceived value of firms, and proxy for the size of the firm for companies that are most widely held (favored) by institutional investors in emerging markets. It is further suggested that since the model was validated without bias, it can be used to predict firms that may attract institutional investors in emerging markets in the future. In order to construct a more complete theory, the aforementioned further research is needed. The evolution and appearance of a complete theory would aid managers, investors, academicians, and investment counselors by providing greater of knowledge on which to base financial decisions.

REFERENCES

Altman, Edward I. 1968. “Financial Ratios, Discriminant Analysis and the Prediction Altman, Edward I. 1968. "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy.” Journal of Finance. 23 (4): (September): 589-609.

Bogle, J.C. and J.M. Tuardowski. 1980. “Institutional Investment Performance Compared: Banks, Investment Counselors, Insurance Companies and Mutual Funds.” Financial Analysts Journal. 36 (Jan./Feb.): 33-41.

Butler, Steven. 2015. “Why is America Scrambling to Dig into Southeast Asia?” Ozymandias.http://www.ozy.com/fast-forward/why-america-is-scrambling-to-dig-into-southeast-asia/62450

Damodaran, Aswath. 2014. Investment Valuation: Tools and Techniques for Determining the Value of any Asset: New York: John Wiley and Sons.

Damodaran, Aswath. 2002. http://people.stern.nyu.edu/adamodar/New_Home_Page/data.html.

Edmister, Robert O. 1982. "An Empirical Test of Financial Ratio Analysis for Small Business Failure Prediction.” Journal of Financial and Quantitative Analysis 7: 1477-1492.

Graham, Benjamin. (1973). “The Intelligent Investor.” New York: Harper-Collins.

Hair, Joseph F., Rolph E. Anderson, Ronald L. Tatham, and William C. Black. 1992. Multivariate Data Analysis. New York: Macmillian.

Kitchen, Philip J. (1985). Effective Public Relations: Principles and Practice, 6th ed. Englewood Cliffs, NJ: Prentice-Hall.

Payne, Bruce C. 2010. “An Analysis of the Financial Variables that Determine the Value of Firms Identified as Institutional Favorites in a Period of Economic Recession and Slow Recovery.” Advances in Investment Analysis and Portfolio Management. 4: 27-47.

Rao, Sujata. 2015. “Deep-Pocketed Institutional Funds Scaling Back Emerging Markets.” Ruthers. http://www.reuters.com/article/emerging-institutions-outflow-idUSL8N12C39A20151012

Reese, John P. 2013. “Four Free Cash Flow Yield All-Stars.” http://www.forbes.com/sites/investor/2013/08/08/four-free-cash-flow-yield-all-stars/

Reilly, F.K. 1985. Investment Analysis and Portfolio Management. New York: Dryden Press.

Sharma, Subhash. 1996. Applied Multivariate Techniques. Hoboken, New Jersey: John Wiley and Sons.

Suozzo, Peter. 2001. Global Equities Research. Stern School of Business. http://pages.stern.nyu.edu/~ekerschn/pdfs/readingsemk/EMK%20NYU%20S07%20Global%20Tech%20Strategy%20Valuation%20Multiples%20Primer.pdf.

Treschmann, James S, and George E. Pinches. 1973. "A Multivariate Model for Predicting Financially Distressed Property-Liability Insurers." Journal of Risk and Insurance. 40 (3): September: 27-333.

Vanguard. 2010. “Investing in emerging markets: Evaluating the allure of rapid economic growth.” https://www.vanguard.com/pdf/icriem.pdf

Zaiontz, Charles. 2014. “Real Statistics Using Excel. http://www.real-statistics.commultiple-regression/testing-significance-extra-variables-regression-model/

TABLE 1
CLASSIFICATION RESULTS
Predicted Results

IFEM - FLHI Classification

Actual Results	IFEM	FLHI
IFEM	830	36
FLHI	209	790

TABLE 2
RELATIVE CONTRIBUTION OF THE VARIABLES

Discriminant Variables	Coefficient	Rank
The Two Year Expected Growth Rate	0.687	1
The Enterprise Value Multiple	0.604	2
The Coefficient of Variation in EBIT	-0.346	3
Market Capitalization	-0.140	4
The Unlevered Sector Beta (Operating Risk)	0.118	5
Long Term Debt to Total Capital (Financial Risk)	-0.115	6
Return to Total Capital	0.044	7