

A Financial Profile of Firms Awarded the Highest Technical Ratings by Value Line in a Period of High Economic Growth

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This study examines the financial characteristics of the group of firms that have been identified by *Value Line* as having the highest technical ratings in their database during the four years preceding the 2020 occurrence and resulting economic downturn of the coronavirus-19 pandemic. That period was characterized by a high level of economic growth, low unemployment, and record-high equity markets. Those highest-ranking firms are compared with firms chosen at random, but from the same industries, to determine whether the firms with the high technical ratings in such an economic environment have a unique risk-return profile, and by implication, a heretofore unknown relationship between technical and fundamental analysis. As in previous studies of this type, multiple discriminant analysis is used to identify the characteristics that most highly separate the two groups of firms, and canonical correlation ranks the discriminant variables.

Keywords: Technical Analysis, Economic Growth, Multiple Discriminant Analysis.

Introduction

The *Value Line* Investment Survey awards each of the 1700 companies in its database a technical rating ranging from one to five. A ranking of one indicates that the company has immediate investment potential over a three to five-month period, and a ranking of five indicates that there is no immediate investment potential and may indeed contain the potential for loss. *Value Line* uses a proprietary formula to predict the short-term (three to six months) future price returns relative to the *Value Line* universe of those 1700 companies (Value Line Pro, 2019). The company has had a proven track record with its technical ranking system since 1965. Their top-ranked stocks for technical ratings outperformed the Dow Jones Wilshire 5000's total-return index by an average of 2.6 percentage points a year over nearly three decades (Hulbert, 2007). Thus, the technical ranking has been of interest to investors and market researchers for years.

Previous studies on the investment potential of highly ranked firms based on technical analysis have ignored the macroeconomic background and risk-return characteristics of those highly ranked firms. This study examines the financial characteristics of that group of firms that have been identified by *Value Line* as having the highest technical ratings in their database during the four years preceding this study. Those four years have been characterized by economic growth, low unemployment, and record-high equity markets. Regardless of the consistently high level of interest and apparent advantages of using the *Value Line* technical ranking to evaluate investments and the intrinsic value of firms in such an economic background, there have been no studies that have determined or established an association between traditional financial measures of risk and return (microeconomic measures) and the *Value Line* technical ratings in that economic environment.

The purpose of this study is to establish a financial profile of those firms with the highest *Value Line* technical ratings in a growing economic environment and to compare those firms with firms chosen at random, but from the same industries as the first group to determine whether the firms with the high technical ratings have a unique risk-return profile. This manuscript contributes to the existing literature by empirically testing a classification model that could allow the identification of firms likely to obtain high technical ratings in future periods of high economic growth. These findings would have important practical implications for financial managers, investors, investment counselors, and academic researchers.

Literature Review

Empirical evidence over time indicates that the relative accuracy of the *Value Line* technical ranking system has been outstanding. As stated, their top-ranked stocks using technical ratings outperformed the Dow Jones Wilshire 5000's total-return index by an average of 2.6 percentage points a year over nearly three decades (Hulbert, 2007). The widespread use of the technical ratings is, however, contrary to the logic contained in all forms of the Efficient Market Hypothesis (EMH). Thus, that extraordinary performance in an efficient market has led many to refer to it as the *Value Line* Anomaly, or the *Value Line* Enigma. Fischer Black, one of the fathers of the EMH, once stated that *Value Line's* results were the big exception to the EMH (Swedroe, 2010). The use of all *Value Line* data in investor decisions has grown steadily and continues to grow steadily in popularity since its inception in 1965 (Reynolds, 2019). Huang (2017) polled advisers, professional stockbrokers, and bond specialists to find the best investing tools, newsletters, websites, and journals for potential investors. The study concluded that *Value Line* is the most reliable source of stock investment research, with a history going back to 1931, and that historically, it has outperformed the competition when it comes to risk-adjusted-performance.

There are, however, other views. Damodaran (2014) suggested that technical analysis should not be used in isolation, but in conjunction with risk analysis and timing data. That study further stated that many traders fail to incorporate sound risk management techniques into their trading systems. Moreover, many traders fail to incorporate stop-loss orders with their initial orders when using technical analysis indicators only Damodaran (2014). The concept of risk is not often associated with technical ratings. However, Waggle et al., (2004) found that Investors selecting *Value Line's* most highly rated stocks based on technical analysis tend to take on relatively high levels of market risk, as measured by beta. The authors concluded that individuals should focus on security betas rather than *Value Line* ranks when making investment decisions. They further concluded that *Value Line's* assignments of technical ranks appear biased toward higher-beta (higher-risk) securities. Lorenzoni et al. (2007) found that traders have a tendency to test their trading systems and technical analysis indicators on an insufficient amount of data and that analysts need to test trading systems and technical analysis indicators on a wide array of data in different types of trading markets. Castater et al. (2020) found that technical ratings are very seldom used in isolation to evaluate investments but are usually used in conjunction with *Value Line's* Timeliness rating and that those two ratings should always be consistent.

Lockwood et al. (2016) found that the *Value Line* effect (i.e., high success of the Value Line technical rankings) is confined to U.S. stocks. They concluded that U.S. listed stocks significantly outperform their benchmarks long after *Value Line* technical rank change announcements. In contrast, they found no evidence of a *Value Line* effect for recommendations made for foreign stocks that list on U.S. exchanges, nor for those that list outside the U.S. Further, their study concluded that for days surrounding rank change announcements, trading volume is abnormally high for the U.S. listed stocks but remains unchanged for the foreign stock sample.

Whereas previous studies ignore the macroeconomic background at the time company rankings are awarded, this study examines those rankings and companies receiving those rankings for the four years preceding the 2020 occurrence and resulting economic downturn of the coronavirus-19 pandemic. That period has been characterized by steady to high economic growth, record low unemployment, stable prices, and record-high equity markets. Thus, conclusions reached in this study apply to these specific market conditions and should not be extrapolated to declining or stagnant markets. Moreover, the fundamental risk-return characteristics of the highly-rated firms at the time those ratings are awarded have received little attention in the literature. As a result, this study adds to the existing body of knowledge of *Value Line's* technical ratings and to the extent that the *Value Line* ratings are consistent with other financial services, then by extension to all technical ratings. Financial data collected and managerial behavior regarding financial positions observed during this period are empirical evidence of the financial characteristics of firms and managerial behavior during such an economic environment. Thus, the period March 2016 to March 2019 provides a workshop for the study of *Value Line's* technical rankings, and the financial characteristics of those firms ranked highest in a period of unusual economic growth.

Methodology

Our approach to studying the financial profile of firms with high technical ratings is two-fold: 1) we develop a classification model, and 2) we evaluate the accuracy of our model's predictions. More specifically, can firms be assigned, based on selected financial variables, to one of two groups: (1) firms that were identified as having the highest ratings for technical analysis in their database and simply referred to here as (HTR) or (2) firms chosen at random (FCR) from the same database and the same industries as the HTR group?

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 (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, 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 HTR firms and the group of FCR firms. The computer program used to perform the analysis is SPSS 25.0 Discriminant Analysis. Since the objective 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

Since all empirical evidence over time indicates that the long-term performance of *Value Line*'s technical ranking system has been outstanding, and as the use of *Value Line* data in investor decisions continues to grow steadily in popularity since its inception in 1965 (Reynolds, 2019), it is used here as the subject of the current study.

All data used in the analysis were gathered from *Value Line Ratings and Reports*.² The first group (HTR) was identified by *Value Line* as the first 100 firms with the highest technical ratings in our sample. The second group (FCR) consists of 100 firms randomly chosen from the *Value Line* database, but from the same industries as the first group. Thus, there are 200 companies in our total sample.

In periods of economic growth or economic decline, all industries will not experience the same effects, whether they are adverse or beneficial. It follows that for an unbiased study, the effects of industry must be held constant. This was accomplished by matching the companies in the HTR group with companies from the same industry in the FCR group. For example, from the restaurant industry, Bob Evan's is in the HTR group, and P.F. Chang's is in the FCR group. From the drugs industry, Forrest Labs is in the HTR group, and Merck is in the FCR group. From the medical services industry, Tenet Healthcare is in the HTR group and Universal Health is in the FCR group. From the entertainment industry, Walt Disney is in the HTR group and Warner Music is in the FCR group. Gentex is in the HTR group from the Auto Parts industry and Dura Auto Parts in the FCR group. In this manner, each company identified by *Value Line* as having high technical ratings was matched with a randomly chosen company from the same industry. Thus, this matching method of randomly choosing and matching companies from the same industries eliminates any bias due to differences in industry listings.

Previous studies using this (and other) statistical methods have chosen explanatory variables by various criteria and theoretically driven arguments. In this study, the group of explanatory variables chosen for analysis includes one measure of the size of the firm, one measure of return on investment, two measures of risk, one measure of capital spending, a measure of the safety of investment, a measure of financial strength, a measure of price predictability, a measure of the timeliness of investment in the firm, and finally, and one measure of how the firm may be perceived by investors at the margin. It is the buying and selling of those investors that establish the market value of both equity and debt. An evaluation of those measures is needed to accomplish the purpose of this study. A basic tenet of this study is that all investors trade-off indicators of risk and return, and their perception of risk and return to establish the value of the firms. Following are the ten explanatory variables:

- X₁ - Sales is included as a measure of the size of the firm. Market capitalization is commonly used to measure the size of the firm, but in this case, sales is the better measure because it is more likely affected by strong economic growth. The literature is mixed on whether the size of the firm is a factor in establishing technical value for investment. Thus, it is included in the set in an attempt to add clarity.
- X₂ - 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 firm 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.
- X₃ - 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, and the debt

to total capital ratio is usually used as a measure of financial leverage (risk) (Van Horne 2001; Brigham & Daves, 2006).

- X₄ - 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. However, the debt to total capital ratio again recognizes that the firm is financed by creditors as well as owners.
- X₅ - The fifth explanatory variable is Capital Spending Per Share. The data gathered from this study were gathered from the period four years preceding this study. It is expected that in periods of strong economic growth, all firms would increase capital expenditures. It will be informative to determine if, indeed, firms that have achieved high technical ratings have increased their capital spending beyond that of firms selected randomly. It has been written that while the price-earnings multiple is a rough measure of the value as a function of past earnings, the capital spending to earnings ratio may be regarded as an indicator of future value (Payne, 2010).
- X₆ - For both individual investors and investment companies, safety is an important criterion. The *Value Line* rank for safety is assigned to each of the approximately 1,700 companies in their database. It measures the total risk of a stock relative to the approximately 1,700 other stocks. It is included here to answer whether a measure of safety is in any way associate with technical ratings.
- X₇ - Just as safety is an essential criterion for both individual investors and companies considering an investment, the financial strength of a company is almost certainly a prime consideration. The purpose here is to determine whether the financial strength of a company is in any way associated with technical analysis.
- X₈ - *Value Line's* price predictability statistic for all firms in their database is related to potential return on investment and, if positive, should be related to high technical ratings. The price predictability statistic is based on the stability of year-to-year earnings comparisons, with recent years being weighted more heavily than earlier ones. The ratings range from 5 to 100 and are derived from the standard deviation of percentage changes in quarterly earnings over eight years (Value Line Pro, 2019).
- X₉ - The *Value Line* timeliness screen ranks a stock's probable market performance one year in advance. All 1700 stocks in the *Value Line* database receive a timeliness ranking from number one, for companies ranked the highest for potential positive movement to number five, those companies ranked lowest for timely investments. The ranking score is derived by *Value Line* via a proprietary computer program using as input the price and earnings history, recent price and earnings momentum, and earnings surprises. The company claims to have a proven track record with the timeliness ranking system since 1965. Timeliness is thus included here and, if positive, should be related to the group of HTR firms (Value Line Pro, 2019).
- X₁₀ - The activity of institutional investors has long been a favored topic in financial literature. The daily trading of such investors varied during this period between 50 and 70 percent of all daily trading on the New York Stock Exchange (Brancato & Rabimov, 2008). We include the buying activity of institutional investors during this period simply as an indicator of how the market or at least a significant part of the market regarded those firms.

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

- X1 - A Measure of Size (Sales)
- X2 – Return to Total Capital
- X3 – Hamada’s Unlevered Beta (Operating Risk)
- X4 – Long Term Debt to Total Capital (Financial Risk)
- X5 – Capital Spending per Share
- X6 – The *Value Line* Measure of Safety of Investment
- X7 – The *Value Line* Measure of Financial Strength
- X8 – The *Value Line* Measure of Price Predictability
- X9 – The *Value Line* Measure of Timeliness for Investment
- X10 – Institutional Buying Activity

The explanatory variable profile contains basic measures of standard 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.

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). However, the construction of this set of explanatory variables is consistent with the purpose of building a financial profile for the HTR firms.

The financial profiles simply consist of, as previously mentioned, one measure of the size of the firm, one measure of return on investment, two measures of risk, one measure of capital spending, a measure of the safety of investment, a measure of financial strength, a measure of price predictability, a measure of the timeliness of investment in the firm, and finally, and one measure of how the firm may be perceived by investors at the margin. It is the buying and selling of those investors that establish the market value of both equity and debt. An evaluation of those measures is needed to accomplish the purpose of this study. If the model can be successfully validated, it suggests that the profile for the highly ranked companies for investment may be used as a tool to forecast companies that will maintain high technical rankings in a growth economy in the future.

Tests and Results

The discriminant function used has the form:

$$Z_j = C + V_1X_{1j} + V_2X_{2j} + \dots + V_nX_{nj} \quad (1)$$

Where:

C_0 is a constant

X_{ij} is the firm’s value for the i^{th} independent variable.

V_i is the discriminant coefficient for each j^{th} firm’s i^{th} variable.

Z_j is the j^{th} individual’s discriminant score.

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

$$Z_j = -2.115 + .082X_1 + .400X_2 - .087X_3 + .096X_4 - .144X_5 - .259X_6 - .124X_7 + .010X_8 + .879X_9 + .004X_{10} \quad (2)$$

The classification of firms is as follows: The values of the ten 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 (FCR). Conversely, a firm’s Z score that is greater than the critical value will place the firm in group two (HTR). Since the two groups are heterogeneous, the expectation is that HTR firms will fall into one group, and the FCR 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 27.99. That exceeds the critical value of Chi-Square 18.31 at the five percent level of significance with 10 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 (For a complete explanation of the test of hypothesis, see Appendix A). This result was, of course, expected since one group of firms experienced very high technical ratings, and the other group was chosen randomly. 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 100 HTR firms in the total sample, 64 were properly classified. When looking at the entire sample of 200 firms, 131 firms were accurately classified between the two groups (i.e., HTR and FCR), representing a success rate of 65.5%. The results are shown in Table 1.

Table 1 – Classification Results

Predicted Results		
HTR - FCR Classification		
Actual Results	HTR	FCR
HTR	64	36
FCR	33	67

To test whether a 65.5 percent correct classification rate is statistically significant, the Press's Q test is performed (Hair et al. 1992). Press's Q is a Chi-square random variable:

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

where:

N = Total sample size

n = Number of cases correctly classified

k = Number of groups

In this case:

$$\text{Press's } Q = [200 - (131 \times 2)]^2 / [200(2-1)] = 19.22 > \chi^2_{.05} 3.84 \text{ with one d. f.} \quad (4)$$

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 65.5 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 higher a firm's value for the variable, the more likely it will be in group two, the HTR group. On the other hand, a negative sign for an adjusted coefficient signifies that the higher a firm's [absolute] value for that variable, the more likely it will be classified in group one, the FCR group. Thus, according to Table 2, the greater the canonical coefficients of size, return on total capital, financial leverage (debt), price predictability, timeliness, and institutional buying activity, the more likely the firm would have a high-*Value Line* technical rating.

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 – Relative Contribution of the Variables

<u>Discriminant Variables</u>	<u>Canonical Coefficient</u>	<u>Rank</u>
Sales	0.057	7
Return to Total Capital	0.208	4
Hamada's Unlevered Beta	-0.042	9
Long Term Debt to Total Capital	0.186	5
Capital Spending Per Share	-0.273	2
Investment Safety	-0.056	8
Company Rank for Financial Strength	-0.034	10
Price Predictability	0.181	6
Rank for Timeliness	0.813	1
Institutional Buying Activity	0.237	3

Table 2 reveals that the measure of timeliness made the greatest contribution to the overall discriminating function. That was followed respectively by the measure of capital spending, institutional buying activity, return to total capital, debt to total capital, price predictability, size, safety of investment, operating risk (leverage), and finally, financial strength.

Some multicollinearity may exist between the predictive variables in the discriminant function since both safety and price predictability 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 in 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 eight 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 65.5 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 eight cases will not be significant with a sample of two groups of one hundred 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 61.5 percent of the firms. Since there are only two samples for analysis, the binomial test is appropriate:

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

(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: $(123 - 200 (.655)) / [200 (.655) (.345)]^{1/2} = -1.19 < t_{05} 1.645$.

(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.

In addition to the validation procedure, researchers usually address the question of the equality of matrices. That equality 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 100 observations. 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 utilizing the 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 13.37 resulted in a zero level of significance. Thus, the null hypothesis that the two matrices are equal cannot be rejected.

Summary and Conclusion

The *Value Line Investment Survey* ranking of each of the 1700 companies in their database on the basis of technical analysis is well-known. It has been a popular source of information for investors since 1965. Previous studies that examined the fundamental characteristics of those firms identified as having the highest technical ratings have ignored the macroeconomic background and conditions in the financial markets at the time those high ratings were awarded. The purpose of this study was to establish a financial profile of those firms identified as having the highest *Value Line* technical ratings in a unique economic environment characterized by high growth, stable prices, and low

unemployment. Then to compare those firms with firms chosen at random, but from the same industries as the first group to determine whether the firms with the high technical ratings have a unique risk-return financial profile.

In this study, the group of explanatory variables chosen for analysis includes one measure of the size of the firm, one measure of return on investment, two measures of risk, one measure of capital spending, a measure of the safety of investment, a measure of financial strength, a measure of price predictability, a measure of the timeliness of investment in the firm, and finally, and one measure of how the firm may be perceived by investors at the margin. It is the buying and selling of those investors that establish the market value of both equity and debt.

A unique set of explanatory variables was found for those firms with high *Value Line* technical ratings. The results of the statistical analysis indicated first that there was a significant difference in the financial profiles of the two groups of firms and that among the ten variables tested, six were unique to the firms with high technical ratings, and four were not characteristic of that group. The arithmetic signs of the adjusted coefficients in Table 2 reveal that distinction. 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 HTR group, and 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 FCR group. Thus, according to Table 2, the greater the canonical coefficients of size, return on total capital, financial leverage (debt), price predictability, timeliness, and institutional buying activity, the more likely the firm would have a high *Value Line* technical rating. Conversely, the greater the measures of capital spending, investment safety, operating leverage (operating risk), and a company's measure for financial strength, the more likely the firm would be a randomly chosen firm. The canonical coefficients in table 2 indicate the strength of each explanatory variable in the discriminant function. That is the relative power to discriminate between the two groups.

Five of these results may have been expected. Four 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 size, return on capital, price predictability, timeliness, and institutional buying activity be characteristics of high technical ratings. There were no apriori expectations regarding safety of investment and either financial or operating leverage. These were simply not known. The study resulted in one mild surprise. It is logical to surmise that financial strength is a desirable characteristic and would be associated with high technical ratings. However, this was not the case; rather, we found that financial strength was not particularly associated with either group, exhibiting the lowest ranking canonical correlation coefficient (-0.034) of the ten explanatory variables. That finding, as well as the other conclusions of the study, is rich in content for avenues of further research.

This study has resulted in a contribution toward the construction of a theory that describes the risk-return, financial strength, and size characteristics of firms that were regarded by *Value Line* as having the highest technical ratings 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 firms that will again be ranked very high by technical analysis in a high-growth, low unemployment economy in the future. To make a more complete contribution to the theory, the aforementioned further research is needed.

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Appendix A

There are four tests of hypothesis in the study. They each follow the procedure illustrated here with slight differences for appropriateness. The tests are standard tests of the significance of the F ratio, Wilk's Lamda transformed to the chi-square distribution and the t distribution. The purpose of the first test was to determine if there was a significant difference between the two mean vectors of z scores computed by the discriminant function.

- i. Ho: There is no significant difference between the mean vector of ten variables from firms that were awarded high ratings for technical analysis in a period of high economic growth and a random sample of firms that did not.
- ii. Ha: The mean vector of ten variables from firms chosen randomly, but from the same industries as the first group in a period of high economic growth is not equal to the mean vector of ten variables that were awarded high ratings for technical analysis.
- iii. Assume that the samples were drawn randomly from a multivariate normal distribution and that the covariance structure is the same for both groups.
- iv. The significance level is .05, and the test is a Chi-Square test.
- v. A Wilk's Lamda – Chi-Square transformation is used to test for a significant difference between the two mean vectors. In this test, the transformed Chi-Square is 27.99. That exceeds the critical value of Chi-Square 18.31 at the five percent level of significance with 10 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.

Since the differences in the two groups are differences in their mean vectors, it can be inferred that the two groups are not homogeneous and that the discriminant function does, in this case, indeed have the power to separate the two groups.