STRATEGIC PLANNING FOR VALUE-BASED MANAGEMENT: AN EMPIRICAL EXAMINATION

Kee S. Kim

Southwest Missouri State University, College of Business Administration (ksk882f@smsu.edu)

Abstract

Companies have obligation to create real economic value for their shareholders. Managers and top executives have been under constant pressures to adopt "value-based management" from their shareholders and other market participants. Participants in financial markets are actively involved in individual companies' operations through leveraged buyouts, hostile take-over, and proxy contests, and top executives have also been increasingly engaged in the financial markets through mergers and acquisitions, restructuring, leveraged buyouts and share repurchases. Hostile takeovers in the U.S. in 1980s, financial crises in Southeast Asian countries in 1998, and a collapse of Internet companies in 2000 show vividly the consequences of ignoring value-based management. However, it has been very difficult to establish and implement strategies for "value-based" management since "value" is an abstract in nature and managers need to have a specific operational guide for implementing value management. This paper developed a model to identify empirically critical strategic variables for value-based management. Since 'value' is abstract in its nature, managers need to know more concrete and clear target measures that derive the value of their business. Common financial variables and their variations are used as input variables to synthesize the market value added (MVA). In this model an Artificial Intelligence (AI) technique is used because it is non-parametric and can capture a dynamic relationship which is anticipated to exist between input and output variables. The study results show that the AI model was able to predict MVA of companies using common financial measures and a set of major strategic variables were successfully identified.

1. Introduction

Financial managers and top executives are aware of importance of "value-based management." They have been under constant pressures from participants in the financial markets since market participants are actively involved in company operations through leveraged buyouts, hostile take-over, and proxy contests. Top executives have also been increasingly engaged in the financial markets through mergers and acquisitions, restructuring, leveraged buyouts and share repurchases [Copland et al., 2000]. We have seen the consequences of ignoring value-based management in corporate strategies and governmental policies: hostile takeovers in the U. S. in 1980s, a collapse of Internet companies in 2000, and financial crises in Southeast Asian countries in 1998. When the management focuses on building shareholder value, they are creating much healthier companies, which are not only good for shareholders and other stakeholders, but also for the economy.

In order to implement value-based management, managers must have something more concrete and clear target measures, since "value" is abstract and vague in its nature. They need to specifically know the strategic variables that derive the value of their business so that they can develop strategic planning and tract its progress. Managers have been using return on assets (ROA), profit margin (PM), return on shareholders' equity (ROE), earnings-per-share (EPS) growth rate, and return on total capital (ROC) [Varadarajan and Ramanujam (1987); Ramanujam, Venkatraman, and Camillus (1986); Singh (1986); Schendel and Patton (1978)]. Although these measures could be coincidently related to stock prices, they were not considered to be primary movers of market values [Bennet and Stewart (1999)]. Security price movements [Lubatkin and Shrieves (1986)] were also used to measure corporate performance. However, security price movements are considered inadequate to gauge the capability of an organization's managers and cannot cope with unsystematic risk such as barriers to entry and other competitive factors within an industry. These traditional performance measures have long been criticized primarily because they did not provide proper guidance for strategic decisions and value management of corporations. As a result, two measures of corporate performance, market value added (MVA) and economic value added (EVA), have been attracting much attention from both investors and corporate managers.

The purpose of the paper is to identify empirically the critical strategic variables that contribute significantly to market value determination and to find guidance for strategic planning for value management. Since value is an abstract in nature, managers need to have a specific operational guide for implementing value management. Managers and CEOs have a strong affinity for these common accounting and financial measures and have been using them as guidance for value management, because these measures are very intuitive, operational, and easy to understand. However, these practices have been confusing at best because these common measures were known to be unrelated to the value of corporation. In this paper, a model is built to identify critical common measures that are directly related to the value of corporations. Once these common measures are identified, they can be used to estimate the value of operating efficiency of corporation, represented by the MVA. The results of the study could also provide ways of

developing corporate planning with a focus and control for their value management. The trained model can also be used to monitor the progress of alternative value-based corporate strategy.

Multivariate statistical techniques are not considered to be appropriate in the model building, because these common measures are correlated among themselves in their nature, and the relationship between individual financial measures and MVA would likely be dynamic and non-linear. Instead, an Abductive Learning Network (ALN) approach, an artificial intelligence technique, is used primarily because it is nonparametric and captures dynamic relationships between input and output variables. In the following MVA and EVA are briefly discussed and an essential characteristics of the ALN approach is presented.

2. MVA and EVA Revisited

The Stern Stewart (SS) & Company publishes "The Stern Stewart Performance 1000," in which the 1,000 largest publicly-owned U.S. industrial and non-financial service companies are ranked according to the Market Value Added (MVA). The SS Company defines MVA as the difference between a company's total market value of both debt and equity of the firm and the amount that investors have contributed to produce that value (or its book value). MVA is considered as the amount of wealth a firm's management creates from the capital that investors have entrusted to management. It is also viewed as the market value assessed in the security market of the company's internal operating efficiency [Walbert, 1994], and therefore can be used as a single comprehensive measure for assessing the value of the management's performance. A positive MVA, for example, represents the amount of wealth the company has created, while a negative MVA shows the amount of capital which management has dissolved. MVA is consistent with shareholders' wealth maximization in which both the risk and the expected net cash flows in the future are reflected.

The Stern Stewart & Company's report also presents Economic Value Added (EVA) as the amount of wealth a firm creates for its shareholders in a given year. EVA is defined as a firm's after-tax net operating profit in a given year minus its cost of capital that year. An economic book value is different from its accounting book value; it includes items such as bad debt reserves and deferred income taxes, and capitalizes R&D spending, amortizing the costs over the five years. Capital cost consists of the costs of debt and equity, applied to total capital at the beginning of the year. Unlike traditional accounting measures of performance, EVA is viewed as value that firms create or dissolve from the capital entrusted to management for that year [Lehn and Makhija, 1996]. Proponents of these two measures contend that that manager should use EVA as their key measure of internal performance in a given year and as the driver of their business decisions. They also assert that EVA drives MVA and is more closely correlated with MVA.

3. The Abductive Learning Networks

Baron (1984) developed the Abductive Learning Networks (ALN) technique from using advanced statistics, expert systems, and artificial intelligence research including neural networks. ALN performs a traditional task of fitting model coefficients to bases of observed data in a trained network form. The network structure of the trained model resembles neurons and synapses of a human brain, and uses mathematical functions that represent numeric knowledge on each processing unit (nodes). The network consists of a number of processing units and interconnections between the units, and each node is represented by a polynomial of n variables in which all cross products appear and combinations of the variables to different degree are included.

Montgomery (1989) developed a very effective computer-based algorithm, called the Abductory Induction Mechanism (AIMTM), from which MarketMiner, Inc. developed ModelQuestTM. ModelQuestTM is a supervised inductive learning tool for synthesizing final solutions in the form of networks. The final model is a layered network of feed-forward functional elements, in which the coefficients, number and types of network elements, and the connectivity are learned inductively and automatically. While users do not have to understand advanced statistics, expert systems and neural networks that underlie the foundation of the model, they can apply the model to diverse problems and generate powerful computer solutions.

ModelQuestTM (1) integrates advanced data modeling algorithms such as StatNetTM with more traditional data analysis technologies in a very easy-to-use and powerful data mining technologies. The use of the ModelQuestTM involves four phases as described in Figure 1 [Users Manual, 2000]. The first phase is to identify and characterize the data and to determine what type of data mining problem you are trying to solve. In this phase the data set is split into training and testing sets in either a random or a sequential manner, depending on the type of the problem involved. For cross-sectional problems, a random sampling works best while a sequential split is desirable for time-series problems. Once the data set is identified, it is necessary to specify the input (predictor) and output (dependent) variables. The user must also identify whether the problem is an estimation or classification type. The output variable of the estimation problem is generally continuous but classification problems have output values that are binary or segmented in multiclass.



Fig.1 ModelQuest[™] Modeling Procedure

The second phase involves transforming the original data set without changing its characteristics. Since algorithm for the ModelQuestTM requires numeric data, it is necessary to transform qualitative into numeric data. Although data coding could be very complex if there is some conceptual overlap between discrete and continuous variables and/or if there is no logical sequence in the qualitative variables, it is mostly straightforward for data set dealing with business decision-making. Data sampling also can be used to transform the original data set in order to prevent any biased solution. ModelQuestTM also can convert the original data set through feature extraction and mapping routines to provide additional inputs and to compensate for outliers and sparse regions.

The third phase involves applying one or several automated algorithms to learn functional relationships among input and output variables. ModelQuestTM provides a set of advanced technologies with a wide range of characteristics that can be applied to different types of modeling problems as appropriate. It enables you to identify multiple modeling experiments for a particular set of data, run them in a batch, and automatically rank the resulting models based on their performance on the Test data. This tool allows analysts to develop and compare more models in less time, and derive accurate models with minimum effort.

The fourth phase is to examine how well the trained model works. It involves testing the trained model on a new data set to see whether this model can be used in practice. The model analysts are looking at a variety of error characterization that describes how well the model matched the actual output values for the test data set. ModelQuestTM also allows graphing several characteristics of the predicted vs. the actual values. It has a sophisticated and automated analysis and reporting capability in an easy-to-understand format and provides exact model performance characteristics from several viewpoints.

The ALN technique is a powerful supervised inductive learning tool, which can reveal a subtle relationship that is not otherwise apparent within the framework of a multivariate statistical technique. The power of the network lies in its ability to decompose complex problems into much smaller and simpler ones, and to solve them. The network structure makes decision making much easier because the number of factors to consider and the alternatives to evaluate become much smaller. The use and maintenance of the model is easy because the ModelQuestTM automatically selects the best network structure, node types, and coefficients.

4. The Model and Data Description

A value oriented manager focuses on the ways of creating the value of firm. The value of a firm's operations is defined as sum of the size of invested capital and the additional value the management has added or subtracted, which is equivalent to MVA [Brigham and Ehrhardt, 2002, p. 475; Copeland (2000), p144]. The major contributing variable to MVA is economic profit that is determined by the return on investment (ROI), weighted average cost of capital (WACC) and the size of the invested capital (CAPITAL), and the value of company depends primarily on the spread between ROI and WACC. If a company earns more than its WACC, management is adding value and, consequently, the company is worth more than its capital invested, and vice versa. For a given ROI, the lower the WACC, the larger the MVA is, too. MVA takes account of not only incurred expenses but also the opportunity cost of the capital employed in the business. Operating margin (OM), profit margin (PM), sales growth, and return on capital (ROC) could also be contributing to the MVA determination and therefore included as input variables in the model. BETA is also included as a risk measure for the model. Included also are market-to-book value ratio (MB), price-earnings ratio (PE), and EVA, which are known to be tied closely to the value of the firm.

The return variables, CAPITAL, MB and PE are average figures over the prior three years and retrieved from the Research Insight (or COMPUSTAT), while WACC are used from the SS data. The three-year average data are used in this model, because the prediction outcomes turned out to be much better than those when used the four- and five-year average data as input variables. The standard deviation of these input variables is also used as inputs to the model. In addition, a single year (1999) input variables are also used as explanatory variables in this model.

The input data for 1999 were collected primarily from the SS Company's Performance 1000 data and COMPUSTAT database. The data set started initially with 1,000 of the largest publicly owned US companies that is included in the Stern Stewart Performance 1000 for 1999. First, the companies in the financial service industry were deleted since they have entirely different financial structure. After deleting observations with an incomplete data set, a sample of 608 observations was used in this study. Next, the sample was divided randomly into one (456 cases) for training and another (152 cases) for evaluating the model. Seventy five percent of total sample is used for training because a large sample is required to obtain an accurate training of the final model.

5. Empirical Results

An Abductive Learning Network (ALN) is synthesized in Figure 2 from the training data set, using the ModelQuest Analyst TM software, which is developed by MarketMiner, Inc. It is a layered network of feed-forward functional elements, which contains the best network structure, node types, coefficients, and connectivity to minimize the predicted squared error (PSE) without outfitting the data. The final model uses five different input variables that contribute significantly to the MVA determination, and the economic value added (EVA) is used twice in the network.

The ALN model includes nodes such as Singles, Doubles, and Triples as a part of the network, and each node is represented by an equation with estimated coefficients.

The equations in the Appendix show the final abductive learning network (ALN) in polynomial equation forms, and each equation number represents the node number of the ALN network in Figure 2.





The five input variables with one repeat are first transformed into standardized normal variables with the mean of zero and a variance of one using Normalizers in the Appendix. These standardized variables are next fed into the first layer to generate a series of intermediate output values. For example, the node T_{18} in Figure 2 was synthesized using normalized values of EVA, CAPITAL, and WACC, and then fed into the node T_{33} with two other inputs: average price-earnings ratio (APE) and economic value added (EVA). The value of the node T_{33} with ROI are again fed into the subsequent node D_{44} in the third layer, and finally converted back to MVA with the mean and variance of the original output variables. This Abductive Learning Network now becomes a knowledge base from which a series of MVA values can be estimated using the five input variables.

	ALN	Regression
Sample	152	152
Ave Abs Error	4,578.7	10,337
Error STD	10,560	19,237
Ave Sqr Error	131,755,010	474,467,606
Sqr Err STD	18,215,159	415,577,099
R-Squared	.8787	.2877

Fig.3 Prediction Statistics by the ALN and Regression Approaches

The prediction performances of the ALN and the multiple regression models on the evaluation sample are shown in Figure 3. The results indicate that the ALN model outperformed the linear regression approach for predicting MVA of firms. For example, the R-square (the squared value of the Pearson Correlation) between the actual and predicted values by the ALN model is 87.87 percent, which is three times higher than that of the linear regression; the R-square of the linear regression is only 28.77 percent. All of the prediction statistics in Figure 3 clearly indicate that the ALN model estimates MVA much more accurately and consistently than the regression model is able to estimate. The selected input variables by the above two approaches are also quite different. The ALN model selected BETA, WACC, AME (average market-to-book value ratio), CAPITAL, and APM (average profit margin). Except WACC and CAPITAL variables, these two approaches selected entirely different set of variables that contribute significantly to MVA determination.

The ALN model selected ROI and WACC, from which we can examine if the company is successful in creating market values from operating activities. In order to build the value of a firm, ROI must first be greater than WACC. The ALN model selected also the CAPITAL variable that determines the scale of corporate value created, given the company's spread between ROI and WACC. These three variables are essential components of economic profit and are considered to be critical variable in corporate value management. Kim (2002) also supports the fact that WACC and CAPITAL are primary contributing variables to MVA determination, and WACC is the most influential variable among them. The ALN model also selected average PE (APE) ratio and EVA as predictor variables for MVA determination. On the other hand, a linear regression approach provided a very poor prediction of MVA and also selected a quite different set of three primary variables: BETA, WACC, and average market-to-book value (AMB) ratio.

In Figure 4 the Sensitivity and Importance Analysis for each selected input variable is presented. The Sensitivity value indicates the relative response of the model output to input changes (for each input variables) that are standardized by the total output changes at the average output point. The Importance value indicates the expected overall contribution of each input variable to the predicted output value changes, which is standardized by the total output variable of the ALN model is very sensitive to changes in WACC as shown in Figure 4. For example, over ninety six percent of variation of the predicted MVA value was explained by WACC and only 3.2 % of the MVA variation was explained by the ROI variation. The rest of the variables, APE, AEVA and CAPITAL, were turned out to be almost negligible in their contribution.

Variables	ALN Model	Linear Regression		
	<u>Sensitivity</u>	Importance	<u>Sensitivity</u>	Importance
WACC ROI APE AEVA CAPITAI	.9604 .0320 .0048 .0025 0002	.9564 .0301 .0007 .0042 .0086	.5626	.2913
BETA AMB AOM APM AROI OM PM	.0002	.0000	.2199 .0563 .0458 .0405 .0281 .0139 .0113	.5884 .0481 .0111 .0128 .0062 .0073 .0019

Selected

Fig.4 Variable Sensitivity and Importance Analysis

The overall Importance value is not much different from that in the Sensitivity analysis. According to the performance of the ALN model, about 96 percent of variation of the predicted values is explained by WACC and only 3% by ROI. On the other hand, the results of the linear regression are quite different. According to the Sensitivity analysis, about 56% of the variation of the predicted MVA is explained by WACC, 22% by BETA, 5.6% by AMB, and 4.6% by average operating margin (AOM). As to their importance, only 29% of the output values are explained by WACC, 59% by BETA, and 5% by AMB.

The results of the study provided important implications to corporate strategic planning. According to the ALN model, WACC is the major determinant of MVA although other input variables were also used in building the final model. Since MVA is largely determined by the spread between ROI and WACC, financial analysts tend to believe that the lower WACC, the higher MVA should be. However, the study results showed that the firms with higher WACC were able to build a larger MVA. This signifies that the firms engaging in risky projects have been successful in generating large excess profits above the costs and, thus, able to build a larger MVA. It appears that there exist value-creating opportunities in risky projects. When firms are successful in generating large excess profit above the costs by undertaking risky projects, EVA will automatically go up. The financial market should also react positively to the firms' operations and provide rewards to the firms. The average PE ratio will then increase automatically and its MVA will increase eventually.

The results of the model showed that the component variables of economic profit become important strategic variables. Among them, WACC is the most influential variables if management tries to maximize the value of firm. The results also indicate that management could use EVA and APE ratio as tracking variables to monitor the progress of the value making strategy. The sales growth rate generally expects to have a positive effect on value, provided the company is profitable, but the final model did not select growth as a predictor variable.

6. Concluding Remarks

This paper has proven that the component variables of economic profit are linked directly to the value of corporation and could be used to estimate the operating efficiency of corporations, represented by MVA. It also identified successfully critical strategic variables that drive the value of corporations. These variables were concrete and directly manageable by managers and therefore could be used when establishing strategic planning for value management. Although economic profit is known to be a short-term performance measure, it is proven that an average economic profit can be used to assess an intrinsic value of corporation, which is normally driven by the long-term cash flows generating ability of the company.

This study was able to use only a sample of 608 observations, which encompassed wide range of industries in manufacturing. As an extension of this study, it would be worthwhile to examine the prediction outcome of MVA if this model is trained and tested within the confine of a set of similar industries. Since individual industries have their own unique characteristics in financial structure, we can safely conjecture that the prediction results would be significantly improved as long as the sample size is large enough for training and testing.

References

- [1] Barron, A.R., "Predicted Squared Error: A Criterion for Automatic Model Selection," *Self-Organizing Methods in Modeling: GMDH Type Algorithms*, edited by S.J. Farlow, Marcel-Dekker, Inc., New York, 1984.
- [2] Barron, R.L., Mucciardi, A. N., Cook, F. J., Craig, J. N., and Barron, A. R., "Adaptive Learning Networks: Development and Application in the U.S. of Algorithms Related to GMDH," *Self-Organizing Methods in Modeling: GMDH Type Algorithms*, edited by S.J. Farlow, Marcel-Dekker, Inc., New York, 1984.
- [3] Brigham, E.F., and M.C. Ehrhardt, *Financial Management; Theory and Practice*, 10th ed., New York: Harcourt College Publishers, 2002.
- [4] Copeland T., Koller T., and Murrin J., Valuation, John Wiley & Sons, Inc., New York, 2000.
- [5] Hess, P., and G.J. Montgomery, "Abduction: Theory and Application," Proceedings of the 4th Annual Aerospace Applications of Artificial Intelligence Conference (AAAIC), October 1988.
- [6] Kim, Kee, "Value Management and Common Accounting Performance Measures for Corporations," forthcoming in the Journal of Expert Systems with Application, 2002.
- [7] Lubatkin, M. and Rogers, R. C., "Diversification, Systematic Risk, and Shareholder Return: A Capital Market Extension of Rumelt's 1974 Study," *Academy of Management Journal*, vol. 32, No. 2 (1989): 454-465.
- [8] Lehn, K. and Hakhija, A.K., "EVA and MVA as Performance Measures and Signals for Strategic Change," *Strategy and Leadership*, May/June 1996, 34-38.
- [9] Lubatkin, M. and Shrieves, R. E., "Toward Reconciliation of Market Performance Measures to Strategic Management Research," Academy *of Management Review*, Vol. 11, No. 3 (1986): 497-512.
- [10] Miller, M.H. and Modigliani, F., "Dividends Policy, Growth, and the Valuation of Shares," Journal *of Business*, October 1961, 411-433.
- [11] ModelQuestTM, User's Manual, MarketMiner, Inc, 2000.
- [12] Montgomery, G.J., "Abductive Diagnostics," Proceedings of the AIAA Computers in Aerospace Conference, Monterey, CA, October 1989.
- [13] Ramanujam, V., Venkatraman, N., and Camillus, J. C., "Multi-Objective Assessment of Effectiveness of Strategic Planning: A Discriminant Analysis Approach," *Academy of Management Journal*, Vol. 29, No. 2 (1986): 347-372.
- [14] Schendel, D. and Patton, G.R., "A Simultaneous Equation Model of Corporate Strategy," *Management Science*, Vol. 24 No. 15 (1978): 1611-1621.
- [15] Singh, J. V., "Performance, Slack, and Risk Taking in Organizational Decision Making," Academy of Management Journal, Vol. 29, No. 3 (1986): 562-585.
- [16] Varadarajan, P. and Ramanujam, V., "Diversification and Performance: A Reexamination Using A New Two-Dimensional Conceptualization of Diversity in Firms," Academy of Management Journal, Vol. 30, No. 2 (1987): 380-393.

- [17] Venkatraman, N. and Ramanujam, V., "Measurement of Business Performance in Strategy Research: A Comparison of Approaches," *Academy of Management Review*, Vol. 11, No. 4 (1986): 801-814.
- [18] Walbert, L. "America's Best Wealth Creators," Fortune, Vol. 128, No. 16 (1993): 64-76.
- [19] Walbert, L. The Stern Stewart Performance 1000: Using EVA to Build Market Value. Pamphlet published by Stern Stewart & Company and excerpted from the *Continental Bank Journal of Applied Corporate Finance*, winter 1994.

Appendix. Abductive Network Equations

NORMALIZERS:

- 1. $AEVA = -.0241 + .0013X_1$ 2. $CAPITAL = -.4369 + 1.0E-4 X_1$
- 3. $WACC = -4.2504 + .4466X_1$ 4. $APE = -.2221 + .0157X_1$
- 5. $ROI = -.6071 + .0664X_1$

TRIPLES:

- 18. TRIPLE = $\begin{array}{l} -.939 + .4612X_{1} + .2191 X_{1}^{2} .0313 X_{1}^{3} + .5721 X_{2} + .04 X_{1}X_{2} .0182X_{1}^{2}X_{2} \\ .0053X_{2}^{2} + .0124X_{1}X_{2}^{2} .0083 X_{2}^{3} + .549X_{3} + .1572X_{1}X_{3} .0983 X_{1}^{2} \\ X_{3} + 1.1579 X_{2}X_{3} + .2262 X_{1}X_{2}X_{3} .1927 X_{2}^{2}X_{3} + .2543 X_{3}^{2} + .0548 \\ X_{1}X_{3}^{2} + .5175 X_{2}X_{3}^{2} .0155 X_{3}^{3} \end{array}$
- 33. TRIPLE = $-.0611 + .7558X_1 + .0925X_1^2 .0129 X_1^3 .1666 X_1^2 X_2 + .048 X_3 + .0131 X_1^2 X_3 + .2011 X_1 X_2 X_3 + .04 X_3^2 .0171 X_1 X_3^2 + .0944 X_2 X_3^2 .0043 X_3^3$

DOUBLES:

44. DOUBLE = $1.0383 X_1 + .0955 X_2 + .2693 X_1 X_2 - .0346 X_1^2 X_2 - .0325 X_2^2 - .1315 X_1 X_2^2$

UNITIZERS:

16. $MVA = 11442.2407 + 31852.2926X_1$