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MULTI-FACTOR ANALYSIS OF FIRM-LEVEL PERFORMANCE THROUGH FEED-FORWARD, FEED-BACK RELATIONSHIPS

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ABSTRACT

This article presents the results of research to develop a descriptive model of firm-level productivity that will allow a myriad of factor interactions to be directly accounted for. The model is a linked set of equations that attempt to capture how changes in one-factor influences the level of another factor, and ultimately bottom-line performance. The model is coded in SIMAN. It is used to determine the best use of an infusion of funds – should they go for additional automation, or training, etc. An application of the model to U.S. industry is presented based on parameter values obtained through a national survey.

1 INTRODUCTION

Measuring and analysis of productivity related performance of an organization is an ever-increasing issue for firms that are concerned with gaining a competitive edge. Truisms such as "You can't improve what you can't measure" guide many companies today, especially those practicing a TQM, "fact-based" approach to management.

This paper focuses on the class of measurement tools generally known as multi-factor productivity models. Specifically, the work reported in this article is concerned with modeling and analyzing the interrelationships among factors that affect bottom-line firm performance. Factors such as the level of training given to employees, the amount of scrap and rework generated, energy usage, and others are included in the model. More importantly, the impact that these factors have on each other and on performance measures such as unit cost, labor productivity, and profits is at the core of our model. Knowledge of how changes in one-factor filters through the organization to affect other factors and in turn, bottom-line performance is vital to making informed decisions concerning resource allocation. Should the firm invest its limited funds in automation, or training, or work methods improvement? What is the most productive use of funds for the firm? Providing insight into such questions is the primary mission of the model described here.

2 LITERATURE REVIEW

Various strategies for assessing organization level productivity have been reported in the literature. These strategies range from single factor measures (Morrison 1985) to multi-factor and econometric models (Harper, Berndt, and Wood 1987). Efforts to model several factors simultaneously range from ratio methods that relate multiple output measures to multiple input measures (see, for example, Miller 1984 and Rymes 1985), to so-called "family of measures" methods such as the objectives matrix procedure (see Riggs and Felix 1983). Normative approaches have also been employed; usually, these procedures utilize a base or benchmark performance standard and assess current productivity relative to that norm. This is the case in Miller (1987) and in Sink (1985). Two good summaries of measurement approaches are provided by Siegel (1986) and Christopher and Thor (1993).

While these multi-factor methods reflect indirect relationships between and among inputs and outputs, they do not use direct estimates or models of these relationships. As a result, cause-effect noise is inherent in traditional multi-factor methods and can thereby provide misleading and myopic analyses of performance. The explicit model approach employed in this paper is an attempt to minimize this problem.

3 THE PROBLEM

The research reported here was initiated to gain insight into the following proposition:

> The implementation of high technology equipment and methods will increase the overall productivity of the firm and thereby reduce the firm's unit manufacturing cost. This will allow the firm to be more flexible in its pricing and therefore capture a larger market share. In turn, this increased volume will enable the firm to cost-justify new plant expansion, more high tech equipment and become even more productive and profitable.

In theory, this circle from high tech investment to higher profitability is sound. However, while it is well known that an increase in productivity can lead to the rest of this chain of events, there is little scientific knowledge about the relationship between advanced manufacturing technologies and the overall productivity level of a firm (Slade 1985). For instance, consider the situation in which a firm wants to install several robots in its plant. Often, such an investment has an immediate effect on reducing direct operating labor requirements (and hence improving "labor productivity"), but it also can have the off-setting effect of increasing the need for indirect labor, energy and investment capital. While there may be no immediate reduction in the plant's total manpower due to the robots, the conventional practice is to assume that future volume will increase and that the additional manpower requirements which this generates can be satisfied out of the robot-replaced personnel rather than having to hire new employees. Under this type of assumption, management automatically credits the use of robots with a labor productivity gain.

However, there are many interacting factors in the workplace that may well prohibit such a gain from coming to pass or produce counter-balancing productivity losses. For instance, the operations in which the robots are installed may not be bottlenecks in the production process; therefore, any potential extra output of the robot would not be realized. There would be no change in the output side of the productivity equation. The input side of the equation could adversely go up if extra skilled maintenance personnel had to be hired to tend the robots, or if extra fixtures had to be installed to orient parts for the robots. The capital investment re-quired to purchase the robots is another negative input requirement. Offsetting effects such as these must be properly considered before a conclusion can be drawn as to the degree to which the firm's overall productivity will change due to the introduction of an advanced manufacturing technology.

There is presently no adequate means of making this assessment. Management typically makes the quantitative part of its go/no-go decisions as to investment in the high tech option by considering only the direct or immediate impacts – number of people replaced, O&M requirements, and so forth. They are not able to draw accurate bottom-line productivity conclusions. And by not examining the net, overall impact these investments have on a firm's "total factor" productivity, management can easily put themselves into a position of losing profitability and competitiveness rather than gaining as they set out to do.

4 THE MODEL

The model developed to analyze total factor productivity is a linked set of difference equations. The model captures: 1) the magnitude of the impact a factor has on all other factors being considered; and 2) the time lag effects on these impacts. Implementation of the model is through the continuous modeling construct of the SIMAN language.

The core of the model is the set of factors that influence the overall performance of the organization. Obviously, this set is company-specific (as are the relationships among the factors). An exhaustive list of such factors would be prohibitive to model (or even to identify). However, a core set, or the "significant few," exists and can be used to construct a meaningful model if not a completely comprehensive one.

The model development process involves: 1) identification of the core set of factors; 2) formulating the nature of the relationships among these factors; 3) fitting these relationships to data in order to get numerical equations; and 4) converting these equations into SIMAN code.

Identification of Factors: Factors (or "model objects") are divided into three categories: resources, activities and performance criteria. For example, inventories would be classified as a resource, training as an activity and customer satisfaction as a performance criterion. There is little "science" to guide the selection of core factors within a category. Experience in the target organization appears to be the most practical guide. The key is to identify those factors that are "difference makers."

That is, what resources have proven to be significant contributors toward performance in the company if they are not managed properly? Which activities are significant resource consumers? And what criteria constitute management's bottom-line "measures of choice," or have a direct bearing on these measures?

While core factors are company specific, we have attempted to identify a generic set. This effort is based on a review of over 10 years of project work with organizations in our region. This work encompasses more than 200 projects involving productivity and quality improvement in over 100 organizations. The difference-makers resulting from this review are shown in Table 1.

Table 1: Factors That Have an Impact on Productivity

Resources	Activities	Performance Criteria
High technology	Work method	Maintenance
Fixed assets	Defect detection	Worker's attitude
Material	Defect prevention	Quality of working life
Working capital	Scrap and rework rate	Quality of finished goods
Inventory	External failure	Capital productivity
Number of workers	Amount of production	Material productivity
	Energy consumption	Energy productivity
	Sales	Labor productivity
	Training	Total productivity
		Profit
		Unit cost
		Cycle time
		Total resources consumption
		Customer satisfaction
		Warranty cost
		On-time delivery
		Labor cost

This list is not intended to be all inclusive, nor firm specific. Other models or choices of factors could be used. Indeed, other fundamental concepts such as "motivation" instead of "worker attitude" could just as readily have been used.

Some of the factors displayed in Table 1 have a positive impact on a bottom-line measure such as productivity, while others have a negative impact. For example, factors such as quality of working life, quality of finished goods, and customer satisfaction will have plus impact on firm-level performance. However, factors such as scrap and rework rate, external failure and energy consumption will have a negative impact. The firm-level performance is analyzed by observing the change in the values over time of both the positive factors and negative factors that are included in the model presented.

Formulating Relationships: Once the factors related with firm-level performance have been identified, causal relationships among the identified factors need to be determined. The causal relationship defines the degree of effect one factor has on the other factors, and in turn, on the firm-level performance. An example of the causal relationship is as follows:

An additional investment in "high technology" usually enhances the "quality of working life." In turn, enhanced work life quality has a positive effect on "worker attitude." This increase in worker attitude tends to decrease "scrap and rework" levels or rates (due to more concern and attentiveness). This decrease in turn increases product quality that leads to improved levels of customer satisfaction. Finally, improved customer satisfaction tends to increase sales.

The causal relationships among the factors in Table 1 are defined as a flow diagram as shown in Figure 1. Each arc in this network identifies a relationship between two factors. The factor indicated by the beginning point of the arrow is an independent factor and the factor indicated by the ending point of arrow becomes a depen-dent factor. If a dependent factor is affected by more than one independent factor, the dependent factor has more than one ending point of arrow. The form of the relationship is modeled as a first order difference equation.

The degree of the impact each factor in Table 1 has on the firm-level performance is time dependent. Time may be needed for the expected impact of a factor to be fully realized. Some of the factors in Table 1 have an immediate impact on other factors and respond directly to the change of independent factor(s), but other factors may need several months for the expected change to appear and respond indirectly to the change of independent factor(s). For the purposes of this research, the time lag imbedded in each factor is divided into three different time-windows: 1) 0 month (immediate); 2) 1-5 month (medium-term); and 3) 6+ month (long-term).

Parameter Fitting: Ideally, a firm would capture over time a sample of observations on the levels of the factors shown in Figure 1. From this data, a regression analysis is used to fit the observed data to the underlying difference equations. In the work presented here, a subjective approach was substituted. The results are described in the next section.

Constructing Simulation Model: The concept of continuous simulation was approached by means of the continuous modeling construct of the SIMAN language. Although there exist other simulation languages which provide the feature of continuous simulation, such as DYNAMO, SIMAN was selected for the author's convenience of accessing the package.

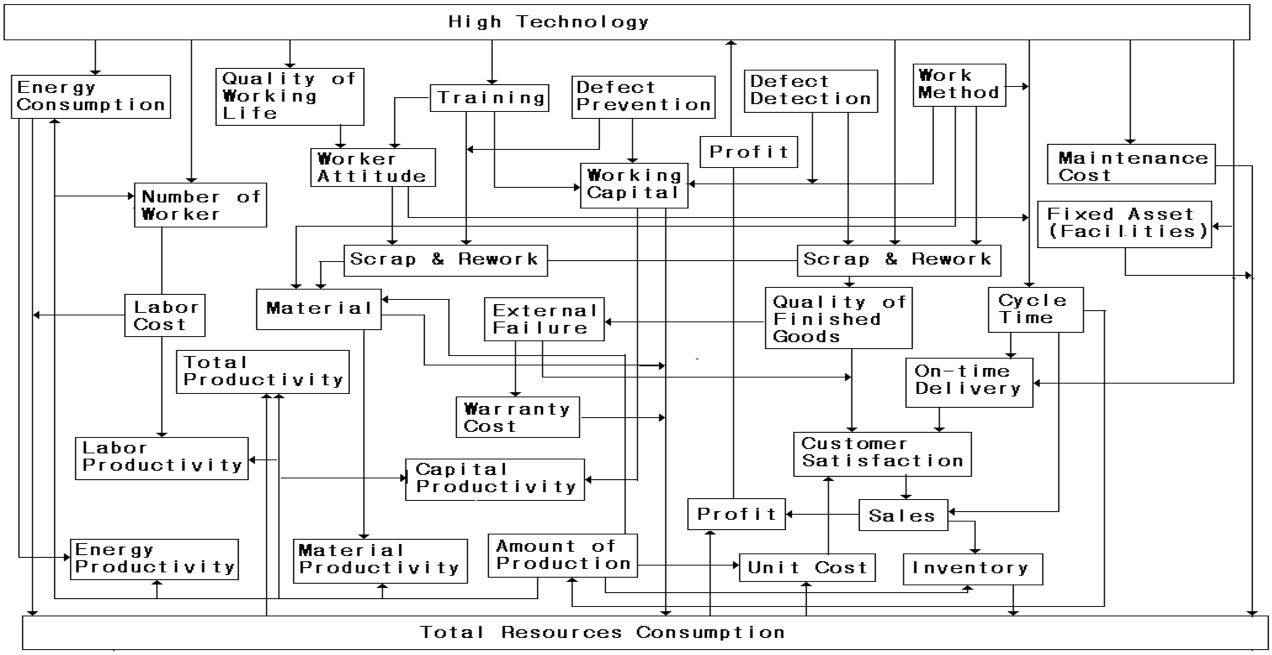

Figure 1: Diagram for Multi-Factor Analysis of Firm-Level

Three SIMAN modules were built for the analysis: model statement, experimental frame, and FORTRAN sub-routine. The model frame defines the characteristics of the model and supervises the analysis. The experimental frame defines the experimental conditions under which the model is run and tallies simulation outputs. The FORTRAN sub-routine defines causal relationships shown in Figure 1 and calculates the impact of one factor on others based on the relationships.

Several modeling processes have been used to perform the multi-factor analysis through the SIMAN continuous modeling structure. First, each of the causal relationships shown in Figure 1 was transformed into a difference equation as shown in Table 3, and coded in FORTRAN. Then the FORTRAN codes alone were complied as a separate module and linked to SIMAN as a sub-routine to create a new executable module. Finally, the module is called by the SIMAN processor to perform the multi-factor analysis through feed-forward and feed-back relationship.

5 SURVEY

In order to illustrate the overall methodology being presented in this paper, an industry-wide focus rather than a specific company focus was adopted. Therefore, in order to obtain a data set to use to fit the relationships in the model, a nationwide survey was conducted. Respondents were Industrial Engineers in a variety of industries in the United States.

The mission of the survey was to determine the level of impact each of the independent factors has on dependent factors. The questionnaire was divided into three sections. The first section asks demographic information on the company and the industry to which it belongs. The second section was the main part of the survey. It asks for relationships between factors –the degree of change each dependent variable will likely experience with a 10% increase or decrease in the level of the independent factors. The last section asks base line values, such as total assets, average scrap and rework rate, and monthly production in dollars.

The questionnaire was mailed to over 200 companies and 69 responses were collected. Average values gathered from the survey are shown in Table 2. The results of fitting the survey information to the relationship depicted in Figure 1 are given in Table 3. The parameters in each equation in Table 3 are the average values obtained from the nationwide survey.

6 APPLICATION/DEMONSTRATION

For purposes of illustration, consider a firm that has the productivity and performance factors already modeled as shown in Tables 2 and 3. Management is interested in infusing a significant amount of capital ($500,000) into the business in order to improve profitability. Their question is: what is the best way to make this infusion — through more training? A high level of quality inspection? More robots? The answer is derived by applying the SIMAN model to analyze the long range (steady state) change in Total Productivity (and Profit) due to an infusion of capital in the area of interest. To illustrate this analysis, we will examine the implication of investing this capital in acquiring and implementing an additional $500,000 worth of “high technology.” Execution of the SIMAN model requires initializing the values of the factors in the relationships.

Table 2: Survey Results

- 10% improvement in customer satisfaction can increase sales by 9.03 %.
- 10% decrease in cycle time can increase sales by 4.22%.
- 10% decrease in unit cost can increase customer satisfaction by 9.08%.
- 10% increase in quality of finished goods increases customer satisfaction by 9.47%.
- 10% increase in on time delivery increases customer satisfaction by 10.03%.
- 10% decrease in external failure increases customer satisfaction by 10.3%.
- 10% decrease in scrap and rework rate increases the quality of finished goods by 3.55%.
- 10% improvement in work method can decrease material usage by 3.35%.
- 10% improvement in manufacturing techniques can decrease material by 4.05%.
- 10% additional investment on high technology increases energy consumption by 2% on average.
- 10% increase in the amount of production increases energy consumption by 5.03%.
- 10% improvement in the level of high technology reduces cycle time by 6.33%.
- 10% increase of the investment in work method reduces cycle time by 7.07%.
- 10% improvement in worker attitude decreases scrape & rework rate by 1.27%.
- 10% improvement in work method decreases scrape & rework rate by 6.46%.
- 10% increase in training decreases scrape & rework rate by 6.82%.
- 10% improvement in the level of high technology reduces scrap and rework rate by 5.28%.
- 10% upgrade in defect prevention decreases scrape & rework rate by 8.93%.
- 10% upgrade in defect detection decreases scrape & rework rate by 3.78%.
- 10% improvement in the quality of working life improves worker attitude by 10.97%.
- 10% increase in training improves worker attitude by 9.38%.
- $100,000 additional investment on high technology increases quality of working life by 6.03%.
- $100,000 additional investment on high technology increases training cost by 4.9%.
- $1,000,000 investment on high technology needs training cost of $66,100.
- 10% improvement in the quality of finished goods decreases external failure by 6.6%.
- $100,000 additional investment on high technology decreases the number of worker by 2.7%.
- 10% increase in the amount of production increases the number of workers by 4.72%.
- $100,000 investment on high technology generates $6,600 for specialist cost.
- 10% decrease in cycle time increases on-time delivery by 4.98%.
- 10% increase in the level of high technology improves on-time delivery by 3.31%.
- 10% decrease in external failure decreases warranty cost by 5.5%.
- Overall maintenance cost is 2.5% of high technology on an industry average.

given in Table 3. Quantitative factors (e.g., level of training) were initially assigned their average value resulting from the survey, while qualitative factors (e.g., worker attitude) were assigned a standardized value of one since the end result of the analysis is a relative evaluation of investment options as opposed to an absolute value.

The simulated operations of the firm reached steady state 36 time periods after the infusion of the additional investment of High Technology. During this time window, there occurred a 27% increase in the quality of work life which lead to an immediate 3.25% increase in worker attitude. However, several periods later the level of worker attitude again increased due to an increase in training required by the addition of the new technology. The composite increase in worker attitude was a 33% gain. On the negative side, the increased training requirement invokes a partial offset expense. Specifically required training cost went from an initial level of $651,000 to a level of $673,569. The overall composite "ripple" effect of increased technology was a 25% gain in labor productivity. In turn, total factor productivity increased by 13%.

In terms of dollar impact, the bottom line of this and the other factor changes was a 43% gain in profit – from an initial base level of $20,280,000 to $29,040,000.

Table 3: Mathematical Model for Multi-Factor Analysis

1. maintenance cost (t) = investment in high technology *.025.
2. total facilities (t) = total facilities(t-1) + additional investment in high technology.
3. training (t) = training(t-1) + additional investment in high technology*.05.
4. quality of working life (t) = quality of working life (t-1)*(1+(additional investment/100,000)*.06).
5. worker attitude (t)=worker attitude (t-1)*(1+change in quality of working life*1.1 + change in training*.938).
6. scrap and rework rate (t) = scrape and rework rate (t-1)*(1-change in worker attitude*.127 – change in work method*.65 – change in high technology*.53 – change in training*.682).
7. quality of finished goods (t) = quality of finished goods (t-1)*(1+change in scrape and rework rate*.355).
8. external failure (t) = external failure (t-1)*(1-change in quality of finished goods *.66).
9. warranty cost (t) = warranty cost (t-1)*(1+change in external failure*.55).
10. cycle time (t) = cycle time (t-1)*(1-change in high technology*.6-change in work method*.71 – change in worker attitude*.5).
11. on-time delivery (t) = on-time delivery (t-1)*(1-change in cycle time*.5+change in high technology*.33).
12. amount of production (t) = 60,000,000*2.822/cycle time (t).
13. number of workers (t) = number of workers (t-1) * (1-(change in high technology / 100000)*.027 + change in amount of production*.47).
14. labor cost (t) = number of worker (t)*2,500.
15. energy consumption (t) = energy consumption (t-1) * (1+(change in high technology/50000)*.02 + change in amount of production*.5).
16. material (t) = material (t-1) * (1-change in work method*.34) * (1+change in amount of production) * (1-change in scrap and rework rate).
17. working capital (t) = working capital (t-1)+change in training +change in work method + change in defect prevention + change in defect detection.
18. total resources consumption (t) = energy consumption (t)+labor cost (t)+material cost (t)+inventory (t-1)*.02+working capital (t)*.01 + total facility(t)*.01 + warranty cost (t) + total facility (t).
19. unit cost (t) = total resources consumption (t)/amount of production (t).
20. customer satisfaction (t) = customer satisfaction (t-1)*(1-change in unit cost*.908 + change in quality of finished goods*.947 + change in on-time delivery*.1 + change in external failure*.1).
21. sales (t) = sales (t) – total resources consumption (t).
22. total productivity (t) = (amount of production (t)/total resource consumption(t)/1.502.
23. labor productivity (t) = (amount of production (t)/labor cost (t)/3.550.
24. material productivity (t) = (amount of production (t)/material (t)/4.317.
25. energy productivity (t) = (amount of production (t)/energy consumption(t)/240).
26. capital productivity (t) = (amount of production (t)/working capital(t)/5.455).

Measures such as ROI on the $500,000 are not useful here since there are other expenses on this investment that are not captured in this model (i.e., the current model is not intended to be a comprehensive financial model). Instead, the model is intended to capture key factors relative to productivity and quality implication of alternative influxes of capital. One such use was examined above. Similar results would be obtained for options such as using the $500,000 directly for training (no new technology) or for, say, improvements in cycle time or delivery performance. The relative changes in base profit would be compared and the option having the greatest change in profit would be selected.

The model suggested in this research can be used to evaluate the change made by the implementation of other advanced manufacturing techniques such as the work method, defect prevention program, and defect detection program. It can also be used to compare these advanced manufacturing techniques and to find the most appropriate method to improve overall firm-level performance with the least implementation cost. Based on the cost-benefit analysis, the improvement in firm-level performance in terms of productivity can be converted into monetary value and then compared to the initial investment or implementation cost of those techniques to make a decision to go or not go for the advanced manufacturing technique.

7 CONCLUSIONS

The above example illustrates the total factor productivity model, as presented here, can be used.

The value of this model is its ability to capture the interrelationships present among productivity factors. This allows the "ripple effect" of changes in factors to be modeled and calculated. Such effects are missing from traditional multi-factor models.

The specific numerical version of the model given here was derived from a broad survey and therefore is useful only for a general industry analysis. To aid a given company, this model would need to be tailored for that firm. This requires identification of core factors for that company, and fitting historical (or subjective) cause-effect data to the underlying difference equations. The SIMAN code can then be employed to address a variety of analytical questions such as the technology investment presented here.

REFERENCES

Christopher, W. and C. Thor. 1993. *Handbook for Productivity Measurement and Improvement*, Productivity Press, Cambridge, MA.

Harper, M.; E. R. Berndt, and D. Wood. 1987. Rates of Return and Capital Aggregation Using Alternative Rental Prices. Working Paper, Bureau of Labor Statistics Working Paper. 170:57.

Miller, D. M. 1984. Profitability = Productivity + Price Recovery. *The Harvard Business Review*. 62(3):145-153.

Miller, D. M. 1987. Analyzing Total Factor Productivity With ROI as a Criterion. Management Science. 33(11):1501-1505.

Morrison, C. J. 1985. Productivity Measurement with Non-static Expectations and Varying Capacity Utilization: An Integrated Approach. National Bureau of Economic Research Working Paper. 1561.

Riggs, J. and G. Felix. 1983. *Productivity by Objectives*. Englewood Cliffs, NJ: Prentice-Hall.

Rymes, T. K. 1985 The Measurement of Multi-Factor Productivity in an Input-Output Framework: New Canadian Estimates. Proceedings of an International Meeting organized by the Austrian Statistical Society, Austria. 19-25.

Siegal, I. 1986. Productivity Measurement in Organizations: Private Firms and Public Agencies; Highlights of the Literature. Work in America Institute, Series in Productivity. 43. NY Pergamon Press.

Sink, S. 1985. *Productivity Management: Planning, Measurement and Evaluation, Control and Improvement*, New York: John Wiley and Sons.

Slade, M. E. 1985. Value Added Total-Factor-Productivity Measurement: A Monte Carlo Assessment. University of British Columbia Department of Economics Discussion Paper: 85036. 30.

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