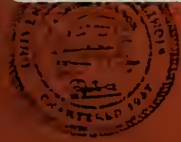


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Construct Validation of Business Economic Performance
Measures: A Structural Equation Modeling Approach

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A Structural Equation Modeling Approach

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CONSTRUCT VALIDATION OF BUSINESS ECONOMIC PERFORMANCE MEASURES:
A STRUCTURAL EQUATION MODELING APPROACH

ABSTRACT

A structural equation modeling approach is employed to assess the measurement properties of the business economic performance construct. Data on three dimensions of performance--sales growth, net income growth, and profitability (ROI)--were collected using two different methods--(i) perceptual assessments of senior executives; and (ii) secondary data sources. The analysis indicate that convergent and discriminant validity were achieved only when systematic sources of variation (method factors) were considered. The advantages of this approach in relation to the commonly-used MTMM framework are highlighted, and implications for strategy researchers are noted.

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Organizational economic performance or a broader concept of organizational effectiveness is fundamental to both descriptive and prescriptive research in many management disciplines, including organization theory and strategic management. In addressing this theme, researchers have adopted a wide array of conceptualizations and operationalizations depending upon their main research question, their disciplinary focus, and data availability. A review of the research literature on the complex topic of organizational performance is not attempted here since good discussions can be found in Campbell (1977), Chakravarthy (1984), Ford and Schellenberg (1982), Hofer (1983), Kanter and Brinkerhoff (1981), Kirchoff (1977), Seashore and Yuchtman (1967) and Steers (1975; 1977).

BUSINESS ECONOMIC PERFORMANCE:
THE ISSUE OF OPERATIONALIZATION IN STRATEGY RESEARCH

Researchers in the emerging discipline of strategic management are centrally concerned with issues of conceptualizing and measuring organizational performance (Schendel & Hofer, 1979). However, recognizing the complexity of organizational performance, they have largely focused their attention on a narrower concept of Business Economic Performance (BEP). Typically, BEP has been conceptualized in terms of indicators such as Return on Investment (ROI), Return on Sales (ROS), Sales Growth, and Price-to-Earnings (P/E) ratio (see Hofer, 1983 for a review of various performance indicators used in strategy research).

In attempting to operationalize BEP, researchers have adopted one of two methods--(a) use of "secondary" data sources such as COMPUSTAT (e.g., Ramanujam, 1984; Schendel & Patton, 1978) or (b) use of "primary" sources by requesting managers to provide perceptual assessments of

their level of performance relative to competition (e.g., the PIMS program) or their level of satisfaction with performance (Bourgeois, 1980; Gupta & Govirdarajan, 1984).

While researchers typically use one of the two methods, an encouraging exception is seen in Dess and Robinson's (1984) study on the correspondence between BEP measures from two different methods. Using data from a sample of 26 units, they reported a positive and significant association between "self-reported objective" and "subjective" data on two performance dimensions--return on assets, and sales growth. Such an approach is a welcome point of departure since it certainly enhances the quality of operationalization. However, their "methods" are conceptually similar in the sense of employing data collected from only primary source and represent the "within method" type of triangulation (Denzin, 1978).

The limitations of this type of triangulation are noted by Denzin, "Observers delude themselves into believing that....different variations of the same method generate....distinct varieties of triangulated data. But the flaws that arise using one method remain.... (1978; pp. 301-302). The weaknesses in the use of a single source of data can be overcome by employing two different data sources--viz., primary and secondary, which is in line with Campbell and Fiske's (1959) call for using "maximally different" methods to assess convergent validity of operationalization.

Such an extension was attempted (Venkatraman & Ramanujam, 1985) by collecting objective data from secondary sources (as opposed to self-reported objective data as in Dess and Robinson's study) and perceptual

assessments of top-level managers (primary data). By treating the two data sources as distinct "methods" within Campbell and Fiske's (1959) MultiTrait, MultiMethod (MTMM) framework, the four general criteria for convergent and discriminant validity of each of the three performance dimensions--net income growth, sales growth, and profitability (ROI)--were broadly satisfied.

In strategic management research, where attempts at construct measurement are not yet systematic (Venkatraman & Grant, 1986), use of MTMM matrix to assess convergent and discriminant validity is a welcome point of departure. However, since the criteria generally employed in a MTMM framework are rather broad and open to researchers' interpretation, this approach is under attack (see Bagozzi, 1980; Schmitt, Coyle, & Saari, 1977). Consequently, in this study we undertake an extended examination of the construct measurement of the three performance dimensions. The rationale for such an extension is that critical evaluations of measurement properties enhance the quality of operationalization, which is essential for rigorously testing theoretical relationships (Schwab, 1980). This is especially important since some studies which satisfied the broad MTMM criteria failed to turn up similar results when the variance in measurement was partitioned into its constituent components (see Bagozzi, 1980; pp. 136-153 for a discussion).

STUDY OBJECTIVES

Our purpose in this paper is to illustrate the benefits of adopting a structural equation modeling approach (Jöreskog, 1969; Jöreskog & Sorbun, 1978; 1979) to address a broader set of measurement questions which cannot be directly addressed within the MTMM framework. We use

the construct of BEP and data collected from two different sources for this purpose. The specific research questions for this study are:

1. To what extent are convergent and discriminant validity of BEP achieved when measurement error is included for consideration, and the variance in measurement partitioned into trait, method, and error components?;
2. Is the "secondary" method superior than the "primary" method? or vice-versa; and
3. Since convergent and discriminant validity are critically dependent on the use of "maximally different methods" (Campbell & Fiske, 1959), are the two methods dissimilar?

The first question addresses the construct validity issues systematically by identifying reasons for the support (or, lack of) for the various validity criteria, by decomposing the measurement variance into its various components. The second question aims to identify the relative superiority of the two methods, and the third aims at an evaluation of the robustness of the measurement properties, which can be inferred when similar results are obtained from dissimilar methods.

ANALYTIC METHOD

This section discusses the analytical method employed to address the three research questions. To begin with a brief outline of the comparative benefits of the structural equation model over the traditional MTMM approach is presented. Subsequently, the proposed analytical scheme is described with the measurement equations and the analytical procedure for testing a set of sequential models.

Comparative Benefits of the Structural Equation Model Approach over the MTMM Method

A major limitation of the MTMM approach to construct validation is its inability to partition the amount of variation in measurement into

its components such as trait, random error, and systematic (i.e. method) error. An alternative approach (confirmatory factor analysis), which is based on the structural analysis of covariance matrices (Joreskog & Sorbum, 1978), has found acceptance in relatively mature disciplines such as psychology, sociology, and marketing (Bagozzi, 1980; Fornell, 1982). In addition, it has also been employed in strategy research by Farh, Hoffman, and Hegarty (1984) for assessing the measurement properties of Hambrick's (1981a) environmental scanning scale.

This method, in addition to examining convergent and discriminant validity, can be used to assess the reliability of indicators and composite measures with less assumptions than those underlying the calculation of other reliability indices (see Bagozzi, 1981; Fornell and Larcker, 1981; and Werts, Linn, and Joreskog, 1974). The comparative benefits of this approach are perhaps best summarized by Kenny:

The application of confirmatory factor analysis to the multitrait, multimethod matrix has a number of advantages over the traditional Campbell-Fiske criteria: (a)...(it) gives estimates of parameters while Campbell-Fiske criteria are only rules of thumb. (b) Significance tests are possible with confirmatory factor analysis. (c) Given marked differences in the reliability of measures, the Campbell-Fiske criteria are misleading....while confirmatory factor analysis takes into account differential reliability (1976; p. 248).

Specifically, the alternative scheme provides: (a) a formal statistic for judging the entire validity of a construct; (b) an indication of the degree to which operationalizations measure the concepts they intend to measure; and (c) a decomposition of the variance in measurement into its components.

Four Measurement Models for BEP

We propose four measurement models for BEP based on Joreskog's general analysis of covariance structures (Joreskog, 1969; 1971; Joreskog & Sorbum, 1978; 1979). We have provided the required analytical equations for the proposed models in the following paragraphs. But our discussion is not highly technical, and those readers requiring more technical details are directed to Bagozzi (1980), Fornell (1982), Joreskog and Sorbum (1978), and Long (1983).

The first model is a test for convergent validity with only the trait factors. If the first model is not supported, then it is extended by adding method factors to evaluate whether the additional incorporation of systematic sources of variation provides better support to the second model. The third model tests for discriminant validity, while the fourth tests for the degree of dissimilarity of the two methods used. The analytical equations for these models and the criteria to be adopted for model-testing are discussed in the following paragraphs.

Testing for Convergent Validity--Model 1. Convergent validity refers to the degree to which two or more attempts to measure the same trait through maximally different methods are in agreement. Following Joreskog's work, the basic model for convergent validity can be written as:

$$X = \Lambda\xi + \delta \tag{1}$$

where, X is a vector of p measurements, ξ is a $k < p$ vector of traits, δ is a vector of unique scores (random errors), and Λ is a $p \times k$ matrix

of factor loadings. With the assumptions of $E(\xi) = 0$, $E(\xi\xi') = \phi$, and $E(\delta\delta') = \Psi$, the variance-covariance matrix of X can be written as

$$\Sigma = \Lambda\Phi\Lambda' + \Psi \quad (2)$$

where, Σ is the variance-covariance matrix of observations, ϕ is the intercorrelation among the traits, and Ψ is a diagonal matrix of error variances (θ_{δ}) for the measures.

Maximum likelihood parameter estimates for Λ , ϕ , Ψ , and a χ^2 goodness of fit index for the null model implied by equations (1) and (2) can be obtained from the LISREL program (Joreskog & Sorbun, 1978). The probability level associated with a given χ^2 statistic indicates the probability of attaining a larger χ^2 value, given that the hypothesized model holds. The higher the value of p , the better is the fit, and as a rule of thumb, values of $p > 0.10$ are considered as indications of satisfactory fit (Lawley & Maxwell, 1971).

This model hypothesizes that all the variation and covariation in the measurement of traits can be accounted for by the theoretical concepts that the measurements are intended to capture plus random error. Figure 1 is a diagrammatic representation of the first model implied by equations (1) and (2) in this study, where three traits (dimensions) of performance are each measured by two methods.

INSERT FIGURE 1 ABOUT HERE

Testing for Convergent Validity With Method Factors--Model 2. If the previous model fails to achieve a satisfactory fit to the data, one can examine potential improvement with explicit modeling of method

factors--"primary" and "secondary" sources of data. The underlying rationale for this model is that the observations are not only a function of the trait and random error, but are also influenced by systematic sources of variation such as the source of data. Two method factors are added to the first model as systematic sources of variation in addition to random variations (i.e., unique uncorrelated errors represented as δ_s). Method factor 1 represents the perceptual source of data provided by the respondents, while method factor 2 represents the objective or secondary data source. A diagrammatic representation of the second model is provided in Figure 2.

INSERT FIGURE 2 ABOUT HERE

The λ parameters indicates the degree of correspondence between the unobservable constructs and the respective observable indicators. The λ parameters connecting the trait factors to the observations, when squared, reflect the amount of variation due to corresponding traits. The λ parameters connecting the method to the corresponding indicators, when squared, reflect the amount of variation in method, and the error variance is provided by θ_{δ_i} . If this model fits the data, it is possible to conclude that convergent validity is achieved only when method factors are taken into account. For the modifications of equations (1) and (2) to incorporate method factors, readers are directed to Bagozzi and Phillips (1982), Farh et al. (1984), Long (1983), and Phillips (1981).

Testing for Discriminant Validity--Model 3. If convergent validity is achieved either through models 1 or 2, one can proceed to assess

discriminant validity. Discriminant validity is achieved when the measures of each trait converge on their corresponding true scores which are unique from other traits. Stated differently, it is the degree to which a trait in a theoretical system differs from other traits in the same theoretical system. This will be achieved when the correlations between the traits (ϕ_s) are significantly lower than unity. This requires a comparison of the model in Figure 2 with a similar model in which the three correlations are considered equal to unity. A significantly lower χ^2 value for the model with the correlations unconstrained provides support for discriminant validity. A χ^2 difference value (χ^2_d) value with an associated p value less than 0.05 (Joreskog, 1971) supports the discriminant validity criterion.

Testing for Association Between the Two Methods--Model 4. Although we can a priori argue that the two methods employed here are more dissimilar than the two methods of Dess and Robinson (1984)--self-reported objective, and subjective--the proposed testing system can be used to explicitly test the level of association between the two methods. Since maximally different methods provide stronger tests of construct validity (Campbell & Fiske, 1959), this is an essential requirement for construct validation--which cannot be tested within the MTMM framework.

This test is analyzed in two ways--one, by testing the statistical significance of the unconstrained parameter ϕ_{45} in Figure 2; and the other by comparing the unconstrained model with a similar model with ϕ_{45} constrained to 1. A significantly lower value of χ^2 for the unconstrained model when compared to the constrained model provides further support for the lack of association between the two methods.

DATA

Primary Measures

Primary measures of performance were collected from senior executives as a part of a larger project (Venkatraman, Ramanujam & Camillus, 1984) between February and April 1984. Although the larger project had a response rate of over 33% (207 cases out of 600), only 86 cases are used in this study. Since anonymity was assured, disclosure of affiliations was voluntary. 86 respondents indicated their organizational affiliations which enabled us to collect corresponding secondary performance data on them.

The justification for using the dimensions--sales growth, net income growth, and ROI--is based on their extensive use in strategy research (see Hofer, 1983 and Woo & Willard, 1983 for reviews). More specifically, they correspond closely to the indicators of Dess and Robinson (1984), and to the dimensions developed by Woo and Willard (1983) based on an analysis of the data from the PIMS program.

Consistent with the relative nature of performance emphasized in the strategy literature, managers were requested for their perceptions, not of their absolute performance, but of their positions relative to their major competitors. It can be argued that organizations refer to their proximate competitors rather than a heterogeneous universe of firms in assessing their performance. Relative performance was obtained on a five-point scale ranging from -2 (much worse than competition) to +2 (much better than competition), with the neutral point of 0 indicating a level equal to that of competition.

Secondary Measures

Secondary measures of performance were assembled from Business Week magazine's "Inflation Scoreboard" for the year 1983, as reported in the March 21, 1984 issue. Business Week compiles these data from Standard & Poor's COMPUSTAT[®] tapes. Relative competitive performance was operationalized as firm performance relative to the industry, where industry refers to the principal SIC industry classification to which the firm is assigned. Relative performance was measured as the difference between the values of the indicator for the firm and the industry. For example, relative sales growth was the sales growth of the focal firm minus the growth rate for its principal industry.

RESULTS

Table 1 presents the correlations among the indicators obtained as discussed in the previous section. All the analyses for model-testing were carried out using the LISREL IV program (Joreskog & Sorbum, 1978).

INSERT TABLE 1 ABOUT HERE

The results of LISREL analysis for the first model yielded a χ^2 (df:10) value of 56.6723; $p=0.00$. This indicates that the underlying hypothesis that all variations are due to underlying trait and random error only should be rejected. However, sole reliance on the χ^2 statistic is criticized for many reasons (Fornell & Larcker, 1981), and researchers increasingly complement this statistic with two additional statistics. One is the Bentler and Bonnet's (1980) incremental fit index Δ --which is an indication of the practical significance of the model in explaining the data. The Δ index is represented as

$$\Delta = (F_0 - F_K)/F_0 \quad (3)$$

where F_0 = chi-square value obtained from a null model specifying mutual independence among the indicators, and F_K = chi-square value for the specified theoretical model.

The other statistic is an evaluation of the difference in χ^2 statistic between two related models. Since this was the first model to be tested, the latter statistic is not appropriate. But the Δ index was 0.71 lending further support to the rejection of the model since as a rule of thumb Δ should exceed 0.95 (Bearden, Sharma, & Teel, 1982). This result indicates that the second model should be tested.

The analysis of the second model yielded an overall statistic $\chi^2(4)$ of 2.97; $p=0.562$, and the difference in χ^2 between the first and the second model was 53.70, significant at $p<0.001$. Further, Δ index of 0.984 indicated that more than 98% of the measure variation is captured by the model. These results provide strong support to the second model and the underlying hypothesis that measures achieve convergent validity only when the method factors (i.e., sources of systematic variation) are explicitly incorporated into the model.

Since convergent validity requirements are satisfied in the second model, we can now test for discriminant validity using model 3. Discriminant validity is achieved when the measures of each dimension converge on their corresponding true scores which are unique from other dimensions. Stated differently, it is the degree to which a dimension in a theoretical system differs from other dimensions in the same theoretical system.

The χ^2 difference in the two models (one with the correlations between the traits each constrained to be 1.0, and the other with these correlations unconstrained), viz., $\chi^2(7)$ minus $\chi^2(4)$ is 32.66 (35.6324 minus 2.97); $p < 0.001$. This satisfies the criteria for discriminant validity (Joreskog, 1971). However, the analysis of model 2 indicated that ϕ_{21} and ϕ_{32} were large and statistically different from zero (see Table 2). This could imply that dimensions 1 and 2 and/or dimensions 2 and 3 may be subdimensions of a broader construct.

In order to rule out this rival interpretation, two separate models were estimated, one with ϕ_{21} constrained to 1.0, and the other with ϕ_{32} constrained to 1.0. A significantly lower value of χ^2 for the unconstrained model indicates that the dimensions are indeed different. The model with ϕ_{21} constrained yielded a χ^2 (df:5) of 26.98; and with ϕ_{32} constrained yielded a χ^2 (df:4) of 2.97, and the difference in χ^2 statistic in both cases are significant at a level better than $p = 0.01$. This further provides support for discriminant validity of the three dimensions of BEP.

The fourth model sought to examine the association between the two method factors. The model with ϕ_{45} constrained to equal 1.0 yielded a statistic of $\chi^2(4)$ of 17.7676, while the alternate model of unconstrained ϕ_{45} yielded a $\chi^2(3)$ statistic of 1.088. The value of χ^2 difference with 1 degree of freedom is 16.6788 and is significant at $p < 0.001$, lending support to the hypothesis of dissimilar methods. In addition, the parameter ϕ_{45} when left unconstrained was 0.264 with a corresponding t-value of 1.557 which is not significant at $p < 0.01$, providing additional support to the hypothesis of dissimilar methods.

Further, the LISREL estimates can be used to partition the measurement variance into trait, method, and error components. Following Joreskog and Sorbum (1979) and Bagozzi (1980), we decomposed the variance as shown in Table 2. Additionally, measure reliability of both individual indicators and composite index, calculated based on the formulae derived in Werts et al. (1974) are included in the table.

INSERT TABLE 2 ABOUT HERE

DISCUSSION

The support received for convergent validity further corroborates the correspondence between secondary and primary sources of data on organizational performance; and the positive results in relative to discriminant validity lends further credence to Woo and Willard's (1983) conclusion regarding the multi-dimensional nature of organizational performance.

Support for the Three Research Questions

More specifically, the results can be used to address the three research questions. For the first question, the results indicate that both convergent and discriminant validity were achieved only when method factors were introduced in the model. It implies that while the MTMM approach may provide general indications of convergent and discriminant validity, additional analyses such as those done here enables one to examine specific reasons for the lack of support for various validity criteria by partitioning the variance into its components.

The partitioning of variance in Table 2 provides a systematic basis for addressing the second question. The average trait variance explained by the primary method is 45.3%, while the secondary method explained 43.3%. The average method variance for the three dimensions is approximately equal with primary method accounting for 34.3% and secondary method for 33.6%; and the random error for the two methods is also similar (primary method - 19% and the second method - 20%).

At an aggregate level, both methods appear to be equally effective, although the ratio of trait variance to error (systematic + random) variance is less than 1.0, indicating poor measure reliability. However, viewing the dimensions individually, some interesting results can be observed. The secondary method is more efficient (i.e., less total error variance) for profitability (ROI), while the primary method is more efficient for sales growth. The general implication of the results is that managers are reasonably accurate in their perceptions of sales growth as a performance measure, while they are not as reliable for profitability measures.

Both methods appear to provide poor indications of net income growth. However, the variance partitioning, in conjunction with the analysis of measure reliability indicate that the use of both methods together is a preferred alternative for net income growth. In other cases, the composite appears to reduce the reliability due to high levels of measurement error for x2 and x5 (see Table 2). The implications for future research is that while multiple methods should be employed to operationalize the construct, only the efficient method (or, methods) should be used for testing substantive relationships.

Further, we strongly advocate that the superiority of one method over another should be explicitly tested as against implicitly assuming that objective (i.e., secondary) data are always more "accurate" than perceptual measures.

For the third question, the study specifically tested the degree of association between the two methods. If methods are somewhat similar, such as two different measuring instruments or self-reported objective and subjective data, it is not difficult to establish convergent validity as demonstrated in Dess and Robinson (1984). Since in this study the two methods are found to be dissimilar, construct validity assessments have a stronger impact than otherwise. The scheme also illustrated a systematic basis to identify poor quality indicators (e.g., x2 and x5), and thereby improve the overall quality of measurement. Increased attention to measurement issues will certainly enhance the confidence which can be placed on substantive research results. Hopefully, this paper will stimulate future strategy research studies to address the measurement concerns raised in this study, prior to testing substantive relationships.

It needs mention that although the analyses were carried out using the LISREL IV Program (Jöreskog & Sörbom, 1978), it is not the only available analytical scheme. Readers may want to consider other related analytical schemes such as the partial least square estimation (Wold, 1982).

Limitations and Extensions

Two limitations are noted with a view to identifying future extensions. One pertains to the size of the sample employed for analysis.

Although the sample size (an average of 80, after accounting for some missing data) satisfies the minimum size for the specified model (Bagozzi, 1980; Lawley & Maxwell, 1971), the chi-squared distribution is sensitive to sample size. However, by relying upon the difference in chi-square (χ^2_d) statistics in the sense of assessing a set of nested models as done here (which is less sensitive to sample size) and the use of Δ index (Bentler and Bonnet, 1980) which is independent of sample size, we attempted to reduce the problems associated with sample size. Nevertheless, a useful extension will be to replicate this study and test these results using a larger sample set.

The other issue pertains to the use of single informant per unit of analysis to collect data on organization-level constructs such as performance. As an extension, multiple informants can be used as separate methods to examine if systematic differences exist between managers based on position, hierarchy, and other organizational differences. It is particularly critical in strategy research since Hambrick's (1981b) study on strategic awareness indicated a negative association between awareness and hierarchical level. By employing data collected from multiple levels and different functions and decomposing the method variance, useful guidelines in relation to research design and selection of respondents can be gleaned.

SUMMARY

Using a structural equation methodology and performance data on 86 firms from two different sources, this paper evaluated the construct measurement properties of business economic performance measures. The

general expectation of correspondence between the two methods was supported, although both methods were not equally efficient for measuring the three dimensions of performance. Implications for future research include an explicit evaluation of one method's superiority over another, and combining methods when composite indices increases the measure reliability. Interesting differences from the results obtained using an MTMM framework in an earlier study (Venkatraman & Ramanujam, 1985) were observed. This calls for researchers to examine the possible adoption of the structural equation modeling methodology discussed in this paper for addressing measurement issues in strategic management research.

REFERENCES

- Bagozzi, R. P. 1980. Causal models in marketing, N.Y.: Wiley.
- Bagozzi, R. P. 1981. An examination of the validity of two models of attitude. Multivariate Behavioral Research, 16: 323-359.
- Bagozzi, R. P., & Phillips, L. W. 1982. Representing and testing organizational theories: A holistic construal. Administrative Science Quarterly, 27: 459-489.
- Bearden, W. O., Sharma, S., & Teel, J. H. 1982. Sample size effects on chi-square and other statistics used in evaluating causal models. Journal of Marketing Research, 19: 425-430.
- Bentler, P. M., & Bonnet, D. G. 1980. Significance tests and goodness of fit in the analysis of covariance structures. Psychological Bulletin, 88: 588-606.
- Campbell, D. T., & Fiske, D. W. 1959. Convergent and discriminant validation by the multitrait-multimethod matrix. Psychological Bulletin, 56: 81-105.
- Chakravarthy, B. S. 1984. Re-search of excellence: Resolving the performance puzzle. Working Paper 84-02, The Reginald H. Jones Center, The Wharton School, U. of Pennsylvania.
- Denzin, N. K. 1978. The research act. 2nd Ed., New York: McGraw-Hill.
- Dess, G. G., & Robinson, R. B. 1984. Measuring organizational performance in the absence of objective measures: The case of the privately-held firm and conglomerate business unit. Strategic Management Journal, 5: 265-273.
- Farh, J. L., Hoffman, R. C., & Hegarty, W. H. 1984. Assessing environmental scanning at the subunit level: A multitrait multi-method analysis. Decision Sciences, 15: 197-220.
- Ford, J. D., & Schellenberg, D. A. 1982. Conceptual issues of linkage in the assessment of organizational performance. Academy of Management Review, 7: 49-58.
- Fornell, C. (Ed.) 1982. A second generation of multivariate analysis. NY: Praeger.
- Gupta, A., & Covindarajan, V. 1984. Business unit strategy, managerial characteristics, and business unit effectiveness at strategy implementation. Academy of Management Journal, 27: 25-41.

- Hambrick, D. C. 1981a. Environment, strategy, and power within top management teams. Administrative Science Quarterly, 26: 253-276.
- Hambrick, D. C. 1981b. Strategic awareness within top management teams. Strategic Management Journal, 2: 263-279.
- Hofer, C. W. 1983. ROVA: A new measure for assessing organizational performance. In R. Lamb (Ed.) Advances in strategic management, Vol. 2, 43-55. New York: JAI Press.
- Joreskog, K. J. 1969. A general approach to confirmatory maximum likelihood factor analysis. Psychometrika, 34: 183-202.
- Joreskog, K. G. 1971. Statistical analysis of congeneric tests. Psychometrika, 36: 109-133.
- Joreskog, K. G., & Sorbum, D. 1978. Analysis of linear structural relationships by method of maximum likelihood. Chicago, Ill.: National Educational Resources.
- Joreskog, K. G., & Sorbum, D. 1979. Advances in factor analysis and structural equation models. Mass.: Abt Books.
- Kanter, R. M., & Brinkerhoff, D. 1981. Organizational performance: Recent developments in measurement. Annual Review of Sociology, 7: 322-349.
- Kenny, D. 1976. An empirical application of confirmatory factor analysis to the multitrait, multimethod matrix. Journal of Experimental Social Psychology, 12: 247-252.
- Kirchoff, B. 1977. Organization effectiveness measurement and policy research. Academy of Management Review, 2: 347-355.
- Lawley, D. N., & Maxwell, A. E. 1971. Factor analysis as a statistical method. London: Butterworth.
- Long, J. S. 1983. Confirmatory factor analysis. Sage University Paper Series on Quantitative Application in the Social Sciences, 07-033. Beverly Hills and London: Sage Publications.
- Montgomery, C., & Singh, H. 1984. Diversification strategy and systematic risk. Strategic Management Journal, 5: 181-191.
- Phillips, L. W. 1981. Assessing measurement error in key informant reports: A methodological note on organizational analysis in marketing. Journal of Marketing Research, 18: 395-415.
- Ramanujam, V. 1984. An empirical examination of contextual influence on corporate turnaround. Paper presented at the Academy of Management meeting at Boston.

- Schendel, D. E., & Hofer, C. W. (Eds.) 1979. Strategic management: A new view of business policy and planning. Boston: Little, Brown.
- Schmitt, N., Coyle, B. W., & Saari, B. B. 1977. A review and critique of multitrait, multimethod matrices. Multivariate Behavioral Research, 12: 447-478.
- Schwab, D. 1980. Construct validity in organizational behavior. In B. M. Staw & L. L. Cummings (Eds.) Research in organizational behavior, Vol. 2, Greenwich, Conn.: JAI Press, 3-43.
- Seashore, S. E., & Yuchtman, E. 1967. Factorial analysis of organizational performance. Administrative Science Quarterly, 12: 377-395.
- Steers, R. 1975. Problems in measurement of organizational effectiveness. Administrative Science Quarterly, 20: 546-558.
- Steers, R. 1977. Organizational effectiveness: A behavioral view. The Goodyear series in management and organizations. Santa Monica, CA: Goodyear.
- Venkatraman, N., & Grant, J. H. 1986. Construct measurement in organizational strategy research: A critique and proposal. Academy of Management Review, forthcoming (January 1986).
- Venkatraman, N., & Ramanujam, V. 1985. On the correspondence between "primary" and "secondary" measures of business economic performance: An attempt at methodological triangulation. Faculty Working Paper No. 1127, Bureau of Economic and Business Research, University of Illinois at Urbana-Champaign.
- Venkatraman, N., Ramanujam, V., & Camillus, J. C. 1984. Modeling the implementation success of strategic planning: A path-analytic investigation. Working Paper, Graduate School of Business, University of Pittsburgh.
- Werts, C. E., Linn, R. N., & Joreskog, K. G. 1974. Interclass reliability estimates: Testing structural assumptions. Educational and Psychological Measurement, 34: 25-33.
- Wold, H. 1982. Systems under indirect observation using PLS. In C. Fornell (Ed.) A second generation of multivariate analysis. Vol. I. Methods. New York: Praeger, 325-347.
- Woo, C. Y., & Willard, G. 1983. Performance representation in strategic management research: Discussions and recommendations. Paper presented at the Academy of Management Meeting at Dallas.

TABLE 1

Zero-order Correlations Between Indicators
(n=86)

	X1	X2	X3	X4	X5	X6
X1	1.000					
X2	0.442	1.000				
X3	0.467	0.237	1.000			
X4	0.332	0.692	0.424	1.000		
X5	0.364	0.153	0.736	0.333	1.000	
X6	0.103	0.020	0.357	0.283	0.514	1.000

- X1 = Sales growth (primary)
- X2 = Sales growth (secondary)
- X3 = Net Income Growth (primary)
- X4 = Net Income Growth (secondary)
- X5 = Return on Investment (primary)
- X6 = Return on Investment (secondary)

TABLE 2

Partitioning of Variance and Measure Reliability

DIMENSIONS	INDICATORS	VARIANCE COMPONENTS			RELIABILITY	
		Trait	Method	Error	Individual ^a	Composite ^b
Sales Growth	x1 (P)	0.68	0.12	0.19	0.68	0.60
	x2 (S)	0.20	0.56	0.20	0.20	
Net Income Growth	x3 (P)	0.33	0.33	0.45	0.33	0.45
	x4 (S)	0.31	0.31	0.44	0.31	
Profitability	x5 (P)	0.35	0.46	0.19	0.35	0.72
	x6 (S)	0.79	0.01	0.20	0.79	

^aFor Individual Indicators:

$$\rho_i = \lambda_i^2 \text{Var}(A) / \{ \lambda_i^2 \text{Var}(A) + \text{Error variance} \}$$

^bFor Composite Measures:

$$\rho_{\text{composite}} = (\sum \lambda_i)^2 \text{Var}(A) / \{ (\sum \lambda_i)^2 \text{Var}(A) + \sum \text{Error variance} \}$$

where

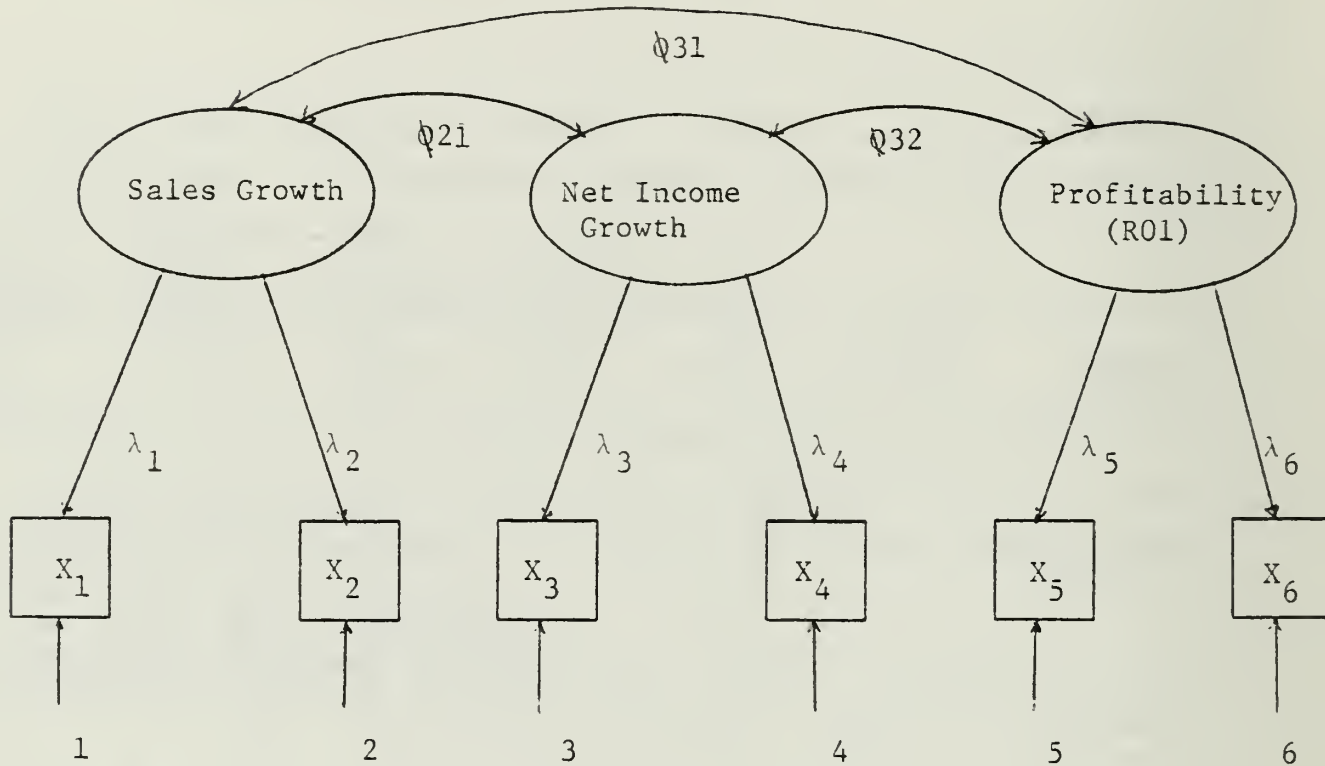
P = primary measure;

S = secondary data source; and

Var(A) = variance of the construct, standardized at unity.

FIGURE 1

A Model of Convergent Validity With Only Trait Factors^{a, b}



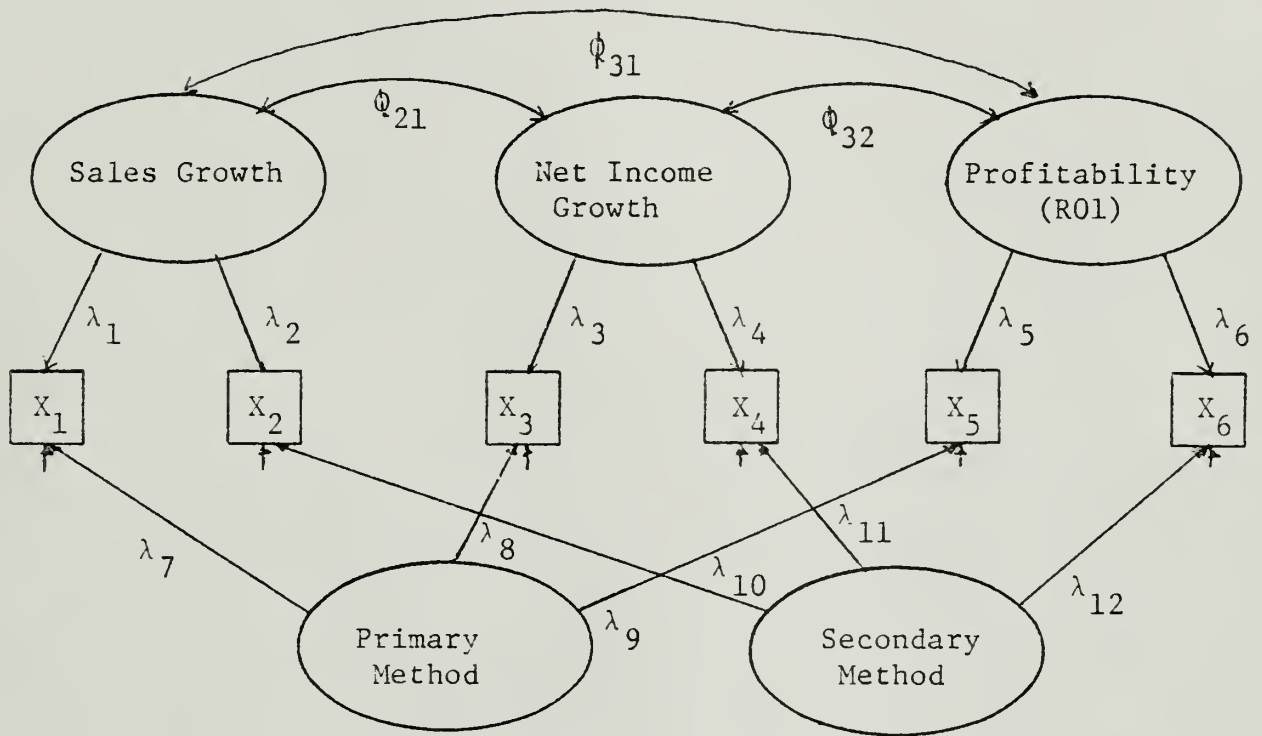
χ^2 (df:10) = 56.6723; p=0.000.

^a $\delta_1 = \delta_3 = \delta_5$; and $\delta_2 = \delta_4 = \delta_6$, for model identification purposes. A model without such constraints did not provide a better fit to the data (χ^2 (df:10) = 56.6723; χ^2 (df:6) = 54.3709; χ^2_d (df:4) = 2.30--not significant). This supports the model as shown; An average sample size of 80 was used for estimating the model.

^bIn Figures 1 and 2, the notations of structural equation modeling are followed. Latent (unobservable) variables or theoretical constructs are drawn as ellipses; observable indicators are presented as squares; measurement relations are shown as arrows; error factors are also represented as arrows but without origin; and parameters to be estimated are depicted as Greek letters.

FIGURE 2

A Model of Convergent Validity With Trait and Method Factors



χ^2 (df:4) = 2.97; p=0.562.

Parameters	ML Estimates (t-value in parenthesis)
λ_1	0.825 (8.620)*
λ_2	0.444 (4.152)*
λ_3	0.577 (4.887)*
λ_4	0.559 (5.343)*
λ_5	0.593 (5.328)*
λ_6	0.892 (9.740)*
λ_7	0.339 (2.869)*
λ_8	0.675 (7.148)*
λ_9	0.681 (7.817)*
λ_{10}	0.749 (8.410)*
λ_{11}	0.661 (6.611)*
λ_{12}	-0.138 (-1.175)*
ϕ_{21}	0.506 (3.891)*
ϕ_{31}	0.198 (1.385)
ϕ_{32}	0.730 (6.793)*
$\delta_1 = \delta_3 = \delta_5$	0.185 (4.072)*
$\delta_2 = \delta_4 = \delta_6$	0.196 (4.523)*

(*) - parameter significant at p<0.05; t-values are calculated as parameter estimates divided by the standard error of estimates.

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