DEVELOPING A PREDICTIVE METHOD: A COMPARATIVE STUDY OF THE PARTIAL LEAST SQUARES VS MAXIMUM LIKELIHOOD TECHNIQUES

Waymond Rodgers
Paul Pavlou
Andres Guiral

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Waymond Rodgers
Professor
Graduate School of Management
University of California
Riverside, CA 92521

Paul Pavlou
Assistant Professor
Graduate School of Management
University of California
Riverside, CA 92521
paul.pavlou@ucr.edu

and

Andres Guiral
Visiting Associate Professor
Graduate School of Management
University of California
Riverside, CA 92521
andresg@ ucr.edu

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Address all correspondence to Prof. Waymond Rodgers, Graduate School of Management, Anderson Hall 233, University of California, Riverside, CA 92521.

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DEVELOPING A BEHAVIORAL PREDICTIVE METHOD: A COMPARATIVE STUDY USING THE PARTIAL LEAST SQUARES VS MAXIMUM LIKELIHOOD TECHNIQUES

ABSTRACT

To compare the PLS and ML techniques in accounting applications, we predict management financial decision-making (a loan making task) by incorporating both the decision makers' perceptions and also financial statement information using a PLS and a ML techniques. The results indicate that PLS is a superior technique than ML for complex predictive methods when data is few, new, and/or in its experimental, developmental stage. Suggestions and guidelines for employing PLS in accounting research are discussed.

PLS provides a very important epistemic relation between theoretical and empirical variables, which becomes particularly advantageous for higher-order constructs. More important, in contrast to ML, PLS allows for testing of *both* types of epistemic relations, *reflective* and *formative*, which becomes useful for predictive methods that combine perceptual constructs (reflective factors), and also financial and accounting statement information (formative factors). To illustrate the use of PLS in developing predictive methods, several exemplar accounting studies that have employed PLS are reviewed.

One of the implications of this study is that financial statements users, such as auditors, loan officers and financial analysts, should be trained to handle non-traditional information, such as environmental risk.

1. INTRODUCTION

The relevance of financial statements has come under increasing scrutiny. “In recent decades the usefulness of financial reports of public companies has steadily declined, despite their increased gloss and girth” (Lev 1998, pp. 66). There is equal concern that including non-financial or intellectual capital information could prove dangerous to investors and analysts. “The most troubling idea of the IC [intellectual capital] generation is to tinker with financial statements, so companies full of smart people who don't make profits look more attractive to investors” (Rutledge 1998, pp. 75).

While, this controversy is ongoing, there is no controversy about the need to understand how users interpret and make decisions based on such information. Due to our rapidly changing knowledge, the demands for non-financial and forecasted information have increased. Given the new information technology environment, the amount of information has dramatically increased, necessitating more complex, information-intensive constructions. Academicians, managers, and decision makers are constantly searching for new ways to improve their assessment of various types of information to develop robust predictive techniques. Such estimation approaches can lead to a better calibration and integration of judgments and objective information to generate more accurate predictions and better forecasting decisions.

The method discussed in this paper is a relatively novel forecasting technique called Partial Least Square (PLS) versus Maximum Likelihood Technique (ML). PLS refers to a class of methods used for relating blocks of variables measured on sets of objects. PLS is a predictive-causal technique, and thus potentially valuable for forecasting applications. It embodies simultaneous equations and differs from econometric approaches since it estimates relationships among unobservable or theoretical variables. The simplicity with which PLS path diagrams can capture a theory with a limited amount of data is one of the method’s most important features. In addition, the use of a small sample size may often be the only alternative basis for projections and forecasts. PLS is more amenable to a small set with many variables as compared to other methods that require large sample sizes (i.e., ML), while permitting analysis of complex structures. Finally, given the impact of information technology on financial reporting, new metrics are rapidly emerging that require methods that can capture and represent new concepts without the benefit of a large sample size. For example, companies that adopt a few non-financial measures for reporting purposes are few; while the study of these measures influences corporate productivity and profitability. Without a methodology to handle small data sets, it becomes quite precarious to introduce new financial reporting methods. A distinction can be made between the use of covariance structural approaching for theory versus predictive application (Fornell and Bookstein, 1982; Chin et al., 2003). This distinction is important because it has basic implications for the choice of estimation method and development of the underlying predictive model. This choice can be characterized as being between (1) a full-information (maximum likelihood (ML) or generalized least squares (GL)) estimation approach[1] (e.g., Bentler, 1983) in conjunction with the common factor method (Rodgers, 1991), versus (2) the PLS estimation approach (e.g., Wold, 1983) in conjunction with the principal-component approach (Rodgers, 1999).

Building on previous research, the present study compares the differences, advantages, and complementarities between techniques that employ a full information estimation approach (e.g., ML) versus PLS methods. The results from a forecasting financial decision-making approach highlight the differences between these two complimentary approaches and provide directions for future research. The PLS findings illustrate the impact of different types of accounting information on decision makers' judgments. In the first processing stage, subjects were presented with positive (or negative) economic and management information when financial statement information was negative (or positive). The results further indicated that economic and management risk perceptions did significantly affect individuals' judgments. That is, individuals placed more weights on financial statement information (i.e., liquidity and income information in the model) based upon their training of loan analysis techniques. Since this approach is derived from normative banking decision processes (Cohen et al., 1966; Shaw and Gentry, 1988), it could be very useful outside the laboratory context for practical economic applications. One of the implications of this study is that financial statements users, such as auditors, loan officers and financial analysts, should be trained to handle non-traditional information, such as environmental risk information (Rodgers and Guiral 2005; Rodgers and Housel 2004).

The paper proceeds as follows: Section 2 describes the PLS technique and its basic properties and characteristics. Section 3 compares PLS with ML techniques, describing each technique's advantages, shortcomings, limitations, and their complementarities. Section 4 cites several empirical research studies in accounting that employed the PLS technique. Section 5 presents the conceptual method used in this study (a two-stage loan making laboratory task). Sections 6 describe the research methodology and results of a comparative study from a financial decision making method between PLS and ML. Section 7 discusses the empirical findings, and proposes how PLS could be further employed in future research studies. Finally, Section 8 concludes by summarizing when PLS is the most appropriate predictive technique.

2. PLS DESCRIPTION

2.1. PLS Overview

PLS, a latent structural equations estimation technique, uses a component-based approach to estimation (Lohmoller 1989). Predicting empirical and/or theoretical variables is the primary purpose of PLS. Residual variances to be minimized are specified by the researcher.

Estimation relies on a stepwise iterating procedure involving the minimization of some residual variance with respect to a subset of the parameters, given either a proxy (fix-point constraint) or final estimates for other parameters. As in ML techniques, identification is not an issue because PLS is not a simultaneous estimation procedure. PLS is better suited for explaining complex relationships (Fornell and Bookstein 1982; Wold 1985, pp. 589-590).

2.2. Measured and Unobservable (Latent) Variables in PLS

The concepts of measured and unobservable (latent) variables are the basis of multifacet and multivariate thinking, and therefore of PLS thinking. Latent variables are intuitive or hidden, summarizing variables that are not directly measurable. Measured variables can be measured directly, but they may not relate to the phenomenon or problem under investigation. In univariate situations, the distinction between latent and measured variables makes no sense; it is of interest only in multivariate situations. For example, linear regression equations are used to model the relations between variables, which can be observed either directly (e.g., questionnaire items and financial statement information) or indirectly (latent variables) by multiple indicators. The latent variables can be estimated as weighted or simple aggregates of their indicators. In contrast, the weights for the aggregates and the regression coefficients are estimated in an iterating way by the PLS algorithm (Fornell and Bookstein 1982; Graham et al. 1994). This iterating method provides successive approximations for the estimates, subset by subset, of loadings and structural parameters, based on Wold's (1965, 1980a, b) theory of fixed-point estimation.

In terms of the nature of theoretical variable relationships, some variables can be constrained to be orthogonal. Both recursive and nonrecursive (bidirectional) can be handled via a combination of the fix-point method (Wold 1965) and PLS estimation (Hui 1982). The evaluation of causal relations is based on the predictive quality of the relationships. Comparisons can also be made between the theoretical (hypothesized) correlation matrix and the correlation matrix of the estimated theoretical variables. Overall, the emphasis of PLS is on forecasting, given a certain causal structure. Definitions of the theoretical variables make individual case values for both empirical (predicted) and theoretical variables readily available. Thus, predictions can be made for both types of variables.

3. COMPARISON BETWEEN PLS AND ML

3.1. PLS and ML Methodological Differences

PLS and ML techniques embody very different views of the role of latent variables in the practice of social science. It is not that the techniques interpret a single coefficient differently, but that they compute different numerical values for the same concept. The calculated PLS quantity coefficient is a different number from the ML coefficient, though both claim to represent the correlation between two latent variables. Furthermore, the weights that PLS compute for the latent variables will also be somewhat different from the loadings estimated by ML.

Technically, PLS technique is simple, and it is equally applicable to the complex problems of reproducible and non-reproducible data. To cope with problems that are simultaneously data-rich and theory-primitive, PLS is intermediate between data analysis and the mainstream ML assumptions of contemporary statistics. When latent variables must be indirectly observed by multiple indicators, the PLS and ML approaches become complementary, rather than competitive. The key difference between PLS and ML is thus the explicit estimation of the case values of the latent variables.

One troubling consequence of using ML techniques is improper solutions, of which there are at least two types: (a) a negative error variance may be computed, and, theoretically, a negative variance is impossible; and (b) one or more implausible structural or measurement parameters may be estimated.

3.2. PLS Advantages

For application and prediction, the PLS approach has relative strength when compared with ML approaches. First, PLS uses a principal-component approach where no random error variance or measure-specific variance (i.e., unique variance) is assumed. Parameters are estimated in a manner that maximizes the variance explained in a set of observed measures. This usually results in explaining a large percentage of the variance in the observed variables. Method fit is evaluated on the basis of the percentage of variance explained in the specific regressions. Second, because the PLS approach estimates the latent variables as exact linear combinations of the observed measures, it offers the advantage of exact definition of component scores. Third, PLS allows to both specify the relationships among the principal construct and their underlying items[2], resulting in a simultaneous analysis of both whether the hypothesized relationships at the theoretical level are empirically true, and also how well the measures relate to each construct. The ability to include multiple measures for each construct provides more accurate estimates of the paths among constructs, which are typically downward biased by measurement error when applying multiple regression analysis (Chin 1998). Finally, PLS has been useful in understanding business events in several business disciplines, including marketing (Jagpal 1981; Fornell and Robinson 1983), negotiations (Graham et al. 1994), information technology (Keil et al. 2000; Pavlou 2003; Yoo and Alavi 2001) and business strategy (Cool et al. 1989).

3.3. ML Advantages

ML approaches have several relative strengths for theory testing and development. For the common factor method, observed variables are assumed to have random error variance and measure-specific variance components (together referred to in the factor analysis literature as *uniqueness*, e.g., Harman 1976) that are of no theoretical interest. This undesirable part of the observed variables is excluded from the definition of the latent constructs and is estimated separately. Also, covariances among the latent constructs are adjusted to reflect the attenuation in the observed covariances due to these unwanted variance components. Due to this assumption, the amount of variance explained in the set of observed variables is not of primary interest. Therefore, full-information methods provide parameter estimates that best explain the observed covariances. ML methods also provide the most efficient parameter estimates (Anderson and Gerbing 1988) and an overall test of method fit. However, because of the underlying assumption of random error and measure specificity, there is inherent indeterminacy in the estimation of factor scores (Steiger 1979). This is not a concern in theory testing, whereas in predictive applications it is likely to result in some loss of predictive accuracy.

3.3.1. Reflective and Formative Factors

PLS provides a very important relation between theoretical (unobservable) and empirical (observable) variables. Often the links between these two types of variables are referred to as epistemic or correspondence rules (Fornell and Bookstein 1982). This paper demonstrates how PLS embodies two types of epistemic rules - *reflective* and *formative*. ML embodies ***only*** reflective rules, which may cause problems of parameter interpretation. That is, reflective indicators suggest that one or more underlying unobservables "cause" the observables. Examples in management might be loan officers or auditors' perceptions and judgments, which are unobservable and are typically considered underlying causes of overt behavior or of measured scores on decision tasks' scales. That is, the observable variables represent a lower level of cognitive processing, but yet one that is important. They represent observable responses resulting from one's unobservable cognitive processes. It is the unobservable concepts or conceptual system that produces individuals' responses on tests, experimental questionnaire items, among others. Often times these traces or responses are implemented in research studies to reflect higher order mental processes, such as judgment. However, higher-level operations should be captured by unobservable concepts (Rodgers 1991).

If formative indicators are used, the unobservables are considered effects rather than causes. An example of formative indicators is the theoretical variable when it is indeed "formed" from one or more observables; e.g., consider "liquidity" as an abstract construct composed of observable variables, such as the current ratio, quick ratio, working capital ratio, and so forth. Most accounting research that demands the use of archival data, such as capital markets research, auditing firm information, internal managerial cost information, etc., requires formative relations, hence cannot be estimated with ML. PLS is most flexible in terms of allowing a researcher to specify both reflective and formative relations.

3.3.2. Higher-Order Factors

Higher-order factors are often used to explain the interrelations among their lower-order variables and constitute an integrative latent construct. The development of higher-order structures is useful for capturing multiple facets of a complex construct that could be subsumed with a unidimensional factor, provide insight into the nature of a phenomenon and the inter-relationships among its underlying factors, and provide a more accurate description of a theoretical construct that can be applied to organizational processes (Segars and Grover 1998). A higher-order factor estimation approach is also a parsimonious explanation of the covariance among the first-order factors.

Similar to first-order constructs, the relationship between lower (first) and higher (second) order constructs refers to epistemic or correspondence rules (Fornell and Bookstein 1982), which can be of two types – reflective or formative. First, reflective structures assume that the latent second order construct "causes" the first order factors (which are indirect constructs and not direct measurement items). Second, for formative structures, the second order factors are conceived to be outcomes caused by the first order factors. These multi-dimensional constructs may not be internally consistent to each other, and the first-order dimensions may not even be correlated. Whereas ML techniques cannot estimated formative higher-order factors, PLS can estimate both reflective and formative higher-order factors.

In PLS, higher-order factors can be approximated using two common procedures (Chin et al. 2003). One approach, which can be estimated by the standard PLS algorithm, uses repeated indicators following Lohmoller's (1989,130-133) hierarchical component method by directly measuring higher-order constructs by observed variables for all the lower-order factors. The second approach methods the paths from the lower order to the overall higher order construct ("molar construct"), and it is used to examine the relative path weights as this "molar construct" is used to predict other constructs (Chin and Gopal 1995). In this procedure, weights of formative constructs are treated as betas in a regression analysis, and the variance explained for the second order constructs will always be unity[3]. Loadings of measurement items for each lower-order construct are loadings taken from a principal components factor analysis. A more detailed description of the PLS estimation procedure for higher-order factors is provided in Appendix 3.

3.3.3. Interaction Effects

Interaction effects are common for estimating moderated relationships, testing contingency hypotheses, and examining conditions under which relationships between variables may vary due to other variables. Whereas the most common techniques employed for testing interaction effects is regression or ANOVA analysis, PLS has a superior advantage over ML. Evidence from the literature suggests that, compared to PLS, ML techniques are technically more demanding, more often cause analytical errors, and may converge less often, especially for small sample sizes and several interaction effects (Bollen and Paxton 1998; Ping 1995). Chin et al. (2003) proposed and tested a new product-indicator approach where the interaction effect is estimated as a latent moderator variable Z (Z=X*Y), formed by the product of all standardized indicators of constructs X and Y. According to the authors, compared to ML and regression techniques, their proposed PLS product-indicator approach is superior in detecting significant interaction terms, a common problem faced by social scientists.

4. EMPIRICAL STUDIES USING PLS

This section reviews accounting research studies that have employed PLS technique[4]. Accounting studies using PLS as the primary data analysis are those of Chenhall (2004), Ittner et al. (1997), Ittner and Larcker (1998), Laitinen (2004), Morril and Morril (2003) and Rodgers (1999)[5]. Chemhal (2004) examined the extent to which cognitive and affective conflict are involved in the relationship between activity-based cost management (ABCM) behavioral implementation factors and the usefulness of ABCM during early applications of the systems. He proposed three constructs of ABCM behavioral implementations: top management support, clarity and consensus of objectives and training. PLS results of a survey study of 56 managers indicated that cognitive conflict intervenes between ABCM behavioral implementation factors and beneficial outcomes. However, there were no significant associations between behavioral implementation factors and affective conflict. Chemhal (2004) emphasized that the use of PLS enables an overall assessment of the construct validity of multi-item variables within the total method.

Ittner et al. (1997) investigated the factors influencing the relative weights placed on financial and non-financial performance measures in CEO annual bonus contracts. They used PLS in the analysis of data from 317 firms for the year 1993 to 1994. PLS results highlighted that the use of non-financial measures increases with the level of regulation, the extent to which the firms follows an innovation-oriented strategy, the adoption of strategic quality initiatives, and the exogenous noise in financial performance measures. In this particular case, the authors justified the appropriateness of PLS analysis since this approach explicitly mitigates the impact of measurement error in the structural equation coefficients. Thus, hypotheses tests based on those coefficients (latent variables) should be less confounded by measurement error than traditional regression techniques.

Ittner and Larcker (1998) discussed whether customer satisfaction indicators are reflected in accounting book values, and if such indicators provide incremental information to the stock market. They used a sample consisting of 2,491 business customers buying a specific service. A customer satisfaction index was constructed using PLS. These items consisted of customers' self reports of recommendations, repurchase intentions, and price tolerance. Results indicated that public disclosure of customer satisfaction measures provides information to the stock market on expected future cash flows. The authors argued that PLS provided superior measurement properties relative to other methods.

Laitinen (2004) examined the ability of non-financial factors to predict value (shareholder book-value) in technology firms. From a postal survey carried out in 1999 for 40 Finnish firms, non-financial variables were classified into six categories: organizational characteristics, strategy, competitive stance, consistency of performance measurement, management control systems (MCS), and quality of MCS. PLS results provided support for the structural approach, highlighting the incremental information of non-financial factors over financial ratios when predicting value drivers, such as growth, profitability, and risk.

Morrill and Morrill (2003) used transaction cost economics (TCE) to explore the conditions under which organizations encourage internal audit participation in the external audit process. They identified three groups of latent variables related to internal audit participation in the external audit: behavioral uncertainty, external uncertainty and specific investment. PLS analysis of survey data collected from 130 directors of Canadian internal audit departments indicated that only audit-specific expertise is strongly associated with internal audit participation in the external audit. The authors emphasized the appropriateness of PLS for three main reasons: (1) in their analysis TCE constructs were not directly observable; (2) many indicators they used were ordinal in nature; and (3) sample size was limited.

Rodgers (1999) indicated that when a decision maker predicts a financial event, a distinction can be made between judgments about possible values for the event and decisions that a given prediction is correct. Forty commercial loan officers and 67 MBA students were told to compare the importance of various information items in forming their decisions about whether a company should receive an unsecured line of credit for one year. PLS was used to categorize subjects perceptions, judgments and decision choices as reflective higher-order factors. Financial information depicted by liquidity, leverage and profitability were captured by formative higher-order factors. Results indicated that novices concentrated only on accounting information, whereas the commercial loan officers used both accounting and non-financial information. Implications supported the notion that PLS embodies decision makers cognitive processes (reflective factors), and financial statement information (formative factors), which are necessary to model their processes and management concepts, respectively.

5. THE PROCESSING METHOD

Hogarth (1981) advocated that behavioral decision research need to focus on continuous prediction occurring in dynamic and complex task environments. Real-world decision-making would be approximated more closely if laboratory researchers adopted such a framework (Kleinmuntz 1990). The approach used in this paper to compare PLS and ML techniques captures a simulated continuous and dynamic laboratory task environment. This approach could lead to new insights about predicting decision making in an information processing context.

For two major reasons, this study is important when examining the effects of financial statement information on bankers' actions. First, a significant portion of auditors' clients are small to medium sized companies with ownership limited; their creditors may be the principal external users of these companies' financial statements. Second, banks lend millions of dollars each day to businesses without collateral or security of any kind, depending on estimates of ability to repay based on the financial statements prepared by accountants (Rodgers 1984).

A two-stage loan making laboratory task is used in this study to highlight real-world decision making (e.g., Rodgers and Housel 1987; Rodgers and Johnson 1988). Loan officers share very similar educational backgrounds, particularly the kinds of training they receive to qualify as loan officers. In the first stage of training, certain necessary conditions are covered before actual analysis of the financial accounting information is begun in the second stage. These conditions represent perceptions of a company's economic, management, and financial risk factors. Also, these conditions are fundamentally related to the credit policy, philosophy, and procedures of the lending institutions (Altman 1980). Loans are made or not made, based upon these representations (Rodgers and Housel 1987). In this study, decision makers' first stage of processing includes their representations both of economic and management risk factors, and also of which accounting information they consider represents financial risk. The three risk factors discussed below are part of decision makers' preliminary credit decisions and may impact their information analysis (i.e., second stage of processing), thereby influencing their loan decisions (Rodgers 1992).

First, decision makers' economic risk perception includes (a) characteristics of the industry (e.g., susceptibility to economic fluctuations), (b) economic climate (e.g., forecasts of the gross national product), (c) company forecasts (e.g., product innovation), and (d) government regulations (e.g., potential impact on industry and company). Second, their management risk perception includes (a) management capability (e.g., well defined objectives and goals), (b) adequate controls (e.g., timely, consistent monitoring, and measurement of progress towards identified objectives), and (c) sound organization and adequate depth (e.g., plan to develop future management). Finally, financial risk may be measured by (a) liquidity (e.g., current ratio), (b) income (e.g., net margin ratio), and (c) risk (e.g., debt/net worth ratio).

Judgmental representation processes, referred to as the next step in the decision making process, require more analysis of the information (Rodgers and Johnson 1988). Hastie et al. (1984) also distinguished between decision processes based on whether or not information has been encoded in accord with an earlier process. *Perceptually based* decisions occur in the first stage, and *memory (judgment) based* decisions occur in the second stage. It is in the judgmental representation processes that certain analytical tools from loan analysis training are used for the interpretation of financial, economic, and managerial information. For example, Rodgers and Housel (1987) demonstrated that before loan officers arrive at their decisions in their judgmental representation processes, they place a significant weight on analyzing financial information.

The cognitive method illustrated in Figure 1 depicts the effects on decision choice of economic, management, and financial risk factors, and judgment. Circles 1-7 represent the theoretical constructs of these processes. Since information is processed subjectively by individuals, it is interdependent with economic and management risk *perceptions* in the conceptual approach (Anderson 1985; Rodgers 1992). Risk *perception* does not only affect judgment but also affect decision choice. For example, loan officers may bias their loan decisions by relying heavily upon their preliminary analysis (i.e., risk perceptions) and bypass the need for a serial search (or analytical analysis) through the judgmental stage (Schneider and Shiffrin 1977).

Liquidity, income, and risk *information* (circles 3-5) also affect judgment. That is, *information* stored in memory affects the judgmental representation processes of individuals. Since the effects of financial accounting information are considered in this method, three major independent concepts were used: liquidity, income, and financial risk. These concepts were chosen because a number of studies point to their significance as indicators of loan approval (e.g., Rodgers and Johnson 1988).

Next, economic and management risk perceptions affect not only judgment but also decision choice. For example, loan officers may bias their loan decisions by relying heavily upon their preliminary analysis (e.g., economic risk perception) and bypass the need for a serial search (or analytical analysis) through the judgmental representation stage (Rodgers and Housel 1987). Finally, judgment affects decision choice of granting or not granting a loan.

5.1. Empirical Comparison of PLS and MLS

To explore the differences between ML and PLS, an experimental setting is proposed. The cognitive approach discussed in this paper is ideal for showing the impact of different types of accounting information on decision makers' judgments. In the first processing stage, subjects were presented with positive (or negative) economic and management information when financial statement information was negative (or positive). Presumably, economic and management risk perceptions should not have a significant affect on individuals' judgments or decision choices; that is, individuals will place more weights on financial statement information (i.e., liquidity, income, and risk information) based upon their training in loan analysis techniques. In the second stage, judgment is assumed to have a significant effect on decision choice, and decision makers' analysis of the problem should influence the accuracy of their choice. If the subjects have been trained properly in loan analysis techniques, confidence and accuracy will covary.

6. METHODS

6.1. Subjects and task

In this experiment, subjects were required to evaluate (a) whether four different companies should obtain short-term financing and (b) to express their confidence in their evaluation. Subjects were provided company data consisting of financial statement information for two companies classified (by Moody's classification of bonds and stocks) as "good" credit risks (B = "good" companies) and for two described as "bad" (C = "bad" companies). The order of presentation of these companies was random across subjects. The company data provided was obtained from three years of Compustat tapes and consisted of ratios, income statement, balance sheet, and statement of changes in financial position. This procedure allowed for a sampling of independent responses from the subjects[6]. Appendix 1 shows data for a sample company and contains a copy of the instrument used to collect responses.

The subjects for this research were 67 MBA students enrolled in a credit analysis course at a Midwest school. Total sample size (responses) was based upon the subjects times the four cases, that is, 67 * 4 = 268. Out of the 268 total cases, 8 were incomplete, leaving 260 independent observations to be analyzed. The cases and the measurement instruments were delivered to each subject in class. For each company rated "good," *hypothesized* economic and management information from the questionnaire was negative. For each company rated "bad," *hypothesized* economic and management information was positive. This was done deliberately to cause a biasing effect on subjects' judgments and decisions. Subjects received extra credit for completing the cases. Average completion time for the entire task was one hour.

"Bankers" hypothesized behaviors under study were discussed in several class meetings before the experiment. In the instructions, subjects were told to act as "bankers" and compare the importance of various information items before forming their decisions about whether a company should receive an unsecured $1,000,000 line of credit for one year (see Appendix 1). Subjects were asked to record their degree of confidence by placing a tick-mark along a four-inch scale interval scale for three sets of questions that reflected their perceptions (economic and management risk factors), judgments, and decision choices. The independent variables are financial statement information and perceptions of economic and management risk factors, while the dependent variables are the subjects' judgments and decision choices. Economic and management risk factors relate to biased information that the subjects use for their predispositions of a company's future performance; judgments relate to their current analysis of the company's liquidity, profitability and leverage in terms of a short term obligation.

6.2. Method Equations

Structural \equations for the first stage, which represent the processing effects of economic risk factors, management risk factors, and information on judgment, are shown below in (1). Equations for the second stage, which represent effects of economic risk factors, management risk factors, and judgment on decision choice, are shown in (2):

$$\eta_1 = \beta_1\gamma_1 + \beta_2\gamma_2 + \beta_3\gamma_3 + \beta_4\gamma_4 + \beta_5\gamma_5 + \varepsilon \qquad (1)$$

$$\eta_2 = \beta_6\gamma_1 + \beta_7\gamma_2 + \beta_8\eta_1 + \varepsilon \qquad (2)$$

Interpreted in the context of a multiple regression equation, Equation 1 indicates that the β_1 value for the effect of economic risk factor on η_1 is the effect of economic risk factor after having controlled in the equation for β_2 (management risk factor), β_3 (liquid assets), β_4

(income), and β_5 (risk) variables. Equation 2 shows the β_6 value for the effect of economic risk factor on η_2 after having controlled for β_7 (management risk factor) and β_8 (judgment). Finally, ε represents the residual error.

6.3. Procedure

γ_1 represents subjects' economic risk perception. This latent variable is measured by the following two indicators (see Appendix 1): (1) Industry sales increased (decreased), and (2) government deregulation has increased (decreased) the company's product cost. γ_2 represents subjects' management risk perception. This latent variable is measured by the following two indicators: (1) Recent management policy changes have increased (decreased) stock price, and (2) management's experience with the company's product lines has increased (decreased). γ_3, γ_4, and γ_5 are measured in terms of liquid assets, income, and risk of a company, respectively. γ_3 is measured by the current and quick ratios. γ_4 is measured by net margin and the return on equity ratios. γ_5 is measured by debt/equity and current liability/equity ratios. These ratios were used in the method because loan officers generally rely on these ratios when they are considering a short-term loan request (Rodgers and Johnson 1988), because they represent, respectively liquidity, income, and risk.

η_1 (equation 1) represents subjects' judgments. Judgment is also represented in equation 2 by η_1. This latent variable of subjects' analysis of a company's information and their evaluation of the loan is measured by five indicators, which represent (1) bank's share of risk, (2) liquid assets of the firm, (3) firm's profitability, (4) firm's credit rating, and (5) bank's classification system of the loan. η_2 (equation 2) represents subjects' decision choices, a latent variable that is measured by two indicators: whether the loan should be approved, and conditions of the loan.

According to the approach depicted in Figure 1, economic risk perception and management risk perception directly affect judgment (β_1, β_2) and decision choice (β_6, β_7). Economic risk perception, management risk perception and financial statement information are correlated. Financial information directly affects judgment (β_3, β_4, β_5), and judgment affects decision choice (β_8) directly.

The above judgment and decision choice questions were selected on the basis of bank procedures for analyzing business loan applications on a normative basis (see Shaw and Gentry 1988). Also, empirical results that support these indicators were based on the practices observed by Cohen et al. (1966) at two large banks. They found very similar results, even when the loan officers were located in different cities.

6.4. Data Analysis

One of the models was estimated using ML with the computer program LISREL 7 (Joreskog and Sorbom 1988). The other latent variable path analysis used PLS (Version 1.8). PLS follows the methods described initially by Wold (1966, 1983), elaborated by Bookstein (1982), and programmed by Lohmoller (1984). The Latent Variable Path (LVP) is a combination of a factor model (measurement model) and a path model (structural equation model). In the factor model, the relation between observed variables and unobserved (latent) variables is represented by a linear equation system. In the path model, it is the relation between the latent variables that is represented by a linear equation system. The LVP model is common to several modeling programs, such as Joreskog and Sorbom’s LISREL (1988), Bentler’s EQS (1989), and Muthen’s LISCOMP (1985). The use of a rapid least-squares based estimation technique (Lohmoller, 1988) is a main advantage in PLS (Appendix 2).

6.5. Relationship between unobserved and measured variables

In our PLS model, observed indicators could be treated as either reflective or formative. The ML method can represent only reflective indicators, which are the typical indicators of classical test theory and factor analysis techniques. They are invoked in an attempt to account for observed variances or covariances, but they suggest that the observables are “caused” by one or more underlying unobservables. Economic risk factor, management risk factor, judgment, and decision choice are unobservable and are considered underlying causes of measured scores on the questionnaire scales. Following standard practice, theoretical variables are indicated by circles, observed variables by squares.

Formative indicators, in contrast, are not designed to account for observed variables; they are used to minimize residuals in the structural relationship. With formative indicators, the unobservables are assumed to be effects rather than causes. Consequently, the arrowheads are directed toward the theoretical variable. An example of a formative indicator is a theoretical variable, which has actually been “formed” from one or more observables. In the PLS, we may consider liquidity, income, and risk information as abstract constructs composed of financial statement information.

Finally, the indicator modes used are shaped by substantive theory behind the model. Constructs, such as *economic risk perception*, *management risk perception*, *judgment*, and *decision choice*, are typically viewed as underlying factors that give rise to something that is observed. Their indicators tend to be realized, then, as reflective. In contrast, when constructs are conceived as explanatory combinations of indicators (such as liquidity or income) that have been determined by a combination of variables, their indicators should be formative (Fornell and Bookstein 1982).

7. RESULTS

7.1. PLS Results

The measurement model enables us to evaluate whether the constructs are measured with satisfactory accuracy. The means and standard deviations for the observed variables are displayed in Table 1. As with EQS and LISREL, convergent and discriminant validity can be evaluated within the PLS model. According to Chin (1998), convergent and discriminant validity is inferred when the PLS indicators (a) load much higher on their hypothesized factor than on other factors (own-loadings are higher than cross-loadings), and (b) when the square root of each construct's Average Variance Extracted (AVE) is larger than its correlations with other constructs (the average variance shared between the construct and its indicators is larger than the variance shared between the construct and other constructs). Convergent validity of a construct is measured by the ratio of the amount of variance of its indicators captured by the construct, relative to the total amount of variance. This includes the variance of its indicators captured by the construct, relative to the total amount of variance, including the variance due to measurement error ("average variance extracted" o_{VC}). As a rule, a ratio of less than 0.50 is judged inappropriate as more variance is due to error. Satisfactory discriminant validity among constructs is obtained when the squared correlation between any two constructs is statistically less than the o_{VC}. This implies that the variance shared between any two constructs is less than the variance shared between a construct and its indicators. Table 2 contains the PLS parameter estimates for the *measurement* model. Average variance extracted (o_{VC}) ranges between 0.66 and 0.98 (except for economic risk perception, o_{VC}= 0.36), indicating satisfactory convergent validity for the constructs. In addition, the low and moderate average squared correlations among constructs show that the model also satisfies the condition for discriminant validity. Thus, it can be concluded that the constructs are measured with sufficient precision.

The results from the decision making model are shown in Table 2. Since the estimates from PLS are standardized, the coefficients relating the theoretical variables can be interpreted as beta coefficients (β), and the coefficients connecting constructs to the observed level as loadings (see Appendix 2). Before the relations at the theoretical unobserved level can be interpreted, the measurement model should be examined in terms of validity. Ideally, measurement residuals (ε and δ) should be small, and the loadings should have the proper signs (i.e., non-negative). In Table 2, most of the loadings have consistent signs, and most residuals are small. Thus, it can be concluded that the measurement model satisfies criteria for convergent validity.

The next discussion relates to the model equations (1) and (2). Liquidity and income are the most powerful constructs in terms of their effect on judgment (see Table 2). Also, economic and management risk perceptions are significantly correlated with liquidity and income (see Tables 3a and 3b). That is, since liquidity and income information are subjectively processed by individuals based upon their perceived importance in reducing uncertainty, they are interdependent with economic and management risk perceptions. Finally, the financial statement information latent concepts of liquidity, income, and risk are significantly correlated at the $p<.05$ level. Since financial statement information items are interrelated, it follows that the formative concepts should also show a relationship.

Economic risk perceptions did not have a significant effect on judgment, whereas, management risk perceptions had no significant effect on either judgment or decision choices. These results from the first stage of the model do not support those reported by Oskamp (1965); that is, our subjects were able to recognize when information was not useful in loan prediction. Economic risk perceptions, however, did have a significant effect on decision choice. Economic risk perceptions may also be part the hypothesis testing process as well as the hypothesis generation process. This suggests that the subjects placed a degree of confidence in their economic risk perceptions when making decisions about loan approval. Also, our results partially support Peterson and Pitz's (1986) suggestion that decision makers may use different pathways (i.e., estimates) before arriving at a decision. Finally, judgment had a significant effect on decision choice. In the problem analysis (i.e., judgment) stage, the decision makers' level of confidence was apparently determined by how accurate they believed the financial statement information (which influenced their choice) was.

Subjects made correct loan decisions in 86 percent of the cases, based upon Moody's classification of bonds and stocks. The results from a non-parametric chi-square test (Table 4) indicated that subjects made better decisions for companies classified as "good" than for those classified as "bad" ($p<.05$). These results can be explained partially by the effect that economic risk perceptions have on decision choice. That is, subjects may have tended to rely upon the economic information when it depicted above average conditions. Using additional information may be a symptom of increased uncertainty, but such use did not enhance accuracy. Oskamp's (1965) study also indicated that additional information might increase a decision maker's confidence without increasing accuracy.

7.2. ML Results

The results from the ML decision-making method are shown in Table 5. Since the estimates from ML are standardized, the coefficients relating the theoretical variables can be interpreted as beta coefficients (β) and the coefficients connecting constructs to the observed level as loadings. In Table 5, most of the loadings have consistent signs and most residuals are small.

Certain limitations arise when using chi-square as a valid statistic for the LISREL technique. That is, large sample sizes tend to increase chi-square over and above what can be expected due to specification error. To deal with this problem, in this paper one reasonable way was implemented, the use of non-statistical chi-square fit indices (see Table 5). In all cases of the indices, the overall fit was good.

The next discussion relates to the structural equations below:

$$\eta_1 = \beta_1\gamma_1 + \beta_2\gamma_2 + \beta_3\gamma_3 + \beta_4\gamma_4 + \beta_5\gamma_5 + \varepsilon \quad (1)$$

$$\eta_2 = \beta_6\gamma_1 + \beta_7\gamma_2 + \beta_8\eta_1 + \varepsilon \quad (2)$$

Only risk information had a significant effect on judgment at the $p<.05$ level of significance (Table 5). Also, economic and management risk perceptions are significantly correlated (see Table 3). As in the PLS, the financial statement information latent concepts of liquidity, income, and risk are significantly correlated at the $p<.05$ level.

Economic and management risk perceptions did not have a significant effect either on judgment or on decision choices. Finally, judgment did have a significant effect on decision choice. Apparently, decision makers were able to express their confidence in the problem analysis (i.e., judgment) stage. Their level of confidence in this stage was determined by how accurate they believed the financial statement information was on which they based their choice.

7.3. Comparison between PLS and ML

The PLS method, with a coefficient of determination (R^2) index of 0.59 explained more than the ML approach, which had an R^2 of 0.50. The interrelation assessments among the unobserved theoretical variables include examining the explained variation in the exogenous (independent) constructs, the size and sign of the endogenous constructs, and the significance of these coefficients. The results indicate that in the PLS the variance explained is higher than in the ML: 58 percent of the variation in judgment (compared to 49 percent for the ML method) and 88 percent of the variation in decision choice are accounted for (compared to 86 percent for the ML method). Since the primary purpose of PLS is to predict empirical and/or theoretical variables, these results are understandable. In other words, the PLS residual variances are minimized more than in the ML method (see Tables 2 and 5). That is, PLS estimation relies on an iterating procedure involving the minimization in each step of some residual variance with respect to a subset of the parameters, given either a proxy (fix-point constraint) or final estimates for other parameters.

In the PLS approach, liquidity and income information significantly affected judgment, whereas in the ML method only risk information significantly affected judgment. Rodgers and Johnson (1988) argued that liquidity and income information constructs are most influential when analyzing short-term credit for a company. ML embodies only reflective rules, a practice which may cause problems of interpreting parameters; reflective indicators suggest that underlying unobservable(s) may "cause" the financial statement information. Formative indicators, in contrast, are not designed to account for observed variables; they are used to minimize residuals in the structural relationship. With formative indicators in the PLS approach, the unobservables are conceived of as effects rather than as causes. Also, the PLS depicted the significant correlations of the independent variables (i.e., economic and management risk with liquidity and income) in light of the experimental manipulation of bad (good) economic and management information with good (bad) financial statement information. The ML method did not illustrate these important relations among the independent latent concepts. Again, since the PLS uses formative indicators, more explained variance is used at the latent concept level to better capture the interactions of the important independent concepts.

Also, factor indeterminacy may have caused the ML technique's risk information to be significant instead of liquidity and income information. That is, a negative variance in the error term (δ_{10} in Table 5) and standardized loading greater than one are unacceptable results. PLS does not produce improper estimates, as all residual variances are actual regression residuals; they are not inferred from the data.

The PLS results are thus interpretable. The approach is satisfactory insofar as the measurement residuals are small and the loadings are significant. Overall, the PLS estimates provide support for the significance of liquidity and income information on judgment. The ML estimates suggest several possibilities: (1) the theory is wrong, (2) the data are inaccurate, (3) the sample size is too small, or (4) covariance structure analysis is not appropriate for the analysis task.

8. DISCUSSION

8.1. Key Findings and Comparisons

This study described an experimental setting that highlighted the difference between ML and PLS techniques. The PLS results illustrated the impact of different types of accounting information on decision makers' judgments. In the first processing stage, subjects were presented with positive (or negative) economic and management information when financial statement information was negative (or positive). The results further indicated that economic and management risk perceptions did significantly affect individuals' judgments. That is, individuals placed more weights on financial statement information (i.e., liquidity and income information in the method) based upon their training of loan analysis techniques.

For the forecasting analyst, ML and PLS techniques apply to the same class of covariance structural equations with unobservable variables and measurement errors. However, these techniques have the following different structures and objectives. First, ML attempts to account for observed covariances, whereas PLS aims at explaining variances (of variables observed and/or unobserved). Second, ML offers statistical precision in the context of stringent assumptions; PLS trades parameter efficiency for prediction accuracy, simplicity, and fewer assumptions. Third, ML requires relatively large samples for accurate estimation and relatively few variables and constructs for convergence; PLS is applicable to small samples in estimation as well as testing, and appears to converge quickly even for large samples with many variables and constructs. Even if not portrayed in the paper's empirical example, this becomes particularly important when interaction effects are present (Chin et al. 2003). Finally, both techniques are able to treat measurement residuals, but they do so in different ways; PLS separates out "irrelevant" variance from the structural portion of the constructions, while ML combines specific variance and measurement error into a single estimate (adjusting for attenuation).

Latent variables' primary purpose is *predictive*, that is, to summarize the implications on blocks of variables for each other. PLS is a technique that accomplishes this purpose. However, ML's tests and estimates are, instead, based on the entire square correlation matrix, which relates (i) variables in different blocks, and (ii) within block correlations of the variables among themselves. In predictive applications, we are not interested in these two aspects of fit. Whether a single block requires more than a single latent variable for explaining its own covariances is irrelevant. ML's chi-square statistic, in attending too closely to improvements in the fitting of the within-block correlations, pays remarkably little attention to the predictive correlations.

The PLS and ML approaches to path constructions with latent variables observed by multiple indicators are complementary, rather than competitive. That is, when a given problem is structured into a model for statistical analysis, all theoretical information available should be incorporated in the model to improve accuracy and power in the statistical inference. ML is very useful in problem areas where the models are relatively simple, namely, when the stringent frequency assumptions behind its optimality aspirations are realistic and when the ML technique is not hampered by too many parameters to estimate. However, when the problem under analysis becomes more complex, the stringent frequency assumptions of ML become less tenable, and the optimality aspirations become more or less illusory. Then PLS is useful, since its estimation technique aims at consistency in the statistical inference rather than at optimality, and provides "instant estimation", even for large constructions with a large number of estimates parameters.

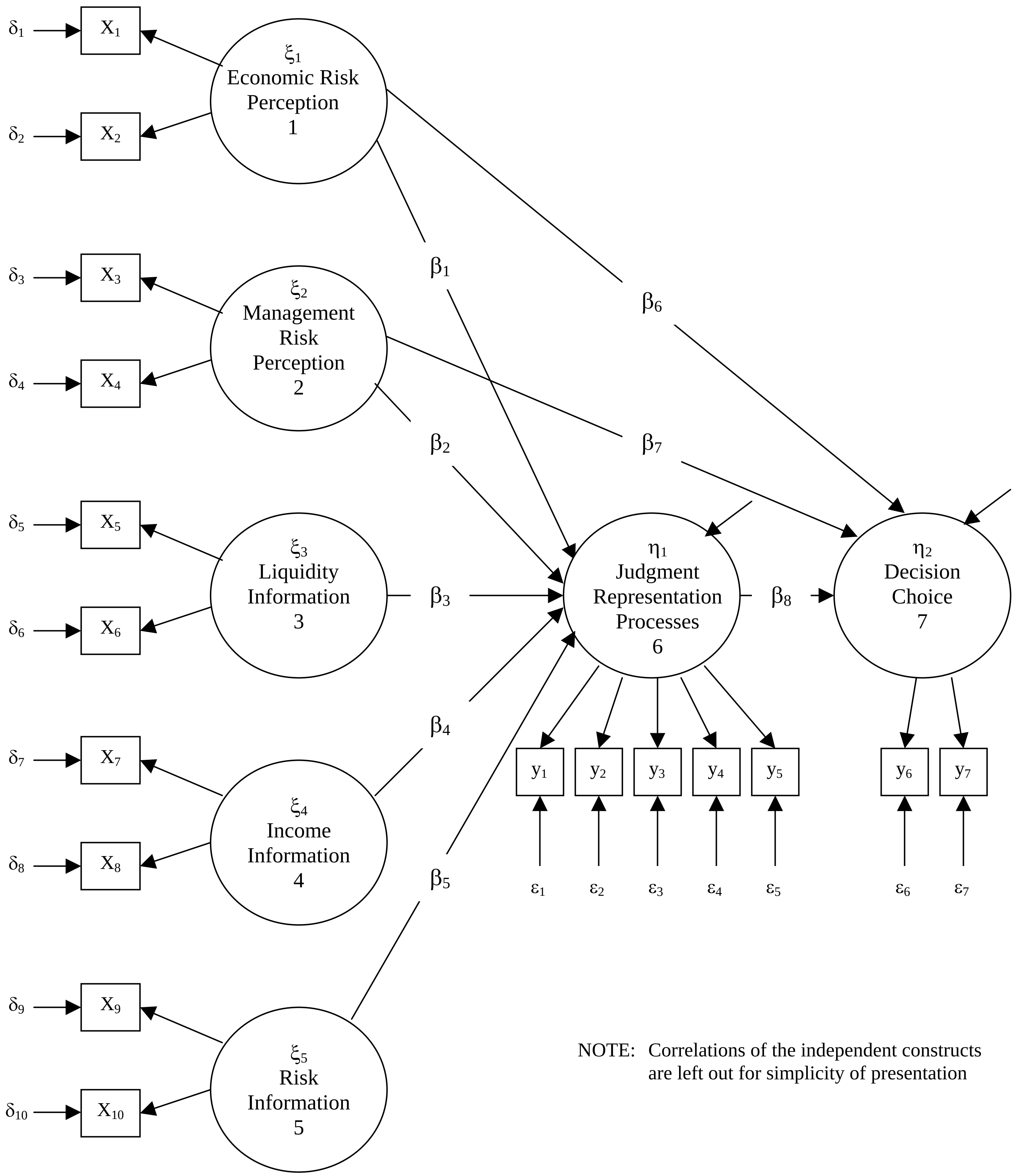
8.2. Limitations and Suggestions for Future Research

PLS allows researchers to test their hypotheses and their assumptions through *reflective* and *formative* indicators. As highlighted in this paper, decision makers' economic and managerial perceptions/judgments of an organization are better captured by formative factors. Conceptually, reflective higher-order factors imply trace knowledge sources of a decision maker. In other words, higher-order factors capturing decision makers' perceptions and judgments represents their response from surveys, experiments, and protocols. Financial statement information, which is depicted to capture liquidity, leverage and profitability concepts lean more to formative factors. These formative higher-order factors combine several pieces of accounting information into one concept representing a financial or managerial view of information. In sum, reflective higher-order factors can better capture knowledge from auditors, bankers, investment analysts, etc., when they are analyzing accounting and managerial information. The formative higher-order factors helps to shape important accounting and managerial concepts such as cash flow, liquidity, activity, profitability, leverage and new non-financial metrics.

9. CONCLUSION

Without loss of generality, the PLS method can be implemented when information is viewed as unobservable variables. It is also useful when problems arise due to violations of multinormality and the necessity of a large sample size. This study emphasizes how PLS can overcome these problems. In contrast to ML procedures, the fixed-point estimation of PLS is distribution-free and can be readily applied to small-sample-size problems. PLS applications can range from forecasting socioeconomic and behavioral sciences with non-experimental and non-reproducible data to the social sciences with experimental and reproducible data (see Rodgers 1991). PLS is also relatively easy to use and is fast on the computer. Also, PLS is designed primarily for systems analysis and other research contexts that are simultaneously data-rich and theory-primitive. Finally, PLS approaching is also very instrumental for application to data-rich situations with an elaborate theory. This is a broad problem area beyond the scope of ML techniques.

Figure 1. The Proposed Approach for Management Financial Decision Making



NOTE: Correlations of the independent constructs are left out for simplicity of presentation

Table 1. Means and Standard Deviations

SYMBOL	*NAME*	*MEAN*	*STANDARD DEVIATION*
X_1	Industry sales	18.054	12.204
X_2	Government regulation	18.027	11.439
X_3	Management policy changes	26.762	14.297
X_4	Management experience	24.650	13.517
X_5	Current ratio	1.328	0.630
X_6	Quick ratio	0.885	0.339
X_7	Net margin	-0.258	3.931
X_8	Return on equity	-9.508	29.663
X_9	Debt/equity	314.750	171.175
X_{10}	Current liability/equity	170.000	119.492
Y_1	Bank's share of risk	48.573	24.712
Y_2	Liquid assets of firm	49.708	24.251
Y_3	Firm's profitability	47.692	24.674
Y_4	Firm's credit rating	49.285	23.254
Y_5	Bank's classification of loan	48.192	24.110
Y_6	Loan approval	35.454	21.308
Y_7	Conditions of loan	331.992	130.696

Table 2. Measurement Parameter Estimates for the PLS technique

CONSTRUCTS AND INDICATORS	*LOADINGS*	*ERROR VARIANCE*	*CONVERGENT VALIDITY*	*DISCRIMINANT VALIDITY*[A]
Economic Risk Perception			0.36	0.01
Industry sales	0.75	0.43		
Government deregulation	-0.40	0.84		
Management Risk Perception			0.66	0.01
Recent management changes	0.80	0.36		
Management's experience	0.82	0.34		
Liquidity Information			0.86	0.43
Current ratio	0.92	0.16		
Quick ratio	0.93	0.14		
Income Information			0.96	0.46
Net margin	0.97	0.06		
Return on equity ratio	0.95	0.10		
Risk Information			0.74	0.47
Debt/equity ratio	0.99	0.02		
Current liability/equity ratio	-0.71	0.50		
Judgment representation processes			0.76	0.42
Bank's share of risk	-0.55	0.70		
Liquid assets of the firm	0.88	0.23		
Firm's profitability	0.90	0.18		
Firm's credit rating	0.97	0.06		
Bank's classification system	0.98	0.04		
Decision choices			0.98	0.43
Whether the loan should be approved	0.99	0.01		
Conditions of the loan	0.99	0.01		

[A] The entry in each row is the average of the squared correlations of the particular construct with all other constructs.

Table 3a. PLS Independent Latent Variables Correlation

	1 Economic Risk Perception	2 Management Risk Perception	3 Liquidity Information	4 Income Information	5 Risk Information
1 Economic Risk	1.00				
2 Management Risk	-.06	1.00			
3 Liquidity	-.10**	-.10**	1.00		
4 Income	-.12*	-.10**	.85*	1.00	
5 Risk	.05	-.09	.89*	.92*	1.00

Table 3b. Maximum Likelihood Independent Latent Variables Correlation

	1 Economic Risk Perception	2 Management Risk Perception	3 Liquidity Information	4 Income Information	5 Risk Information
1 Economic Risk	1.00				
2 Management Risk	.07**	1.00			
3 Liquidity	.09	-.03	1.00		
4 Income	.01	-.04	.83*	1.00	
5 Risk	-.02	.03	-.73*	-.87*	1.00

*Significant at $p < .05$
**Significant at $p < .10$

Table 4. Non-Parametric Chi-Square Goodness of Fit Test

Loan types	*TOTAL CORRECT DECISIONS* f_o	*TOTAL OBSERVED DECISIONS* f_e	f_o-f_e	$(f_o-f_e)^2$	$\frac{(f_o-f_e)^2}{f_e}$
"Good"	117	130	-13	169	1.300
"Bad"	106	130	-24	576	4.431
				chi-square	5.731*

*Significant at $p < .05$

Table 5: Measurement Parameter Estimates for the ML technique

CONSTRUCTS AND INDICATORS	*LOADINGS*	*ERROR VARIANCE*
Economic Risk Perception		
Industry sales	0.42	0.82
Government deregulation	0.71	0.48
Management Risk Perception		
Recent management changes	0.36	0.87
Management's experience	0.84	0.29
Liquidity Information		
Current ratio	0.75	0.44
Quick ratio	0.86	0.26
Income Information		
Net margin	0.99	0.01
Return on equity ratio	0.99	0.01
Risk Information		
Debt/equity ratio	0.95	0.10
Current liability/equity ratio	1.03	-0.05
Judgment representation processes		
Bank's share of risk	0.87	0.25
Liquid assets of the firm	0.81	0.34
Firm's profitability	0.88	0.22
Firm's credit rating	0.95	0.11
Bank's classification system	0.98	0.05
Decision choices		
Whether the loan should be approved	0.67	0.56
Conditions of the loan	0.75	0.44

Goodness of fit index (*GFI*) = 0.747
Adjusted Goodness of fit index (*AGFI*) = 0.617
Root Mean Square Residual (*RMR*) = 0.060

FOOTNOTES

[1] Statistical packages such as AMOS, EQS, LISREL etc., are popular versions that handle full information systems, such as ML. In this paper, ML refers to the aforementioned statistical packages.

[2] The weights of the underlying items for the constructs are estimated by the PLS algorithm in an iterative method based on Wold's (1985) theory of fixed point estimation of structural equation techniques with unobservable variables.

[3] PLS does not directly allow for testing second-order factors. Therefore, second order factors need to be derived from the first-order factors.

[4] Since PLS is predominantly used to analyze small sample sizes, most studies use primary data, either from survey questionnaires or experimental studies. Nonetheless, PLS is also capable of analyzing secondary data.

[5] Examples of studies that performed PLS as a complementary approach are those of Bens (2002, 5) and Cohen et al. (1994, 133).

[6] The *t*-tests are asymptotic and based on the assumption that the errors in the structural equations are normally distributed. Based upon the sample size and sampling procedures used in this study, statistical inference should not be interpreted here in its traditional sense. Indeed, the sample size is large and important enough without statistical generalizations. The significance levels presented in the Table 5 do not provide generalization from the sample to a population, but they do present some evidence that relations exist, as opposed to the hypothesis that they are the result of a spurious arrangement (Fornell and Robinson 1983).

REFERENCES

Altman, E. I. 1980. Commercial bank lending: process, credit scoring and costs of errors in lending. *Journal of Financial and Quantitative Analysis* 15 (November): 813-832.

Anderson, J. C., and Gerbing, D. W. 1988. Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin* 103: 411-423.

Anderson, J. R. 1985. *Cognitive Psychology and Its Implications*. San Francisco, CA: Freeman.

Bentler, P. M. 1983. Some contributions to efficient statistics in structural models: Specification and estimation of moment structures. *Psychometrika*, 48:493-517.

________ . 1989. *Theory and Implementation of EQS: A Structural Equations Program (2.0)*. Los Angeles: BMDP Statistical Software.

Bentler, P. M., and Chou, C. P. 1988. *Practical Issues in Structural Modeling*. Beverly Hills, CA: Sage.

Bens, D. A. 2002. The determinants of the amount of information disclosed about corporate restructurings. *Journal of Accounting Research* 40 (March): 1-20.

Bollen, K. A., and Paxton, P. 1998. Interaction of latent variables in structural equation models. *Structural Equation Modeling* 5:267-293.

Bookstein, F. L. 1982. Data Analysis by Partial Least Squares. In *A Second Generation of Multivariate Analysis*, edited by C. Fornell. NY: Praeger.

Chenhall, R. H. 2004. The role of cognitive and affective conflict in early implementation of activity-based cost management. *Behavioral Research in Accounting* 16: 19-44.

Chin, W. W. 1998. Issues and opinion on structural equation modeling. *MIS Quarterly* 22 (March): 7-16.

________ , and Gopal, A. 1995. Adoption intention in GSS: Relative importance of beliefs. *DATA BASE for Advances in Information Systems* 26: 42-64.

________ , Marcolin, B. L., and Newsted, P. R. 2003. A partial least squares latent variable modeling approach for measuring interaction effects: Results from a monte carlo simulation study and an electronic mail emotion/adoption study. *Information Systems Research*, 14 (June): 189-217.

Cohen, J. K., Gilmore, T. C., and Singer, F. A. 1966. Bank Procedures for Analyzing Business Loan Applications. In *Analytical Methods in Banking*, edited by K. J. Cohen and F. S. Hammer, 218-251.Homewood, IL: Irwin.

Cohen, J., Pant, L., and Sharp, D. 1994. Behavioral determinants of auditor aggressiveness in client relations. *Behavioral Research in Accounting* 6: 121-143.

Cool, K., Dierickx, I., and Jemison, D. 1989. Business strategy, market structure and risk-return relationships: A structural approach. *Strategic Management Journal* 10 (November/December): 507-522.

Dijkstra, T. 1983. Some comments on maximum likelihood and partial least squares methods. *Journal of Econometric* 22: 67-90.

Fornell, C., and Larcker, D. F. 1981. Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research* 18: 39-50.

________ ,and Bookstein, F. L. 1982. Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research* 19: 440-452.

________ , and Robinson, W. T. 1983. Industrial organization and consumer satisfaction/dissatisfaction. *Journal of Consumer Research* 9: 403-412.

Graham, J. L., Mintu, A.T., and Rodgers, W. 1994. Explorations of negotiation behaviors in ten foreign cultures using a model developed in the United States. *Management Science* 40 (January): 72-95.

Harman, H. H. 1976. *Modern Factor Analysis*. Chicago: University of Chicago Press.

Hastie, R., Park, B., and Weber, R. 1984. Social Memory. In *Handbook of Social Cognition,* edited by R. S. Wyer, Jr., and T. K. Srull,151-212. Hillsdale, NJ: Erlbaum.

Hogarth, R. M. 1981. Beyond discrete biases: Functional and dysfunctional aspects of judgmental heuristics. *Psychological Bulletin* 90: 197-217.

Hui, B. S. 1982. On Building Partial Least Squares Models with Interdependent Inner Relations. *In Systems Under Indirect Observations: Causality, Structure, Prediction*, Vol. 2, edited by K. R. Joreskog and H. Wold, 249-272. Amsterdam: North-Holland.

Ittner, C. D. and Larcker, D. F. 1998. Are nonfinancial measures leading indicators of financial performance? An analysis of customer satisfaction. *Journal of Accounting Research* 36 (Supplement): 1-35.

________ , ________ , and Rajan, M. V. 1998. The Choice of performance measures in annual bonus contracts. *The Accounting Review* 72 (April): 231-255.

Jagpal, H. S. 1981. Measuring joint advertising effects in multiproduct firms. *Journal of Advertising Research* 21: 65-69.

Joreskog, K. G., and Sorbom, D. 1988. *LISREL 7: User's Guide*. Mooresville, IN: Scientific Software.

________ ,and Wold, H. 1982. The ML and PLS techniques for modeling with latent variables: Historical and comparative aspects. In *Systems under Indirect Observation: Causality, Structure, Prediction. Part I*, edited by K.G. Joreskog and H. Wold, 263-270. Amsterdam: North-Holland.

Keil, M., Tan, B. C., Wei, K. K., Saarinen, T., Tuunainen, V. and Wassenaar, A. 2000). A cross-cultural study on escalation of commitment behavior in software projects. *MIS Quarterly* 24 (June): 299-325.

Kleinmuntz, B. 1990. Why we still use our heads instead of formulas: Toward an integrative approach. *Psychological Bulletin* 107: 296-310.

Laitinen, E. K. 2004. Nonfinancial factors as predictors of value creation: Finnish evidence. *Review of Accounting and Business Finance* 3: 84-123.

Lev, B. 1998. The old rules no longer apply. *Forbes ASAP*, 159 (7): 35-36.

Lohmoller, J. B. 1984. *LVPLS Program Manual Version 1.6: Latent Variable Path Analysis with Partial Least Squares Estimation*. Zentralarchiv fur Empirische Sozialforschung, Universitst zu Koln.

________. 1988. The PLS program system: Latent variables path analysis with partial least squares estimation. *Multivariate Behavioral Research* 23: 125-127.

________. 1989. *Latent Variable Path Modeling with Partial Least Squares*. Springer-Verlag, New York.

Hall, M., Smith, D., and Langfield-Smith, K. 2005. Accounts' Commitment to Their Profession: Multiple Their Profession: Multiple Dimensions of Professional Commitment and Opportunities for Future Research. *Behavioral Research in Accounting* 17: 89-109.

Morrill, C., and Morrill, J. 2003. Internal auditors and the external audit: a transaction cost perspective. *Managerial Auditing Journal* 18: 490-504.

Muthen, B. O. 1985. *LISCOMP: Analysis of Linear Structural Equations Using a Comprehensive Measurement Model*. Mooresville, IN: Scientific Software.

Oskamp, S. 1965. Overconfidence in case-study judgments. *Journal of Consulting Psychology* 29: 261-265.

Pavlou, P. A. 2003. Consumer acceptance of electronic commerce – integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce* 7 (Spring): 69-103.

Peterson, D. K., and Pitz, G. F. 1986. The effects of amount of information on predictions of uncertain quantities. *Acta Psychologica* 61: 229-241.

Ping, J. R. 1995. A parsimonious estimating technique for interaction and quadratic latent variables. *Journal of Marketing Research* 32: 336-347.

Rodgers, W. 1984. *Usefulness of Decision Makers' Cognitive Processes in a Covariance Structural Model Using Financial Statement Information*, Unpublished Doctoral Dissertation, Graduate School of Business, University of Southern California, Los Angeles, CA.

________. 1991. Evaluating accounting information with causal models: Classification of methods and implications for accounting research. *Journal of Accounting Literature* 10: 151-180.

________. 1992. The effects of accounting information on individuals’ perceptual processes. *Journal of Accounting, Auditing and Finance* 7 (Winter): 67-96.

________. 1999. The influences of conflicting information on novices’ and loan officers’ actions. *Journal of Economic Psychology* 20 (April): 123-145.

________, and Guiral, A. 2005. Auditors' Forecasting in Going Concern Decisions: Framing, Confidence and Information Processing. *Documento de Trabajo de FUNCAS* 223: 1-43.

________, and Housel, T. 1987. The effects of information and cognitive processes on decision-making. *Accounting and Business Research* 69 (Winter): 67-74.

________, and Housel, T. 2004. The Effects of Enviromental Risk Information on Auditors' Decisions about Prospective Financial Statements. *European Accounting Review* 13 (3): 523-540.

________, and Johnson, L. W. 1988. Integrating accounting information with loan officers' decision processes. *Accounting and Finance* 28: 1-22.

Rutledge, J. 1998. You're a fool if you buy into this stuff [i.e., intellectual capital]. *Forbes ASAP*, 159 (7): 43-45.

Schneider, W. and Shiffrin, R. M. 1977. Controlled and automatic human information processing: I. Detection, Search, and Attention. *Psychological Review* 84: 1-66.

Segars, A. H., and Grover, R. 1998. Strategic information systems planning success: An investigation of the construct and its measurement. *MIS Quarterly* 22: 139-165.

Shaw, M. J., and Gentry, J. A. 1988. Using an expert system with inductive learning to evaluate business loans. *Financial Management* 17 (Autumn): 45-56.

Smith, D., and Langfield-Smith, K. 2004. Structural equation modeling in management accounting research: Critical analysis and opportunities. *Journal of Accounting Literature* 23: 49-86.

Steiger, J. H. 1979. Factor Indeterminacy in the 1930's and the 1970's: Some interesting parallels. *Psychometrika* 44: 157-166.

Wold, H. 1965. A fixed-point theorem with econometric background, I-II. *Arkiv for Matematik* 6: 209-240.

________. 1966. Estimation of Principal Components and Related Modes by Iterating Least Squares. In *Multivariate Analysis*, edited by P.R. Krishnaiah. NY: Academic Press.

________. 1980a. Model Construction and Evaluation When Theoretical Knowledge is Scarce--Theory and Application of Partial Least Squares.In *Evaluation of Econometric Models*, edited by J. Kmenta and J. G. Ramsey, 47-74. NY: Academic Press.

________. 1980b. Soft modelling: Intermediate between traditional model building and data analysis. *Mathematical Statistics* 6: 333-346.

________. 1983. Soft Modeling: The Basic Design, and Some Extensions. In *Systems Under Indirect Observation*, edited by K.G. Joreskog and Wold. Amsterdam: North-Holland.

________. 1985. Partial Least Squares. In *Encyclopedia of Statistical* Sciences, Vol. 6, edited by S. Kotz and N. L. Johnson, 581-591. New York: Wiley.

Yoo, Y., and Alavi, M. 2001. Media and group cohesion: Relative influences on social presence, task participation, and group consensus. *MIS Quarterly* 25 (September): 371-390.

APPENDIX 1

Questionnaire for Credit Situations

This study is designed to determine the information you, as a creditor, need to make financing decisions. Your responses will be kept strictly confidential and only aggregate responses will be reported.

Attached you will find a number of credit evaluation cases and response forms for evaluating these cases. Please respond to these cases as if they had occurred in your organization. Evaluate them as you would any other new customer's request for credit. Assume that the loan is a one year unsecured commercial loan (line of credit) of $1,000,000 for the purchase of raw materials. Assume that the source of repayment will be made through the collection of receivables and cash flow. After reading each case, you will be asked to evaluate it in three different dimensions:

(1) your impression of the economic and management information;
(2) your analysis and evaluation of the loan; and
(3) your approval of the loan.

The below four classifications have the following meanings in relationship to a loan:

Excellent - minimum loss exposure to the investment; the probability of serious rapid financial deterioration is very small.

Satisfactory - average or slightly-below-average quality with a definite possibility of deterioration if adverse factors prevail; careful observance will be necessary.

Substandard - loss exposure to the investment is high. Volume and earnings deterioration may be already underway; very close scrutiny by the loan officer will be crucial.

Doubtful - significant loss exposure to the investment is very high. Serious financial situation is evident, and the probability of serious rapid financial deterioration is very high.

Please mark your answers on the following questionnaire along the scale in the manner indicated on the "example" below.

Select "only" one of the following classifications for the overall financial statements of the company:

/______________/______________/______________/______________/
Doubtful Substandard Satisfactory Excellent

How useful is the information below in helping you reach your loan decision?

Industry Sales over the last		1982	1983	1984
3 years have increased by	10%	15%	24%	

very useful /____/ not useful

Government deregulation has decreased the company's product cost by:	1982	1983	1984
	12%	18%	21%

very useful /____/ not useful

Recent management policy changes	1982	1983	1984
have increased stock price as follows:	1.87	2.50	9.37

very useful /____/ not useful

Management's experience with the company's product lines has increased by	1982	1983	1984
	5 years	10 years	15 years

very useful /____/ not useful

Based on your analysis of this company's information, evaluate the company in terms of...

A. Your Bank's share of risk.

/______________/______________/______________/______________/

Doubtful Substandard Satisfactory Excellent

B. The liquid assets of this firm.

/______________/______________/______________/______________/

Doubtful Substandard Satisfactory Excellent

C. This firm's profitability.

/______________/______________/______________/______________/

Doubtful Substandard Satisfactory Excellent

D. This firm's credit rating.

/______________/______________/______________/______________/

Doubtful Substandard Satisfactory Excellent

E. Your bank's classification system of the loan.

/______________/______________/______________/______________/

Doubtful Substandard Satisfactory Excellent

<u>Please answer questions A and B</u>

A. Now decide whether the loan should be:

Approved Low degree of Confidence High Degree of Confidence

/____/

Not Approved Low degree of Confidence High Degree of Confidence

/____/

B. Assuming that the loan is approved, which condition would you select:

Unsecured/Do Not

Modify Terms Low degree of Confidence High Degree of Confidence

/____/

Unsecured/Modify

Terms Low degree of Confidence High Degree of Confidence

/____/

Secured/Do Not

Modify Terms Low degree of Confidence High Degree of Confidence

/____/

Secured/Modify

Terms Low degree of Confidence High Degree of Confidence

APPENDIX 2

PLS Method of Prediction

The systematic part of the predictor relation in PLS is the conditional expectation of the predictands for given values of the predictors. The structural relations are thus specified as stochastic. This is written as

(1) $E(\eta|\eta, \varepsilon) = \beta^*\eta + \Gamma\varepsilon$

where $\eta = (\eta_1, \eta_2, \ldots \eta_m)$ and $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots \varepsilon_n)$ are vectors of unobserved dependent and independent variables, respectively, β^* (m * m) is a matrix of coefficient parameters (with zeros in the diagonal) for η, and Γ (m * n) is a matrix of coefficient parameters for ε.

The measurement equations are

(2) $y = \Lambda_y\eta + \varepsilon$

(3) $x = \Lambda_x\varepsilon + \delta$

where $y' = (y_1, y_2, \ldots y_p)$ and $x' = (x_1, x_2, \ldots x_q)$ are the observed dependent and independent variables, respectively, Λ_y (p * m) and Λ_x (q * n) the corresponding regression matrices, and ε and δ are residual vectors.

In PLS, the unobservable variables are estimated as exact linear combinations of their empirical indicators

(4) $\eta = \pi_\eta y$

(5) $u = \pi_\varepsilon x$

where π_η $(p * m)$ and π_ε $(p * m)$ are regression matrices.

Estimation

The PLS technique is estimated by (1) the loadings (Λ_y, Λ_x) which describe how the observations relate to the unobservables, and (2) the structural relations (β, Γ), whereby values of unobservables influence values of the other unobservables in the system. PLS estimates by way of a nonlinear operator for which the vector of all estimated item loadings (Λ_y, Λ_x) is a fixed point (Sands and Young, 1980).

PLS estimation minimizes residual variances under a fixed point constraint. Also, PLS operates as a series of interdependent ordinary least squares (OLS) regressions, presuming no distributional form at all (Fornell and Bookstein, 1982). Finally, PLS limits its explicit optimization computations to ordinary multiple regression. The separate analyses are jointly adjusted by nonlinear algebraic constraints according to the method specification.

Assumptions

We have from equation 1 that $E(\eta\zeta') = E(\varepsilon\zeta') = E(\zeta) = 0$, where $\zeta = \eta - E(\eta)$ is a vector of residuals. From the measurement equations, 2 and 3, it follows that $E(\varepsilon) = E(\delta) = E(y\varepsilon') = E(x\delta') = 0$.

The residual covariance structure is not restricted in PLS. We define $E(\varepsilon\varepsilon') = \Theta_\varepsilon$, $E(\delta\delta') = \Theta_\delta$, and $E(\zeta\zeta) = \Psi$. PLS attempts to minimize the trace (sum of the diagonal elements) of W and, with reflective specification, also Θ_ε and Θ_δ. Because the off-diagonal elements are not among the unknowns of the method and because the unobservables are explicitly estimated, there are no identification problems for recursive PLS models. The fixed point estimation depicts the problem of unknown unobservables by replacing the proxy estimates in an iterating manner.

There are no distributional requirements in PLS estimation since there are no assumptions about the population scale of measurement. Finally, residual variances are minimized to enhance optimal predictive power.

APPENDIX 3

Estimation of Higher-Order Factors in PLS

The existence of a higher-order structure is usually assessed through a series of tests following the procedure prescribed by (Chin 1998). The first step is to examine the magnitude of the inter-correlations of the lower (first) order factors, and the significance of their t-values. According to Chin (1998), for reflective factors, a large percentage of the paths should be at 0.7 and above to achieve an adequate method fit. These correlations suggest that the relationships among first-order factors can be explained in a more parsimonious way by higher-order constructs, implying the existence of such structure. However, for formative factors, these correlations may be lower since the first-order dimensions do not necessarily move in the same direction (Chin 1998).

Higher-order factors should not be proposed merely to explain the covariation among the lower factors. Chin's basic recommendation is to theorize the relationships among the lower and the higher-order factors, which in turn must also be theoretically related to other constructs in a conceptual approach that are at a similar level of abstraction, irrespective of whether the other factors are measured directly from measurement items or from other first order factors (p. 10). In addition to the direct measurement items for the first-order constructs, indicator variables should also be assessed for the latent higher-order constructs. These indicators are used to assess whether the second-order measures created by the aggregate of the first order constructs are highly correlated with the aggregates. Even if the indicator serves as a mere proxy for the second-order construct (in principle, the second-order factor is a latent, non-measurable construct), it can still provide an indication whether the aggregate variable describes what it is intended to capture (content validity).

The final step is the examination of higher-order factor structures is to test whether the higher-order factors fully mediate the relationships between the lower-order factors and the dependent variables (Chin 1998). This step assures that the higher-order structures do indeed completely represent the lower-order dimensions by fully mediating the impact of their lower-order dimensions on any dependent variable they are theorized to predict.

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