2010

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ESTIMATION METHODS FOR DETECTING NON-LINEAR EFFECTS IN LATENT VARIABLE STRUCTURAL EQUATION MODELS: AN EXHIBITION OF THE TWO-STAGE LEAST SQUARES METHOD*

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* This work is supported a) by the European Social Fund (ESF), Operational Program for Educational and Vocational Training II. (EPEAEK II): Program PYTHAGORAS & b) ECR Europe International Commerce Institute (ICI) – Unilever Research Grant.

ESTIMATION METHODS FOR DETECTING NON-LINEAR EFFECTS IN LATENT VARIABLE STRUCTURAL EQUATION MODELS: AN EXHIBITION OF THE TWO-STAGE LEAST SQUARES METHOD

Marketers call for the examination of more complex functional structures of the links between service evaluation constructs. However, it seems that including and estimating non-linear effects in the latent variable structural equation modeling framework is a daunting task. Therefore, marketers need to be acquainted with the use of these methodologies in a concise and simple manner. Building from Joreskog (1998), who suggests using Bollen's (1995) estimation method, the present study reviews the relevant literature and exhibits the use of Bollen's (1995) two-stage least squares estimation method (2SLS) in the context of marketing evaluation frameworks. The 2SLS method-a limited information, two-step procedure- presents many favorable features over other methods. It is simple and easy to implement even with conventional software packages, it does not require observed variables to be multivariate normal, and presents low bias for standard error estimates.

Keywords: Bollens' Two-Stage Least Squares Estimation Method, Nonlinear structural equation modeling, Service Evaluation, Trust

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INTRODUCTION

Marketers have not readily examined the potential for higher-order conceptualizations of prominent evaluation constructs (like quality, satisfaction, trust and value judgments) in marketing models involving latent variable structural equation models (SEM). Although, traditional SEM incorporates linear relationships among latent variables, marketing researchers sometimes wish to estimate a SEM with interaction and/or quadratic effects (Klein and Muthen 2007). Interactions between multiple indicator latent variables as well as latent quadratic effects are rarely used because of implementation complexity and competing strategies (Marsh, Wen and Hau 2004). However, interactions (e.g., BxC in $A = b_0 + b_1*B + b_2*C + b_3*BxC + b_4BxB$) and quadratics (e.g., BxB) should be routinely investigated to help interpret significant first-order effects (Ping 2004). This is discouraging since it seems that ignoring the possible existence of threshold and saturation effects in marketing structural equation models is arguably causing the results to be meaningless. Failing to account for non-linearities in the service evaluation networks may lead to misallocation of resources and consequently to incorrect priorities in the effort to build loyalty. For example, the satisfaction-trust paradigm has been recently criticized regarding its ability to deliver positive consumer behavioral outcomes (Yim, Tse and Chan 2008). Though the relationship marketing literature builds on this paradigm, strictly loyal consumers have become the exception rather than the rule (Gijsbrechts, Campo and Nisol 2008). Arguably, a reason for this unpleasant situation may be the failure of managers to account for non-linearities in the satisfaction-trust paradigm which leads to incorrect priorities in the process of building consumer loyalty. In the same vein Zeithaml, Berry and Parasuraman (1996) and more recently Anderson and Mittal (2000) note the importance of research in understanding the non-linearities inherent in the service evaluation-consumer outcomes chain.

In retrospect, marketers need to be acquainted with the use of methodologies capable of detecting latent variable higher-order effects, in a concise and simple manner. The present study, demonstrates the use of Bollen's (1995) two-stage least-squares method (2SLS) methodology for detecting statistically significant latent interactive and quadratic effects. This method presents many important advantages over other similar methods, in terms of simplicity, bias, precision, power and type I error rates (Im, Hussain and Sengupta 2008).

AVAILABLE METHODS FOR DETECTING NON-ADDITIVE EFFECTS IN STRUCTURAL EQUATION MODELS

Estimating latent interaction and quadratic effects is an important theoretical, substantive, and empirical issue in social and behavioral sciences (Marsh, Wen and Hau 2004). Given this importance, for estimating interaction and quadratics effects, numerous techniques have been proposed in the literature (see Table 1). In the marketing literature, the most widely used approach in testing higher-order effects, is OLS estimation with multiplicative interaction terms (Im, Hussain and Sengupta 2008). However, this method may result in biased estimators in the presence of correlation between random error terms and latent variables (Bollen 1995).

There are several other methods for testing higher-order effects in the methodological literature. According to Ping (2003) there are at least six estimation methods pertaining to estimating parameter estimates and standard errors for higher-order effects. Joreskog (1998) distinguishes interaction and non-linear effects estimation methods in three classes of procedures: (a) product variables procedures; (b) no product variables procedures; and finally (c) two-step procedures. Which one of these estimation methods a researcher should use? Ping (2003), points that for models including more than three exogenous variables (that is "interesting" models) and 4 to 6 or more indicators, most of these techniques will yield interpretational equivalent results. Joreskog (1998) suggests utilizing Bollen's (1995) 2SLS estimator approach. This approach presents many important advantages compared to other SEM-based procedures. Besides its ease of use and implementation (i.e., with conventional statistical software), this limited information method, provides consistent estimates, it is robust even when multivariate normality assumptions do not hold, it has no convergence problems and it generates estimated asymptotic standard errors for significance tests. All in all, the 2SLS estimator provides a simpler procedure with fewer restrictions (Li and Harmer 1998).

Based on these important qualities and the suggestions of Joreskog (1998), in the following section we exhibit the use of Bollen's (1995) two stage least squares estimator. Note that the exhibition relates to the detection of curvilinear effects (i.e., quadratic effects). It should be noted, that the procedure is exactly the same when it comes to the detection of interactive effects.

Table 1. Prominent Estimation Methods for Obtaining Coefficient Estimates and Estimates of Standard Errors for Higher-Order Effects (Adapted from Joreskog (1998) and Ping (2003)

Estimation Method	**Type of Procedure**	**Short Description**
Subgroup/ Multigroup Analysis	Indirect estimation	Indirect estimation procedure (Ping 1998) that involves dividing the sample into subgroups of cases based on different levels (e.g. low and high) of a suspected interaction. It involves constraining the model coefficients to be equal between subgroups, and comparing the chi-square statistic for the unconstrained and the constrained models.
Kenny and Judd (1984)	Product variables	Specifies an interaction/quadratic using indicators that are the unique cross products of the indicators of the first order latent variables involved, e.g., for latent variables X and Z with indicators x1, x2, ... , xn and z1, z2, ... , zm , XZ is specified with n times m product indicators, x1z1, x1z2, ..., x1zm, x2z1, x2z2, ... , x2zm, ... , xnz1, xnz2, ... , xnzm. Nonlinear constraints are imposed to define relations between product indicators and the latent interaction factor
Bollen and Paxton (1998)	Two step procedure	XZ is specified with Kenny and Judd (1984) product indicators, and 2SLS estimation is used.
Jöreskog and Jonnson (1996)	Product variables	Uses the Kenny and Judd (1984) product indicators and LISREL 8, and produces intercepts for the structural equations. Yoreskog and Yang Johnson (1996) showed that one product variable is sufficient to identify all the parameters of the model.
Ping (1995)	Two step procedure	XZ is specified with a single indicator termed x:z = (x1 + x2 + ... + xn)(z1 + z2 +... + zm). x:z can be specified with either a free, but constrained, loading and error term (direct estimation), or a previously calculated and fixed loading and error term (2-step estimation).
Ping (1996a)	Product variables	XZ is specified with the Kenny and Judd product indicators. Coefficients are estimated using 2-step estimation
Ping (1996b)	Two step procedure	Uses an adjusted covariance matrix and OLS regression to estimate the coefficient(s) of interactions
Jonnson	Two step	In the first step the measurement model is

(1998)	procedure	estimated and factor scores for these latent variables are computed. In the second step the structural equation model is estimated as if the latent variables were directly observed
Jaccard and Wan (1995)	Product variables	XZ is specified with a 4-indicator subset of the Kenny and Judd (1984) product indicators method.
Marsh, Wen and Hau (2004)	Product variables	XZ is specified with a subset of the 4-indicator subset of the Kenny and Judd (1984) product indicators method. No nonlinear constraints are imposed to define relations between product indicators and the latent interaction factor.
(Klein & Muthen, 2002)	Direct Estimation/No Product Variables	Uses all of the original first-order factor indicators to estimate the latent interaction effect without forming any new indicator for the interaction term

BOLLENS' TWO-STAGE LEAST SQUARES ESTIMATION METHOD

The exhibition builds from the consumer service evaluation literature as well as the structural equation modeling literature and hypothesizes the potential for curvilinear effects of perceived service quality, satisfaction and perceived value on the trust outcome employing Bollen's (1995) two-stage least squares estimator (2SLS). Specifically, building from content need theories of motivation, we hypothesize, that consumers' perceptions of cumulative satisfaction, service quality and economic value have a negative quadratic effect on trust perceptions. In higher levels for these variables each additional unit will bring less in incremental trust. The behavioral context for this study was the grocery retailing context. A total of 942 respondents were "intercepted" in supermarket stores, employing a face-to-face personal interviewing method. Items used were adapted from the existing services marketing literature (e.g., Sirdeshmukh, Singh and Sabol 2002).

The following equations depict algebraically the 2SLS procedure for estimating the parameter estimates for the 3 quadratics hypothesized, namely SQxSQ, SATxSAT and VALxVAL.

First-order and non-linear effects equation

$$TRUST=\alpha_{TRUST}+ \beta_{SQ}*SQ+ \beta_{SAT}*SAT+ \beta_{VAL}*VAL+$$

$$+\beta_{SQxSQ}*SQxSQ+ \beta_{SATxSAT}*SATxSAT+ \beta_{VALxVAL}*VALxVAL+\zeta \quad (1)$$

Measurement equations

$$SQ_1=1*SQ+ \varepsilon_1 \Rightarrow \underline{SQ= SQ_1 - \varepsilon_1 \ (2)}$$

$$SQ_2=\alpha_2+\lambda_{2SQ}*SQ+ \varepsilon_2$$

$$SAT_1=1*SAT+ \varepsilon_5 \Rightarrow \underline{SAT= SAT_1 - \varepsilon_5 \ (3)}$$

$$SAT_2=\alpha_6+\lambda_{6SAT}*SAT+ \varepsilon_6$$

$$SAT_3=\alpha_7+\lambda_{7SAT}*SAT+ \varepsilon_7$$

$$VAL_1= \alpha_8+\lambda_{8VAL}*VAL+ \varepsilon_8$$

$$VAL_2= \alpha_9+\lambda_{9VAL}*VAL+ \varepsilon_9$$

$$VAL_3=1*VAL+ \varepsilon_{10} \Rightarrow \underline{VAL= VAL_3 -\varepsilon_{10} \ (4)}$$

$$VAL_4=\alpha_{11}+\lambda_{11VAL}*VAL+ \varepsilon_{11}$$

Following Bollen (1995), we use as reference variables the ones that seem to be more close to the conceptual domain of each latent variable of interest. After writing down the measurement equations, we substitute equations (2), (3) and (4) in the structural equation (1). This leads to the next equation:

$$TRUST_1=\alpha_{TRUST}+ \beta_{SQ}*SQ_1+ \beta_{SAT}*SAT_1+ \beta_{VAL}*VAL_3+\beta_{SQxSQ}*SQ_1xSQ_1+ \beta_{SATxSAT}*SAT_1xSAT_1+ \beta_{VALxVAL}*VAL_3xVAL_3+u_1 \quad (5)$$

Were u_1 is a composite disturbance:

$$u_1 = -\beta_{SQ}*\varepsilon_1- \beta_{SAT}*\varepsilon_5 -\beta_{VAL}*\varepsilon_{10} -2\beta_{SQxSQ}*SQ_1* \varepsilon_{1+} \beta_{SQxSQ}*\varepsilon_{1x}\varepsilon_1-2\beta_{SATxSAT}*SAT_1*\varepsilon_{5+} \beta_{SATxSAT}*\varepsilon_{5x}\varepsilon_5-2\beta_{VALxVAL}*VAL_3*\varepsilon_{10+} \beta_{VALxVAL}*\varepsilon_{10x}\varepsilon_{10}+\zeta-\delta_{TRUST}$$

In equation (5) essentially we rewrite the structural equation model with latent variables depicted in equation (1) into an equation of observed variables and a composite disturbance term. One can easily note that equation (5) is essentially the familiar multiple regression equation but there is a key difference that makes the use of 2SLS procedure necessary: the composite disturbance term is correlated with the observed variables SQ_1, SAT_1, VAL_3, SQ_1xSQ_1, SAT_1XSAT_1, VAL_3xVAL_3, the parameters of which we want to estimate. This violates a basic assumption of OLS regression, meaning that we cannot use OLS regression as an unbiased estimator of β_{SQ}, β_{SAT}, β_{VAL}, β_{SQxSQ}, $\beta_{SATxSAT}$ and $\beta_{VALxVAL}$. This violation leads us to the selection of instrumental variables, namely manifest variables that are correlated with variables SQ_1, SAT_1, VAL_3, SQ_1xSQ_1, SAT_1XSAT_1, VAL_3xVAL_3, but are uncorrelated with the terms of the composite disturbance u_1. The 2SLS procedure has two steps: In the first step each of the next set of variables SQ_1, SAT_1, VAL_3, SQ_1xSQ_1, SAT_1XSAT_1, VAL_3xVAL_3 is regressed on the selected instrumental variables and predicted values for these variables is formed. In the second step these predicted values replace variables SQ_1, SAT_1, VAL_3, SQ_1xSQ_1, SAT_1XSAT_1, VAL_3xVAL_3, and then OLS regression is used to estimate the modified equation (1). According to Bollen (1995), the second stage parameter estimator is a consistent estimator with a known asymptotic distribution for which we can estimate standard errors and perform significance tests.

Till so far, we have thoroughly described the 2SLS procedure. However, we have not yet selected the instrumental variables necessary for proceeding with the first step of the 2SLS procedure. Based on the rules suggested by Bollen (1995) (e.g., include all non-scaling indicators of exogenous latent variables that are on the right-hand side of the equation but are not part of the product interaction/quadratic term, the indicators of the dependent latent variable should not be included as instrumental variables etc.), we selected the next set of instrumental variables: VAL_1, VAL_2, VAL_4, SAT_2, SAT_3, SQ_2, SAC_1, SQ_2xSQ_2, SAT_2xSAT_2, SAT_3xSAT_3, VAL_1xVAL_1, VAL_2xVAL_2, and VAL_4xVAL_4. For example, we include all non-scaling indicators of the exogenous latent variables existent in the right-hand-side of the structural equation as instrumental variables, and we are careful not to select those that scale the latent variables that are in the equation to be estimated. So as to gauge the quality of the instrumental variables selected we regress each explanatory variable (SQ_1, SAT_1, VAL_3, SQ_1xSQ_1, SAT_1XSAT_1, and VAL3xVAL3) on this set of instrumental variables. For example, we regressed SQ_1, on VAL_1, VAL_2, VAL_4, SAT_2, SAT_3, SQ_2, SAC_1, SQ_2xSQ_2, SAT_3xSAT_3, SAT_2xSAT_2, VAL_1xVAL_1, VAL_2xVAL_2, and VAL_4xVAL_4. As one can see from Table 2, R^2 for each explanatory variable is considered large enough (i.e. larger than .10) so as to suggest appropriate instrumental variables.

Table 2. Gauging the quality of selected instrumental variables via the R^2 statistic

Explanatory Variables	R^2
SQ_1	.71
SAT_1	.55
VAL_3	.64
$SQ_1xSQ_{1,}$	.63
$SAT_1XSAT_{1,}$	.30
VAL_3xVAL_3	.45

Note: all R^2 values are significant at a .001 level

Results from these analytical steps indicate that SATxSAT and SQxSQ are statistically significant at the .05 level (two-tailed and one-tailed test correspondingly, t-values=-2.04 and -1.83 correspondingly; unstandardized B=-.08 and -.06, correspondingly). VALxVAL seems to have a positive quadratic effect on trust (B=.16, t=3.43). These findings imply that that investing resources in satisfaction and service quality programs do not do a good job in building trust from a point on, whereas economic value does, since it probably presents incrementally increasing returns to scale. These results indicate that managers should be aware of the possibility that linear and straightforward linkages are probably inadequate in describing relationships between evaluative judgments and important outcomes. Trust responses influenced by satisfaction and service quality improvement programs can be different than a linear-model specification would suggest. In retrospect, if curvilinearities found are taken into account, overspending on satisfaction and service quality judgments for building lasting relationships with consumers (i.e., through trust) can be avoided.

The application just presented builds from the services marketing literature. However, Bollen's (1995) method can be used to estimate interaction and quadratic effects in any marketing topic. For example, the following equation depicts a non-linear terms trust model that investigates whether values-driven corporate social responsibility (CSR)-induced motives impact trust in a way not strictly linear.

$$\text{SALESPERSON TRUST} = \alpha_{TRUST} + \beta_{str}*\text{STRATEGIC} + \beta_{eg}*\text{EGOISTIC} + \beta_{val}*\text{VALUES} + \beta_{stak}*\text{STAKEHOLDER} + \beta_{valxval}*\text{VALUESxVALUES} + \zeta \quad (6)$$

Specifically, it is likely that values-driven CSR-induced motives present diminishing returns to scale on trust from a point on. Too much of benevolent-motivated giving on behalf of firms is probably a misguided priority and a compromise to profitability. The context for this study was the sales department of a global, consumer packaged goods company that heavily invests in CSR activities. Specifically, the study investigated whether multiple types of salesperson attributions regarding the motives underlying a firm's CSR activities influence salesperson's attitudes. 63 usable responses from a total of 300 salespeople were collected using a questionnaire posted in the company's internal web portal. Items used were adapted from the existing CSR literature (e.g., Ellen, Webb and Mohr 2008).

We employed the exact same methodological steps demonstrated in the previous services marketing example. Again, we followed Bollen and Paxton's (1998) rules for including and excluding instrumental variables.

Furthermore, besides stressing the importance of satisfying the counting rule (i.e., that one must have at least as many instrumental variables as has variables in the right-hand side equation that is routinely estimated in the 2SLS procedure), Bollen and Paxton (1998) also point out the importance of evaluating the selected instrumental variables. In particular, the selected instrumental variables should do a good job in predicting the observed variables that will replace. Again, we use as a gauge of quality the coefficient of determination, the coefficient of determination for the instrumental variables used in this example ranges between .21 and .67. 2SLS Estimation results for the hypothesized quadratic effect indicate that the values-driven X values-driven term negatively influences a salesperson's organizational trust (unstandardized $B= -.12$, $p<.05$), indicating a non-linear relationship between values-driven motives and organizational trust. These results indicate that managers should not go too far when communicating their values-driven motives to their "internal customers". At this point, it should be noted that a disadvantage of the 2SLS method is its low power (i.e., the ability to detect statistically significant effects when they are actually existent in the population), which indicates that the 2SLS methods requires the use of large sample sizes (Li and Harmer 1998). Though our sample size was relatively small in this second example, and given the size of the model tested (see equation 6) the 2SLS method provided enough power in order to detect this effect. However, given this limitation of the 2SLS method, we tested the hypothesized quadratic effect using again a product indicator approach, but now with another procedure namely partial least squares (PLS). PLS is a powerful second generation multivariate technique for analyzing latent variable structural equation models with multiple indicators (Ringle, Wende and Will 2005). PLS is more appropriate than LISREL-type models when sample sizes are small, models are complex and the goal of the research is in explaining variance (Smith and Barclay 1997). Statistical significance results coincide with the results of the 2SLS estimation approach.

Though the two 2SLS examples used in this study involve only quadratic effects, it should be noted that this procedure can be used in any marketing investigation involving interaction effects as well. For example, Im, Hussain and Sengupta (2008), use the 2SLS estimator, in order to test a model that examines the interaction effects of the three dimensions of market orientation—customer orientation, competitor orientation, and cross-functional integration—on generation of marketing program creativity.

CONCLUSIONS

Investigating non-linear effects in structural equation models is a necessity for both theoretical and methodological reasons. Importantly, managers should be aware of the possibility that linear and straightforward linkages are probably inadequate in describing relationships between evaluative judgments and important outcomes. However, employing existent estimation methods is a daunting task and marketers need to be acquainted with these methods. The present study exhibits the use of Bollen's (1995) 2SLS estimator for the detection of significant quadratic and interaction effects in structural equation models. Bollen's 2SLS estimator is consistent, easy to use and it does not assume multivariate normality for observed variables. This latter characteristic entails correct estimation of standard errors and goodness of fit

(Joreskog 1998). However, though the 2SLS method has many advantages over other methods for detecting latent variable non-linear effects, it has its limitations as well. Specifically, the 2SLS estimator's results largely draw on asymptotic theory, therefore necessitating the use of relatively large sample sizes (Bollen and Paxton 1998). Furthermore the 2SLS estimator does not estimate all the parameters of a model (i.e., it is a limited information method), and consequently does not give a measure of overall fit (Joreskog 1998). Finally, the method does not make use of all the data, since only one of the indicators of the dependent latent variable needs to be used (Joreskog 1998). It is likely that the estimates of the interaction and quadratic effects and their standard errors, likely depend on which indicators are selected as reference/scaling variables.

In retrospect, if one takes on a more practical research stance that considers a typical social science empirical researcher, with a theory suggesting a non-linear effect, and a sample consisting of a few hundred cases, Bollen's (1995) 2SLS method is probably the most reasonable to use (Joreskog 1998).

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