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Miguel I. Aguirre-Urreta
DePaul University, maguirr6@depaul.edu

George M. Marakas
University of Kansas, gmarakas@ku.edu

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THE USE OF PLS WHEN ANALYZING FORMATIVE CONSTRUCTS: THEORETICAL ANALYSIS AND RESULTS FROM SIMULATIONS

L´utilisation des méthodes PLS pour analyser des construits formatifs : analyses théoriques et résultats issus des simulations

Completed Research Paper

Miguel I. Aguirre-Urreta
DePaul University
1 East Jackson Blvd.
Chicago, IL 60604 USA
maguirr6@depaul.edu

George M. Marakas
University of Kansas
1300 Sunnyside Ave.
Lawrence, KS 66045 USA
gmarakas@ku.edu

Abstract

Partial Least Squares (PLS) has become an increasingly popular approach to testing research models with multiple proposed causality links. Moreover, recent interest in the specification of constructs in a formative manner has accentuated this tendency, given the purported ability of PLS to handle this methodological development. While a review of the literature reveals an extensive use of PLS in this capacity, there is neither theoretical nor empirical evidence supporting this property of the technique. An examination of the inner workings of PLS shows several limitations of PLS when used in 'formative' (Mode B) estimation, and compares it to linear regression and covariance-based approaches. Results from Monte Carlo simulations comparing the performance of PLS and covariance-based techniques in estimating models with formatively specified constructs in either exogenous or endogenous positions reveals important biases for PLS, but not for covariance-based SEM. The results are discussed and recommendations for researchers are proposed.

Keywords: Template, formats, instructions, length, conference publications

Résumé

Les méthodes PSL sont de plus en plus utilisées dans la recherche en systèmes d´information. La spécification des variables latentes comme des indicateurs formatifs a accentué cette tendance. Cette recherche révèle quelques limites inhérentes aux méthodes PLS lorsqu'elles sont utilisées selon une approche d'estimation « formative ». Cette recherche démontre à l'aide de simulations que l´utilisation des méthodes PLS peut être inappropriée à ces situations.

Abstract in Native Language

El método de mínimos cuadrados parciales (PLS por sus siglas en inglés) es muy popular en la literatura de sistemas de información. Recientes desarrollos respecto a la especificación de variables latentes de manera formativa ha acentuado esta tendencia, debido a la supuesta habilidad de PLS para acomodarlas. Esta investigación resalta algunas limitaciones de PLS al respecto y, mediante simulaciones, demuestra que el uso de PLS puede no ser recomendable en estas situaciones.

Introduction

While most of the focus on the theory building and testing process is generally placed in the substantive relationships between constructs of interest, almost forty years ago Costner (1969) noted the need to include what he termed *auxiliary theories*, those relating abstract dimensions and their empirical indicators, as an integral part of scientific theories. In addition, he argued that these should be treated as any other theoretical proposition. Empirical testing of auxiliary theories, then, would serve to tentatively establish the adequacy of particular sets of indicators for testing the implications of their respective abstract formulations. In more modern terms, researchers should establish whether validity is adequate, although the original emphasis was solely on the issue of measurement error and its implications for theory testing. Having found that the indicators are not inadequate for this purpose, only then should researchers attempt to ascertain whether the relationships between constructs are themselves tenable.

A significant amount of attention has been given to issues of instrument validity in the past, including content, construct, internal and statistical conclusion validity, as well as reliability (Straub, 1989). Only recently, however, have researchers begun to focus on the underlying relationship between constructs and their empirical indicators, prompted by the seminal work of Diamantopoulos and Winklhofer (2001), although much of the theoretical development dates from earlier (Bollen, 1984; Bollen & Lennox, 1991; P. Cohen, Cohen, Teresi, Marchi, & Velez, 1990; Curtis & Jackson, 1962). This relationship can be either *reflective* or *formative*. While the former is quite well understood, recent efforts have been made to better understand the alternative, formative specification, and its implications for research. Exemplars of this work include Jarvis, Mackenzie and Podsakoff (2003), Mackenzie, Podsakoff and Jarvis (2005), and recently in the information systems literature, Petter, Straub and Rai (2007) and Marakas, Johnson and Clay (2007).

In an effort to assess the degree to which formatively specified constructs are actively being employed in mainstream IS research, as well as which statistical techniques are employed in the estimation of research models involving those, journal issues of *MIS Quarterly*, *Information Systems Research*, the *Journal of Management Information Systems*, and the *Journal of the Association for Information Systems* for the period January 1998 – June 2008 were examined. Results are displayed in Table 1, noting the sample size for the study, position of the formative construct(s) in the research model, and the statistical technique used to analyze the data. This review of extant research was confined only to first-order formative constructs, which are the main focus of interest in this paper. It should be noted that this is a comprehensive listing of all research involving first-order formative specification in these four major journals. Whereas the research included in Table 1 represents only a relatively small fraction of all research published in this period and outlets, a relatively large proportion of these (15 out of 21, or 71.4%) has appeared in the last three years alone, we believe reflecting the newly found interest of researchers in this topic. Examples of formatively specified constructs include Virtual Copresence (a subjective feeling of being together with others in a virtual environment; "I find that people respond to my posts quickly", "I am usually aware of who are logged on online") (Ma & Agarwal, 2007), and Technology Interaction (IT interactions undertaken with the purpose of accomplishing an individual or organizational task; "I use this system (or application) to solve various problems", "I use this system (or application) to justify my decisions") (Barki, Titah, & Boffo, 2007).

Defining for what reasons and under which circumstances researchers would want to specify the relationship between constructs and their indicators as formative or reflective is beyond the scope of this work, and other authors (Jarvis et al., 2003; Mackenzie et al., 2005; Petter et al., 2007) have provided quite extensive treatments of the issue. However, once a decision has been made to specify a construct as formative, the researcher is then left with a choice between two families of statistical techniques, component- and covariance-based SEM, for data analysis and model estimation. As expected, PLS was the most popular procedure used for this purpose in the reviewed research, with only one study using a covariance-based technique (LISREL in particular) to analyze the research model. Puzzlingly, two published articles analyzed posited formative constructs using least-squares regression; a rather surprising finding given the consensus that OLS regression can only model reflective specifications (and this only by approximation) (Gefen, Straub, & Boudreau, 2000). We will return to this point later in the paper.

Table 1. Recent Research involving First-Order Formative Constructs

Article	Sample Size	Structural Position	Technique
Ma and Agarwal (2007)	500, 166	Exogenous only	PLS
Malhotra, Gosain and El Sawy (2007)	41	Exogenous and endogenous	PLS
Barki, Titah and Boffo (2007)	190	Exogenous only	LISREL

Table 1. Recent Research involving First-Order Formative Constructs

Article	Sample Size	Structural Position	Technique
Yi and Davis (2003)	95	Endogenous only	PLS
Pavlou and Gefen (2005)	134, 270	Exogenous only	PLS
Agarwal, Sambamurthy and Stair (2000)	186	Exogenous only	PLS
Armstrong and Sambamurthy (1999)	153	Exogenous only	PLS
Au, Ngai and Cheng (2008)	922	Exogenous only	PLS
Hsieh, Rai and Keil (2008)	451	Exogenous only	PLS
Choudhury and Karahanna (2008)	338	Exogenous only	PLS
Limayen, Hirt and Cheung (2007)	227	Endogenous only	PLS
Liang, Saraf, Hu and Xue (2007)	77	Endogenous only	PLS
Srite and Karahanna (2006)	181, 166	Exogenous only	PLS
Zhu, Kraemer, Gurbaxani and Xu (2006)	1394	Exogenous and endogenous	PLS
Rai, Patnayakuni and Seth (2006)	110	Exogenous only	PLS
Venkatesh and Ramesh (2006)	201, 169, 766	Endogenous only	PLS
Gattiker and Goodhue (2005)	111	Exogenous only	Regression
Chatterjee, Grewal and Sambamurthy (2002)	62	Exogenous only	PLS
Fichman (2001)	608	Exogenous only	Regression
Wixom and Watson (2001)	111	Exogenous only	PLS
Marakas, Johnson and Clay (2007)	476, 57	Exogenous only	PLS

Note: Sample size indicates the number of subjects included in the research; values separated by commas indicate multiple studies or samples. Structural position indicates whether formatively specified variables were included in research models only as exogenous or endogenous variables, or whether research models included formatively specified constructs in both endogenous and exogenous positions.

An examination of the research included in Table 1 indicates IS researchers testing models that include formative constructs operate largely on two main assumptions: (a) covariance-based techniques (of which LISREL is an example, but by no means the only one) cannot handle models postulating first-order formative relationships (Choudhury & Karahanna, 2008; Liang, Saraf, Hu, & Xue, 2007; Limayen, Hirt, & Cheung, 2007; Ma & Agarwal, 2007), and (b) PLS is a viable alternative for doing so (Chin, Marcolin, & Newsted, 2003; Gefen et al., 2000; Petter et al., 2007).

Despite its widespread use in this regard, an extensive review of the literature on the PLS method and associated simulations was unable to uncover a single study empirically examining the degree to which PLS can appropriately handle first-order formative relationships[1]. More to the point, given our understanding of PLS and its inner workings, we would not expect the technique to be able to model formative constructs even if, on the surface, it would appear capable of doing so. Finally, as the simulation portion of this study will demonstrate, not only are covariance-based techniques capable of modeling formative constructs but, in our opinion and to the best of our knowledge, these are the only ones that can accurately accommodate them.

Given that researchers are interested not only on the significance but also on the magnitude of the structural relationships among constructs in their theoretical models, the objective of this research is to provide a first glimpse into the ability of PLS to accurately recover true relationships (e.g., those existing in the population of interest), and estimate the degree of bias present in those estimates when research models include formatively specified constructs. We believe this is of direct relevance to recent calls (Marcoulides & Saunders, 2006) to more strictly set the boundaries for the appropriate use of the technique in applied research.

Why should researchers be concerned about the presence or absence of bias in the estimation of their research models? There are at least two important reasons for giving careful consideration to this issue. First, the estimate of a parameter of interest is one piece of information used in estimating the statistical significance of the relationship between two constructs (the standard error of the estimate being the other), and the presence of bias in the estimate

[1] A complete list of the research reviewed could not be included due to space limitations and is available from the first author upon research. The work of Cassel, Hackl and Westlund (1999) was the only one we could find that attempted to do so. However, and examination of their research model reveals one that is not identified (see our discussion on identification of models with formative constructs below) and thus does not represent an appropriate population model from which conclusions can be derived by simulation.

may lead researchers to conclude the presence of a significant relationship when one does not exist (if the estimate is biased upwards, resulting in a Type I error), or the absence of a significant relationship when there is actually one (if the estimate is biased downwards, leading to a Type II error). In addition, even if the existence of bias (positive or negative) does not lead to an incorrect decision regarding the significance of the estimate, it will have an important impact on how important (e.g. its practical magnitude) researchers believe the relationship to be, which will in turn impact the amount of future research in that specific area, as well as provide an inaccurate estimate, beyond the effects of sampling error, to researchers conducting power analyses for follow-up research.

While some other work has challenged some of the purported advantages of PLS when modeling interactions (Goodhue, Lewis, & Thompson, 2007) or highlighted the power limitations of the procedure (Goodhue, Lewis, & Thompson, 2006), this is the first study, to our knowledge, that extensively looks at the technique's capability to appropriately analyze data when formative constructs are involved. To the extent that PLS appears to be the preferred choice of IS researchers engaged in these efforts, we believe an examination of its appropriateness to this endeavor is warranted.

The remaining of this paper is organized as follows: First, we review the formative and reflective specifications of latent variables, and note the most important differences between them. Additionally, we discuss the processes involved in PLS estimation, and show where confusion may arise as to the proposed ability of the technique to handle both reflective and formative variables. Next, we report on a Monte Carlo simulation that compares the effectiveness and accuracy of PLS compared to a covariance-based alternative, and highlights their quite different performance for both endogenous and exogenous formative constructs. Finally, an overall discussion and implications for research is provided.

Model Specification in Latent Variable Theory

Formative and reflective are the two alternative specifications of the relationship between observed variables and latent constructs in latent variable theory (actually, Hayduk et al, 2007, recently introduced the idea of 'reactive' indicators, those that are both cause *and* effect at the same time; we are unaware of any extensive application of this recent concept). Although, as noted above, these ideas have been around for some time, there has recently been a renewed interest in the topic, sparked by the work of Diamantopoulos and Winklhofer (2001) and more recently by that of Jarvis and colleagues (Jarvis et al., 2003; Mackenzie et al., 2005). Researchers have also engaged in extensions to the idea of formative measurement, and serious debates have ensued to the point of some researchers questioning its value for theory development and testing (Bagozzi, 2007; Wilcox, Howell, & Breivik, in press). Two major research journals, *Psychological Methods* and the *Journal of Business Research*, have recently published special issues on the formative specification of constructs (Bagozzi, 2007; Bollen, 2007; Diamantopoulos, Riefler, & Roth, in press; Edwards & Lambert, 2007; Franke, Preacher, & Rigdon, in press; Gudergan, Ringle, Wende, & Will, in press; Howell, Breivik, & Wilcox, 2007a, 2007b; Wilcox et al., in press). The interested reader is referred to these exemplars for a more thorough and updated treatment of the topic

This section draws heavily on the work of Bollen and Lennox (1991) and MacCallum and Browne (1993).. Following the latter, we adopt the terms latent variable for conventional, reflective models, and composite variable when discussing formative specifications. The distinction between the two is best made when referring to a graphical depiction of these two alternatives, shown in Figure 1. In both cases, the relationship is specified between a latent entity (either a variable or a composite) and three observed variables.

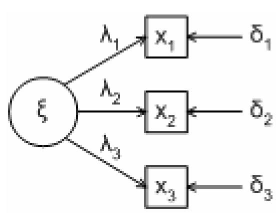

Figure 1(a) – Reflective Specification

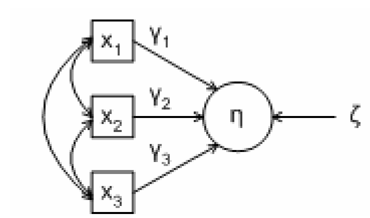

Figure 1(b) – Formative Specification

The formal definition is as follows. In the case of reflective models, three observed variables, x_1, x_2, and x_3 are posited to reflect differences in level in the latent variable ξ. In Figure 1(a), three coefficients λ_1, λ_2, and λ_3 depict the magnitude of the effect of ξ on each manifest indicator x1, x2, and x3. Unexplained residual variance in each of the *xi* variables is represented by three δ symbols; these are generally referred to in the extant literature as random measurement error, e.g. Edwards and Bagozzi (2000). Given that it has been shown that these do not necessarily correspond to the measurement error traditionally associated with classical test theory and true scores, we believe this only adds to the confusion, and prefer to label them as residuals.

When discussing formative models, on the other hand, the relationship between observed and latent variables reverses, and thus the manifest indicators have an effect on the composite variable η, denoted by the coefficients γ_1, γ_2 and γ_3. The disturbance term is represented by ζ and the double-headed arrows in Figure 1(b) imply that the indicators are allowed to co-vary among themselves. In the reflective specification, on the other hand, δ_i are assumed to be uncorrelated with the latent variable ξ, and with each other (e.g. implying that $COV(\delta_i, \delta_j) = 0$ for $i \neq j$) (Bollen & Lennox, 1991). Then, the equations relating observed and latent variables are as follows (Bollen & Lennox, 1991):

$$x_i = \lambda_i \xi + \varepsilon_i$$ for reflective specifications, and

$$\eta = \gamma_1 x_1 + \gamma_2 x_2 + \ldots + \gamma_i x_i + \zeta$$ for formative ones.

Although researchers have referred to the disturbance term ζ as construct-level measurement error, Diamantopoulos (2006) clearly shows this is incorrect, and it should rather be conceptualized as representing unmeasured causes of the composite variable. The author demonstrates that the disturbance is not associated with the measured variables, and therefore cannot represent measurement error. The choice of mathematical model also implies a number of requirements and assumptions about the behavior of manifest indicators and their relationships with their latent variables or composites; these have been summarized in Table 2 (adapted from Jarvis et al, 2003).

Table 2. Distinctive Characteristics of Formative and Reflective Specifications

Reflective	Formative
1. Direction of Causality between Construct and Indicators	
Direction of causality is from construct to items. Indicators are manifestations of the construct. Changes in the construct cause changes in the indicators, while the converse does not occur.	Direction of causality is from items to construct. Indicators are the defining characteristics of the construct. Changes in the indicators cause changes in the construct, while the converse does not occur.
2. Interchangeability of the Indicators	
Indicators should be interchangeable, have the same content and share a common theme. Dropping an indicator does not alter the domain of the construct.	Indicators need not be interchangeable, nor have the same or similar content or share a common theme. Dropping an indicator alters the domain of the construct.
3. Covariation Among the Indicators	
Indicators are expected to covary with each other, and change in one indicator should be associated with changes in other related to the same construct.	It is not necessary for indicators to covary with each other, although this may occur. There is also no need for changes in one indicator to be associated with changes in other related to the same construct.
4. Nomological Net of the Indicators	
The nomological net for the indicators should not differ, since these represent manifestations of the same construct. Indicators are required to have the same set of antecedents and consequents.	The nomological net may differ for the different indicators employed. These are not required to have the same antecedents and consequents.

A Review of Partial Least Squares

The PLS algorithm essentially entails the generation of estimates for three different sets of parameters in a model: the block structure (also called outer relations) which relates indicators to latent variables such that each indicator is subject to predictor specification, and produces a loading for each indicator; the inner relations, which specify path coefficients between the latent variables, according to the theoretical model proposed by the investigator; and weight relations, which help provide explicit estimates for each latent variable, as a weighted aggregate of its indicators. In all cases both latent and manifest variables are scaled to zero means and unit variances in order to eliminate constant terms from the equations. PLS arrives at estimates for these parameters by means of a three-stage procedure, which is depicted in Figure 2 and described in more detail below.[2]

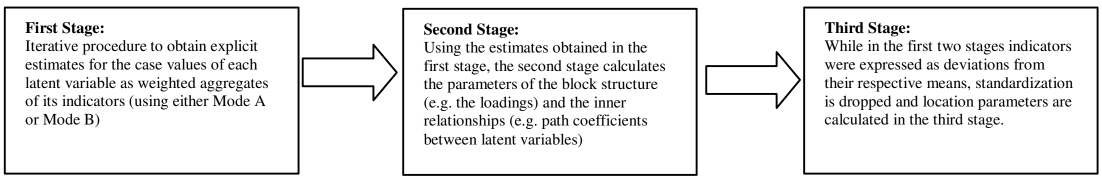

Figure 2. Stages of the PLS algorithm (adapted from Wold, 1982)

In the first stage, an iterative procedure is used to obtain explicit estimates of the latent variables through a weighted combination of their indicators. This is accomplished by iteratively calculating weights and estimates of weighted composites for each latent variable until a convergence criterion is reached (as when weights calculated in successive iterations change by less than a predetermined amount, for instance 10^{-5}). There are two distinct procedures used to calculate estimates for the weights in each iteration, depending on whether these are obtained by either single (Mode A) or multiple (Mode B) regression, using the prior estimate of the latent variable as an instrumental variable. Thus, the algorithm starts by calculating an estimate for the latent variable, such that $Y = f\,\Sigma\,(w_i * x_i)$, where f is a scalar that gives the estimate unit variance, w_i is the set of weight estimates, and x_i is the set of indicators for the latent variable, measured as deviations from their means. In the next step, using the estimate for the latent variable Y obtained as described above, a new set of indicator weights is derived; if using Mode A through solving for the set of weights w_i in the formula $x_i = w_i * Y + e_i$; if using Mode B for the particular latent estimate, through solving for w_i in the formula $Y = \Sigma\, w_i * x_i + e_i$.

Having thus obtained a new set of weights, the algorithm iterates by obtaining a rescaled estimate of the latent variable Y by using the first formula presented in the prior paragraph. After iteration stops because of a lack of change in subsequent weight estimates, the PLS algorithm has produced an estimate for each latent variable in the model as a weighted aggregate of each indicator in its block structure, which is then fed into the next stage of the process. Using these estimates, the second stage entails estimating the path coefficients between latent variables adjacent in the theoretical model, by simple OLS regression between the weighted components obtained in the first stage, and the calculation of the estimated block structure (e.g. loadings) by regressing each indicator on the latent variable estimate for its corresponding block. The third and last stage of PLS removes the standardization imposed above and estimates means and location parameters for both manifest and latent variables.

Identification, Weights, and Latent Variables

While identification is critical to any structural equation model, it is particularly troublesome for those that include formative constructs in them. In general, identification issues relate to two specific aspects of a model: (a) whether a solution exists, and (b) assuming the existence of a solution, is that the only possible one? (Hayashi & Marcoulides, 2006). The identification of formative constructs is subject to the joint achievement of two conditions (MacCallum & Browne, 1993). First, the scale for the latent factor must be established by any of the two common procedures of constraining a loading to equal one or constraining the variance of the latent variable to equal one (although see Little, Slegers and Card, 2006, for an alternative identification procedure which does not impose arbitrary

[2] The account of PLS provided in this section is adapted from Wold (1982) and Lohmöller (1989); see also Chin (1998) for a more accessible narrative account of this procedure.

constraints on parameters); this is a requirement common to both reflective and formative latent variables. Second, formative factors must emit paths to at least one of the following: (a) at least two unrelated reflective factors, or (b) at least two appropriate reflective indicators added to the formative factor, or (c) one reflective indicator added to the formative factor and one independent factor with reflective indicators. A review of the research included in Table 1 shows several models which do not comply with these necessary requirements for identification.

PLS, on the other hand, sidesteps the issue of identification altogether by portraying latent variables as weighted composites of their indicators; this is always the case regardless of whether one is modeling them as 'reflective' (Mode A) or 'formative' (Mode B) (another point to which we shall return shortly). Given that PLS appears to be the default choice for this endeavor within our discipline, this leads researchers employing formative constructs to largely ignore issues of identification. Petter et al (2007) rightly cautioned researchers against altering their research models to fit the statistical tool being used to analyze them. However, the current practice of specifying models with formative constructs as if they were latent variable models, but not considering whether they are identified since PLS will provide estimates for the models, is a clear example of this issue. If researchers specify models as if they were latent variable ones, but which are not identified (i.e., there is no unique solution to them), and are still able to obtain parameter estimates, this should be a clear warning that *the research model being analyzed by PLS must be different from the one they have proposed; otherwise, a unique solution would not be possible.*

McDonald (1996) warned about the use and interpretation of path analysis employing composite variables, a family of techniques to which PLS belongs. In particular, the author noted that:

> "*Although the composites in such a model need not necessarily be thought of as approximations to latent traits/common factors, it is likely that they will be thus regarded, and in applications will be interpreted as though they were common factors, even though there is no clear justification for such an interpretation, since they cannot explain the covariation of their indicators except approximately*" (pp. 239-240).

PLS and ordinary least squares regression are much more alike each other than any of them is to covariance-based techniques such as factor analysis. Both estimate paths between variables through the minimization of squared residuals, and both form the composites involved in these relationships as weighted combinations of their indicators. It should be noted, on the other hand, that PLS and regression differ in their approach to statistical significance testing: bootstrap and normal theory, respectively. However, bootstrapping is not an integral part of the PLS algorithm per se, even if included together in statistical packages, any more than normal theory testing is of regression, as evidenced by bootstrapping approaches to interactions with manifest variables and path analysis (Edwards & Lambert, 2007). In essence, the only difference between regression and PLS is in the weights used to combine the indicators to form the composite variable involved in the structural relationship, since both then estimate this relationship through the same principle. Table 3 compares regression, both estimation modes included in PLS, and latent variable formative formulations as to their use and interpretation of weights.

Table 3. Comparison of Techniques using Weights and their Interpretation

Technique	Composite	Weights	Current Interpretation
Regression	$\sum_{i=1}^{j} x_i w$	Weights are all equal	Reflective
PLS (Mode A)	$\sum_{i=1}^{j} x_i w_i$	Iterative through estimation of: $x_i = w_i Composite + \delta_i$	Reflective
PLS (Mode B)	$\sum_{i=1}^{j} x_i w_i$	Iterative through estimation of: $Composite = \sum_{i=1}^{j} x_i w_i + \delta_i$	Formative
Formative latent variable	$\sum_{i=1}^{j} \gamma_i x_i + \zeta$	Generally estimated by Maximum Likelihood	Formative

Several things are of interest in the preceding table. First, regression using composites calculated as equally weighted sums of their indicators (i.e., "ordinary regression") represents a special case of PLS, special in that all the weights are equal (as noted above, both regression and PLS rely on least squares to estimate the relationships between composites) and requires somewhat more stringent assumptions to operate. However, while much has been made of the distribution-free nature of PLS, it does share some of the same restrictions that regression has; for instance, neither is appropriate when the dependent variable is categorical in nature (other procedures, such as those based on logits, would be required). Further, and more to the point, to what extent PLS is still reliable when faced with serious deviations from normality has not been extensively examined.

Second, both regression and PLS (Mode A) are generally regarded as able to model reflective factors (e.g., Gefen et al, 2000) although, as noted above by McDonald (1996) and others (e.g., Borsboom 2006), this is only done by approximation, since neither technique models measurement error separately from the latent variable, even though PLS is widely assumed to do so by virtue of estimating each weight separately. For instance, Goodhue et al (2007) in their study comparing interaction effect estimation using PLS and regression, noted that one avenue for future research involved the adjustment of regression beta weights to account for unreliability, implying that doing so would not be necessary for those formed with PLS. Chin, Marcolin and Newsted (2003) explicitly make the same point. It is not clear why researchers believe that composites formed with unequal weights (note that there is no restriction in PLS that the weights have to be all different, it would be perfectly possible for PLS to estimate composites with all weights of an equal magnitude) are able to account for unreliability (e.g., measurement error) while those with equal weights cannot. To the extent that PLS resembles factor scoring techniques (e.g., Lastovicka and Thamodaran 1991), and how PLS compares with other techniques has not been studied so far, the optimal weighting of manifest measures in a composite results in maximally reliable components, that is, components with high reliabilities but still subject to measurement error, that can then be used in traditional regression models. If the reliabilities thus obtained are high enough, researchers may focus less on potential attenuation bias for measurement error – however, such bias does not go away (McDonald, 1996; Ree & Carretta, 2006).

Third, PLS (Mode B) is generally regarded by researchers as modeling formative constructs. However, a comparison of the formulas by which composites are calculated in both Modes A and B (and regression, for that matter) shows that, regardless of the procedure by which the weights are calculated, the composites are always weighted averages of their indicators. This has always been very clear in both technical (Wold, 1982) and narrative (Chin, 1998; Chin & Newsted, 1999) descriptions of PLS. What is less clear, paralleling the preceding discussion, is why varying the weights would make a formative construct reflective, or vice versa. Aside from the way the weights are calculated, there is no difference between Modes A and B as it refers to the nature of the composite, nor is there any restriction on the resulting set of weights, such they have to be different for the two estimation modes. If one were to estimate a model using Mode B for a certain construct and obtain equal weights, it is not clear what interpretation should then be attached to that construct, since there is general agreement that equally weighted sums of indicators (i.e., regression) stand as proxies for reflective factors (Gefen et al., 2000; McDonald, 1996). Some researchers (e.g. Gattiker and Goodhue 2007, Fichman 2001), on the other hand, have used equally weighted sums of indicators in a regression while conceptualizing these as formative constructs; it is not clear how that interpretation dovetails with currently accepted research practice (e.g. Gefen et al 2000).

As a rule of thumb, Wold (1982) proposed that Mode A be used for endogenous variables, and Mode B for exogenous ones; unless he was considering that only models with formative exogenous variables and reflective endogenous variables were possible, no particular significance seemed to be attached to the mode of weight estimation as it relates to formative or reflective specifications. On the other hand, McDonald (1996) shows some of the differences in operation of Modes A and B in PLS: while the former maximizes the sum of the covariances of directly connected composites, the latter maximizes the sum of the correlations. These two modes, however, are given the treatment of alternative weighting schemes, among others studied by the author, with no particular relationship to the nature of the latent variable their composites stand for. In addition, results from various simulations (Chin et al., 2003; Chin & Newsted, 1999; Goodhue et al., 2006, 2007; Hui & Wold, 1982) have shown that both PLS (Mode A) and regression provide decent, if at times somewhat biased approximations to reflective latent variables, there appears to be no reason to expect that a different weighting scheme, but a weighting scheme after all, would provide a good approximation to formative ones. We show this to be the case in our simulations.

Finally, even if one still wished to consider Mode B estimates as standing for formative constructs, an additional complication arises from comparison of the formulas for PLS-Mode B and formative latent variables in Table 3, i.e., the lack of disturbance term in PLS-Mode B. Bollen (2007) distinguished between equations for formative latent variables that did or did not contain a disturbance term in them; in particular, he noted that those that contained the disturbance term remain latent even if the researcher knows all the values associated with both indicators and weights, whereas in the second case this knowledge would make the composite not latent anymore, since it would be perfectly determined. Indeed, constraining the residual term in the formative specification to equal zero is one alternative (not included above) way of achieving identification in latent variable models (Diamantopoulos & Winklhofer, 2001); it is argued this implies that the formative measures perfectly represent the latent construct, which may not be theoretically appropriate (Jarvis et al., 2003; MacCallum & Browne, 1993). Petter et al (2007) comment on this approach, and recommend against it, as one way of force-fitting a research model to a statistical tool. However, this is exactly what is done when estimating models including formative constructs using PLS, as is evident from the formulas in Table 3. Removing the construct-level residual variance from the equation would also prevent researchers from diagnosing the content and indicators of the construct in the manner advocated by Diamantopoulos (2006).

To summarize, the preceding two sections present a number of arguments, derived from an understanding of the inner workings of PLS and relevant methodological research, for the limited ability of PLS to accurately estimate structural models that include formatively specified latent variables. In addition, our literature review could not uncover any empirical evidence supporting the use of PLS in this capacity. However, as shown in Table 1, researchers are actively using PLS to analyze this type of models, which could potentially lead to biases in the estimation of the relevant parameters. Through an extensive simulation study, detailed in the next section, this research attempts to provide a first test of the accuracy of PLS in this regard.

Methodology

Two popular models from past research, depicted in Figures 3 (a and b), were employed as the population parameters from which simulated data could be generated. These were originally developed by Jarvis, Mackenzie and Podsakoff (Jarvis et al., 2003), and form the basis of most extant theoretical research in this area. The original authors generated data from these population models and fitted them to misspecified ones where formative constructs were incorrectly included as reflective ones, in order to assess the extent of bias obtained by misspecification. Follow up research using simpler models confirmed the large effect that misspecification of formative constructs has on estimates of structural parameters (Mackenzie et al., 2005). These models also provide the starting point for the simulation conducted by Petter et al (2007). As such, we deem these to be representative of the type of models that would be of interest to applied researchers.

The model shown in Figure 3 (a) includes five latent variables, with the formative construct as an exogenous one (e.g. Ksi 1), that is, only emits paths to other latent variables. In addition, three variations of the model are specified, by varying the inter-item correlation of the indicators of the formative construct, as depicted in the figure. Following Jarvis et al (Jarvis et al., 2003), we label these Models 1A, 1B and 1C throughout this paper. Figure 3 (b), on the other hand, presents a model with the formative latent variable as an endogenous one (e.g. Eta 1) which both emits and receives path to and from other latent factors in the model, all of which are specified as reflective. Same as above, three variations of this model are included, labeled Models 2A, 2B and 2C.

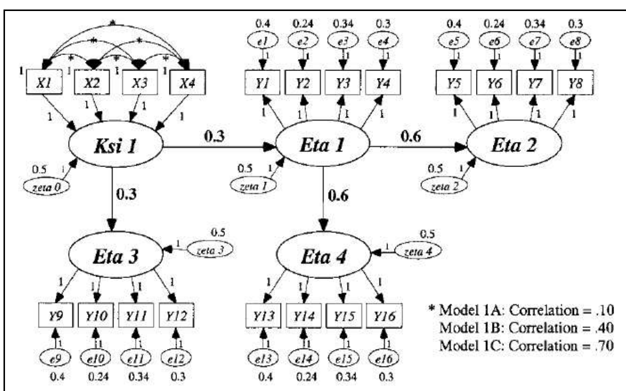

Figure 3 (a). Population Models with Exogenous Formative Construct (from Jarvis, Mackenzie and Podsakoff, 2003)

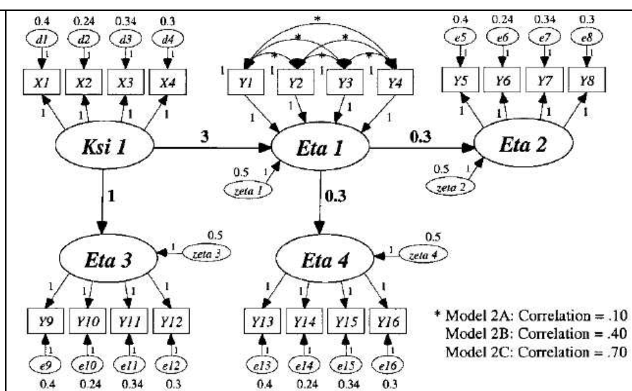

Figure 3 (b). Population Models with Endogenous Formative Construct (from Jarvis, Mackenzie and Podsakoff, 2003)

Simulated data for this research were generated by applying a LISREL (Jöreskog & Sörbom, 1996) implementation of the Cholesky matrix decomposition procedure (Raykov, Marcoulides, & Boyd, 2003) to the covariance matrix procured from the original authors of the two models[3]. Using this technique, a population covariance matrix S from which one wishes to generate data is decomposed into a lower triangular matrix L and an upper triangular matrix U such that both L' = U and S = LU. Then, independent normal standard variables are obtained from a random number generator, and these are multiplied by the weights of the corresponding elements in the successive rows of the matrix L previously obtained. The new variables, those resulting from the multiplication procedure, have thus been simulated as multivariate normal with mean zero means and as if they had been sampled with a population with covariance matrix S (technical details of this procedure are available in Raykov et al, 2003).

There are three additional checks, all of which were performed in this research, to ensure that the decomposition and generation process outlined above has produced data with the desired distributional properties. First, it is possible to reverse the procedure and obtain the original population matrix S starting from the lower triangular matrix L produced by the Cholesky decomposition, and compare that the original and obtained S matrices match. Second, the fit resulting from such a process should be perfect. Finally, in order to check for any clerical errors in the transcription process from the matrix L to the data generation code, a large-size (e.g, half a million cases) sample can be generated, where its covariance matrix should closely resemble the population covariance S. Again, all three procedures were performed for each of the simulated conditions to ensure accuracy of the resulting data.

In addition to the structural position of the formative construct in the population model (exogenous in Figure 3 (a) and endogenous in Figure 3 (b)), and the inter-indicator correlation present amongst indicators of the formative latent variable (0.10, 0.40 and 0.70), the sample size of the generated samples was varied between 100 and 500 to better understand its effects on parameter accuracy. The range is similar to that employed in previous research (Petter et al, 2007, used sample sizes of 250 and 500 for their simulations), and we believe it appropriately represents the range observed in behavioral and social science research (Jaccard & Wan, 1995). Data were analyzed using PLS 3.0 (Chin, 2001) and Mplus 3.0 (Muthén & Muthén, 1998-2001), a popular structural equation modeling software package.

In summary, the following factors were manipulated in a factorial design, for each of the two population models: (a) sample size (100, 200, 300, 400 and 500); (b) inter-correlation of the indicators of the formative construct (0.10, 0.40 and 0.70); and (c) type of estimation method (partial least squares or maximum likelihood). This resulted in 60 (5 x 2 x 3 x 2) different analysis being run in this research, with 500 replications in each cell[4]. The primary performance measures of interest focused on the accurate estimation of the structural paths in the research model, evaluated in terms of mean relative bias[5] (Chin et al., 2003), as well as statistical power for two-tailed tests of significance at $p < 0.05$.

Simulation Results

Tables 4, 5 and 6 report the results of the Monte Carlo simulations described in the preceding section. While the first two focus on the average bias of the path coefficients with respect to the population value, as established by the models in Figure 3 (a, b), over the five hundred replications that were run for each combination, Table 6 focuses on the statistical power achieved in each case. In all cases the same simulated datasets were analyzed with the two techniques of interest, and only correctly specified models were included. Our results for SEM are similar to those obtained by both Jarvis et al (2003) and Petter et al (2007) for comparable sample sizes, which further validates that our data generation and analysis procedures were appropriate.

Table 4 displays results for both PLS and SEM analysis techniques for models where the formative construct is in an exogenous position (those depicted in Figure 3 (a)), for all three indicator inter-correlations and five different sample

[3] Sample code for the data generation process is available from the first author upon request. We appreciate the assistance of Dr. Cheryl Jarvis by providing us with the covariance matrices used in the original study.

[4] Custom software was written to compile the results obtained from all the replications into a file that could be analyzed. We appreciate the assistance of Hector J. Aguirre-Urreta in developing this application.

[5] Mean Relative Bias was calculated as (estimate – population parameter) / population parameter, and averaged over the five hundred replications performed in each cell.

sizes. One thing that should be perfectly evident from this table is that covariance-based techniques are not only perfectly capable of handling models with formative constructs, but are also very accurate when doing so. Although only properly specified models are tested here, even for samples as small as 100 subjects per study no convergence problems arose (i.e., not a single one of five hundred replications failed to converge); however, convergence issues are also frequently cited reasons to prefer the use of PLS over covariance-based techniques. The precision in estimating path coefficients is high enough at small samples that there is no much room for improvement in this respect. As the degree of formative indicator inter-correlation increases precision improves slightly, from a maximum bias of +4.5% to one of -0.74% in path estimates, and no noticeable effect of sample size. The performance of PLS is notably worse, with bias ranging from +7.92% to -8.01%, with sample size and indicator intercorrelation showing similar effects as for the other technique.

Next, a mixed-design set of ANOVAs were run on each path, with the percentage of bias as the dependent variable, the technique employed as the within variable, and the degree of indicator correlation and sample size as between variables. The use of a mixed design with repeated (within) factors was required in order to account for the fact that the same data was analyzed using PLS and SEM. The pattern of results was identical (in terms of both significance and magnitude) for all parameters and are thus discussed as a group[6]. In the within-factor analysis (that is, PLS vs. SEM) the main effect of the statistical technique employed as well as the technique by intercorrelation interaction were both large and significant, with the bias using SEM being significantly smaller than with PLS, and the difference decreasing as the indicator intercorrelation increased. At the between-factor level, which uses the average bias for both techniques as the dependent variable, a significant but small effect of intercorrelation was found, such that the general level of bias decreased as the correlation amongst formative indicators increased. In neither case did sample size show a significant effect.

Results for models with endogenous formative constructs (Figure 3 (b)) are shown in Table 5. As before, SEM showed little bias in the estimation of path coefficients, ranging from +2.60% to -2.11%. The performance of PLS, on the other hand, was dismal. While the paths between reflective variables and those from the formative to the reflective variable showed a moderate degree of bias (ranging from -26.57% to -6.91%, decreasing as the indicator correlations increased), the path going into the formatively specified variable was severely underestimated, ranging from -101.05% to -94.64%, with no noticeable effects of indicator intercorrelation or sample size. The outcome of the statistical analyses performed on the results shown in Table 5 differed on whether they involved the formative variable or the estimated paths were between only reflective variables. In the first case, there were main effects for technique employed and the interaction with sample size (for the within-factor) and small but significant effects of sample size (for the between-factor). When estimates only involved reflectively specified variables, results show a significant main effect for technique as well as its interaction with indicator intercorrelation, as well as a small but significant effect of intercorrelation at the between level of analysis.

Finally, Table 6 shows the proportion of times a significant effect was detected, for each model type, inter-indicator correlation, and sample size combination. The statistics for SEM show that the level of power is well above the commonly accepted cutoff of 0.80 (J. Cohen, 1988) for all population models where the formative construct is in an exogenous position. For models with endogenous formative variables power levels can drop well below 0.80 when the sample size is as small as 100, and get increasingly worse with higher levels of inter-indicator correlation, for the SEM case. On the other hand, for samples of size 200 or more, power levels are again well above conventionally accepted levels. Statistical power results for PLS are included in the table for the sake of completeness; however, given the extreme degree of bias shown by path estimates produced by PLS, we do not recommend that researchers attempt to interpret these power results in any substantive manner. The main objective of including Table 6 is showing the adequacy of covariance SEM for handling constructs with formative indicators.

Discussion

We fully agree with the recommendation made by Petter et al (2007) when they noted that "*Reviewers should ensure that researchers are using the best statistical method for data analysis rather than choosing a method that is perceived as 'easier' because the model has one or more formative constructs within the model*" (p. 644). However, in light of the arguments and results presented here, we believe PLS represents an example of the latter, and not the former, of the types of statistical methods referred to by the authors.

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[6] The complete analyses are available from the first author upon request.

PLS has enjoyed a great deal of attention and use within the IS community since its inception. It has been viewed as a viable approach where sample sizes are too small to meet the requirements of other SEM techniques. In addition, its ease of use has been a significant attraction to researchers. That said, the results of this study suggest that the use of PLS where formative constructs exist in either endogenous or exogenous form, will likely produce results that are significantly biased when compared to the true parameter values under study.

By their very nature, implications drawn from simulations are limited to the type of models and range of conditions, in this case sample size and formative indicator intercorrelation, and for specific values of each, that were included in the experimental design. Keeping that limitation in mind, we believe scenarios examined and results obtained from our simulations are interesting enough to warrant further investigation of the issue. Possible avenues would include more complex models with more than one formatively specified construct, smaller sample sizes, and deviations from normality, to name a few. Although research performed on sample sizes smaller than the ones used here is published from time to time, we believe a sample of one hundred data points to lie close to the limit of what would be acceptable in premier journals, barring cases where large samples are impractical due to the specific nature of the population or research question of interest.

Subject to the discussion above, our simulations showed a number of important results, which we summarize next. First, in contrast to frequent claims that covariance-based techniques cannot accommodate formatively specified constructs, it should be clear from Tables 4 and 5 that not only are these techniques appropriate in these situations, but also notably accurate, even for samples as small as one hundred. In addition, no issues related to either factor indeterminacy or convergence were observed, for any condition, even though 15,000 runs were performed the with covariance-based technique (five sample sizes, three levels of intercorrelation, two types of models, and five hundred replications in each combination). Taken together, these two outcomes should provide evidence to the clear adequacy of covariance-based approaches to modeling formatively specified constructs.

The results from PLS, on the other hand, cast some doubt on the applicability of the technique for these situations, and question whether researchers should continue employing it – particularly in light of the existence of a more adequate alternative in the covariance-based approach. In all variations of Model 1, where the formatively specified construct was in an exogenous position, the degree of bias shown by the estimates obtained from PLS was moderate to low, with ±8% of the true parameter value, and decreasing with increasing interindicator correlations. When the formatively specified construct was in an endogenous position, however (e.g., Model 2), the degree of bias in the coefficient impacting this construct was severe, with PLS greatly underestimating the true value by close to a 100%. In addition, other parameters in the same model show moderate bias, of up to 26% underestimation of the true value.

How the misinterpretation of the correct application of PLS Mode B occurred is beyond the scope of this discourse. As stated previously, the two modes differ only in how the weights are calculated and not with regard to whether or not a model contains formative indicators. The original development of the technique by Wold and colleagues made no claims in this regard, and only later did authors attach this particular significance to the alternative estimation modes. One point of speculation lies with the fact that *regardless of correct or incorrect application of the technique, PLS will provide the researcher with results*. This may suggest to the researcher that all is well since the application did not object to anything. If this abdication hypothesis has any merit, then we must revisit our understanding of PLS to ensure we are using it correctly. If not, then future research needs to be conducted into the continued attraction PLS brings to the researcher investigating formative indicators when no mathematical or statistical basis for this attraction is present. Regardless of the source of the misinterpretation, through this study we have been able to determine that potentially serious bias results from any application of the technique to formative indicators and, as such, must bring forth a recommendation to not continue to use PLS in these situations, as well as critically reexamine the conclusions resulting from past research performed with this technique. It is our hope that this study will produce the necessary debate and investigation such that our understanding of the value and limitations of this popular statistical technique will be enhanced.

Table 4. Path Coefficients and Bias for Models with Exogenous Formative Constructs							
Sample Size	**Paths**	**M1A (correlations = 0.10)**		**M1B (correlations = 0.40)**		**M1C (correlations = 0.70)**	
		PLS	**SEM**	**PLS**	**SEM**	**PLS**	**SEM**
100	K → E1	-7.15%	-0.24%	-4.99%	-0.15%	-4.08%	-0.59%
	K → E3	-7.22%	-0.57%	-4.85%	-0.07%	-3.74%	-0.24%
	E1 → E2	-7.35%	-0.16%	-6.09%	+0.09%	-5.85%	-0.18%
	E1 → E4	+7.92%	+4.48%	-7.50%	-1.34%	-6.69%	+0.21%
200	K → E1	-7.75%	-0.69%	-5.24%	-0.20%	-4.18%	-0.19%
	K → E3	-7.70%	-0.74%	-5.25%	-0.28%	-3.83%	+0.20%
	E1 → E2	-7.98%	-0.38%	-6.41%	-0.01%	-5.71%	+0.06%
	E1 → E4	+7.69%	+4.75%	-7.11%	-0.71%	-7.01%	+0.09%
300	K → E1	-7.60%	+0.22%	-5.22%	-0.03%	-4.13%	-0.01%
	K → E3	-7.82%	-0.08%	-5.11%	+0.06%	-4.17%	-0.08%
	E1 → E2	-8.01%	-0.38%	-6.48%	-0.05%	-6.11%	-0.20%
	E1 → E4	+7.29%	+4.26%	-6.59%	-0.19%	-7.41%	-0.17%
400	K → E1	-7.84%	-0.19%	-5.34%	+0.06%	-4.06%	0.00%
	K → E3	-7.71%	-0.07%	-5.24%	+0.22%	-4.12%	-0.07%
	E1 → E2	-7.65%	+0.03%	-6.71%	-0.33%	-5.60%	+0.34%
	E1 → E4	+7.19%	+4.10%	-6.75%	-0.30%	-7.06%	+0.14%
500	K → E1	-7.73%	-0.14%	-5.28%	+0.10%	-4.01%	+0.07%
	K → E3	-7.94%	-0.40%	-5.23%	+0.17%	-4.09%	-0.03%
	E1 → E2	-7.82%	-0.13%	-6.47%	-0.06%	-5.61%	+0.31%
	E1 → E4	+7.47%	+4.70%	-6.92%	-0.49%	-7.04%	+0.17%

Note: Five hundred replications were performed for each combination of population research model and sample size. Average bias is shown. K is the formative construct, all the others are modeled as reflective.

Table 5. Path Coefficients and Bias for Models with Endogenous Formative Constructs

Sample Size	Paths	M2A (correlations = 0.10)		M2B (correlations = 0.40)		M2C (correlations = 0.70)	
		PLS	SEM	PLS	SEM	PLS	SEM
100	K → E1	− 94.64%	− 2.11%	− 98.91%	− 0.09%	− 95.93%	+ 2.29%
	K → E3	− 18.45%	+ 0.95%	− 19.37%	− 0.40%	− 18.02%	+ 0.82%
	E1 → E2	− 13.15%	− 0.45%	− 9.21%	− 0.06%	− 7.34%	− 0.89%
	E1 → E4	− 13.32%	− 0.46%	− 9.03%	+ 0.09%	− 6.91%	− 0.54%
200	K → E1	− 97.83%	+ 2.60%	− 99.75%	+ 0.76%	−101.05%	+ 0.51%
	K → E3	− 24.34%	− 0.71%	− 24.12%	− 0.15%	− 24.33%	− 0.21%
	E1 → E2	− 14.49%	− 0.53%	− 9.42%	− 0.20%	− 7.31%	− 0.20%
	E1 → E4	− 13.68%	+ 0.19%	− 9.19%	+ 0.04%	− 7.35%	− 0.35%
300	K → E1	− 99.67%	+ 1.20%	− 98.10%	+ 1.45%	− 99.38%	+ 0.89%
	K → E3	− 25.03%	+ 0.60%	− 24.69%	− 1.65%	− 24.45%	+ 1.17%
	E1 → E2	− 14.19%	+ 0.03%	− 9.48%	− 0.13%	− 7.34%	− 0.16%
	E1 → E4	− 14.15%	− 0.08%	− 9.56%	− 0.19%	− 7.33%	− 0.15%
400	K → E1	−100.38%	− 0.01%	− 99.77%	+ 0.78%	− 99.73%	+ 0.60%
	K → E3	− 26.51%	− 0.01%	− 26.09%	− 1.27%	− 26.29%	+ 0.28%
	E1 → E2	− 14.04%	− 0.04%	− 9.58%	+ 0.21%	− 7.32%	− 0.01%
	E1 → E4	− 14.46%	− 0.51%	− 9.62%	− 0.17%	− 7.44%	− 0.10%
500	K → E1	− 99.00%	+ 0.45%	− 99.10%	+ 0.88%	− 98.60%	+ 1.84%
	K → E3	− 26.57%	− 0.02%	− 25.61%	+ 0.89%	− 26.96%	− 0.07%
	E1 → E2	− 14.55%	− 0.34%	− 9.75%	− 0.03%	− 7.36%	− 0.10%
	E1 → E4	− 14.35%	− 0.11%	− 9.46%	+ 0.23%	− 7.41%	− 0.19%

Note: Five hundred replications were performed for each combination of population research model and sample size. Average bias is shown. E1 is the formative construct, all others are modeled as reflective.

Table 6. Statistical Power for Models involving Formative Constructs

Size	Paths	M1A (correlations 0.10)		M1B (correlations 0.40)		M1C (correlations 0.70)		M2A (correlations 0.10)		M2B (correlations 0.40)		M2C (correlations 0.70)	
		PLS	SEM	PLS	SEM	PLS	SEM	PLS	SEM	PLS	SEM	PLS	SEM
100	K → E1	100.0%	99.8%	100.0%	98.8%	100.0%	87.0%	4.6%	70.4%	6.0%	67.2%	4.6%	49.8%
	K → E3	100.0%	99.8%	100.0%	98.8%	100.0%	87.2%	85.4%	73.2%	85.2%	73.8%	85.2%	74.6%
	E1 → E2	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.4%	100.0%	98.8%	100.0%	85.8%
	E1 → E4	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.4%	100.0%	98.8%	100.0%	95.6%
200	K → E1	100.0%	100.0%	100.0%	100.0%	100.0%	99.6%	3.6%	100.0%	4.2%	99.4%	5.2%	98.0%
	K → E3	100.0%	100.0%	100.0%	100.0%	100.0%	99.6%	98.6%	99.0%	98.8%	98.6%	98.8%	99.4%
	E1 → E2	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.4%
	E1 → E4	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.6%
300	K → E1	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	4.0%	100.0%	5.4%	100.0%	5.0%	99.8%
	K → E3	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.8%	100.0%	99.8%	99.8%
	E1 → E2	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.8%
	E1 → E4	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	99.8%
400	K → E1	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	4.8%	100.0%	5.0%	100.0%	5.6%	100.0%
	K → E3	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
	E1 → E2	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
	E1 → E4	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
500	K → E1	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	4.6%	100.0%	6.0%	100.0%	4.0%	100.0%
	K → E3	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
	E1 → E2	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
	E1 → E4	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Note: Statistical power calculated using an alpha level of 5%. Power results for PLS are included for completeness purposes; however, ***given the severe degree of bias shown in Table 5, researchers should not attempt to interpret power for the second model in any meaningful manner.*** The objective of this table is to provide the reader with some measure of the degree to which the latent variable technique performs with respect to statistical power.

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