How to Address Endogeneity in Partial Least Squares Path Modeling

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Abstract

Some of the models using partial least squares (PLS) in Information Systems (IS) field may have serious problems because do not properly address endogeneity. This may suppose a problem in IS theory building because it may lead IS scholars to non-correct results. Although the IS community's awareness is rising, we do not have a clear understanding of the problem nor fine-grained practical guidelines on how to address the endogeneity in IS empirical research using PLS. Further, none of the PLS software packages has test of endogeneity capabilities. This paper explains and illustrates how to address endogeneity in research using PLS path modeling, and contribute to IS research in two ways: (1) we define the problem of endogeneity in empirical research and explain its main causes with IS research examples, (2) we show how to address endogeneity by correcting for omitted variables in PLS path modeling with composite and factor models.

Keywords

Endogeneity, partial least squares, omitted variables, and reverse causality.

Introduction

Some of the research models using structural equation modeling (SEM) in the field of Information Systems (IS) may not be causally interpreted because they neither check nor properly address/correct for endogeneity. Endogeneity occurs when one or more antecedent variables are correlated with the error term of the endogenous variable, that is, the residual or disturbance in a regression (Roberts & Whited 2013; Semanedi et al. 2014), violating a key causal modeling assumption (Macintosh et al. 2014). Thus, endogeneity may suppose a problem in testing hypotheses and theory building through the usage of the SEM technique because it may bias the findings that IS scholars achieve in relation to the proposed structural relationships (Hamilton & Nickerson 2003). This problem is not an exception in the partial least squares (PLS) path modeling, one of the available methods of estimation in SEM (Henseler et al. 2014).

The problem of endogeneity can appear in a research model, among others, mainly due to two reasons: (1) there are some omitted variables that may be also involved in the relationships hypothesized or controlled in the model (Antonakis et al. 2010), and (2) it is plausible to expect one or more bidirectional relationships (i.e., simultaneous/reverse causality) among some of the constructs included in the model (Abdallah et al. 2015). For example, Chen et al. (2015) study the impact of information technology (IT) capabilities on product innovation performance. They find that the firm's portfolio of IT capabilities facilitates corporate entrepreneurship to improve the firm's product innovation performance, which is amplified in presence of competitive intensity. Although this study is extremely valuable for the research on business value of IT, and as many other research models, this theoretical model does not check nor address for the potential causes omitted in the model. Thus, we do know that IT affects firm performance by enabling other organizational capabilities such as knowledge management (Tanriverdi 2005), new product development capabilities (Pavlou & El Sawy 2006), business agility (Benitez & Ray 2012; Chen et al. 2014), or the management of talent (Benitez et al. 2015). In this sense, based on prior IS research, knowledge management, new product development capabilities, business agility, and talent management are potential omitted variables in the Chen et al.'s (2015) model.

Similarly, Chen et al. (forthcoming) examine the impact of IT on firm performance through strategic flexibility. They find that IT support for core capabilities positively affects strategic flexibility to increase firm performance. While they provide strong arguments on the influence of IT support for core capabilities on strategic flexibility, one may discuss that it is also rational (at least to consider) that flexible firms may be faster in leveraging IT to develop core capabilities, which may suggest a bidirectional relationship between these two variables. In this sense, based on this alternative theoretical rationale, this potential bidirectional relationship has not been considered in the Chen et al.'s (forthcoming) model. These models should be only considered as two examples to illustrate the problem covered in this study.

When endogeneity is not properly checked neither corrected in PLS path modeling may generate errors (greater, lower, or even a different sign) in the estimation of the path coefficients, thus potentially leading to non-correct results. Also, it is more probable to find out statistically significant coefficients as endogeneity increases (Semadeni et al. 2014). For this reason, the problem of endogeneity has been considered as "an inconvenient truth" (Antonakis et al. 2010) in a similar way to the environmental degradation of the planet.

Despite the importance of this problem and although the review panels of the top-tier IS journals have started to seriously be conscious of the problem, claim the need of take it seriously, and demand to check/address endogeneity, we do not have a clear understanding of the definition and dimension of the problem, nor a fine-grained practical guidelines to know well how to address endogeneity in empirical research using PLS. This paper also aims to satisfy the explicit call for developing sound methodologies in PLS path modeling to correct the bias originated by endogeneity, given the practical absence of proven approaches to explicitly tackle such a problem in PLS (e.g., Benitez & Ray 2012; McIntosh et al. 2014). In fact, Vittadini et al.'s (2007), and Lovaglio and Vittadini (2013) works are the unique exceptions that have explored the endogeneity issue in PLS, but they fail to deal with some endogeneity causes, such as omitted variables (McIntosh et al. 2014). The author panel has proven expertise teaching courses on PLS path modeling in different countries. As another illustrative motivation, we would like to mention that we receive a great number of emails every week from the IS community asking for support on how to address for endogeneity on its research in progress. This is another key motivation that has moved to us to work on this paper.

The objective of this paper is to explain and illustrate how to address endogeneity in research using PLS path modeling. We define in detail the problem of endogeneity in empirical research using PLS, and provide one plausible solution to this problem by explaining how to correct for omitted variables. After that, we illustrate on two examples how to address endogeneity by correcting for the omitted variables bias. The first example examines the effect of competitor Facebook pressure on the development of firm's Facebook capability by using a composite model with PLS (Braojos et al. 2015a; Henseler 2015). The second example is a technology acceptance model (TAM) (Benbasat & Barki 2007; Davis et al. 1989; Roldán & Sánchez-Franco 2012) with reflective constructs using consistent PLS (PLSc) (Dijkstra & Henseler 2015a). Our paper shows how to address endogeneity by correcting for omitted variables in PLS path modeling with both composite and factor models. In this sense, correcting for endogeneity due to omitted variables is possible. This is also "a convenient truth".

The paper is organized as follows. Next section describes the problem of endogeneity. In the third section, we explain how to cope with endogeneity in PLS path models. After that, two examples of how to address the problem of endogeneity are provided. The paper finishes with the discussion and conclusions and with a section with the references.

The Problem of Endogeneity

PLS path modeling is a variance-based SEM technique that is very popular and has been broadly used in prior IS research (e.g., Benitez & Walczuch 2012; Pavlou & El Sawy 2006; Ringle et al. 2012; Roldán & Sánchez-Franco 2012). PLS is a full-fledged SEM method of estimation that can conduct exact test of model fit, which converts it in a suitable method of estimation for both exploratory and confirmatory research (Henseler & Dijkstra 2015; Henseler et al. 2016). PLS enables to estimate and test more complete and complex research models than ordinary least squares (OLS) regression. However, PLS path modeling as other research technique (e.g., OLS) is susceptible of suffering the problem of endogeneity.

The problem of endogeneity refers to the questioning or having some doubts on what is the endogenous variable and the exogenous variable. The presence of endogeneity implies that the exogenous variable and the error term of the endogenous variable are correlated (Abdallah et al., 2015). In this situation, the research model has a problem of endogeneity, which may be caused by various reasons, such as errors in variables (i.e., measurement error), omitted variables, reverse causality, selection bias, and common method effects (Bascle, 2008; McIntosh et al., 2014). In this study, we focus on one of them: omitted variables: there are some omitted variables that may be also involved in the relationships hypothesized or controlled in the model (Antonakis et al. 2010; Benitez & Ray 2012).

When endogeneity is not properly corrected in PLS path modeling may potentially generate errors (greater, lower, or even a different sign) in the estimation of the path coefficients, thus potentially leading to a non-correct inference, which has the potential to conduct scholars to an inappropriate theory building in the field of IS. This potential concern does not imply that we have to dramatically critique a significant portion of past IS research. However, our field demands increasingly of rigorous empirical research and this is a potential problem that requires an effective solution. The problem of endogeneity should be taken very seriously. This is what this paper aims to do by providing an initial step on that direction.

Coping with Endogeneity in PLS Path Models

The problem of endogeneity is inextricably linked with the recursivity of a structural model. Traditionally, scholars have required that PLS path models be recursive (Tenenhaus et al. 2005). Recursivity entails that models are free from feedback loops and correlated residuals, which comes down to a complete denial of endogeneity. Consequently, if analysts want to include endogeneity in a PLS path models, they must find a way to relax the requirement of recursivity. In order to understand the origin of the requirement of recursivity, it is indispensable to visualize that the PLS path modeling framework can be viewed as consisting of four steps (Dijkstra & Henseler 2015b):

1. The nonlinear iterative partial least squares algorithm (NIPALS; Wold 1975) provides composite weights such that the interrelatedness of the composites is maximized. This algorithm is the most important part of PLS path modeling (Hanafi 2007) and serves as its eponym. Alternatively, alternative least squares algorithm can be applied (Hwang et al. 2015). A focal output of this first step is a construct correlation matrix that consists of the correlations between all composites.

2. If an analyst is not interested in a composite, but rather a factor underlying a set of indicators, the corresponding composite correlations must be corrected for attenuation. Dijkstra and Henseler (2015a) introduced ρ_A as a consistent reliability estimate for PLS composite scores, which can be used to disattenuate those inter-construct correlations which involve factors instead of composites. The result of the second step is a consistent construct correlation matrix.

3. Based on the final construct correlation matrix one can obtain consistent and asymptotically normal estimates for linear equations expressing the relationships between constructs. Classically, OLS is used for this task. OLS assumes that the regression residual is uncorrelated with the predictor(s).

4. The path coefficient estimates can be used to calculate total effects, which are the sum of direct and indirect effects.

A glimpse at these four steps makes clear that although the requirement of recursivity has been ascribed to PLS path modeling in general, it is actually only the conventional implementation of the third step that requires recursivity. A modification of the third step thus appears the most promising avenue to make PLS fit for non-recursive models. In this way, PLS path models would be enabled to cope with endogeneity.

Drawn on the Dijkstra and Henseler's (2015b) work, we propose to modify the third step of PLS path modeling by replacing one traditional econometric method, OLS, by another established econometric method: two-stage least squares (2SLS). 2SLS is a limited-information technique that estimates each structural equation separately. Its complexity hardly exceeds that of OLS. First attempts to combine the NIPALS algorithm with 2SLS were reported by Hui (1982), who employed an iterative version of 2SLS, Wold's fix-point method, right after step one. However, neither did they apply step two as described above, nor does 2SLS require additional iterations. 2SLS is a viable option if direct effects in a structural equation model are subject to endogeneity while the total effects remain unaffected. It exploits thus the fact that the error term is uncorrelated with the exogenous variables.

Using 2SLS within the PLS path modeling framework essentially means that the third and the fourth step are executed in reversed order. Based on the (consistent) construct correlation matrix one first needs to determine the total effects, and then one can calculate the direct effects. In order to better understand the way how 2SLS obtains the path coefficient estimates for the direct effects between endogenous variables, let us more deeply inspect how information from the construct correlation matrix is extracted in order to determine the path coefficient estimates. For this purpose, Figure 1 depicts a construct correlation matrix Φ that contains the correlations between p exogenous constructs ξ_i and q endogenous constructs ηj.

OLS uses the correlations between exogenous and endogenous constructs in order to estimate the direct effects of exogenous on endogenous variables, which is unproblematic. However, it uses the correlations between endogenous constructs to estimate the direct effects between endogenous variables. Since these correlations are not only a reflection of the causal relationships among endogenous constructs, but can also be evoked by common causes not included in the model (omitted variables), they do not contain sufficient information to unanimously estimate the effects between endogenous variables.

2SLS relies on the construct correlation matrix in a different way. It uses the correlations between exogenous and endogenous constructs in order to estimate the total and direct effects of exogenous on endogenous variables. Since the residuals are uncorrelated with the exogenous variables, this approach is unproblematic. However, analysts must take care that this block of the construct correlation matrix contains sufficient information to estimate all parameters of interest. In essence, a sufficient number of direct effects must be theorized to be zero. In the methodological literature, this is discussed under the term identifiability. The correlations between endogenous constructs only help quantify the residual correlations, but are no longer used to determine the path coefficient estimates.

Two Illustrative Examples Coping with Endogeneity

Example 1: Competitor Facebook Pressure and Development of Firm Facebook Capability

The first example examines the effect of competitor Facebook pressure on the development of firm Facebook capability by using a composite model with PLS (Henseler 2015) on a sample composed of the 100 small U.S. firms included in the 2013 Forbes America's Best Small Companies ranking. Social Facebook pressure refers to the influence exerted on the firm by the industry rules and values, and the key competitors to adopt Facebook (Braojos et al. 2015a). Social Facebook pressure is a composite construct that assesses the average Facebook activity of the firm's key competitors (i.e., those firms operating on the same industry included in the 2013 Forbes database) in terms of number of events, experience, number of fans, and updates, with information collected in February 2014 from the Facebook site of the firm's key competitors. We use the Braojos et al.'s (2015a) measure scheme. Experience is measured as the average number of months that the key competitors operated in Facebook. We measure the average Facebook updates by scoring with 1: Low# or 5: High degree of content updating in Facebook. For each firm, we scored with 1-5 when the firm had made a comment on Facebook more than one month ago/in the last month/two weeks ago/in the last week/in the last two days respectively. After that, we estimate the average degree of content updating of the firm's key competitors (Braojos et al. 2015a).

Firm Facebook capability indicates the firm's ability to use and leverage Facebook for business activities (Braojos et al. 2015b). We measure and collected data for firm Facebook capability in February 2014 (firm Facebook capability t_1) and June 2014 (firm Facebook capability t_2) from the Facebook site of each firm on an identical way as per competitor Facebook pressure but related to the focal firm. Figure 2 shows the conceptual model of the example 1.

Since all constructs are operationalized as composites, we apply traditional PLS to estimate the composite weights and to obtain the construct correlations (Henseler et al. 2014) by using the statistical software package Advanced Analysis for Composites (ADANCO) 2.0 Professional (http://www.composite-modeling.com/) (Henseler & Dijkstra 2015). The estimated construct correlation matrix is:

$$\Phi = \begin{bmatrix} 1 & 0.4177 & 0.3372 \\ 0.4177 & 1 & 0.9681 \\ 0.3372 & 0.9681 & 1 \end{bmatrix}$$

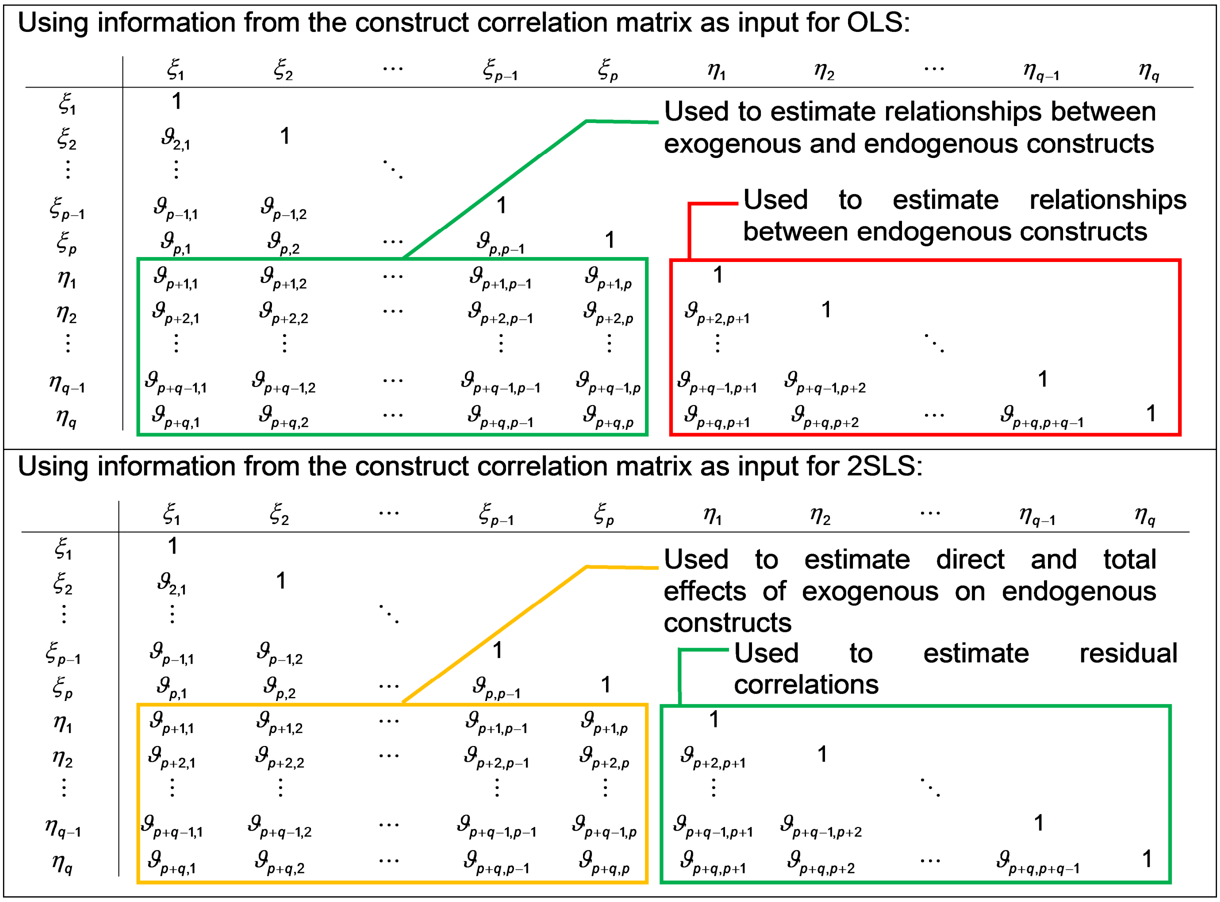

Figure 1. Extracting Information from a Construct Correlation Matrix in Order to Obtain Path Coefficient Estimates

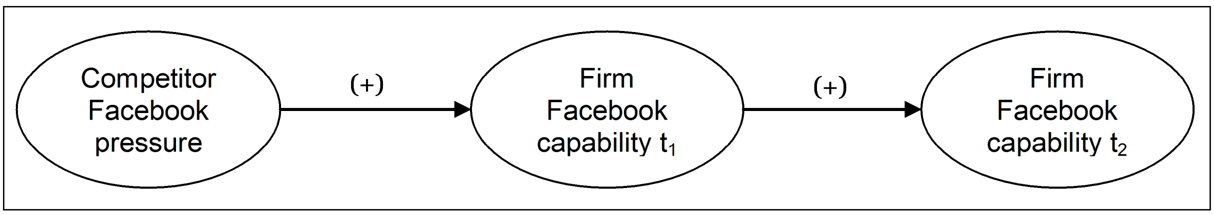

Figure 2. Conceptual Model of Example 1

We now apply OLS and 2SLS on this construct correlation matrix to obtain the two path coefficients by using Microsoft Excel 2010 for Windows. Since every endogenous construct has exactly one predictor, the calculus is quite simple. The standardized coefficient for the effect of competitor Facebook pressure on firm Facebook capability t_1 equals the correlation between these two constructs and can thus immediately be read from the construct correlation matrix: 0.4177. Since this relationship does not involve endogeneity (our assumption), there is no ambiguity of how to determine this coefficient. In contrast, the coefficient for the effect of firm Facebook capability t_1 on firm Facebook capability t_2 differs depending on whether endogeneity is taken into account or not. Using OLS, we would proceed as before: we would simply read out the corresponding value from the construct correlation matrix, which in this case is 0.9681. Note that this approach assumes that the residual of firm Facebook capability t_2 is uncorrelated with firm Facebook capability t_1. Given the plethora of potential variables that influence the firm Facebook capability at both times (omitted variables), this assumption appears untenable. There is also empirical evidence against this estimate: the total effect of competitor Facebook pressure on firm Facebook capability t_2 ($0.4177 \times 0.9681 = 0.4044$) should equal the correlation between these constructs (i.e., 0.3372), which is not the case. This total effect becomes pivotal when we take into account endogeneity. The core idea of 2SLS is that whereas the direct effect of firm Facebook capability t_1 on firm Facebook capability t_2 is affected by endogeneity, the total effect of competitor Facebook pressure on firm Facebook capability t_2 is not. Using 2SLS, we first read out the total effect from the construct correlation matrix (0.3372), and use it to determine the direct effect of firm Facebook capability t_1 on firm Facebook capability t_2 ($0.3372 \div 0.4177 = 0.8073$). The discrepancy between this path coefficient and the corresponding correlation of 0.9681 is then captured by the residual correlation.

Example 2: The Relationships between User Tuenti Attitude, Usage Intention, and Usage in TAM

The second example focuses on a portion of the TAM (e.g., Davis et al. 1989), which has been contextualized in the social media usage from an individual perspective (i.e., it is at user level instead of at firm level as example 1). We focus on Tuenti, the most popular social media among the Spanish student population during the period 2006-2010 (Sánchez-Franco & Roldán 2010). In this model, user Tuenti attitude influences user Tuenti usage intention, which in turn affects to user Tuenti usage. In this vein, user Tuenti attitude indicates the individual's positive or negative feelings about Tuenti usage. A positive attitude toward using Tuenti will determine Tuenti usage intention, and in turn, this usage intention leads to actual Tuenti usage (Roldán & Sánchez-Franco 2012). In this model, we have deliberately omitted a key variable of the theory of planned behavior that influences both user Tuenti intention and user Tuenti usage. We refer to user Tuenti perceived behavioral control that indicates user Tuenti perception of the difficulty of performing a behavior or act (Ajzen 1991). Therefore, both intention and usage may be influenced by perceptions about how much control a Tuenti user has over an outcome, such as faith in his/her ability. In this sense, user Tuenti perceived behavioral control is an example of omitted variable in the equation between user Tuenti usage intention and usage. This example purposely engages in one of the causes that usually generate endogeneity, that is, the existence of omitted variables that may be involved in a proposed conceptual model. According with prior IS research (e.g., Sánchez-Franco & Roldán 2010), this is a factor model (i.e., the three constructs are specified as reflective). The data for this example come from a sample of 278 undergraduate students from a School of Business in the South of Spain, who were users of Tuenti. These participants answered an offline survey in January 2009. Figure 3 shows the conceptual model of the example 2.

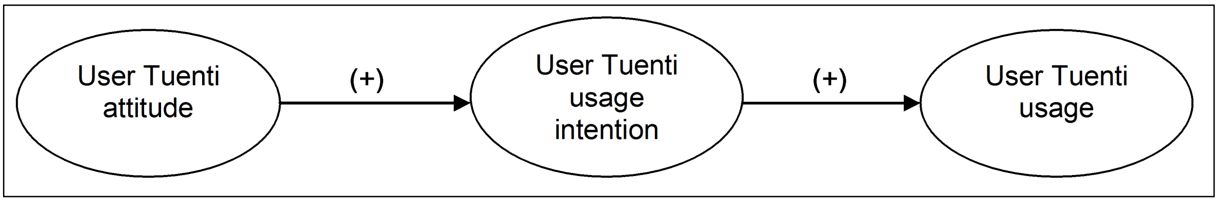

Figure 3. Conceptual Model of Example 2

Since all constructs are operationalized as factors, we apply PLSc to obtain the construct correlations (Dijkstra & Henseler 2015a) by using ADANCO 2.0 Professional. The estimated construct correlation matrix for this model is:

$$\Phi = \begin{bmatrix} 1 & 0.4694 & 0.1886 \\ 0.4694 & 1 & 0.4999 \\ 0.1886 & 0.4999 & 1 \end{bmatrix}$$

Again, we apply OLS and 2SLS on this construct correlation matrix to obtain the two path coefficients by using Microsoft Excel 2010 for Windows. The standardized coefficient for the effect of user Tuenti attitude on user Tuenti usage intention equals the correlation between these two constructs, i.e. 0.4694. In analogy to the first example, this relationship does not involve endogeneity. In contrast, the effect of user Tuenti usage intention on user Tuenti usage is subject to endogeneity. Using OLS (i.e., not modifying the third step of the PLS estimation), we would estimate this effect to have a standardized coefficient of 0.4999. In the light of the well-known intention-behavior gap (Lee et al. 2003) and a plethora of meta-studies on the intention-behavior link (King & He 2006; Schepers & Wetzels 2007), such a path coefficient for a relationship between a usage intention and the actual usage behavior appears somewhat high. The picture becomes different if we take into account endogeneity by changing OLS by 2SLS in the third step of the PLS estimation. The total effect of user Tuenti attitude on user Tuenti usage is 0.1886, which results in a direct effect of user Tuenti usage intention on user Tuenti usage of 0.1886 ÷ 0.4694 = 0.4018, a somewhat healthier coefficient. The discrepancy between this path coefficient and the corresponding correlation of 0.4999 is again captured by the residual correlation.

One may discussed that introducing instrumental variables is needed to properly run 2SLS in PLS path modeling. As long as a system of equations has sufficient exogenous variables, it will be identified. Declaring a variable to be an “instrumental variable” is simply an act of name-giving, just like calling a certain variable a “control variable” (which is simply an exogenous variable in whose effect one usually is less interesting). Our two examples above have enough exogenous variables and these models are identified.

Discussion and Conclusions

PLS is a full-fledged SEM method of estimation that can conduct exact test of model fit, which converts it in a suitable method of estimation for both explore and build new IS theories. However, some of the research models using PLS path modeling in the field of IS may have serious problems because do not check nor properly address/correct for endogeneity. This may suppose a problem in testing hypotheses and IS theory building because it may lead IS scholars to non-correct results (i.e., greater, lower, or even a different sign in path coefficients) (Semadeni et al. 2014). Consequently, the review panels of the top-tier IS journals have started to be conscious of the problem, claim the need of take it seriously, and are demanding to check and address endogeneity in empirical IS research. However, we do not have a clear understanding of the problem nor fine-grained guidelines on how to address the endogeneity in IS research using PLS (i.e., one of the methods of estimation most popularized and used in the field of IS). Further, none of the PLS statistical software package has test of endogeneity capabilities. This makes very difficult in reality to address endogeneity in a PLS estimation, and it may convert endogeneity capabilities in “the Holy Grail” of the PLS estimation.

This paper explains and illustrates how to address endogeneity in research using PLS path modeling. The problem of endogeneity refers to the questioning or having some doubts on what is the endogenous variable and the exogenous variable. The problem of endogeneity can appear in a research model due to mainly two reasons: (1) omitted variables: there are some omitted variables that may be also involved in the relationships hypothesized or controlled in the model (Antonakis et al. 2010); and (2) reverse causality: it is plausible to expect one or more bidirectional relationships between some of the variables included in the model (Abdallah et al. 2015). In this study, we focus on the first reason.

In PLS path modeling, endogeneity due to omitted variables may be addressed by modifying the third step of PLS path modeling by replacing OLS by 2SLS. 2SLS is a limited-information technique that estimates each structural equation separately. In this modification, 2SLS is preferred to full-information estimators (e.g., maximum likelihood, three-stage least squares) because 2SLS is less vulnerable to model misspecification. Although full-information techniques are consistent when the model is correctly specified, any misspecification in the model can bias parameter estimates throughout the model. In contrast, given that 2SLS estimates each equation separately, misspecification in one equation does not affect the parameter estimates in other equations, which it enables the scholar to isolate potential model misspecification (Paxton et al. 2011). Unless the scholar is fully confident with the model specification, we would urge to use 2SLS to change the third step of the PLS path modeling to cope with endogeneity.

The main limitation of this research is that our practical guidelines are only focused on how to address the existence of endogeneity due to omitted variables. In a further research we plan to provide fine-grained practical guidelines on how to address endogeneity in PLS path modeling due to reverse causality.

This paper has two key contributions to the field of IS. First, we define in detail the problem of endogeneity in empirical research using PLS, and explain the dimension of the problem of endogeneity with IS research examples. Second, this paper shows how to address endogeneity by correcting for omitted variables in PLS path modeling with both composite (i.e., example 1) and factor models (i.e., example 2), and both by using secondary (i.e., example 1) and perceptual data (i.e., example 2). We argue that to correct for endogeneity in a PLS path model, the third step of the PLS estimation should be modified by replacing OLS by 2SLS. Next step is to incorporate in the current statistical software packages of PLS this suggestion. The team of ADANCO software developers is working very hard to implement this modification in next version (3.0 Professional). In this sense, we show "a convenient truth": correcting for endogeneity due to omitted variables in a PLS estimation is plausible and possible. This paper explains how to do it.

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