Common method bias in PLS-SEM: A full collinearity assessment approach

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Full reference:

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1-10.

Abstract

We discuss common method bias in the context of structural equation modeling employing the partial least squares method (PLS-SEM). Two datasets were created through a Monte Carlo simulation to illustrate the discussion: one contaminated by common method bias, and the other not contaminated. A practical approach is presented for the identification of common method bias based on variance inflation factors generated via a full collinearity test. Our discussion builds on an illustrative model in the field of e-collaboration, with outputs generated by the software WarpPLS. We demonstrate that the full collinearity test is successful in the identification of common method bias with a model that nevertheless passes standard convergent and discriminant validity assessment criteria based on a confirmation factor analysis.

KEYWORDS: Partial Least Squares; Structural Equation Modeling; Common Method Bias; Monte Carlo Simulation

Introduction

The method of path analysis has been developed by Wright (1934; 1960) to study causal assumptions in the field of evolutionary biology (Kock, 2011), and now provides the foundation on which structural equation modeling (SEM) rests. Both path analysis and SEM rely on the creation of models expressing causal relationships through links among variables.

Two main types of SEM exist today: covariance-based and PLS-based SEM. While the former relies on the minimization of differences between covariance matrices, the latter employs the partial least squares method (PLS) developed by Herman Wold (Wold, 1980). PLS-based SEM is often referred to simply as PLS-SEM, and is widely used in the field of e-collaboration and many other fields.

Regardless of SEM flavor, models expressing causal assumptions include latent variables. These latent variables are measured indirectly through other variables generally known as indicators (Maruyama, 1998; Mueller, 1996). Indicator values are usually obtained from questionnaires where answers are provided on numeric scales, of which the most commonly used are Likert-type scales (Cohen et al., 2003).

Using questionnaires answered on Likert-type scales constitutes an integral part of an SEM study's measurement method. Common method bias is a phenomenon that is caused by the measurement method used in an SEM study, and not by the network of causes and effects among latent variables in the model being studied.

We provide a discussion of common method bias in PLS-SEM, and of a method for its identification based on full collinearity tests (Kock & Lynn, 2012). Our discussion builds on an illustrative model in the field of e-collaboration, with outputs from the software WarpPLS, version 5.0 (Kock, 2015).

The algorithm used to generate latent variable scores based on indicators was PLS Mode A, employing the path weighting scheme. While this is the algorithm-scheme combination most commonly used in PLS-SEM, it is by no means the only combination available. The recent emergence of factor-based PLS-SEM algorithms further broadened the space of existing combinations (Kock, 2014).

We created two datasets based on a Monte Carlo simulation (Robert & Casella, 2005; Paxton et al., 2001). One of the two datasets was contaminated by common method bias; the other was not. We demonstrate that the full collinearity test is successful in the identification of common method bias with a model that nevertheless passes standard validity assessment criteria based on a confirmation factor analysis.

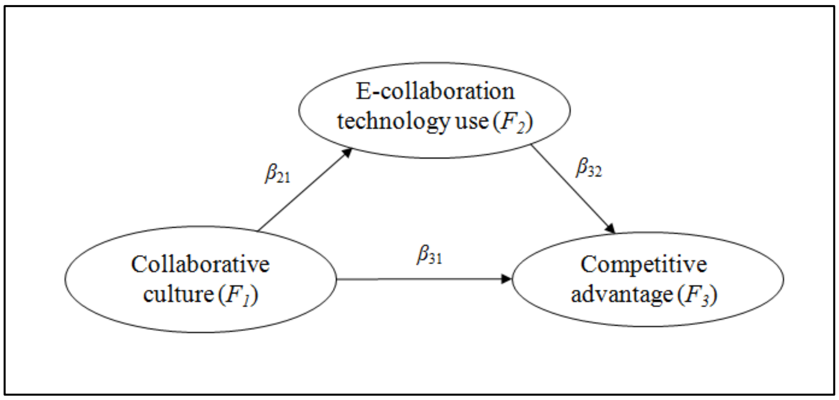
In our discussion all variables are assumed to be standardized; i.e., scaled to have a mean of zero and standard deviation of one. This has no impact on the generality of the discussion. Standardization of any variable is accomplished by subtraction of its mean and division by its standard deviation. A standardized variable can be rescaled back to its original scale by reversing these operations.

What is common method bias?

Common method bias, in the context of PLS-SEM, is a phenomenon that is caused by the measurement method used in an SEM study, and not by the network of causes and effects in the model being studied. For example, the instructions at the top of a questionnaire may influence the answers provided by different respondents in the same general direction, causing the indicators to share a certain amount of common variation. Another possible cause of common method bias is the implicit social desirability associated with answering questions in a questionnaire in a particularly way, again causing the indicators to share a certain amount of common variation.

A mathematical understanding of common method bias can clarify some aspects of its nature. The adoption of an illustrative model can help reduce the level of abstraction of a mathematical exposition. Therefore, our discussion is based on the illustrative model depicted in Figure 1, which is inspired by an actual empirical study in the field of e-collaboration (Kock, 2005; 2008; Kock & Lynn, 2012). The illustrative model incorporates three latent variables, each measured through six indicators. It assumes that the unit of analysis is the firm.

Figure 1. Illustrative model



The latent variables are: *collaborative culture* (F_1), the perceived degree to which a firm's culture promotes continuous collaboration among its members to improve the firm's productivity and the quality of the firm's products; e-*collaboration technology use* (F_2), the perceived degree of use of e-collaboration technologies by the members of a firm; and c*ompetitive advantage* (F_3), the perceived degree of competitive advantage that a firm possesses when compared with firms that compete with it.

Mathematically, if our model were not contaminated with common method bias, each of the six indicators x_{ij} would be derived from its latent variable F_i (of which there are three in the model) according to (1), where: λ_{ij} is the loading of indicator x_{ij} on F_i, θ_{ij} is the standardized indicator error term, and $\omega_{\theta j}$ is the weight of θ_{ij} with respect to x_{ij}.

$$x_{ij} = \lambda_{ij}F_i + \omega_{\theta j}\theta_{ij}, i = 1 \ldots 3, j = 1 \ldots 6. \quad (1)$$

Since θ_{ij} and F_i are assumed to be uncorrelated, the value of $\omega_{\theta j}$ in this scenario can be easily obtained as:

$$\omega_{\theta j} = \sqrt{1 - \lambda_{ij}{}^2}.$$

If our model *were* contaminated with common method bias, each of the six indicators x_{ij} would be derived from its latent variable F_i according to (2), where: M is a standardized variable that represents common method variation, and ω_M is the common method weight (a.k.a. common method loading, or the positive square root of the common method variance).

$$x_{ij} = \lambda_{ij} F_i + \omega_M M + \omega_{\theta j} \theta_{ij},\ i = 1 \ldots 3,\ j = 1 \ldots 6. \qquad (2)$$

In this scenario, the value of $\omega_{\theta j}$ can be obtained as:

$$\omega_{\theta j} = \sqrt{1 - {\lambda_{ij}}^2 - {\omega_M}^2}.$$

In (2) we assume that the common method weight ω_M is the same for all indicators. An alternative perspective assumes that the common method weight ω_M is not the same for all indicators, varying based on a number of factors. Two terms are used to refer to these different perspectives, namely congeneric and noncongeneric, although there is some confusion in the literature as to which term refers to what perspective.

Note that the term $\omega_M M$ introduces common variation that is shared by all indicators in the model. Since latent variables aggregate indicators in PLS-SEM, this shared variation has the effect of artificially increasing the level of collinearity among latent variables. As we will see later, this also has the predictable effect of artificially increasing path coefficients.

Data used in the analysis

We created two datasets of 300 rows of data, equivalent to 300 returned questionnaires, with answers provided on Likert-type scales going from 1 to 7. This was done based on a Monte Carlo simulation (Robert & Casella, 2005; Paxton et al., 2001). The data was created for the three latent variables and the eighteen indicators (six per latent variable) in our illustrative model.

Using this method we departed from a "true" model, which is a model for which we know the nature and magnitude of all of the relationships among variables beforehand. One of the two datasets was contaminated by common method bias; the other was not. In both datasets path coefficients and loadings were set as follows:

$$\beta_{21} = \beta_{31} = \beta_{32} = .45.$$
$$\lambda_{ij} = .7,\ i = 1 \ldots 3,\ j = 1 \ldots 6.$$

That is, all path coefficients were set as $.45$ and all indicator loadings as $.7$. In the dataset contaminated by common method bias, the common method weight was set to a value slightly lower than the indicator loadings:

$$\omega_M = .6.$$

In Monte Carlo simulations where samples of finite size are created, true sample coefficients vary. Usually true sample coefficients vary according to a normal distribution centered on the true population value. Given this, and since we created a single sample of simulated data, our true sample coefficients differed from the true population coefficients.

Nevertheless, when we compared certain coefficients obtained via a PLS-SEM analysis for the two datasets, with and without contamination, the effects of common method bias became visible. This is particularly true for path coefficients, which tend to be inflated by common method bias. As noted earlier, path coefficient inflation is a predictable outcome of shared variation among latent variables.

Path coefficient inflation

Table 1 shows the path coefficients for the models not contaminated by common method bias (No CMB) and contaminated (CMB). As we can see, all three path coefficients were greater in the model contaminated by common method bias. The differences among path coefficients ranged from a little over 20 to nearly 40 percent.

Table 1. Path coefficients

	$\boldsymbol{\beta_{21}}$	$\boldsymbol{\beta_{31}}$	$\boldsymbol{\beta_{32}}$
No CMB	.447	.409	.357
CMB	.625	.512	.435

Note: CMB = common method bias.

This path coefficient inflation effect is one of the key reasons why researchers are concerned about common method bias, as it may cause type I errors (false positives). Nevertheless, common method bias may also be associated with path coefficient *deflation*, potentially leading to type II errors (false negatives).

As we can see, the inflation effect can lead to marked differences in path coefficients. In the case of the path coefficient β_{21}, the difference is of approximately 39.82 percent. As noted earlier, path coefficient inflation occurs because common variation is introduced, being shared by all indicators in the model. As latent variables aggregate indicators, they also incorporate the common variation, leading to an increase in the level of collinearity among latent variables. Greater collinearity levels in turn lead to inflated path coefficients.

One of the goals of a confirmatory factor analysis is to assess two main types of validity in a model: convergent and discriminant validity. Acceptable convergent validity occurs when indicators load strongly on their corresponding latent variables. Acceptable discriminant validity occurs when the correlations among a latent variable and other latent variables in a model are lower than a measure of communality among the latent variable indicators.

Given these expectations underlying acceptable convergent and discriminant validity, one could expect that a confirmatory factor analysis would allow for the identification of common method bias. In fact, many researchers in the past have proposed the use of confirmatory factor analysis as a more desirable alternative to Harman's single-factor test – a widely used common method bias test that relies on exploratory factor analysis. Unfortunately, as we will see in the next section, conducting a confirmatory factor analysis is not a very effective way of identifying common method bias. Models may pass criteria for acceptable convergent and discriminant validity, and still be contaminated by common method bias.

Confirmatory factor analysis

Table 2 is a combined display showing loadings and cross-loadings. Loadings, shown in shaded cells, are unrotated. Cross-loadings are oblique-rotated. Acceptable convergent validity would normally be assumed if the loadings were all above a certain threshold, typically .5. As we can see, all loadings pass this test. This is the case for both models, with and without common method bias contamination. That is, both models present acceptable convergent validity.

These results highlight one interesting aspect of the common method bias phenomenon in the context of PLS-SEM. There appears to be a marked inflation in loadings, similarly to what was observed for path coefficients. Since convergent validity relies on the comparison of loadings against a fixed threshold, then it follows that common method bias would tend to artificially increase the level of convergent validity of a model.

Table 3 shows correlations among latent variables and square roots of average variances extracted (AVEs). The latter are shown in shaded cells, along diagonals. Acceptable discriminant validity would typically be assumed if the number in the diagonal cell for each column is greater than any of the other numbers in the same column.

Table 2. Assessing convergent validity

	No CMB			**CMB**		
	F_1	F_2	F_3	F_1	F_2	F_3
x_{11}	.742	.010	-.095	.902	.072	-.075
x_{12}	.730	.029	.010	.912	.060	-.100
x_{13}	.772	.051	-.043	.900	-.075	.054
x_{14}	.771	-.061	.109	.891	.004	-.064
x_{15}	.766	.004	.042	.913	-.085	.176
x_{16}	.729	-.033	-.044	.890	.026	.001
x_{21}	.022	.690	-.102	.011	.900	.031
x_{22}	-.060	.709	-.027	-.003	.892	-.063
x_{23}	.049	.701	.005	.080	.893	-.113
x_{24}	.018	.766	.031	-.068	.921	.077
x_{25}	-.106	.731	.040	.020	.905	.002
x_{26}	.055	.766	.033	-.036	.924	.057
x_{31}	.022	-.003	.721	.020	-.005	.911
x_{32}	-.039	.029	.712	.052	-.013	.908
x_{33}	-.029	-.063	.693	-.003	-.012	.913
x_{34}	-.018	-.008	.724	-.037	.035	.909
x_{35}	.013	-.060	.754	-.065	-.072	.920
x_{36}	.041	.088	.762	.030	.065	.903

Notes: CMB = common method bias; loadings are unrotated and cross-loadings are oblique-rotated; loadings shown in shaded cells.

Table 3. Assessing discriminant validity

	No CMB			**CMB**		
	F_1	F_2	F_3	F_1	F_2	F_3
F_1	.752	.447	.568	.901	.625	.785
F_2	.447	.728	.540	.625	.906	.756
F_3	.568	.540	.728	.785	.756	.911

Notes: Square roots of average variances extracted (AVEs) shown on shaded diagonal.

That is, if the square root of the AVE for a given latent variable is greater than any correlation involving that latent variable, and this applies to all latent variables in a model, then the model presents acceptable discriminant validity. As we can see, this is the case for both of our models, with and without common method bias contamination. Both models can thus be assumed to display acceptable discriminant validity.

Here we see another interesting aspect of the common method bias phenomenon in the context of PLS-SEM. While correlations among latent variables increase, the same happens with the AVEs. This simultaneous increase in correlations and AVEs is what undermines the potential of a discriminant validity check in the identification of common method bias.

In summary, two key elements of a traditional confirmatory factor analysis are a convergent validity test and a discriminant vadity test. According to our analysis, neither test seems to be very effective in the identification of common method bias. An analogous analysis was conducted by Kock & Lynn (2012), which prompted them to offer the full collinearity test as an effective alternative for the identification of common method bias.

The full collinearity test

Collinearity has classically been defined as a predictor-predictor phenomenon in multiple regression models. In this traditional perspective, when two or more predictors measure the same underlying construct, or a facet of such construct, they are said to be collinear. This definition is restricted to classic, or vertical, collinearity.

Lateral collinearity is defined as a predictor-criterion phenomenon, whereby a predictor variable measures the same underlying construct, or a facet of such construct, as a variable to which it points in a model. The latter is the criterion variable in the predictor-criterion relationship of interest.

Kock & Lynn (2012) proposed the full collinearity test as comprehensive procedure for the simultaneous assessment of both vertical and lateral collinearity (see, also, Kock & Gaskins, 2014). Through this procedure, which is fully automated by the software WarpPLS, variance inflation factors (VIFs) are generated for all latent variables in a model. The occurrence of a VIF greater than 3.3 is proposed as an indication of pathological collinearity, and also as an indication that a model may be contaminated by common method bias. Therefore, if all VIFs resulting from a full collinearity test are equal to or lower than 3.3, the model can be considered free of common method bias.

Table 4 shows the VIFs obtained for all the latent variables in both of our models, based on a full collinearity test. As we can see, the model contaminated with common method bias includes a latent variable with VIF greater than 3.3, which is shown in a shaded cell. That is, the common method bias test proposed by Kock & Lynn (2012), based on the full collinearity test procedure, seems to succeed in the identification of common method bias.

Table 4. Full collinearity VIFs

	F_1	F_2	F_3
No CMB	1.541	1.472	1.739
CMB	2.619	2.347	3.720

Note: CMB = common method bias.

While it is noteworthy that the full collinearity test was successful in the identification of common method bias in a situation where a confirmation factor analysis was not, this success is not entirely surprising given our previous discussion based on the mathematics underlying common method bias. That discussion clearly points at an increase in the overall level of collinearity in a model, corresponding to an increase in the full collinearity VIFs for the latent variables in the model, as a clear outcome of common method bias.

Discussion and conclusion

There is disagreement among methodological researchers about the nature of common method bias, how it should be addressed, and even whether it should be addressed at al. Richardson et al. (2009) discuss various perspectives about common method bias, including the perspective put forth by Spector (1987) that common method bias is an “urban legend”. Assuming that the problem is real, what can we do to avoid common method bias in the first place? A seminal source in this respect is Podsakoff et al. (2003), who provide a number of suggestions on how to avoid the introduction of common method bias during data collection.

Our discussion focuses on the identification of common method bias based on full collinearity assessment, whereby a model is checked for the existence of both vertical and lateral collinearity (Kock & Gaskins, 2014; Kock & Lynn, 2012). If we find evidence of common method bias, is there anything we can do to eliminate or at least reduce it? The answer is arguably “yes”, and, given the focus of our discussion, the steps discussed by Kock & Lynn (2012) for dealing with collinearity are an obvious choice: indicator removal, indicator re-assignment, latent variable removal, latent variable aggregation, and hierarchical analysis. Readers are referred to that publication for details on how and when to implement these steps.

Full collinearity VIFs tend to increase with model complexity, in terms of number of latent variables in the model, because: (a) the likelihood that questions associated with different indicators will overlap in perceived meaning goes up as the size of a questionnaire increases, which should happen as the number of constructs covered grows; and (b) the likelihood that latent variables will overlap in terms of the facets of the constructs to which they refer goes up as more latent variables are added to a model.

Models found in empirical research studies in the field of e-collaboration typically contain more than three latent variables. This applies to many other fields where path analysis and SEM are employed. Therefore, we can reasonably conclude that our illustration of the full collinearity test of common method bias discussed here is conservative in its demonstration of the likely effectiveness of the test in actual empirical studies.

Kock & Lynn (2012) pointed out that classic PLS-SEM algorithms are particularly effective at reducing model-wide collinearity, because those algorithms maximize the variance explained in latent variables by their indicators. Such maximization is due in part to classic PLS-SEM algorithms not modeling measurement error, essentially assuming that it is zero. As such, the indicators associated with a latent variable always explain 100 percent of the variance in the latent variable.

Nevertheless, one of the key downsides of classic PLS-SEM algorithms is that path coefficients tend to be attenuated (Kock, 2015b). In a sense, they reduce collinearity levels “too much”. The recently proposed factor-based PLS-SEM algorithms (Kock, 2014) address this problem. Given this, one should expect the use of factor-based PLS-SEM algorithms to yield slightly higher full collinearity VIFs than classic PLS-SEM algorithms, with those slightly higher VIFs being a better reflection of the true values.

Consequently, the VIF threshold used in common method bias tests should arguably be somewhat higher than 3.3 when factor-based PLS-SEM algorithms are used. In their discussion of possible thresholds, Kock & Lynn (2012) note that a VIF of 5 could be employed when algorithms that incorporate measurement error are used. Even though they made this remark in reference to covariance-based SEM algorithms, the remark also applies to factor-based PLS-SEM algorithms, as both types of algorithms incorporate measurement error.

Our goal here is to help empirical researchers who need practical and straightforward methodological solutions to assess the overall quality of their measurement frameworks. To that end, we discussed and demonstrated a practical approach whereby researchers can conduct common method bias assessment based on a full collinearity test of a model. Our discussion was illustrated with outputs of the software WarpPLS (Kock, 2015), in the context of e-collaboration research. Nevertheless, our discussion arguably applies to any field where path analysis and SEM can be used.

Acknowledgments

The author is the developer of the software WarpPLS, which has over 7,000 users in more than 33 different countries at the time of this writing, and moderator of the PLS-SEM e-mail distribution list. He is grateful to those users, and to the members of the PLS-SEM e-mail distribution list, for questions, comments, and discussions on topics related to SEM and to the use of WarpPLS.

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