

Harman's single factor test in PLS-SEM: Checking for common method bias

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Abstract

Common method bias can be defined, in the context of structural equation modeling via partial least squares (PLS-SEM), as a phenomenon that is caused by the measurement method used in a study, and not by the network of causes and effects connecting the latent variables in the study. We illustrate how Harman's single factor test of common method bias can be conducted with WarpPLS, a leading PLS-SEM software tool.

Keywords: Common Method Bias; Harman's Single Factor Test; Average Variance Extracted; Structural Equation Modeling; Partial Least Squares; WarpPLS.

Introduction

Common method bias can be defined, in the context of structural equation modeling via partial least squares (PLS-SEM), as a phenomenon that is caused by the measurement method used in a study, and not by the network of causes and effects connecting the latent variables in the study. For example, the instructions provided by a researcher administering a questionnaire used for data collection may influence the answers provided by different respondents in the same general direction, causing the indicators to share a certain amount of common variation.

A widely used test of common method bias is the highest full collinearity variance inflation factor (FCVIF) test (Kock, 2015; Kock & Lynn, 2012), whereby the highest FCVIF in a model is compared against a threshold (usually 3.3). Another widely used test of common method bias is Harman's single factor test. This test can be easily carried out with WarpPLS, a leading software tool that implements classic composite-based and more modern factor-based PLS-SEM algorithms (Kock, 2019a; 2019b), among other attractive features (Kock, 2020b; 2020c; 2020d). We use WarpPLS version 7.0 (Kock, 2020a) to illustrate two variations of Harman's test, equivalent to the two main implementation of this test – via principal components and exploratory factor analyses.

Harman's single factor test

Harman's single factor test is sometimes performed via a principal components analysis, and other times via an exploratory factor analysis. The latter is generally seen as more appropriate. In the context of PLS-SEM, Harman's single factor test entails creating a model with one single latent variable and conducting a composite-based or a factor-based analysis. The former is

equivalent to conducting the test via a principal components analysis, and the latter via an exploratory factor analysis.

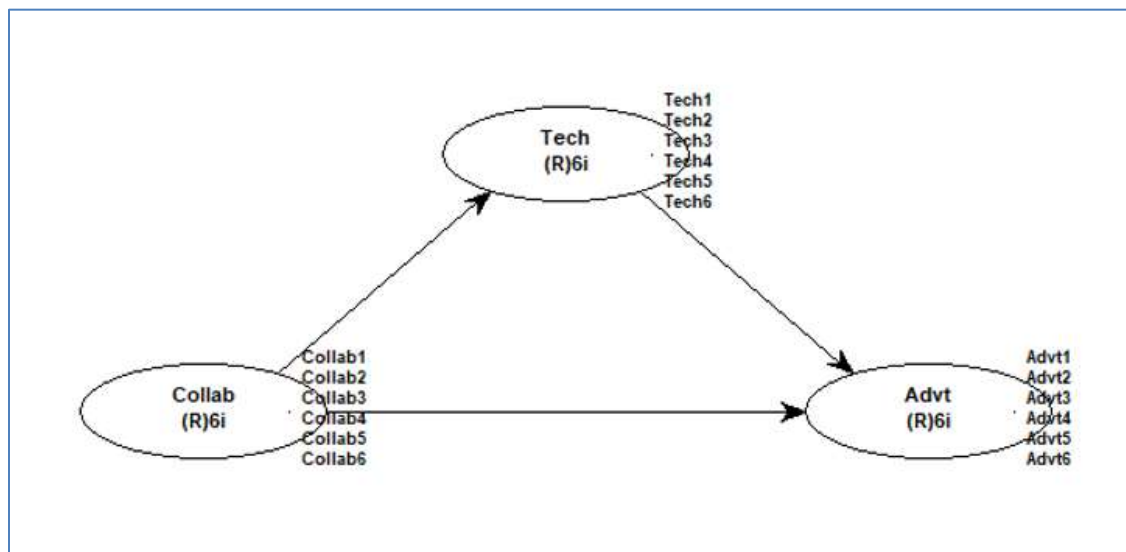
In Harman's single factor test, the percentage of variance associated with the first component (or factor), the one referring to the highest eigenvalue, is compared against the threshold of 0.5. Such percentage is also referred to as the "total variance explained" by the first component (or factor) extracted through the analysis. This could be confusing to users of the test, because it may give the impression that it is the total variance in the latent variable explained by the indicators; which is in fact 1 (100 percent) for the first component, and for the corresponding factor it equals the factor's reliability.

In PLS-SEM, after we create a model with one single latent variable and conduct a composite-based or a factor-based analysis, the "total variance explained" is in fact the average variance extracted (AVE) for the latent variable. If the AVE is greater than 0.5, in either case, one concludes that the dataset used is contaminated by common method bias.

Illustrative model and data

The illustrative model shown in Figure 1 is used as a basis for our discussion. Kock (2015) used the same model, in the context of another common method bias discussion in PLS-SEM. It contains three latent variables: collaborative culture (Collab), the degree to which a firm's culture promotes continuous collaboration among its members; e-collaboration technology use (Tech), the degree of use of e-collaboration technologies by the members of a firm; and competitive advantage (Advt), the degree of competitive advantage that a firm possesses in its industry.

Figure 1: Illustrative model used



Notes: Collab = collaborative culture; Tech = e-collaboration technology use; Advt = competitive advantage; notation under latent variable acronym describes measurement approach and number of indicators, e.g., (R)6i = reflective measurement with 6 indicators.

We created data employing the Monte Carlo simulation method (Kock, 2016); using the model above and related prior empirical research as a basis. Two datasets with 300 rows of data were

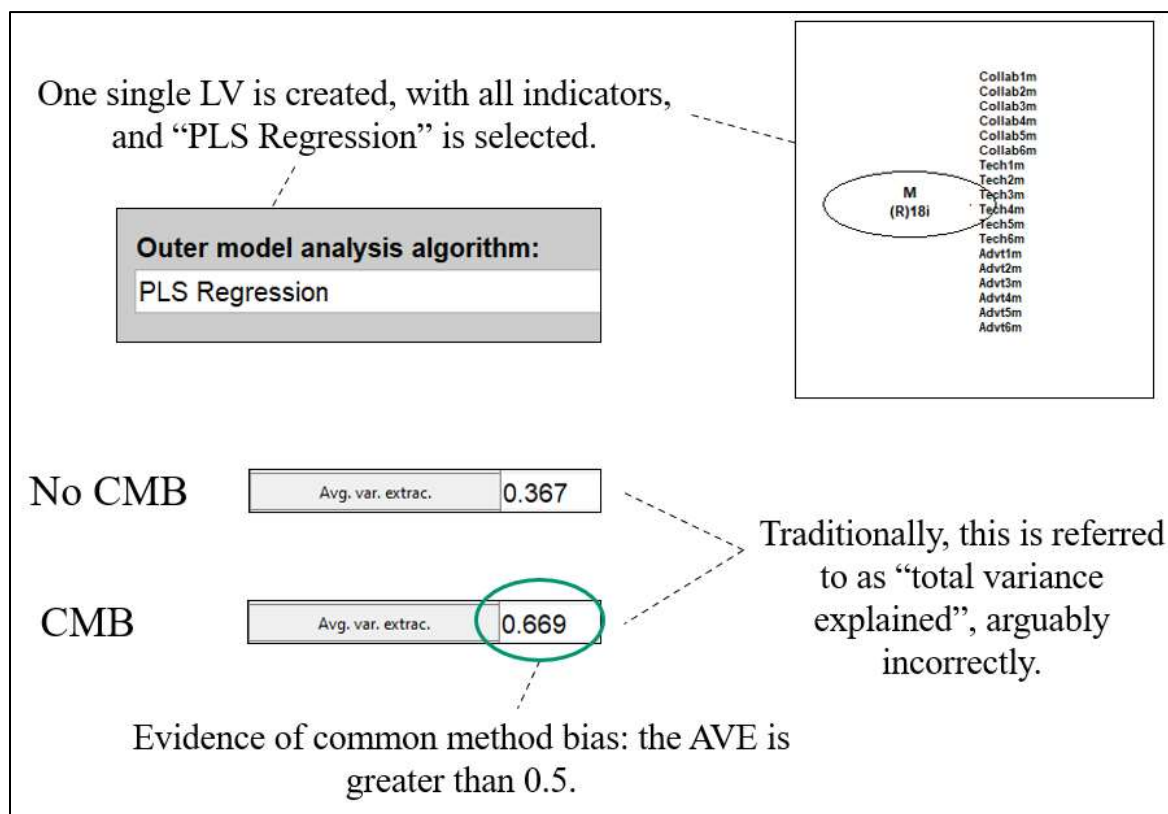
created, equivalent to 300 returned questionnaires, with answers provided on Likert-type scales going from 1 to 7. Each row refers to one firm.

One of the two datasets was contaminated by common method bias; the other was not. All path coefficients were set at 0.45 at the population level. Each latent variable was associated with 6 indicators, with all loadings set at 0.7. All common method weights were set at 0.6, for the contaminated dataset.

Composite-based PLS-SEM test

Figure 2 provides a schematic representation of the steps involved in the composite-based PLS-SEM implementation of Harman's test, performed for each of the two datasets. First, the outer model analysis algorithm is set as "PLS Regression", which is the PLS-SEM equivalent of the algorithm underlying a principal components analysis. Second, all indicators are associated with one single latent variable. Third, the "View latent variable coefficients" menu option is selected; this option is available when the "View/save analysis results" button is clicked. Finally, the average variance extracted (AVE) for the single latent variable in the model is inspected.

Figure 2: Composite-based PLS-SEM test



Notes: CMB = common method bias; LV = latent variable.

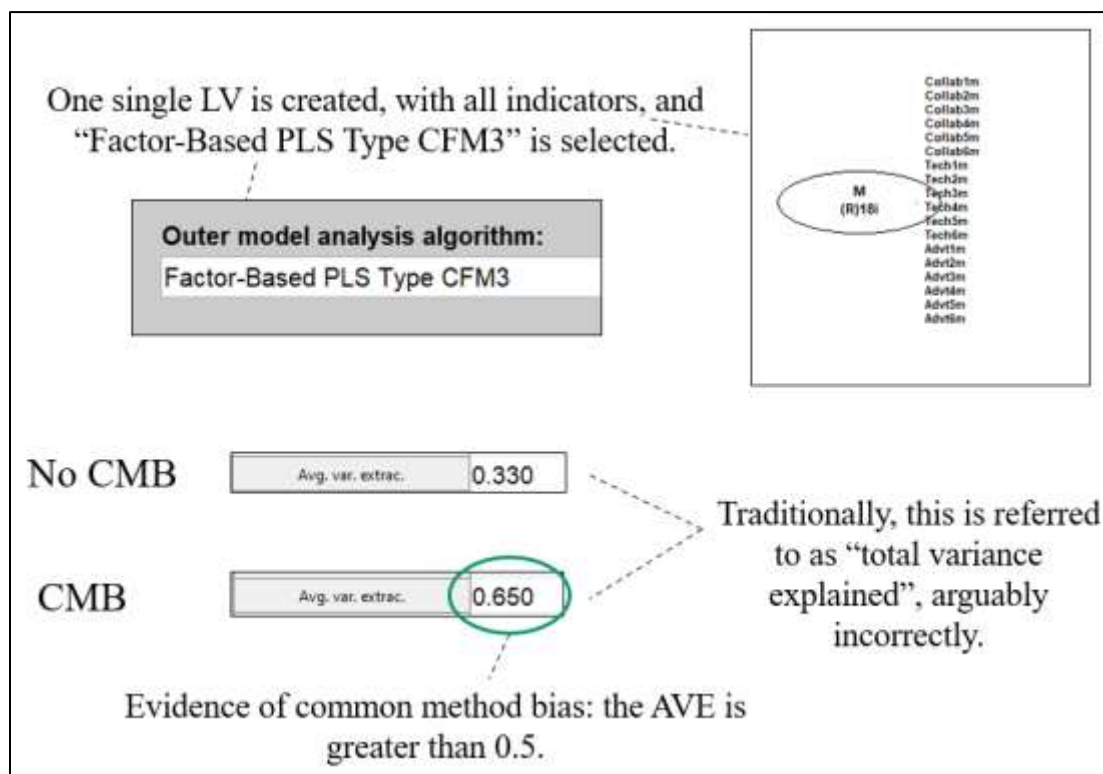
The AVEs for both datasets are shown, contaminated and not contaminated by common method bias. The AVE for the dataset contaminated by common method bias is 0.669, which is greater than the threshold of 0.5. This is interpreted as evidence of common method bias. That is,

the composite-based PLS-SEM implementation of Harman's single factor test succeeded in identifying common method bias in our contaminated dataset.

Factor-based PLS-SEM test

Figure 3 provides a schematic representation of the steps involved in the factor-based PLS-SEM implementation of Harman's single factor test. First, the outer model analysis algorithm is set as "Factor-Based PLS Type CFM3", which is the PLS-SEM equivalent of the algorithm underlying an exploratory factor analysis. Second, all indicators are associated with one single latent variable. Third, the "View latent variable coefficients" menu option is selected; under the "View/save analysis results" button. Finally, the AVE is inspected.

Figure 3: Factor-based PLS-SEM test



Notes: CMB = common method bias; LV = latent variable.

Again, the AVEs are shown for both datasets, contaminated and not contaminated by common method bias. The AVE for the dataset contaminated by common method bias is 0.650, which is greater than the threshold of 0.5 – providing evidence of common method bias. This means that the factor-based PLS-SEM implementation of Harman's single factor test also succeeded in identifying common method bias in our contaminated dataset.

Conclusion

Table 1 shows the AVEs for the composite-based and factor-based PLS-SEM implementations of Harman's single factor test. The bottom row of the table shows the percentage differences between AVEs for each of the tests. For example, for the composite-based test, the AVE for the contaminated dataset is 96.97 percent higher than that for the corresponding dataset without contamination.

Table 1: Average variances extracted

	Composite	Factor
No CMB	0.367	0.330
CMB	0.669	0.650
Difference (%)	82.29%	96.97%

Note: CMB = common method bias.

These results suggest that the factor-based test presents a wider spread in terms of the percentage difference between AVEs in contaminated and not contaminated datasets (i.e., 96.97 percent), which could be seen as a sign of higher sensitivity to common method bias. On the other hand, the composite-based test yields a higher absolute AVE (i.e., 0.669); being the one most likely to correctly identify contamination, but also the most likely to incorrectly suggest contamination. Given these results, researchers are encouraged to conduct both types of Harman's single factor tests, and report their results.

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