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Using causality assessment indices in PLS-SEM

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Abstract

We discuss the use of four causality assessment indices, through an illustrative model analyzed with WarpPLS, a leading software tool for structural equation modeling via partial least squares (PLS-SEM). The indices are the: Simpson's paradox ratio (SPR), R-squared contribution ratio (RSCR), statistical suppression ratio (SSR), and nonlinear bivariate causality direction ratio (NLBCDR). We provide an example of how the causality assessment indices can be presented in a journal article, conference paper, or other research report document.

Keywords: Causality; Simpson's Paradox; Statistical Suppression; Nonlinear Relationship; Structural Equation Modeling; Partial Least Squares; WarpPLS.

Introduction

Certain statistical anomalies in path models with causally linked latent variables (LVs) can be seen as indications that causal assumptions are incorrect. Examples of such anomalies are Simpson’s paradox occurrences, negative R-squared contributions by LV predictors, and statistical suppression instances (Kock, 2015c; Kock & Gaskins, 2016). Causality can be assessed, in the context of structural equation modeling via partial least squares (PLS-SEM), through model indices that measure the extent to which these statistical anomalies are present in models (Kock, 2022a).

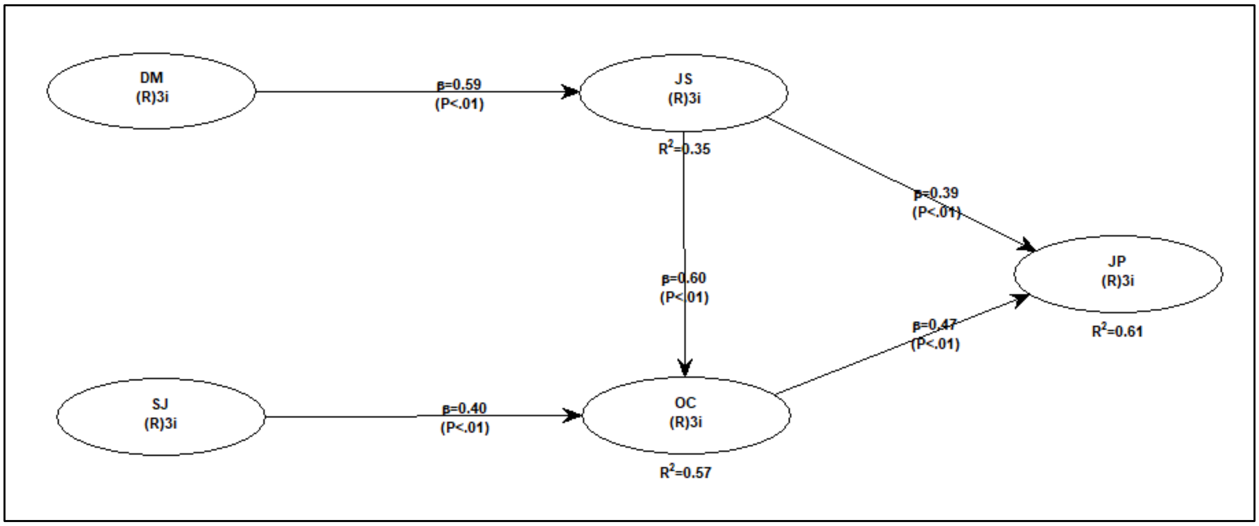
We discuss the use of four causality assessment indices, through an illustrative model analyzed with the software WarpPLS, Version 8.0 (Kock, 2022a). This software is a leading SEM tool that implements classic composite-based as well as more modern factor-based PLS-SEM algorithms (Kock, 2019a; 2019b), among other features that are useful in advanced SEM analyses (Amora, 2021; Canatay et al., 2022; Hubona & Belkhamza, 2021; Kock, 2015a; 2015b; 2016; 2020a; 2020b; 2020c; 2021a; 2021b; 2021c; 2022a; 2022b; Kock & Lynn, 2012; Moqbel et al., 2020; Morrow & Conger, 2021; Rasoolimanesh, 2022).

Illustrative model and data

The illustrative model shown in Figure 1 contains two exogenous LVs, namely DM and SJ; and three endogenous LVs, which are JS, OC and JP. The results shown are based on a simulated dataset, created through the Monte Carlo method (Kock, 2016). The simulated dataset has a size of 500, and was created based on the illustrative model. Because of this, the network of causal relationships shown is by definition the correct one.

The outer model analysis algorithm used to generate the results in the illustrative model was "Factor-Based PLS Type CFM3". Like covariance-based SEM algorithms, this algorithm is factor-based and fully compatible with common factor model assumptions (Kock, 2019a; 2019b). The inner model analysis algorithm used was "Linear". This algorithm does not perform any warping of relationships. Both outer and inner model algorithms are fully compatible with the way in which the simulated data was created via the Monte Carlo method.

Figure 1: Illustrative model used



Notes: DM = democratic management; SJ = scarcity of comparable jobs; JS = job satisfaction; OC = organizational commitment; JP = job performance; notation under LV acronym describes measurement approach and number of indicators, e.g., (R)3i = reflective measurement with 3 indicators.

Given that we know that the network of causal relationships shown on the illustrative model is the correct one, we would expect that any trustworthy causality assessment of the model would suggest a good fit between the simulated data and the causal structure of the model. In other words, we would expect the assessment to suggest that the model is likely to be causality correct. We demonstrate that this is the case later with our illustrative model, when we use the four causality assessment indices mentioned earlier in this paper. These indices are discussed next.

Causality assessment indices

Ever since their initial development, four main model indices have been frequently used in the assessment of causality in PLS-SEM (see, e.g.: Behl et al., 2022; Dubey et al., 2021; Kock, 2021c). They are the: Simpson's paradox ratio (SPR), R-squared contribution ratio (RSCR), statistical suppression ratio (SSR), and nonlinear bivariate causality direction ratio (NLBCDR). The paragraphs below provide an overview of each of these indices. The recommended thresholds are based on extensive Monte Carlo simulations.

SPR. The SPR index is a measure of the extent to which a model is free from Simpson's paradox instances. An instance of Simpson's paradox occurs when a path coefficient and a correlation associated with a pair of linked variables have different signs. A Simpson's paradox instance is a possible indication of a causality problem, suggesting that a hypothesized path is either implausible or reversed. The SPR index is calculated by dividing the number of paths in a model that are not associated with Simpson's paradox instances by the total number of paths in the model. Ideally the SPR should equal 1, meaning that there are no instances of Simpson's paradox in a model; acceptable values of SPR are equal to or greater than 0.7, meaning that at least 70 percent of the paths in a model are free from Simpson's paradox.

RSCR. The RSCR index is a measure of the extent to which a model is free from negative R-squared contributions, which occur together with Simpson's paradox instances. When a predictor LV makes a negative contribution to the R-squared of a criterion LV, where the predictor points at the criterion, this means that the predictor is actually reducing the percentage of variance explained in the criterion. Such a reduction takes into consideration the contributions of all predictors. This index is similar to the SPR. The key difference is that it is calculated based on the actual values of the R-squared contributions, not on the number of paths where these contributions have specific signs. The RSCR index is calculated by dividing the sum of positive R-squared contributions in a model by the sum of the absolute R-squared contributions (be they negative or positive) in the model. Ideally the RSCR should equal 1, meaning that there are no negative R-squared contributions in a model; acceptable values of RSCR are equal to or greater than 0.9, meaning that the sum of positive R-squared contributions in a model makes up at least 90 percent of the total sum of the absolute R-squared contributions in the model.

SSR. The SSR index is a measure of the extent to which a model is free from statistical suppression instances. An instance of statistical suppression occurs when a path coefficient is greater, in absolute terms, than the corresponding correlation associated with a pair of linked variables. Like a Simpson's paradox instance, a statistical suppression instance is a possible indication of a causality problem, suggesting that a hypothesized path may be either implausible or reversed. The SSR index is calculated by dividing the number of paths in a model that are not associated with medium or greater statistical suppression instances by the total number of paths in the model. A medium or greater statistical suppression instance is characterized by an absolute path-correlation ratio that is greater than 1.3. Acceptable values of SSR are equal to or greater than 0.7, meaning that at least 70 percent of the paths in a model are free from material statistical suppression.

NLBCDR. One interesting property of nonlinear algorithms is that bivariate nonlinear coefficients of association vary depending on the hypothesized direction of causality. That is, they tend to be stronger in one direction than the other, which means that the residual is greater when the hypothesized direction of causality is in one way or another. As such, they can be used, together with other coefficients, as partial evidence in support or against hypothesized causal links. The NLBCDR index is a measure of the extent to which bivariate nonlinear coefficients of association provide support for the hypothesized directions of the causal links in a model. The NLBCDR index is calculated by dividing the number of path-related instances in a model where the support for the reversed hypothesized direction of causality is more than weak (with a ratio that is greater than 1.3) by the total number of path-related instances involved in this test. All of the available nonlinear algorithms are used in this test. Therefore, the total number of path-related instances involved in this test is greater than the total number of paths. Acceptable values of NLBCDR are equal to or greater than 0.7, meaning that in at least 70 percent of path-related instances in a model the support for the reversed hypothesized direction of causality is weak or less. Here "less" may mean that the support for reversed hypothesized direction of causality is less than weak (e.g., neutral), or that the hypothesized direction of causality is supported.

Assessing causality

As soon as an SEM analysis is completed with WarpPLS, namely after Step 5 is executed, the software shows the results in graphical format on a window, which also contains a number of menu options that allow the user to view and save more detailed results. The model fit and quality indices are available under the “View general results” menu option (see Figure 2). In WarpPLS, Version 8.0, a total of ten model fit and quality indices are provided. The last four indices are the causality assessment indices discussed in the previous section of this paper.

Figure 2: Obtaining the indices

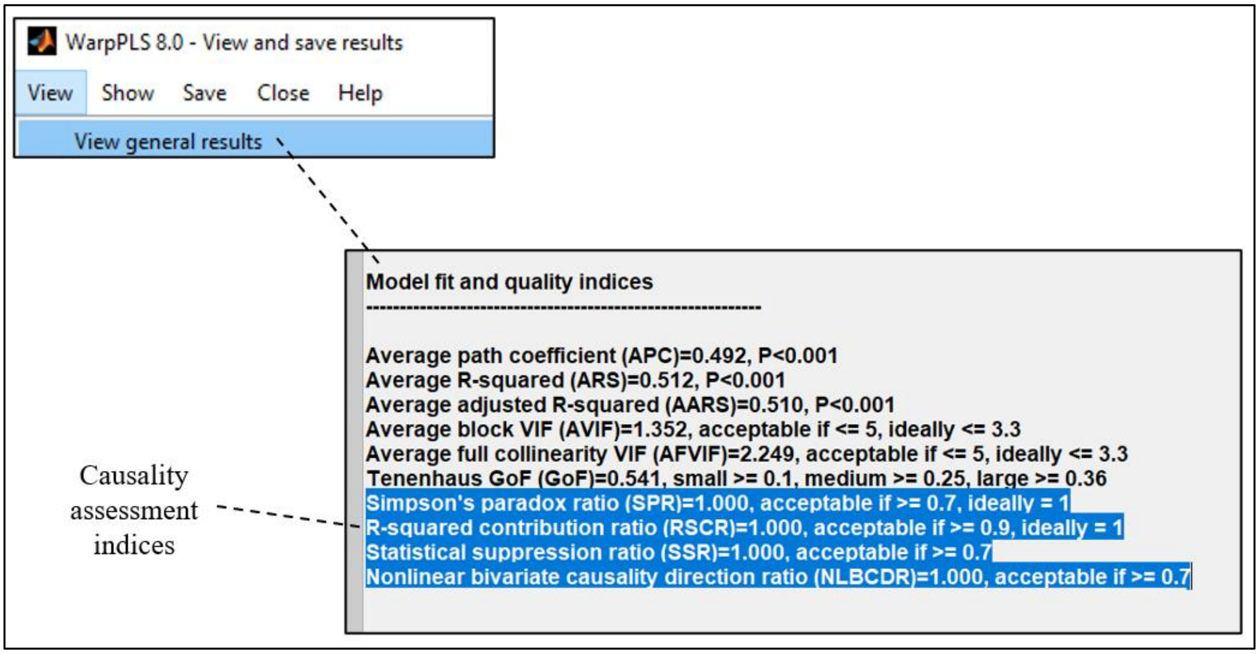


Table 1 provides an example of how the causality assessment indices could be presented in a journal article, conference paper, or other research report document. It is recommended that all four indices be reported, since they reflect multiple aspects of causality assessment. As we can see from the causality assessment indices shown, our illustrative model appears to be causality correct. That is, the indices suggest a good fit between the simulated data and the causal structure of the model.

Table 1: Assessing causality

Index	Value	Assessment
Simpson's paradox ratio (SPR)	1.000	acceptable if >= 0.7, ideally = 1
R-squared contribution ratio (RSCR)	1.000	acceptable if >= 0.9, ideally = 1
Statistical suppression ratio (SSR)	1.000	acceptable if >= 0.7
Nonlinear bivariate causality direction ratio (NLBCDR)	1.000	acceptable if >= 0.7

The good fit was to be expected, since we know that the network of causal relationships shown in the illustrative model is the correct one, because we created the data based on the illustrative model. In fact, the fit is as good as it could possibly be, which is indicated by the fact that all indices achieved the highest possible value of 1. The interpretation of the results is fairly straightforward.

The SPR being equal to 1 means that there are no instances of Simpson's paradox in the model. The RSCR being equal to 1 means that there are no negative R-squared contributions in the model. The SSR being equal to 1 means that 100 percent (or all) of the paths in the model are free from material statistical suppression. Finally, the NLBCDR being equal to 1 means that in 100 percent (or all) of the path-related instances in the model the support for the reversed hypothesized direction of causality is either weak or less than weak.

Conclusion

Certain statistical anomalies in path models with causally linked LVs are indicative of incorrect causal assumptions. We discussed in this paper the use of four causality assessment indices, through an illustrative model analyzed with the software WarpPLS, Version 8.0. The indices are the: Simpson's paradox ratio (SPR), R-squared contribution ratio (RSCR), statistical suppression ratio (SSR), and nonlinear bivariate causality direction ratio (NLBCDR). We provided an example of how the causality assessment indices might be presented in a journal article, conference paper, or other research report document.

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