Assessing multiple reciprocal relationships in PLS-SEM

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Abstract

Two latent variables may influence each other in both directions, in what characterizes a reciprocal relationship. This paper discusses how one can assess multiple reciprocal relationships in the context of structural equation modeling via partial least squares (PLS-SEM). We discuss the assessment of multiple reciprocal relationships, through an illustrative model analyzed with the software WarpPLS.

Introduction

Two latent variables (LVs) may influence each other in both directions, in what characterizes a reciprocal relationship. This paper discusses how one can assess multiple reciprocal relationships in the context of structural equation modeling via partial least squares (PLS-SEM). It is a follow-up on an article by Morrow & Conger (2021), which describes the process used in determining the presence of reciprocal relationships between the two job crafting constructs.

We discuss the assessment of multiple reciprocal relationships, through an illustrative model analyzed with the software WarpPLS, Version 8.0 (Kock, 2022a). This software is a widely used SEM tool that implements both classic composite-based as well as more modern factor-based PLS-SEM algorithms (Kock, 2019a; 2019b), among other features that can be useful in advanced SEM analyses (Amora, 2021; 2023; Canatay et al., 2022; Hubona & Belkhamza, 2021; Kock, 2015a; 2015b; 2015c; 2016; 2020a; 2020b; 2020c; 2021a; 2021b; 2021c; 2022a; 2022b; Kock & Gaskins, 2016; Kock & Lynn, 2012; Ma & Zhang, 2023; Moqbel et al., 2020; Morrow & Conger, 2021; Rasoolimanesh, 2022).

Illustrative model and data

The illustrative model shown in Figure 1 contains two direct links that are to be tested for reciprocity. The model 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. It was created in such a way as to have only one true reciprocal relationship; the JS <> OC relationship, but not the OC <> JP relationship. The latter is a true direct relationship OC > JP.

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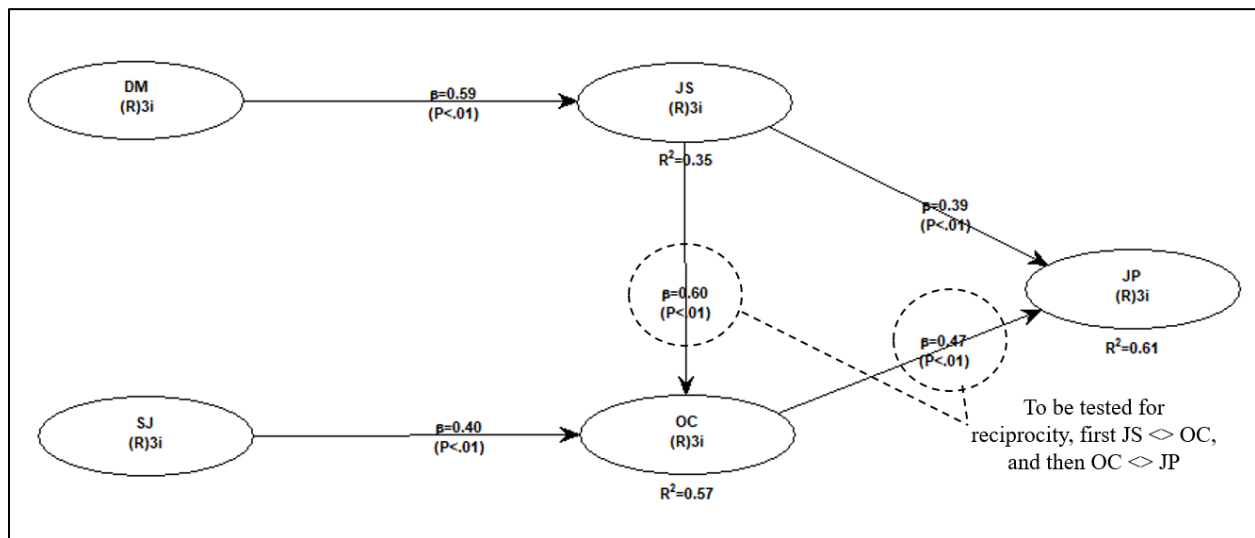
Notes: DM = democratic management; SJ = scarcity of comparable jobs; JS = job satisfaction; OC = organizational commitment; JP = job performance; notation under LV acronym describes measurement approach and number of indicators, e.g., (R)3i = reflective measurement with 3 indicators.

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In order to check for reciprocity with respect to the JS <> OC relationship, we first remove the link between JS and OC (Figure 2), and then control for endogeneity with respect to JS and OC (Figure 3). The endogeneity control is accomplished by employing the procedure discussed by Kock (2022b). It uses the menu option "Explore analytic composites and instrumental variables" of the software, with sub-options "Instrumental variable" and "Single stochastic variation sharing". Here we control for endogeneity with respect to JS by using one instrument, namely SJ. We control for endogeneity with respect to OC by using one instrument, namely DM.
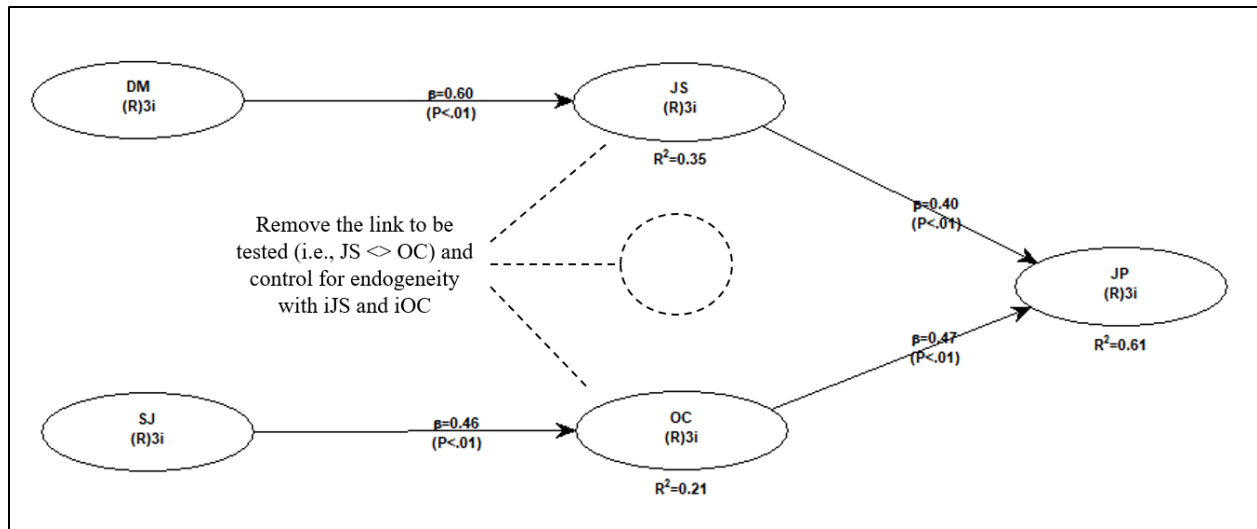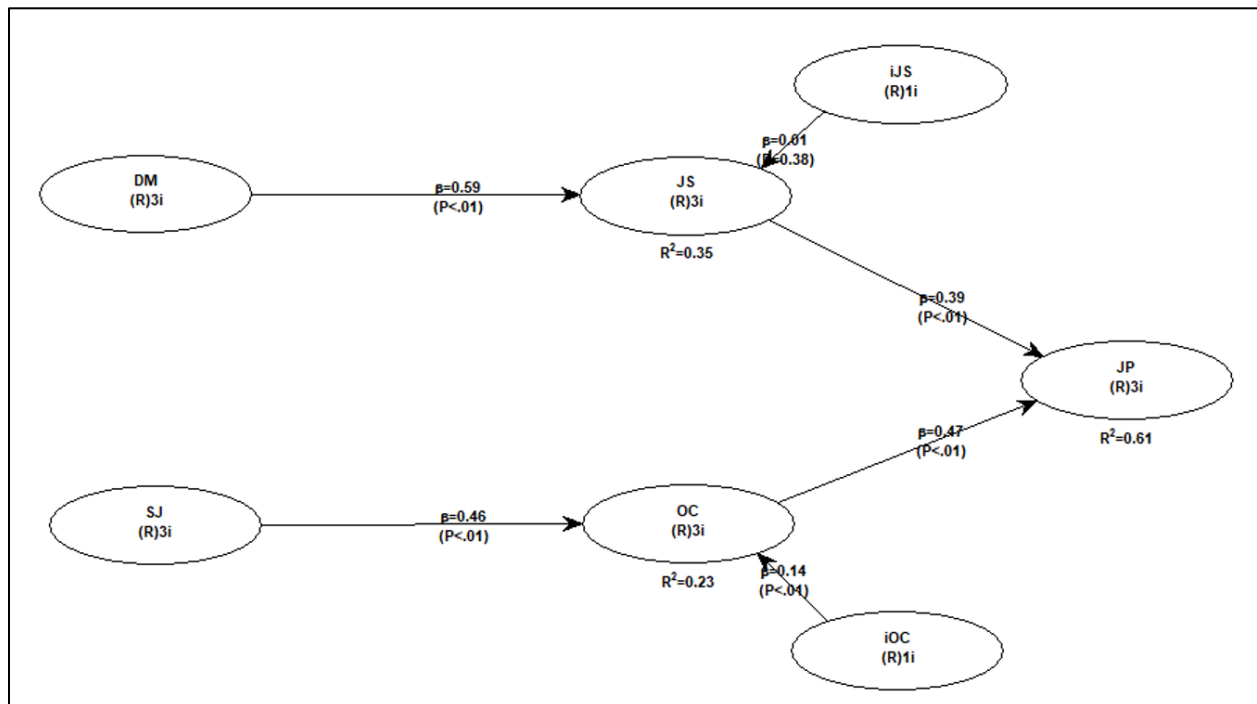
Figure 2: Removing the link to be assessed

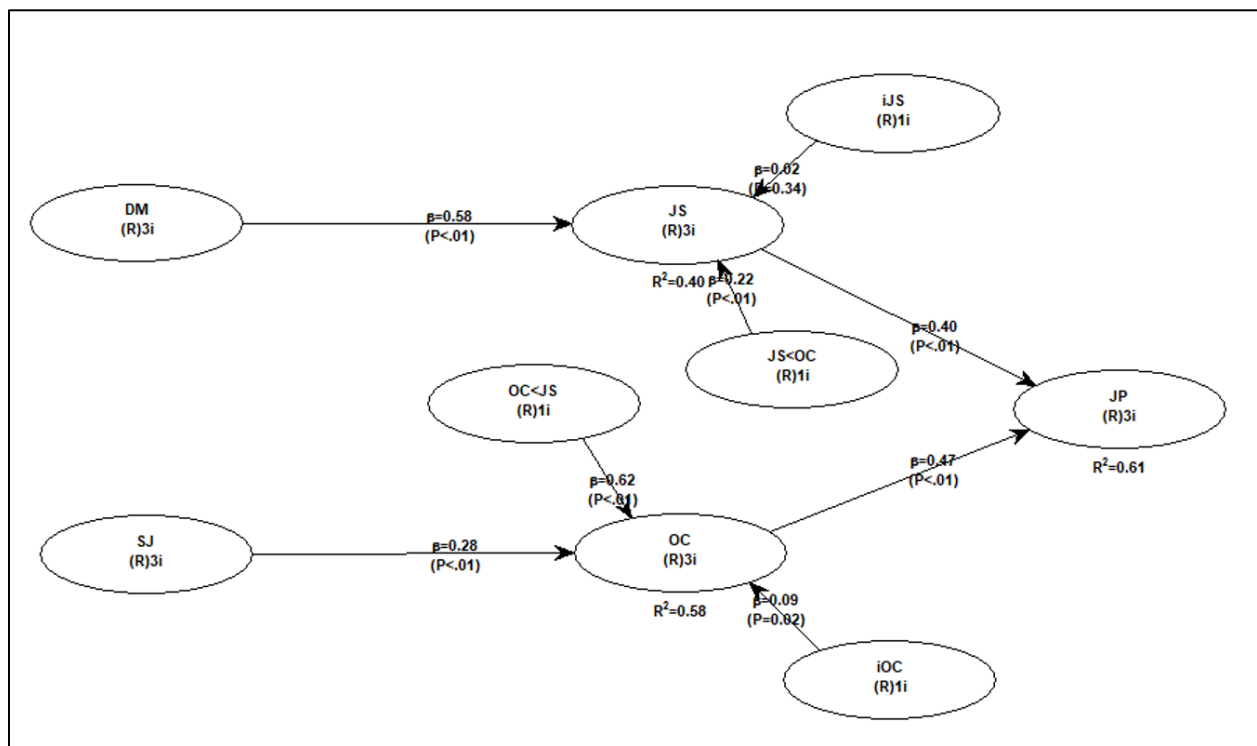**Figure 3: Controlling for endogeneity**

We then proceed to check for reciprocity with respect to the JS <> OC relationship by using again the menu option "Explore analytic composites and instrumental variables" of the software, but now with sub-options "Instrumental variable" and "Reciprocal stochastic variation sharing" (Figure 4). As we can see, the software suggests that there is a reciprocal relationship. We then click "Yes" to create two instrumental variables, which we then add to the model (Figure 5).
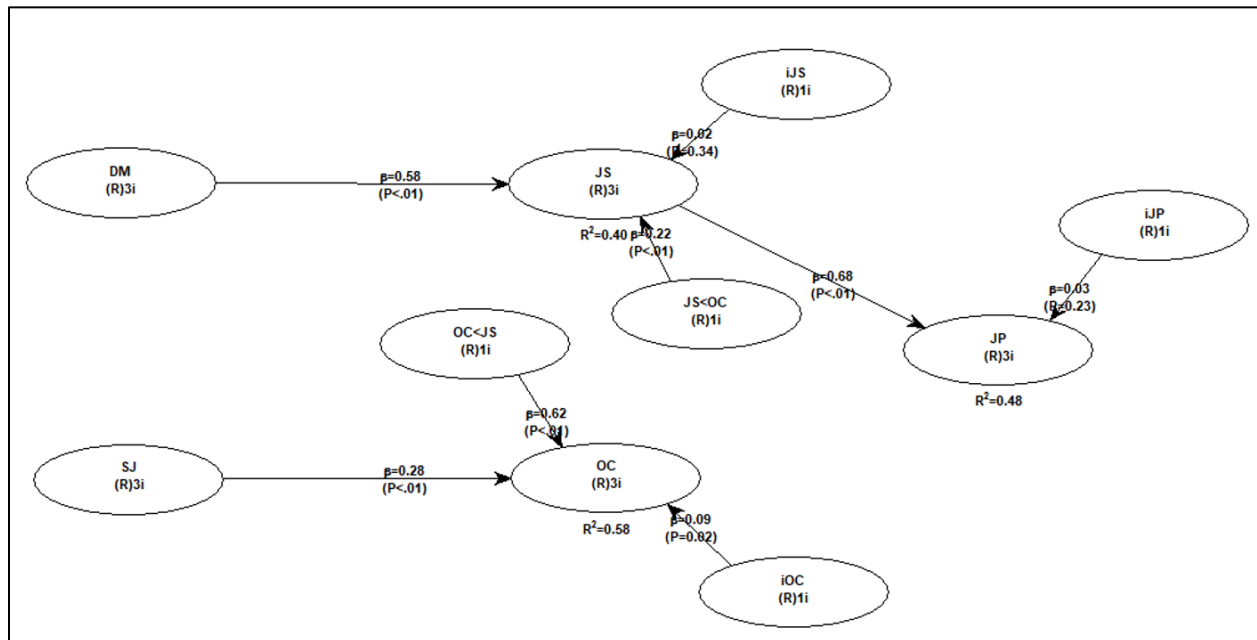
Figure 4: Checking for reciprocity and finding it

What to create?				Instrumental variable creation mode		
Instrumental variable	⌄			Reciprocal stochastic variation sharing		⌄

Notes: start by choosing what to create; analytic composites are aggregations of indicators with set weights, wh(... research; instrumental variables can be used in many applications, such as controlling for endogeneity and ana(...

Create instrumental variables						
*****************************						
Mode: Reciprocal stochastic variation sharing						
*** Reciprocal latent variables						
Available (click to choose only two):	DM	SJ	JS	OC	JP	iJS iOC
Selected (click to remove):	JS	OC				
*** Reciprocal links and coeffs.						
Link:	JS -> OC	OC -> JS				
Std. regression coeff.:	0.618	0.192				
P value:	<0.001	<0.001				
*** Create two instrumental variables (click)?	Yes					

Figure 5: Model with reciprocal relationship

Analogously, in order to check for reciprocity with respect to the OC <> JP relationship, we first remove the link between OC and JP, and then control for endogeneity with respect to JP (Figure 6). As before, the endogeneity control is accomplished by employing the procedure discussed by Kock (2022b). Here we control for endogeneity with respect to JP by using two instruments, namely DM and SJ.

Figure 6: Removing the second link to be assessed and controlling for endogeneity

We then proceed to check for reciprocity with respect to the OC <> JP relationship by using again the menu option "Explore analytic composites and instrumental variables" of the software, with sub-options "Instrumental variable" and "Reciprocal stochastic variation sharing" (Figure 7). As we can see, the software indicates that it cannot find a viable solution, which can be taken as evidence that there is not a reciprocal relationship. If we had originally hypothesized based on theory a direct relationship OC > JP we then conclude that the direct relationship is supported, keeping it in the final model (Figure 8).

Figure 7: Checking for reciprocity and not finding it

Figure 8: Final model

Conclusion

Two LVs may influence each other in both directions, in what characterizes a reciprocal relationship. This paper discussed how one can assess multiple reciprocal relationships in PLS-SEM. It is a follow-up on an article by Morrow & Conger (2021), which describes the process used in determining the presence of reciprocal relationships between the two job crafting constructs. We discussed the assessment of multiple reciprocal relationships, through an illustrative model analyzed with the software WarpPLS, Version 8.0.

Acknowledgments

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